Forest Structure and Biomass in a Mixed Forest-Oil Palm Landscape in Borneo

Oil Palm Plantation-Fragmented Lowland Tropical Forest Interface in Sabah, Malaysian Borneo (Photo: SAFE Project, 2011)

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ABSTRACT:

The research focusses on differentiating between the AGB and forest stand parameters of riparian and non-riparian zones of a mixed land use type in Malaysian Borneo comprising of lowland forests, logged forests and oil palm plantations. Detailed field surveys were carried out to collect forest mensuration data.Field work was complemented by extensive remote sensing analysis. Fourier analysis and grey level co-occurrence based texture analysis techniques were applied on SPOT 5 data for both differentiating and predicting the AGB values for different forest types. It was found Fourier based methods could both differentiate and predict the biomass of different land use types without undergoing saturation. The research establishes thresholds for disturbances these forests zones can undergo before their AGB values decline. The research also determined that AGB value is much higher for riparian margins than for surrounding oil palm plantations. Hence the retention of riparian margins can yield significant carbon storage benefits.

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TABLE OF CONTENTS

LIST OF FIGURES

Appendix – I

Appendix - II

Appendix - III

LIST OF TABLES

TABLE OF ACRONYMS

AGB	Above Ground Biomass
AVHRR	Advanced Very High Resolution Radiometer
BA	Basal Area
BGB	Below Ground Biomass
CO_2	Carbon Dioxide
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
DN	Digital Number
DVCA	Danum Valley Conservation Area
EA	Experimental Area
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
FAO	Food and Agricultural Organization
FFT	Fast Fourier Transform
FOTO	Fourier Transform Textural Ordination
GEM	Global Ecosystems Monitoring

GLCM	Grey Level Co-Occurrence Matrix
H	Height
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LF	Logged Forests
LFE	Logged Forest edge
LULC	Land Use Land Cover
LULCF	Land Use, Land Use Change Forestry
N	Number of Pixels
MBCA	Maliau Basin Conservation Area
MODIS	Moderate Resolution Imaging Spectroradiometer
NDII	Normalized Difference Infrared Indices
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
NPP	Net Primary Productivity
OG	Old Growth forests

OP	Oil Palm plantation
PC	Principal Components
PCA	Principal Component Analysis
PDF	Probability Distribution Function
POM	Point of Measurement
PPI	Pixel Purity Index
R SPECTRUM	Radial Spectrum
RS	Remote Sensing
REDD	Reducing Emissions from Deforestation and Forest Degradation
SAFE	Stability of Altered Forest Ecosystems
SAVI	Soil Adjusted Vegetation Index
SMA	Spectral Mixture Analysis
SPOT	Satellite Pour l'Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SWIR	Short Wave Infrared
T_C	Texture Indices

TAGB	Total Above Ground Biomass
TM	Thematic Mapper
VHR	Very High Resolution
VJR	Virgin Jungle Reserve
WD	Wood Density
YSFMA	Yayasan Sabah Forest Management Area

Chapter 1: Introduction

1.1 BACKGROUND

Over the past 20 years, Borneo has lost over 50% of its native tropical rainforests, an outcome that reflects the expansive and on-going impact of human activities throughout the region (Curran et al., 2004). The rate of deforestation in this region is now the greatest in the world (Morel et al., 2012). Moreover, the rainforests of Borneo have been identified as particularly interesting, since the above ground biomass (AGB) is, on average, 60% higher than that of similar eco-systems elsewhere (Slik et al., 2010). Oil palm cultivation has expanded significantly in Malaysia and has been accommodated by the removal of significant areas of the primary forest (Koh and Wilcove, 2008). Significant portions of Borneo's rainforests now exist as forest fragments and riparian forest zones. Hence, there is a need to maintain a functional ecosystem (preserve ecosystem services, carbon storage, biodiversity) in an oil palm dominated-mixed forest tropical ecosystem. Riparian forests have been identified as having the potential to maintain ecological diversity and functioning in human modified landscapes (Turner et al., 2011).

Riparian zone management has been proven to be effective in addressing many ecological issues related to land use and improving environmental quality (Naiman et al., 1997; Piegay et al., 1997). For example, riparian zones serve as corridors for terrestrial animals and birds (Gillies and St Clair, 2008). Owing to this and to many other advantages, the retention of riparian margins has been recommended for landscape designs, especially in tropical ecosystems that seek to maintain vital ecosystem functioning such as AGB storage, biodiversity conservation (Williams-Linera et al., 1998). The retention of riparian buffer zones has the potential to improve the environmental quality of oil palm plantations (Wilcove and Koh, 2010). Moreover, given that a significant portion of Malaysian Borneo is now dominated by human dominated landscapes like logged forests and oil palm plantations (Reynolds et al., 2011), the study of biodiversity, AGB and structural dynamics of riparian forests has become vitally important aspects of environmental management. This, therefore, is the focus of this research.

Field studies and remote sensing data have been used extensively for the monitoring of forests (Langner et al., 2012; Morel, 2010; Helmer et al., 2012). Modelling using satellite imagery is particularly useful in providing information about the status of the rainforests at a landscape scale (Tottrup et al, 2007), particularly where access is very difficult, as is the case in the Borneo rainforests (Foody et al., 2003). Variables that can be monitored in this way include rate of forest clearance, mapping of above ground level biomass (AGB) (Foody et al, 2003; Cummings et al., 2002; Baccini et al., 2008), forest degradation (Margono et al., 2012), and the structural organisation of the forest canopy (Couteron et al., 2006; Ploton et al., 2012). However, it must be noted that there are no remote sensing techniques that can measure carbon stocks *directly* and these techniques need to be used in conjunction with field data (Gibbs et al., 2007). This research has made use of a combination of field, remote sensing and GIS techniques for estimation of forest stand parameters and AGB in the different forest types of the study area. How these have contributed to the research is illustrated in Figure 1.1 adapted from Maniatis et al. (2010):

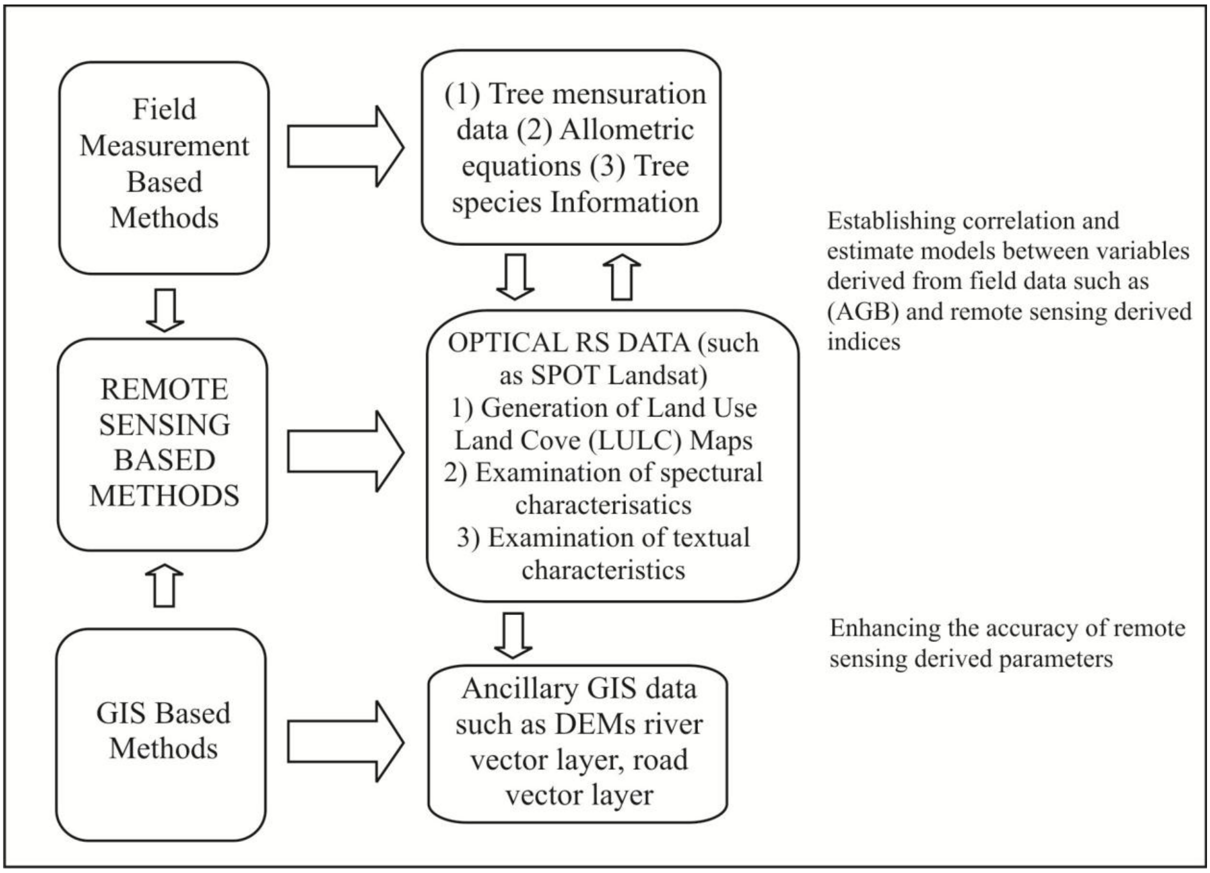

Figure 1.1: Techniques Used For Forest Stand and AGB Estimation (derived from Maniatis et al., 2010)

The research by Berry et al. (2010) indicated that human modified landscapes such as logged forests retain significant carbon storage potential. Little research has been done to evaluate the impact of varying levels of disturbance on AGB storage and the level of disturbance tropical forests of Borneo can take before facing a decline in their AGB storage potential. This research attempts to resolve the problematic nature of forest structure and AGB evaluation especially of forests that have undergone different rounds of logging and ecosystem isolation (as is the case with riparian forests). This study will accomplish this through a usage of more traditional (site-based) and emerging (remote-based) observation technologies. Additionally, this research also seeks to examine the biomass and structural dynamics of remnant, isolated forests which in this case are the riparian forest zones of the study area. Moreover, this particular research also seeks to advance such findings from a monitoring perspective, developing a more comprehensive and replicable field data-RS model that can be used in future monitoring initiatives. This research aims to address the following research questions:

1 What methodology should be employed in order to accurately evaluate and explain the forest structures and AGB dynamics of different forest types ranging from forests that have undergone different logging intensities to oil palm plantations to lightly logged forests?

2. Is optical remote sensing a reliable method for monitoring the current distribution of AGB in vegetation and distinguishing between different types of forests.

3. What are the effects of different degrees of disturbance in the various types of surrounding land use types to the structural and biomass dynamics of the riparian forests?

The existing methods of monitoring using satellite data have significant limitations in estimating biomass levels owing to the complex nature of dense rainforest area and high biomass mass density (Lu et al., 2012). Both of these are present in the study area. Hence it was found necessary to examine complementary techniques and algorithms such as Fourier analysis, principal component analysis (PCA) to use these datasets for identifying the various types of vegetation and of the biomass dynamics within the study area. These techniques do not have a significant coverage in the literature to date and their application represents a contribution to reducing the knowledge gap.

1.2 AIMS

This research has focused on distinguishing the structural and biomass dynamics of the different forest types in the study area and examining the possibility of distinguishing differences in these variables between the riparian forest zones from the surrounding forests. Both field survey and remote sensing survey techniques were employed in this research. Although the ideal value of such research can be linked to monitoring practices and conservation initiatives, from an epistemological and methodological standpoint, this research seeks to contribute differently by presenting new knowledge regarding the practical application of optical remote sensing technology and how it may complement field data. It is expected that this research will enable a deeper understanding of dynamics between AGB storage of forest that have undergone different levels of disturbance and the impact of this disturbance gradient on the adjacent riparian forest zones. On the basis of these primary focal points, the following research aims have been defined:

1. To examine how different degrees of disturbance in the surrounding land use types ranging from light logging to the creation of oil palm plantations influence the structural and biomass dynamics of the riparian forests.

2. To quantify the ranges of AGB values across riparian and non-riparian zones of differing land cover types (e.g. intact and degraded forest and oil palm).

3. To assess the reliability of optical remote sensing for monitoring the current distribution of AGB in vegetation and distinguishing between forests that have undergone variable logging intensities and between riparian-non riparian zones.

4. To develop accurate estimate models (combining field and remote sensing data) to explain the variation in forest structure and AGB dynamics of the different land use types.

This research addresses these aims and objectives, attempting to overcome many of the methodological limitations of past research most of which stem from the limitations posed by optical remote sensing datasets. More importantly, the subsequent chapters will address key gaps in the literature which vary from methodological focal points (lack of replicable methodology across most forest monitoring initiatives) to evaluating the reliability of optical remote sensing for structural and AGB monitoring, (and distinguishing between forest types) to critical appraisal of land use impacts.

1.3 PAPER COMPOSITION

This research is divided into two parts. The first part aims to examine the variation in AGB stocks between riparian and non-riparian zones of the different land use types in the study area and evaluate how disturbances in the surrounding land use type (ranging from light logging to oil palm conversion) may influence the AGB stocks in the riparian zones of the different land use types. The first paper, which is presented in chapter 4, presents the results of the statistical analysis of the AGB data collected in the riparian and non-riparian zones and addresses the research questions pertaining to the first two aims.

The second part of the research focuses on the evaluation of the efficacy of optical remote sensing data in distinguishing between the different land use types in the study region and their biomass dynamics, especially for forests that have undergone different logging rotations. Chapter 5 and 6 present the use and limitations of remote sensing data in distinguishing the different land use types (and related biomass dynamics) in the study area and the possibility of using texture based methods in distinguishing between land use types and their biomass dynamics.

1.4 THESIS STRUCTURE

The structure of the thesis complies with Oxford University's guidelines applicable when using the Submitted Papers Route. Therefore Chapters 3 to 6 have been written in the appropriate format so that they could be submitted to international, peer-reviewed journals (see Appendices IV-VI).

The purpose of the introduction, Chapter 1, is to describe the approach that the author will take to the study, to emphasise the study's aims and to highlight those gaps in the literature that this study addresses.

Chapter 2 presents a review of the academic literature that is specific to fulfilling the aims of the study and that provides the framework for the research questions. It is composed of three key sections that support each aspect of the study and commences with a discussion of the relative richness of the geographical area in terms of its carbon density with respect to rainforests in other parts of the world, such as the Amazon. The sections of the review prepare the basis for the chapters that follow:

1. Introduction in the form of a critical appraisal of the ecosystem within the Borneo rainforests and a discussion of carbon storage.

2. The drivers that surround land use are discussed. Issues in measuring the rate of deforestation and the consequential impact on the survival of various species as a result of new commercial uses, such as extensive logging to satisfy the demand for timber and extension of palm oil growth as a means of food and biofuel production, are considered.

3. The final section examines the methods of assessing the extent of AGB storage in the different land use types in the study area ranging from old growth forests to oil palm plantations. The extent of above ground biomass (AGB) is the key indicator of carbon storage and is estimated by a variety of techniques discussed in this chapter. A second group of carbon storage assessment methods relies on advanced RS technology. Its applications to other forestry based studies are discussed and critically appraised.

Chapter 3 describes the Materials and Methodology associated with the study. It is divided into two sections. The first part centres on the description of the location where the study took place – the Stability of Altered Forest Ecosystems (SAFE) project in Sabah, Malaysian Borneo. The chapter describes the collection and processing of ground and remote sensing data for this study. The limitations of data collection and processing are included. Finally, the chapter focuses on describing advanced remote sensing techniques such as texture analysis which have been used with view of distinguishing between different land use types and their biomass dynamics.

Chapter 4 undertakes examination of the variance in forest structure among riparian and non-riparian zones which have been exposed to different types of land usage and levels of disturbance. The implications which these have for AGB are also examined. A special emphasis is placed on the examination of the species richness, forest structure and AGB values of riparian forests in different land use types and how these variables may be influenced by varying levels of disturbance in the adjacent areas. The forest mensuration data was collected and used to calculate the AGB. The variation in forest structure and AGB was examined between the riparian margins located in different land use types and between riparian and non-riparian zones using statistical modelling. These analyses helped quantify the AGB values of the non-riparian and riparian zones of the different land use types and the levels of disturbance these can undergo before facing a reduction in their AGB values.

Chapter 5 critically evaluates the existing remote sensing techniques that could be employed to distinguish between the different land use types and their biomass dynamics in the study area. The limitations of Landsat TM and SPOT 5 data are considered. Detailed analyses of the different techniques such as those based on spectral characteristics and texture-based measures to evaluate variation in forest stand parameters and AGB across the study area are presented. The analyses identified that spectral based characteristics such as vegetation indices have a limited ability to distinguish between the forests that have undergone different logging rotations. On the other hand, texture-based variables derived from Grey Level Co-Occurrence Matrix (GLCM) could distinguish between the stand and biomass characteristics of the different land use types effectively.

Chapter 6 presents the use of Fourier transform based texture analysis in distinguishing between the different land use types in the study region and deriving individual biomass estimate models for them. Fourier Transform Textural Ordination (FOTO), which uses a combination of Fourier analysis and multivariate ordination techniques was used for this purpose. This method was applied on very high resolution (VHR) SPOT data in order to decompose the spatial information into frequency signals. The results demonstrated that different frequency signals were emitted for varying degrees of disturbance within the tropical forest. This type of analysis when used in conjunction with field study data, allowed for distinguishing between logged forests, riparian forests zones, and oil palm monocultures. Moreover, it allowed for the derivation of individual biomass estimate models.

Chapter 7 is the chapter of conclusions. It provides a review of the results of the three papers presented in the dissertation (Chapter 4, Chapter 5 and Chapter 6) and of the implications of their findings for conservation planning. The main contributions of this thesis are presented as well. These include a description of how the inclusion ground data and application of advanced remote sensing techniques (such as texture analysis) to optical RS data can help overcome many of its shortcomings like saturation and allow for distinguishing between different forest types and their biomass dynamics. By allowing for distinguishing between different land use types and quantification of their biomass values, this research has the potential to inform conservation planning and assist with the operationalization of REDD projects in the future. A review of future research that could be undertaken to extend the scope of the current research is provided.

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Chapter 2 : Literature Review

2.1 INTRODUCTION

The rainforests of Borneo have been identified as global carbon sequestration hotspots with an above ground biomass (AGB) that has been assessed as 60% higher than similar ecosystems in the Amazon (Slik et al., 2010). It has been estimated that over the last 20 years Borneo has lost over 50% of its native tropical rainforest (Curran et al. 2004). In terms of carbon storage value for South East Asia, it demonstrates the largest carbon density, increased with canopy cover – 137 Mg-C/ha for 10% canopy, 155 Mg-C/ha for 25% canopy, 159 Mg-C/ha (Saatchi et al., 2011).

Forest loss is linked to changes in land use and, primarily, commercial logging and oil palm cultivation (Wicke et al., 2011; McMorrow and Talip, 2001). This results in deforestation, subsequent fragmentation, and increased edge effects on trees and associated species diversity. Creation of oil palm plantations is a leading cause of deforestation in Malaysia (Wilcove and Koh, 2010; Fitzherbert et al., 2008). Oil and coffee plantations have carbon stocks 6-31% lower than in natural forests and in general agroforestry and plantation farms have carbon stocks that are 4-27% lower than in undisturbed forests (Lasco 2002). In Sabah alone, approximately 53.4 Tg CO2e was released as a result of conversion of forests to oil palm plantations from 2000-2008 (Morel et al., 2012).

There is debate as to the most effective method to estimate carbon stocks qualitatively as this can affect the perception of the true impact of activities such as deforestation on carbon storage. Comparative research suggests a combination of methods (such as combination of field and remote sensing data) should be used to for monitoring of carbon stocks (Hawes et al., 2012; Ryan et al., 2012; Eva et al., 2012). Accurate estimates of global carbon emission through deforestation can then provide input into reduction strategies, e.g. UN REDD+ (United Nations strategy for Reduction of Carbon Emissions form Deforestation and Forest Degradation) (Gibbs et al. 2007; Burgess et al., 2010).

Conversion of tropical biomes is a source of 1.3±0.2 PgC/year with tropical Asia acting as a source of carbon emissions (Malhi, 2010). This makes the examination of above ground biomass (AGB) dynamics, forest structure and the different factors influencing them in the tropical forests of Borneo of vital importance. This review also examines the impact of changes in land-use, particularly deforestation, logging and oil palm cultivation. The efficacy of monitoring methods of carbon storage (such as field studies and remote sensing data) that are used to quantify carbon storage have been examined.

2.2 CARBON STORAGE AND THE RAINFORESTS OF BORNEO

Tropical and boreal forests contribute significantly more than temperate forests in terms carbon storage. Tropical forests in Asia alone store 35.4 Pg C/yr of carbon (Baccini et al., 2012). Evidence illustrates that large trees in particular play a significant role in carbon storage (Saner et al., 2012). Dipterocarp forests have higher canopies and higher AGB values compared to forests in other parts of the tropics (Gouvenain and Silander, 2003). In Borneo, Dipterocarps store greater carbon volumes (11.3 ± 0.7 m^2ha^{-1}) than smaller pioneer genera such as *Maccaranga* (8.6 ± 0.2 m^2ha^{-1}) (Saner et al, 2012). Tropical forest species composition plays a significant role in carbon sequestration; with above ground carbon sequestration varying up to 60% depending on tree species (Bunker et al. 2005). Saner et al. (2012) suggest that carbon sequestered in growing Dipterocarps in unlogged areas yields the highest amount of carbon storage. Research has shown that in a diverse rainforest such as that found in Borneo, wood density, water content, tree mortality and diameter at base height can vary considerably. These can affect the value of individual trees and groups as representative samples to calculate AGB at a higher landscape level (Osunkoya et al. 2007).

2.3 IMPACT OF LAND USE CHANGE

2.3.1 Creation of Forest Fragments

Tropical forest ecosystems, notably such as those in Southeast Asia face very high levels of deforestation (Miettinen et al., 2011; Sodhi et al., 2004). This has led to forests existing as patches or fragments or riparian zones in an agriculturally dominant landscape. These forest fragments become increasingly isolated over time (Benedick et al., 2003; Brook et al., 2003). In Sabah, forest fragments exist as isolated patches in an oil palm dominated landscape (Bruhl and Eltz, 2008; Koh et al., 2009). Forest fragmentation results from deforestation and the subsequent edge effects can extend deep into the remnant forest fragments (Numata et al., 2011). Selective logging and related fragmentation can lead to an alteration of forest bio-physical properties and changes in micro-meteorological conditions (Broadbent et al., 2008). These, in turn, can lead to increased tree mortality which lead to changes in biomass stocks and carbon fluxes in the forest fragments (Nascimento and Laurance, 2004).

Further changes in the surrounding land use too can have a significant impact on the carbon fluxes of the fragments (Ramankutty et al., 2007). Edge effects have been associated with rapid biomass collapse in the remnant forest fragments (Numata et al., 2011). Logged forests in Borneo are characterized by a lack of big trees and even two decades after recovery, they only store 60% of the biomass stored by primary forests (Hector et al., 2011). Research carried out by Lasco and Pulhin (2009) in the Philippines indicated a 50% loss in AGB values subsequent to logging. While a significant proportion of research has been devoted to examining the impact of fragmentation and changes in surrounding land use types on the biodiversity of forest fragments (Laurance et al., 2011; Struebig et al., 2008), evaluation of variation in AGB stocks in the remnant forest fragments such as the riparian zones of Borneo have not been subjected to similar research scrutiny.

2.4 CAUSES OF FOREST LOSS

Drivers of deforestation vary significantly across the tropical regions. While cattle ranching is a leading cause of deforestation in the Brazilian Amazon (Barona et al., 2010)), deforestation and land use change in Borneo has been driven by an increased demand for timber and more recently, for oil palm.

2.4.1 Deforestation and Timber Extraction

The impact of deforestation has been estimated to be in the region of 1-2 billion tonnes per year in terms of the release of carbon dioxide. This accounts for 15-25% of annual global greenhouse gas emissions (Gibbs et al 2007; van der Werf et al., 2009). Southeast Asia suffers from the highest rates of deforestation of all the tropical regions (Morel et al., 2012). The export of Dipterocarp timber from Borneo in the last two decades has been greater than tropical wood export from Africa and Central America combined (Curran et al. 2004). Removing the trees, especially the larger Dipterocarp trees like the *Shorea* can then result in an increase in canopy opening and increase in smaller pioneer vegetation species that fix less carbon per plant (Cannon et al. 1998). This significantly reduces carbon storage volumes per unit of ground area within forest cover.

In Borneo, uncontrolled deforestation rates have resulted in a 57% reduction of forest cover (Saner et al. 2012). Pioneer tree species have also become prevalent in logged forests as opposed to native Dipterocarp species which accounted for 28 % of basal area in logged forest compared to 61% in undisturbed forest (Saner et al. 2012). An evaluation of logging shows felling of hardwood species causes the AGB to be reduced from 70 to 10 MgC/ha with a recovery rate measured in decades. Based on current rates (Saner et al. 2012), recovery of trees to storage capacity age average forty years from felling to re-establishment. Logging releases emissions of 30MgC/ha per year and it requires at least 5 years initial regeneration before the carbon sink process initiates effective carbon storage again, illustrating the long term difficulties in restoring carbon stocks through the restoration of the tropical rainforest (Houghton 2005). It has been assessed that the loss of tropical rainforests and carbon storage has halved volumes between 1980 and 2000 whilst in the same period the establishment of plantation forest has increased to at least 4 times their original areas (Houghton 2005). This global trend is reflected in evidence relating to the loss of Borneo tropical rainforest estimated by data to be around 53% in a comparative 19 year period (Berry et al. 2010).

2.4.2 Oil Palm Expansion

Over the past few decades, the oil palm has become one of the most rapidly expanding crops in the world (Koh & Wilcove 2007). It occupies 13.8 million hectares in the tropics (FAO, 2009). In Malaysia, the area under oil palm plantations has expanded significantly since 1950, making the country, along with Indonesia, one of the largest producers of oil palm in the world. As of 2005, oil palm plantations in Malaysia stood at about 4,050,000 hectares (Sumathi et al., 2008). The expansion of area under oil palm plantations from 1950 to 2008 is shown in figure 2.1:

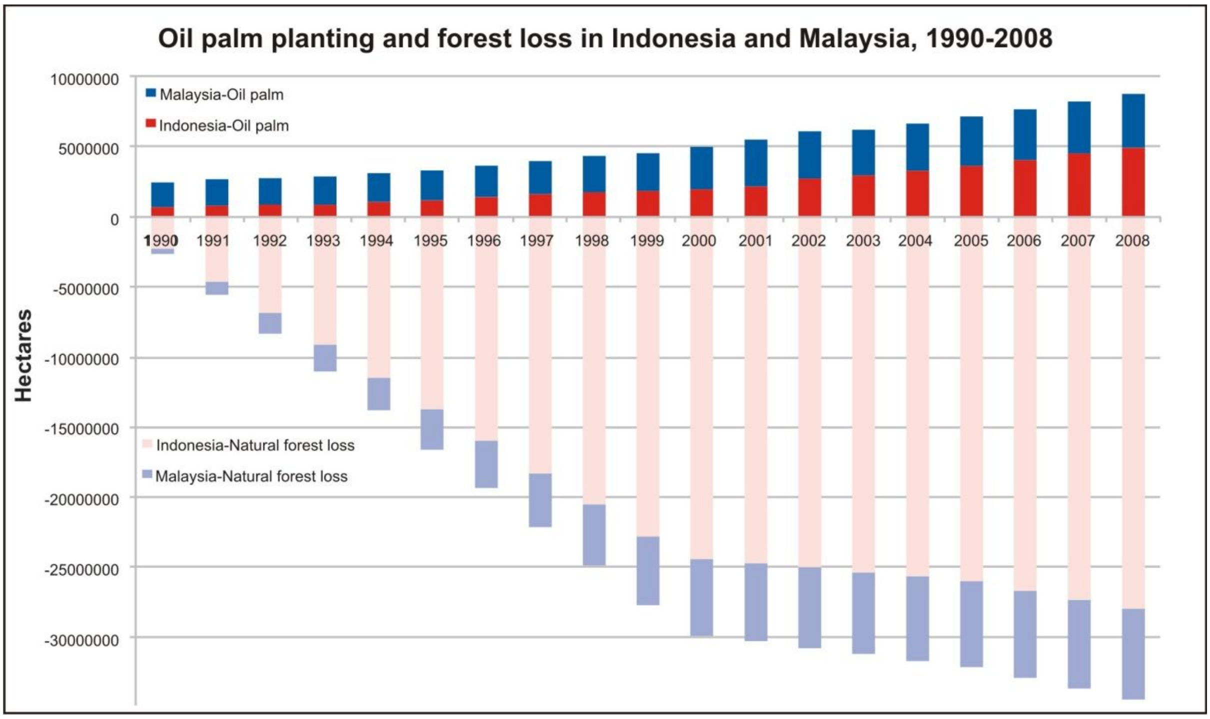

Figure 2.1: Oil palm expansion in Malaysia from 1950-2008 (from Mongabay, 2012a)

Oil palm plantations today cover large areas of former tropical lowland rainforests in Southeast Asia and are rapidly expanding on the island of Borneo. In Sabah alone they cover 15% of the land area (Bruhl and Eltz, 2008). The rapid growth of the oil palm industry can be attributed to its uses, which include food products, and other consumer goods such as cosmetics, industrial lubricants and biofuels (Corley & Tinker 2003). Rapid oil palm monoculture expansion has been taking place at the cost of primary forests in the tropics (Corley, 2009). In Malaysia, a significant percentage of oil palm expansion has taken place at the cost of primary forests (Koh and Wilcove, 2008). For instance, in Sabah, primary forest cover has reduced from 2.8 million hectares to 300,000 hectares from 1975 onwards (Reynolds et al., 2011).

A substantial body of literature indicates that the expansion of oil palm plantations affects a wide variety of species in the Southeast Asia. Palm oil monoculture plantations support lesser biodiversity than the forests they replace. Across all taxa, only 15% of species recorded in primary forests were found in oil palm plantations (Fitzherbert et al., 2008). In addition to affecting biodiversity, the creation of oil palm plantations also influences the regional biomass stocks. Deforestation followed by plantation establishment has a significant effect on carbon stocks and greenhouse gas emissions. Henson (2005) estimated that the expansion of agricultural plantations from 1981 to 2000 led to an overall decline in biomass carbon stocks in forests and tree crops in Malaysia.

The emissions from land-use change associated with plantation expansion may be significant. Use of areas such as forests with higher carbon stocks would result in net emissions (Henson 2005). Even though monocultures, including those of oil palm are known to sequester carbon at a faster annual rate compared to a naturally regenerating forest, towards the end of its life, the oil palm plantation will store 50–90% less carbon (estimated over 20 years) than the original forest cover (Ch'nget al. 2009). Danielsen et al. (2008) regarded oil palm cultivation as a double jeopardy for biodiversity and carbon stocks in Southeast Asia. According to the authors' estimate, 75 to 93 years would be required for the carbon emissions saved through use of biofuel to compensate for the carbon lost through forest conversion (Danielsen et al., 2008). These findings have been corroborated by Achten and Verchot (2011) who examined changes in carbon stocks owing to land use conversion. Their findings suggest biofuels obtained from conversion of natural ecosystems (notably oil palm) cannot be efficient and that oil palm plantations create carbon debt that could last for decades.

2.5 ASSESSMENT OF CARBON STORAGE

2.5.1 Field Methods

Modelling using large scale satellite imagery alongside ground-based physical data has enabled significant progress in the global assessment of carbon stocks. The most important predictors of AGB of a given tree are its trunk diameter (or diameter at breast height, DBH), wood specific gravity, tree height and forest type, specifically, whether the forest is wet, dry or moist (Maniatis, 2010). These equations have been generated through the destructive sampling of trees in a given tropical biome (Chave et al., 2003). In order to calculate AGB and subsequent carbon storage in the field, the general equation prescribed by Chave et al. 2005 is used. The equation is:

$$\ln(TAGB) = c + \alpha \ln(DBH) + \beta \ln(WD) \qquad (2.1)$$

Where TAGB (Total above ground biomass) in kg/tree, is related to Diameter at Breast Height (DBH) in cm and Wood Density (WD) in g/cm and B is the slope coefficient of the regression for mixed species forests (Saner et al. 2012). Carbon storage is then assumed to be 50% of the biomass (Berry et al. 2010). Berry et al. (2010) indicated that it is the Chave et al. (2005) calculations that generally form the majority of estimates of AGB carbon stocks within the research community. Other methods utilize measurement of canopy characteristics such as tree crown coverage to establish a baseline from which to test and compare (Osunkoya et al. 2007). The measurement at ground level to collect data to determine AGB and carbon are relatively simple by measuring standing live and deadwood through measuring tree basal area and density to calculate a volume which can be extrapolated depending on species, sampling regime such as transects or quadrants (Saner et al., 2012).

2.5.2 Use of Remote Sensing Data

Over the past few years, there has been an increased proliferation of remote sensing data in forest management and monitoring of land use changes (Putz et al., 2008; Olander et al., 2008). The use of RS data products has been given a significant boost by the availability of remote-sensing systems such as Landsat and AVHRR which are operational at the global scale and provide a globally consistent record for the past three decades (Gibbs et al., 2007). Remote sensing offers a practical way to evaluate forest conditions at a landscape scale, especially for remote and inaccessible areas (Saatchi et al., 2007). The most common applications of remote sensing have been in the field of monitoring spatio-temporal changes in land use/land cover and evaluation of deforestation and degradation (Meyfroidt and Lambin, 2009; Hansen et al., 2009). Margono et al. (2012) utilized Landsat TM data for monitoring deforestation and degradation trends in Sumatra. Their analyses quantified the extent and change in primary forests in the region; which amounted to a 70% of conversion of forested area by 2010. The study further distinguished between areas that had undergone deforestation and degradation. A combination of Landsat ETM+ and MODIS was used to analyse the per annum spatio-temporal variation in land cover changes in Sumatra and Kalimantan (Broich et al., 2011). A similar regional study focusing on the island of Borneo was undertaken by Yamagata et al. (2010). The authors used AVHRR data in conjunction with SPOT VEGETATION data to map the changes in forest cover from 1983 to 2008. High resolution SPOT data was used in conjunction with medium resolution satellite data to generate a land cover map of insular South East Asia that included Peninsular Malaysia and the islands of Sumatra, Java and Borneo. These data were used for both analysing the structure of land cover classes and generating biomass estimates for the major ecosystems in the study area (Miettinen and Liew, 2009). Combination of Landsat ETM+ and high resolution IKONOS data have been used for mapping the structural parameters and species composition of riparian zones in tropical savvanas of Australia (Johansen and Phinn, 2006).

Remote sensing data can be used for identifying drivers of deforestation in a given region. Norwana et al. (2010) used temporal Landsat data from 1979, 1991 and 2005 to evaluate land use changes and drivers of forest loss in Sabah, Malaysian Borneo. Similar results have been obtained from the analysis of Landsat imagery over the neighbouring state of Sarawak, which indicated that forests are being deforested at a rate of 0.64% per annum and the leading cause of this is the expansion of oil palm plantations (Tsuyuki et al., 2011). Similar remote sensing based analysis of deforestation drivers has been undertaken in Brazilian Amazon (Ometto et al., 2011). Remote sensing is a valuable tool for quantifying, mapping and monitoring AGB (Basuki, 2012). Remote sensing based estimation of AGB is usually carried out using radar or optical remote sensing datasets (Langner et al., 2012).

2.5.3 Use of Optical Remote Sensing Data for AGB Estimation

Optical data such as that obtained from Landsat, MODIS, AVHRR has been widely used for estimating biomass of a number of different tropical forest ecosystems. Landsat TM and ETM+ data were used to derive an index which was used to study the crown conditions of two logging coupes situated in the lowland Dipterocarp forests of Malaysian Borneo. One of the coupes is under a conventional logging management scheme while the other follows sustainable forestry management practises and follows reduced impact logging. The Landsat index-based analysis estimated that by following sustainable forestry management practices, the logging coupe gained 6.1tC/ ha/annum from 2000-2007 (Langner et al., 2012). Landsat ETM+ derived variables were used in conjunction with field inventory data to derive biomass estimates for a forest concession (selectively logged from 1976-2003) in East Kalimantan. The analysis indicated a strong correlation between the Landsat derived variables and the field AGB values (Basuki, 2012). Landsat TM data was used in conjunction with field data to estimate the AGB of bamboo forests in China (Xu et al., 2011). Medium resolution MODIS data was used in conjunction with extensive field data to develop an AGB map of tropical forests in Africa (Baccini et al., 2008). Landsat TM data over Central America, South America and the Caribbean was utilized to evaluate forest change between 1990, 2000 and 2005 and associated carbon emissions (Eva et al., 2012). Hence it may be inferred that optical

RS datasets are effective in predicting variations in AGB for a number of different tropical ecosystems at a variety of geographical locations and different spatial scales. However, optical RS data have a number of shortcomings such as inability to penetrate the thick canopy (Langner at et al., 2012), saturation at high biomass values (Barbier, 2010; Steinger, 2000) and the presence of persistent cloud cover (Ju and Roy, 2007).

Optical RS data have been used in conjunction with other types of remote sensing data (notably radar data) for the purpose of biomass estimation. For instance, Yamagata et al. (2010) used ALOS PALSAR radar data in conjunction with AVHRR and SPOT to generate a land cover map of Borneo and to identify the spatial distribution of biomass in the region. Landsat ETM+ and ALOS PALSAR satellite data were used by Morel et al. (2011) to evaluate the land use changes and carbon released as a result of forest degradation that had taken place in Sabah from 2000 to 2008. The research established the capability of Landsat ETM+ to distinguish between forested areas and oil palm plantations. The research also indicated that Landsat ETM+ derived indices showed stronger correlation to oil palm as compared to indices derived from high resolution imagery. The radar data, on the other hand was unable to distinguish the biomass stocks of oil palm plantations from the other forested area (Morel et al., 2011). Radar data has the ability to penetrate the thick canopy of the forests (Morel, 2010) and these data are unaffected by cloud cover (Asner, 2001). Radar data can overcome many of the shortcomings of optical data and field based research. These data are very effective for mapping forest extent and deforestation but are limited in their scope to measure AGB in dense, close-canopied tropical forests (Woodhouse et al., 2012). This makes it necessary to examine to different processing techniques that maybe applied to optical RS data in order to enable its usage for AGB estimation.

2.5.4 Comparison of Spectral versus Texture Based Techniques

Calibration of satellite data derived variables with in-situ ground measurements of AGB is the generic methodology for generating biomass estimate models (Goetz et al., 2009). Indices derived from spectral characteristics of remote sensing data such as vegetation indices, band reflectance values have been commonly used in conjunction with forest structure and AGB from the field to study these variables at a landscape level (Freitas et al., 2005; Yang et al., 2003). However the use of spectral parameters for estimation of AGB and forest structure has produced mixed results. Lu et al. (2004) used vegetation indices, reflectance values of

Landsat bands along with other variables derived from Landsat TM data in conjunction with field AGB data from the Brazilian Amazon. Their analysis found significant correlation between many of the Landsat TM derived variables and field AGB values. However, for lowland Dipterocarp forests of Borneo, spectral characteristic based variables have produced mixed results. Okuda et al. (2004) carried out an examination of TAGB data collected at the Pasoh Forest Reserve (Peninsular Malaysia) with Landsat reflectance values and vegetation indices such as NDVI, This examination indicated a weak correlation with field and RS values. On the other hand, Tangki and Chappell (2008) reported a strong strength of association between the radiance values of band 4 and field AGB data collected from a logging concession in the Malaysian Borneo.

As opposed to spectral parameters, texture analysis based methods have shown a greater promise with regards to the generation of biomass estimate models. Landsat TM and JERS-1 SAR data was used to estimate biomass at three different geographical locations Brazil, Thailand and Malaysia. Texture measures were derived from the JERS-1 SAR data and coupled with multi-spectral data as inputs into an artificial neural network model. Ground data from 144 plots were used in order to generate biomass estimate models that are transferable across different regions (Cutler et al., 2012). Application of texture analysis to optical RS data too has yielded valuable insights. Wijaya et al. (2010) used a number of Landsat derived measures including vegetation indices and texture variables to examine the spatial variations in AGB and forest stand parameters in Kalimantan. Their research indicated that biomass and forest stand values had a significantly higher strength of association with variables such as statistical texture measures derived using grey level co-occurrence (GLCM) matrices (Wijaya et al., 2010). These findings are corroborated by a similar research carried out by Castillo-Santiago et al. (2010) in Mexico which derived GLCM texture variables from SPOT-5 data. These texture variables showed a strong correlation with different aspects of forest parameters such as basal area, canopy height and bole volume. In the studies conducted byEckert 2012 and Tsuyoshi et al., 2009, texture variables showed a high strength of correlation with the forest stand parameters as well. In addition to statistical based measures like GLCM, Fourier based techniques such as Fourier transform textural ordination (FOTO) has proved to be effective in biomass estimation for tropical forests. Priosy et al. (2007) have used FOTO derived texture indices to generate a biomass model for the mangroves of French Guiana. Ploton et al. (2012) have applied the same methodology to generate FOTO texture indices based biomass estimation for Westerns Ghats in India.

The use of satellite imagery to map areas and the development of models has also increased the accuracy of measuring carbon storage levels, especially at landscape and regional levels. It is important, however, that the satellite imagery is ground checked through practical field measurements based on tree species, density and size. This must be carried out to qualitatively support the results of the imagery interpretation (Foody et al. 2003).

2.6 CONCLUSIONS

Trees play a significant role alongside soil and in carbon storage with trees providing functional fixation through a variety of above ground and below ground activities. The composition of Borneo rainforests and more specifically the distribution of Dipterocarp species are important globally in terms of carbon storage. There is little current understanding about the impacts of deforestation and fragmentation (especially that arising out of oil palm conversion) on the AGB storage of the Bornean rainforests. This knowledge can only be gained through improving techniques to quantify the volume of AGB stored and corresponding increases and decreases in storage capacity as a result of land use changes. Evidence reviewed suggested that whilst field based detailed surveyed are the most accurate methods to determine carbon capacity as a result of the diversity of the rainforest ecosystem, technological developments in remote sensing are increasingly improving large scale global assessments. Research indicates that techniques that help assess vegetation characteristics at a three dimensional level will take into consideration local variations in forest size and fragmentation will, in the future, replace the interpretation of satellite and visual imagery at the wider scale in the future.

This review has highlighted the need to investigate the variations in AGB storage in Borneo's different forests and the impact of land-use activities on it as there is limited data to quantify carbon sequestration values of long-term Dipterocarpus hardwood stands compared with plantations, and logged forests. Further, the review has discussed the use of ground and remote sensing data in investigating the carbon storage in different ecosystems present in Borneo. These examples from the bedrock of research carried out and discussed in this dissertation. In the long term it is expected that the results of these investigations will determine not only the current value but the future value of tropical rainforests (and especially remnant forests) such as the riparian forests found in the study area with regard to above ground biomass storage.

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Chapter 3: Materials and Methods

Chapters 1 and 2 provided a background and an extensive explanation of the different ground based and remote sensing techniques used in the research. So far, the philosophical and methodological foundations of the research have been fleshed out. The research has used remote sensing data in conjunction with field data with the view of distinguishing between the structure and biomass dynamics forest types that have faced varying levels of disturbance. Further, by the use of remote sensing and ground based techniques, the research has sought to determine whether the structural and biomass dynamics of remnant forests (in this case riparian zones) could be distinguished from the surrounding land use types.

This chapter provides an overview of the field site where the field data collection was carried out along with a description of the ground and remote sensing data that has been used. The description of the study area and RS data is provided in section 3.1. The processing techniques applied on the ground and remote sensing data are provided in section 3.2. A further section, section 3.3 provides description of the more advanced remote sensing techniques that have been used later in the dissertation.

3.1 MATERIALS

3.1.1 Study Area

The study area is located in Sabah, Malaysian Borneo. This part of Malaysian Borneo experienced a steep rise in commercial logging activities from the 1970s. As a result, by 1990 there was a dominance of commercially logged forests over primary intact forests. The decline in the area of primary forest has continued unabated over the past two decades (Reynolds et al., 2011) (Figure 3.1):

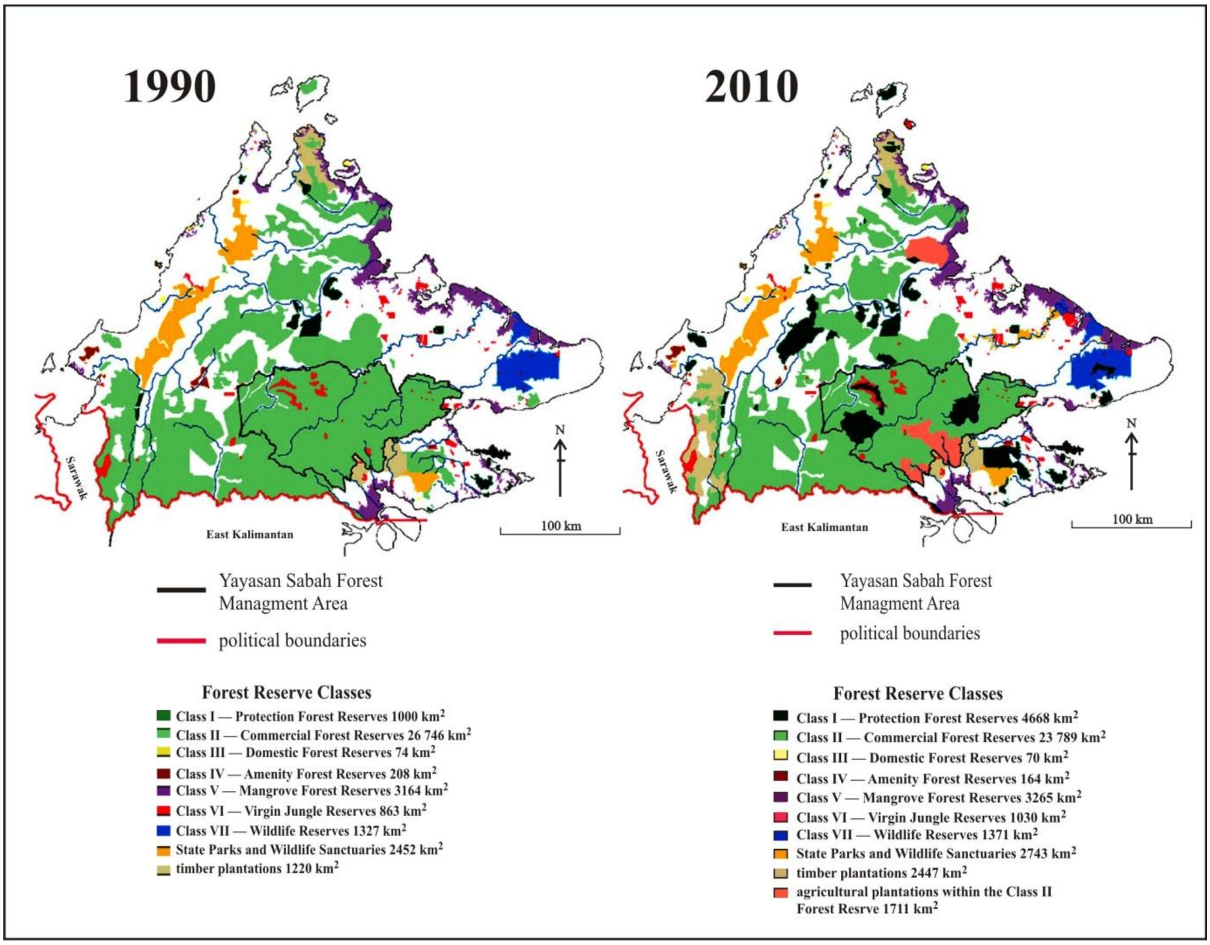

Figure 3.1: Changes in Forest Classes from 1990-2010 (Reynolds et al., 2011)

Even though the deforestation rates are significantly lower as compared to the regional average, forest conversion in the form of repeated logging or conversion to plantations remains a significant problem. For instance, since 1990, most of the forest land under Commercial Reserves has been logged once; and in some cases, subjected to repeated rounds of logging. Another worrying trend has been the sharp decline in the land under primary lowland forests. In 1990, Sabah had 5000 square km of primary land (a significant portion of it being held in Commercial Reserves). By 2010, the forest cover had declined to 700 square km. Most of the primary lowland forests are now concentrated in the Danum Valley Conservation Area or DVCA (438 square km) and around Maliau Basin (Reynolds et al., 2011). This remainder of the primary forest remains under the management of the Yayasan Sabah Forest Management Area (YSMFA). YSMFA has forest concession rights of over 1 million hectares of land. About 750,000 hectares of forests have been selectively harvested since the 1970s while 60,000 hectares have been devoted to agriculture and exotic timber plantations. An estimated 80,000 hectares were converted to oil palm plantations by 2010

(SEARRP, 2010). Over the past few years, oil palm expansion has become a significant driver of deforestation in Malaysia. For instance, Sabah has been the largest producer of oil palm in Malaysia and accounts for 31% of all of Malaysia's oil palm production (Norwana et al., 2011). Hence, the landscape in Sabah (and increasingly elsewhere in Southeast Asia) has been dominated by mixed landscapes where primary lowland forests have been increasingly isolated in a logged forest-oil palm dominated matrix (Turner et al., 2011; Reynolds et al., 2011).

This mixed landscape also forms the backdrop of the study area site at the SAFE (Stability of Altered Forest Ecosystem) project in East Sabah. Figure 3.2 illustrates the mixed land use nature of the landscape and the detailed layout of the study area.

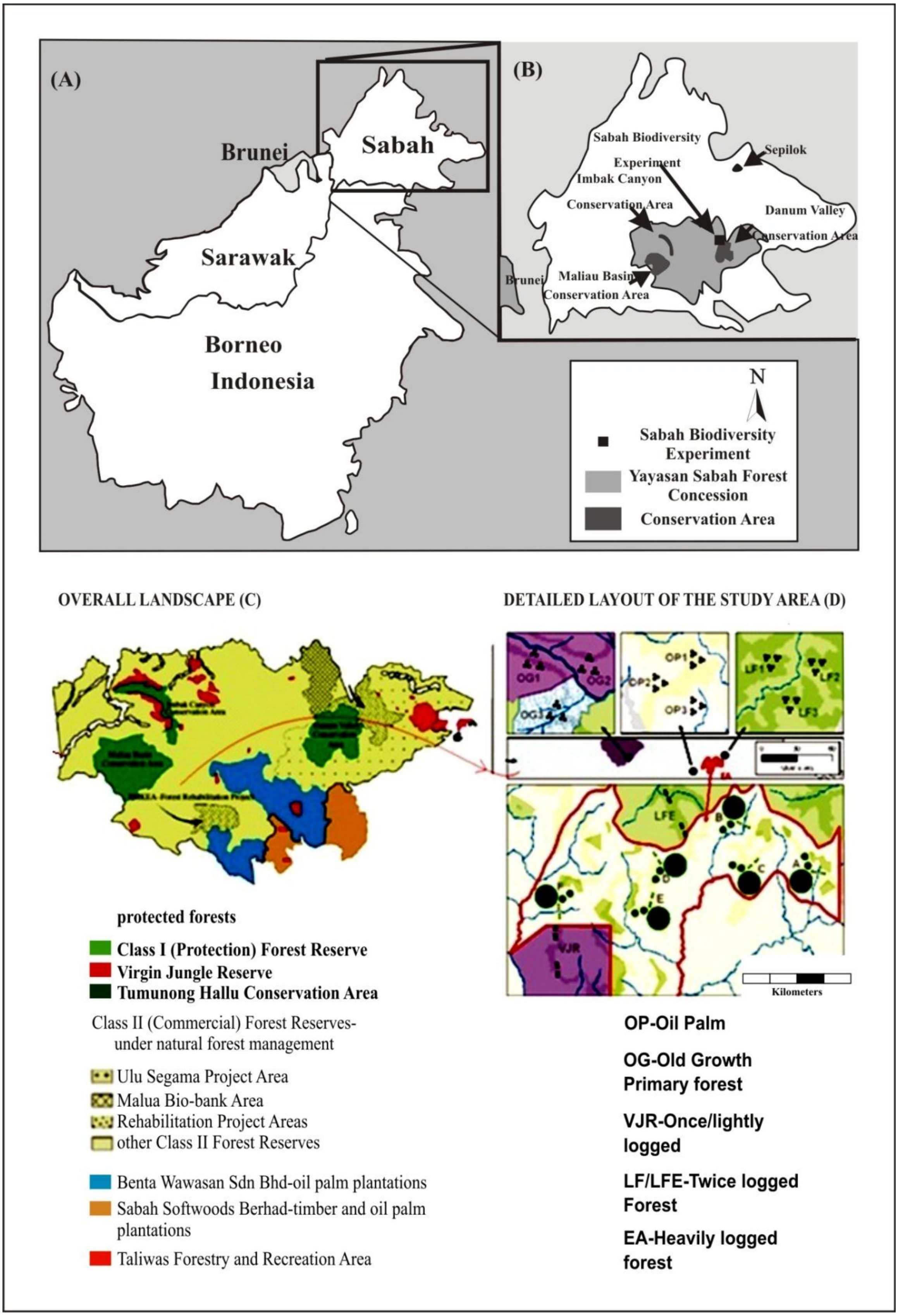

Figure 3.2: (A) and (B): Boundary of Borneo and Sabah (Hector et al., 2011). (C) Description of Yayasan Sabah Concession Area(Reynolds et al., 2011)(D) Detailed Layout of the Study Area (SAFE , 2011)

The project is located in the Yayasan Sabah Concession Area as shown in figure 3.2. The area is comprised of a mixed landscape that includes areas of a twice logged forest (LF), virgin jungle reserve (VJR), oil palm plantations and a 7200 ha heavily-logged area known as the experimental area (EA), which has been ear-marked for conversion to oil palm plantations beginning in December 2011. The research study area extends to the Maliau Conservation Basin (116.87^{O} E, 4.82^{O} N) and the surrounding areas. At the mouth of the MBCA, near the Maliau river are 58,840 hectares of undisturbed, old growth, lowland primary forests (Turner et al., 2011). These forests mainly comprise of trees belonging to the Dipterocarp family and many of these reach heights of up to 30 m and beyond (Jones, 2000). Research plots have also been set up in the old growth primary forests (OG) at Maliau Basin to act as a control. Further control points have been included in the OP plantation which covers 45,016 hectares and contains palm trees of varying ages (Cusack, 2011). In the proposed OP concession, 800 ha of forest was to be spared clearance, and these were to be maintained in an arrangement of circular fragments together with the maintenance of a few riparian vegetation zones as shown in Figure 3.2 (SAFE, 2011). The Malaysian law requires the maintenance of 30m of riparian forest strips on either side of rivers (Ewers et al., 2011; Foster et al., 2011). The SAFE project is considered to be the world's largest ecological experiment that seeks to examine the impact of forest loss, fragmentation and creation of oil palm plantations on biodiversity and ecosystem functioning of forests (Turner et al., 2011).

As a part of the ground data collection, topographic data of the study area was collected. On average, most of the area has an altitude of less than 600m and in many areas, such as the sites of OG, parts of EA and LF, the altitudes are less than 300m. In majority of the areas, the slope too ranges between 0^0-30^0. A notable exception to this is the VJR area, which is dominated by slopes having angles around or greater than 40^0. Further, a survey of the tree species was carried out by the researcher in the riparian zones and some of the non-riparian areas in each of the land use types. While Dipterocarp trees like *Shoreajohorensis*, *Parshoreas*, *P. tomentella* dominated the species composition in the riparian and non-riparian zones of pristine unlogged forests, more disturbed forest areas such as those in EA were dominated by smaller, successional trees belonging to genera *Macaranga* and *Eugenia*. Extensive botanical surveys have been carried out in the neighbouring DVCA and qualitatively, tree species distribution of DVCA bears cognizance to tree species distribution in the SAFE sites. DVCA too has a dominance of *Shorea* trees (DVCA comprises of an intact primary lowland forests), followed by the presence of smaller, successional trees such as *Eugenia*, *Dillennia* around the riverine streams (SEARRP, 2010).

3.1.2 Satellite Data Used

Optical datasets such as those obtained from Landsat, SPOT, MODIS are very effective in producing detailed forest maps and discriminating between different forest/vegetation types. With higher spatial resolution of the sensor, more land cover details and consequently better defined land cover maps can be created (Langner, 2009). A major aim of the MPhil research has been to discriminate between the different forest types (and their biomass dynamics) present in the region. This makes the higher resolution optical data, such as those obtained from Landsat and SPOT 5 suitable for achieving the stated objectives. Specifications of these remote sensing datasets have been discussed in the next section.

3.1.2.1 Landsat TM Data

Landsat TM imagery has a resolution 30m and has 6 spectral bands. Out of this, three bands are in the visible range (these are the blue, green and red bands). Three visible bands are followed by one band in the near infrared region (this is the NIR band or band 4), and two shortwave infrared bands (band 5 and band 7). Although band 6 comprises of thermal bands, these have not been included in the analysis (Purkis and Klemas, 2011). The spectral resolution of the Landsat data allows for the target features (in this case vegetation) to have a well-defined and distinct profile as shown in figure 3.3:

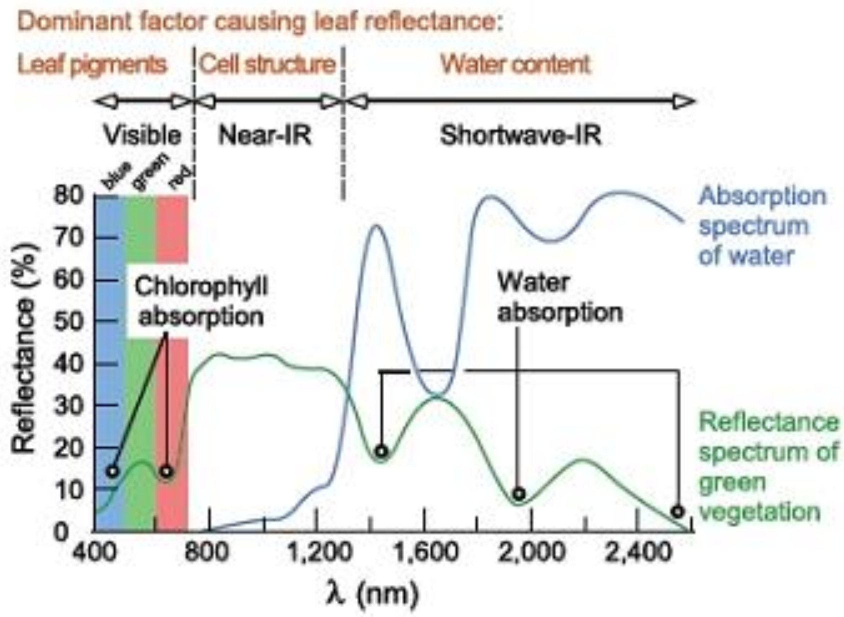

Figure 3.3: Response of vegetation in different bands of Landsat TM data (Purkis and Klemas, 2011)

Spectral response of green vegetation (and its constituents) varies across the different bands of Landsat. Chlorophyll component of the leaf has a strong absorption in the visible bands, blue, green and red vary from 450nm to 670 nm. Green vegetation has high reflectance in the near infra-red bands and shows a distinct absorption pattern in the short wave infrared band (Purkis and Klemas, 2011). Hence, it can be seen that the spectral resolution of the Landsat data allows key landscape features such as different kinds of vegetation to have a distinct spectral “signature”, making it distinguishable from other features.

3.1.2.2 SPOT 5 Data

The SPOT 5 image has five bands, covering one panchromatic band with 5-meter spatial resolution, two visible (green and red) bands whose wavelengths vary between 0.5µm-0.59µm and 0.61µm-0.68µm respectively. Additionally, there is one (near infra-red) NIR band with 10-meter spatial resolution, and one (short-wave infrared) SWIR band with 20-meter spatial resolution (Lu et al., 2008) whose wavelengths vary between 0.78µm-0.89µm and 1.58µm-1.75µm respectively. The 20m SWIR band is usually resampled to produce a 10m image. The data acquisition process specific to SPOT 5 also allows an image sampled at 2.5 m to be produced from two 5-m resolution panchromatic images taken simultaneously. The possibility of combining this 2.5 image with a third, 10-m resolution, image in multispectral mode results in a fused image made up of three bands (green, red and near-infrared) too allows for enhancing the spatial resolution of the SPOT dataset (Vela et al., 2008). The 2.5m SPOT images are thus like a three band colour image with a panchromatic view. The 2.5 m resolution fused SPOT data has been used in chapter 6. In the said chapter, the AGB of tropical the forest was estimated from Fourier transform of high resolution remotely sensed canopy image. For more details refer to chapter 6.

3.2 METHODS

3.2.1 Collection of Ground Data

3.2.1.1 Sampling strategy

Riparian plots were set up in three riparian zones of the individual land use types which have been identified both as a part of ground work carried out by the SAFE project. The basic premise of any sampling methodology is to reduce bias. This is achievable by using simple random sampling for most ecological applications (Sutherland, 2006). However, for the purpose of creating carbon inventory and collection of forest mensuration data, stratified random sampling is known to yield more precise estimates (MacDicken, 1997). The collection of forest mensuration data was carried out for fulfilling the research objectives identified in Chapter 1. It is recommended that forest areas should be stratified according to objectively chosen variables, with random sampling within stratifications so as to adequately capture variation (Maniatis, 2010). It is also important to choose an appropriate number of sample plots. The ground survey focused on collecting forest mensuration data from the riparian and non-riparian zones of the different land use types. Hence, the focus on including the different land use types in the study allows for stratification. The selection of riparian zones and location of riparian plots has been done randomly to capture variation in spatial structure and biomass across the riparian zones and avoid the “majestic forest bias[1]” (Lewis et al., 2009; Malhi et al., 2002).

RAINFOR and GEM protocols recommend the setting up of square or rectangular plots (Marthews et al., 2012). In each of the riparian zones, 6 plots were set up, each measuring 10m by 50m with the 50m side running parallel to the river. The location of the first plot was

[1]Majestic forest bias is the tendency to establish plots were a lot of trees are present as opposed to taking an unbiased sample of the study area.

selected by random sampling. The hydrological map of the study area was obtained and a square grid was superimposed on it. The lines of the superimposed grid were taken to be 500m apart. The square grids were numbered and a pair of numbers was obtained through random number generation (Sutherland, 2006). This methodology seeks to provide representativeness of the spatial distribution of trees in the riparian zones. Simple random sampling such as this has the benefit of yielding data that can be analysed by the means of inferential statistics. Using this sampling strategy, locations were selected on each side of the river and 3 plots were established on each side of the river.

In order to avoid disturbance from river flooding, the starting point of each of the plots was kept 5-8m away from the river (depending on the shape of the river). Hollow steel rods (painted red on the top) were used as corner markers. But first, temporary plastic/wood markers were tied to establish a starting point from where the measurements were carried out as shown in Figure 3.4:

Figure 3.4: Taking plot measurements (Photographs taken by the author in November 2011 at the SAFE site)

One of the biggest challenges in establishing rectangular/square plots is the maintenance of the different vertices of the plot at right angles. In the study area, this was done using a clinometer. Whenever possible, steep slopes were avoided. When encountering a slope, a cosine based correction was applied to ensure the length and breadth of the plots could confirm to the desired measurement. The correction factor was taken from the RAINFOR-GEM Manual (Marthews et al., 2012):

$$Measurement\ on\ ground = \frac{ideal\ plot\ measurement\ \ (10m\ or\ 50m\ in\ this\ case)}{\cos(slope)} \qquad (3.1)$$

Once the plot measurements were taken, the steel plot markers were located at the four extreme corners of each of the plots.

3.2.1.2 Allometric Equations

Allometric equations that can be used to calculate AGB stocks have been developed for most tropical regions of the world. Development of allometric equations involves the destructive harvesting of a representative sample of tree species in a given region and correlating the biomass value obtained with tree mensuration data such as diameter at breast height (DBH) and properties such as wood specific gravity (Chave et al., 2004). Brown (1997) focused on generating allometric equations for three different climatic zones in tropical forests, as opposed to focussing on individual tropical species. The three climatic zones were tropical dry forests, tropical moist and wet forests and were demarcated on the basis of the per annum rainfall each received. The advantage of using generic equations, stratified by in the case of tropical forests, ecological zones is that they tend to be based on a large number of trees (e.g. Brown, 1997; Brown and Schroeder, 1999) and span a wider range of diameters. This in turn helps increase the accuracy and precision of the equations. The generic equation for tropical moist forests developed by Brown (1997) is:

$$TAGB = \exp[-2.134 + 2.53 * Ln(DBH)] \qquad (3.2)$$

In this equation, TAGB stands for Total Above Ground Biomass (in ton/ha) and DBH stands for diameter at breast height (in cm). An improvement over this method was suggested by Ketterings et al. (2001), which allowed for the equations to be tailored to a specific study area by including the variable of wood specific gravity which varies between different tropical regions:

$$TAGB = r * \rho^{avg} * (DBH)^{2+c} \qquad (3.3)$$

Here ρ is the wood specific gravity across different regions and a factor "c" is a function of height. Even though height is an important explanatory variable for evaluating the AGB, many of the allometric equations tend to omit this variable. However, Chave et al. (2005) tested explanatory variables such as DBH, height and ρ for 20 sites in the tropical forests of the world and recommend the inclusion of height in allometric equations. They recommend the following allometric equations for AGB estimation in the dry, moist and wet tropical forests:

$$(AGB)_{dry} = \exp[-2.187 + 0.196 * Ln(\rho D^2\, H)] \equiv 0.112*(\rho D^2\, H) \tag{3.4}$$

$$(AGB)_{moist} = \exp[-2.997 + Ln(\rho D^2\, H)] \equiv 0.0509*(\rho D^2\, H) \tag{3.5}$$

$$(AGB)_{wet} = \exp[-2.557 + 0.94 * Ln(\rho D^2\, H)] \equiv 0.0776*(\rho D^2 H) \tag{3.6}$$

Allometric equations have been developed for specific tropical tree species such as *Dipterocarpus* in Kalimantan (Basuki et al., 2009) and for three tree species in central Africa (Ebuy et al., 2011). Allometric equations have been developed for specific tropical ecosystems such as logged forests in Sarawak (Kenzo et al., 2009) and for Peninsular Malaysia (Okuda et al., 2004). However, no specific allometric equations have been derived for within or around the study region and hence it was decided to use a generic allometric equation (3.6) for AGB stock estimation.

3.2.1.3 Collection of Tree Mensuration Data

From these plots, forest mensuration data was collected using the RAINFOR (RAINFOR, 2011). The RAINFOR protocols require all trees having a DBH of greater than or equal to 10cm to be measured. However, the riparian zones (and many non-riparian zones) in the study area are dominated by trees having DBH less than 10cm. Hence, in addition to measuring trees with DBH>=10cm, all smaller trees where the DBH was greater than 2 cm were recorded. The RAINFOR protocols recommend taking the point of measurement (POM), i.e. measuring the DBH of trees from 1.3m above the ground level and/or 50cm upwards of a buttress. The measuring protocols have to be modified accordingly as prescribed by the GEM-RAINFOR (Marthews et al., 2012) protocols and shown in figure 3.5:

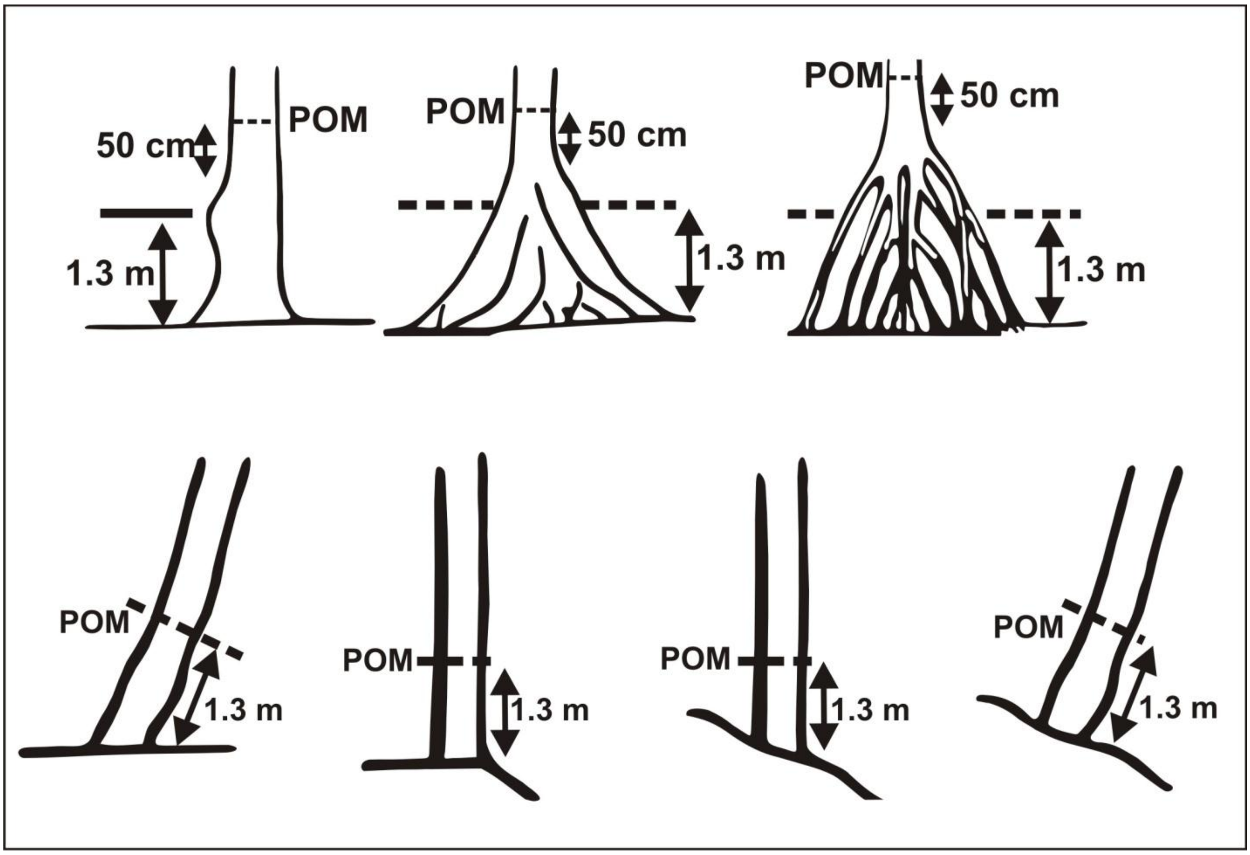

Figure 3.5: The POM for DBH For Trees Having Different Shapes (Marthews et al., 2012)

The biggest challenge was faced in the measurement of large trees. Larger trees have higher POMs owing to having higher POMs caused by larger buttresses or irregular trunks as shown in figure 3.6(ii) :

Figure 3.6: DBH Measurements. From clockwise direction: (i) Measuring the DBH in Field (Marthews et al., 2012) (ii) Measuring the DBH of a Tree with a large buttress (Photograph taken by the author in October 2011 at the SAFE site) (iii) Measuring DBH while excluding a liana (SAFE, 2011)

The measurement of larger trees requires the use of ladders (Phillips et al., 2009) as shown in figure 3.6. It must be noted that all the larger trees (including the one shown in figure 3.6 ii) were measured using a ladder to reach the recommended POM.

Some of the allometric models require height as an input. Indeed the lack of height data is a significant drawback of many forest inventory datasets available for the region. For instance, the tree inventory data collected for the 195 SAFE plots too omitted to collect height estimates. In addition, the height of all the trees was recorded together with the species information. In order to compare the functioning of the riparian margin with the surrounding land use type, the study also made use of the vegetation plots set up earlier as a part of the SAFE project. These consist of 195 vegetation plots which measure 25 m × 25 m and are distributed across the different land use types (SAFE, 2011). A subset of these was included in the research, and the height, species information and DBH of trees measuring 2-10 cm for this subset of plots was collected.

3.2.2 Collection and Processing of Remote Sensing Data

Remote sensing data from two different satellite sensors, Landsat-5 TM and SPOT-5 HRG images were used in this research. An image-to-image registration between Landsat and SPOT images was performed. The Landsat image was used as a reference image, and the SPOT image was registered to it using the Geographic Lat/Long coordinate system (Lu et al., 2008). After this, a number of pre-processing and processing techniques were applied on both the satellite imageries. These have been described in the next sections.

3.2.3 Image Pre-processing

Atmospheric correction of the satellite data was carried out as a way of compensating for the atmospheric effects of scattering and absorption. This has to be undertaken before classification and change detection analysis of the images can be carried out. In this study, the Dark Object Subtraction (DOS) method of atmospheric correction was carried out. This is an image-based absolute atmospheric correction approach and is preferred for change detection and classification approaches (Song et al., 2001; Foody et al., 2003). Atmospheric correction thus helps reduce the error in estimating surface (Song et al., 2001). Further, cloud coverage is a significant issue with optical satellite data, such as Landsat and SPOT imagery obtained over tropical forests. For the purposes of carrying out classification and calculations (such as those of vegetation indices), the band data (which is in the form of digital numbers or DN) were first converted to apparent or ground reflectance according to equation specified in Chander et al. (2009):

$$\rho_\lambda = \frac{\pi - L_\lambda \text{-d}^2}{\mathrm{ESIN}_\lambda - \cos\theta_s} \qquad (3.7)$$

3.2.4 Unsupervised Classification

A false colour composite from bands 3, 4, 5 was created. These bands (band 3- red, band 4- NIR, band 5- MIR) are best for characterization and representation of vegetation features. Unsupervised classification was then carried out using ISODATA function provided by the IDRISI Selva software. This is an iterative algorithm which creates separate classes/clusters based solely on the spectral information provided by the image. A major problem with the generated classes through ISODATA is that they may not match the land cover classes on the ground. However, unsupervised classification allows for the derivation and isolation of physiologically meaningful classes such as clouds, shadows, water, soil (Hayes and Sader, 2001; Jones and Vaughan, 2010). ISODATA classification was carried out to identify the statistically similar segments within the image and isolate irrelevant features such as clouds, cloud shadows and water pixels.

3.2.5 Supervised Classification

Subsequent to carrying out unsupervised classification, the next step for processing remote sensing data is to carry out supervised classification. The three key steps involved in supervised classification are: training, classification, and accuracy assessment (carried out post classification) (Purkis and Klemas, 2011). Generating training sites forms the basis of supervised classification algorithms. Supervised classification requires the initial identification of ground pixels or training data of areas whose land use is already known. In this research, these training samples have been created on the basis of land use land cover information gathered as a part of the fieldwork. During the course of ground survey the different land use and land cover classes (except oil palm) were categorized on the basis of their logging intensity: (a) old growth primary forest (these are intact pristine lowland forests) (b) disturbed forests (these have been exposed to slight anthropogenic disturbance, clearance) (c) virgin jungle reserves or once/lightly logged forests (d) twice logged forests (e) heavily logged forests which have undergone three rounds of logging and face severe degradation.

Maximum Likelihood classification algorithm[2] of the supervised classification methodology was used. The algorithm uses the probabilistic approach for classification of the pixels. In this the algorithm assigns individual pixels to different classes on the basis of probability distribution function (PDF) and the class with the highest PDF secures the pixel (Gupta, 1992). As a way of delineating between classes having different logging intensities, spectral signatures of the individual land use types were collected. The outcome of applying Maximum Likelihood classification has been described in chapter 5.

3.2.6 Advanced Remote Sensing Data Processing Techniques Used

The above section described the basic remote sensing data processing techniques that have been used in this research. By basic it is meant that these remote sensing techniques are used in majority of the research that uses remote sensing data, including the present research. In addition to these, some advanced remote sensing techniques have been used in order to fulfil the specific aims of the different papers presented in this thesis. These have been described below:

3.2.6.1 Texture Measures

Many of the remote sensing applications, such as the calculation of vegetation indices, classification of satellite imagery depend on correlating the canopy reflectance captured at the sensor with field measurements and other direct estimates. However, using canopy reflectance values is fraught with significant uncertainties, most of them arising from atmospheric effects, cloud cover and signal saturation (Barbier et al., 2011). It is proposed that a better measure of evaluating the spatial variation in forest structure (and related parameters) across a heterogeneous landscape may be done using texture measures (Cutler et al., 2012). In remote sensing terms, texture is defined as a "measure of homogeneity of neighbouring pixels" (Jones and Vaughan, 2010). In remote sensing data, pixels have a substantial degree of spatial dependence on one another, i.e. neighbouring pixels may be similar to one another. The variation in the tonal patterns of the imagery can give an indication of "roughness" and "smoothness" of a given area. Since texture values are

[2] Maximum Likelihood Classifier is a parametric classifier that assumes normal distribution for the training data statistics for each class in each band. It is based on the probability that a pixel belongs to a particular class. It takes variability of classes into account by using the covariance matrix, thus it requires more computation per pixel than MDC. (Lu,2004). Along with being statistically robust, this technique depends heavily in use of detailed ground survey data.

calculated pixel by pixel, such measures in turn may be associated with vegetation structure or types. Image texture has the potential to capture the internal heterogeneity of the different vegetation types in a region (Gallardo-Cruz et al., 2012). However, analysis of the textures present in satellite imagery can be carried out only if the imagery has a sufficiently high resolution (Jones and Vaughan, 2010; Gallardo-Cruz et al., 2012). The extraction of texture features from high resolution remote sensing imagery is essential in land use types in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous and overlapping landscape units.

3.2.6.2 Grey Level Co-Occurrence Matrix (GLCM)

GLCM is a second order statistical measure which seeks to establish the relationship between grey levels of pixels in specified directions or distances. These matrices contain the probabilities of co-occurrence of pixel values for pairs of pixels/two grey scale values in a given direction and distance (Jones and Vaughan, 2010; Gallardo-Cruz et al., 2012). Eight different statistical texture measures were obtained including- mean, variance, entropy, second moment, correlation, homogeneity, contrast. These textural variables were derived because they have the ability to provide vital information about the forest stand parameters and biomass dynamics (Eckert, 2012, Castillo-Santiago et al., 2010). Details of this method and how it is applied to the examination of structure and biomass of different forest types is explained in detail in chapter 5.

3.2.6.3 Fourier Analysis Based Method- Use of Fourier Transform Textural Ordination (FOTO)

In the field of remote sensing, Fourier analysis based techniques have been significantly used for noise removal, stripping and image sharpening (Gao, 2009). Fourier Transform Textural Ordination (FOTO) which uses a combination of Fourier analysis and multivariate ordination techniques is a novel texture based approach for texture analysis. Fourier analysis provides a mathematical framework for the frequency based analysis of images, the Fourier power spectrum has been proposed for characterizing texture in remote sensed imagery (Jones and Vaughan, 2010). Application of Fourier analysis to an image converts data from the spatial domain to frequency components that can be expressed as sine and cosine components having different amplitudes (Proisy et al., 2007). The Fourier spectrum of different image windows will be characteristic of the spatial scale components and the texture of the different components in the image. The preferred method of obtaining a Fourier power spectrum of the spatial data is to apply Fast Fourier Transform algorithm (Couteron et al., 2005, 2006). Spectral radiance of the image expressed in spatial domain by a function $f(x\ ,y)$ of image column (x) and row (y), is transposed into the frequency domain as a function $F(p, q)$, where p and q are spatial frequencies along the XY directions. The highest resolvable sampled frequency (Nyquist frequency) is $N / 2$, so $1 \leq p \leq N / 2$ and $1 \leq q \leq N / 2$ (Proisy et al., 2007). For the purpose of explanation let us assume a continuous image represented as f(x, y) in the spatial domain. Let the two dimensional Fourier transform of the image be called as F(u, v) and is obtained by:

$$F(u,v) = \iint_{-\infty}^{\infty} f(x,\ y) e^{-2\pi i(ux+uy)} dxdy \qquad (3.8)$$

Where the Fourier power spectrum is obtained by $F^2 = FF^*$ where * is the complex conjugate.

The radial distributions of values in the power spectrum or F^2 are related to the coarseness in the texture of the image. Higher values of F^2 represent a coarser texture (and are concentrated near the origin) and lower values of F^2 represent a finer texture thus are more spread out (Gao, 2009). The characterization of coarseness or fineness of the image texture can be obtained by averaging the power spectrum over ring shaped regions that are centred at the origin as described in the equation:

$$\emptyset_r = \int_0^{2\pi} |F(r,\theta)|^2\ d\theta \qquad (3.9)$$

Here r is the radius of the ring and F(r, Θ) are the polar form of the Fourier transform (Proisy et al., 2007). The power spectrum thus obtained can be used to derive texture measures by carrying out standardized Principal Component Analysis (PCA) which can be correlated to a number of canopy and forest mensuration features (Priosy et al., 2007; Barbier et al., 2011; Ploton et al., 2012; Ploton 2010).

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Chapter 4: Biomass, Forest Structure and Tree Diversity of Riparian Zones in an Oil-Palm Dominated Mixed Landscape in Borneo

(In preparation for journal: *Forest Ecology and Management*)

ABSTRACT

Logging, deforestation and oil palm plantation conversion have reduced forests in Borneo to fragments and isolated forest zones, such as riparian forests. Given the extent of forest loss and logging, it is essential to evaluate the ability of remnant forests, especially fragments and riparian margins to provide above-ground biomass (AGB) storage and tree biodiversity conservation services. This research focuses on examining the variation in the AGB and tree species richness of riparian margins located in land uses with different disturbance intensities ranging from a pristine old growth forest to an oil palm monoculture. The research found that the AGB of riparian margins shows no significant variation for the riparian margins located in an unlogged, once/lightly logged and twice logged forests but undergoes a sharp decline for the riparian margins located in the heavily logged forests and oil palm. However, the riparian zones in oil palm plantations have a significantly higher AGB value than oil palm monocultures. An examination of tree species richness indicated that oil palm riparian margins have the highest species richness of all the riparian margins. Based on this, it could be argued that the retention of riparian margins in OP plantations can yield significant AGB storage and tree species conservation benefits which can help counteract some of the detrimental effects of OP plantations.

Key words: Riparian Zones, Biomass, Forest Structure, Tree Diversity, Palm Oil, Species richness.

4.1. INTRODUCTION

Forest clearance for the creation of agricultural plantations such as those of soy in the Brazilian Amazon (Laurence et al., 2007) and oil palm plantations in Southeast Asia (Persey and Anhar, 2010) is a leading cause of forest loss and fragmentation in the tropics. Research by Laurence et al. (2011) indicates that habitat fragmentation brought on by agricultural plantations has a detrimental effect not simply on biodiversity but also on AGB dynamics.

4.1.1 Impacts of logging and deforestation on biodiversity and AGB

The forest fragments created by deforestation have significantly altered, and, in many cases, drastically reduced in biodiversity as compared to intact forests (Laurance et al., 2011). Edge effects are a significant driver of change in fragmented landscapes. Forest edges are more vulnerable to microclimatic variations, wind turbulence and elevated mortality of large trees. This has an impact on the AGBs dynamics of the fragmented patches. This has implications for the carbon storage potential of these areas (Nascimento and Laurence, 2004; Saner, 2009). Even after two decades of recovery, logged forests in the Malua Forest Reserve, Sabah only had 60% carbon storage of primary forests (Hector et al., 2011). Additionally, palm oil monoculture plantations support less biodiversity than the forests they replace. Across all taxa, a mere 15% of species recorded in primary forest were found in OP plantations (Fitzherbert et al., 2008).

In addition to having a detrimental effect on biodiversity, the creation of oil palm plantations also contributes to carbon emissions in Southeast Asia (Koh et al., 2011). Conversion of forests to oil palm monocultures is estimated to release approximately 650 mg carbon dioxide equivalents per hectare. Carbon emissions from peat forest conversion are even higher due to the decomposition of drained peat and the resulting emission of greenhouse gases (Germer and Sauerborn, 2006). This conversion creates a "biofuel carbon debt" by releasing 17 to 420 times more CO_2 than the annual greenhouse gas reductions that these biofuels provide by displacing fossil fuels (Fargione et al., 2008).

4.1.2 Role of riparian margins in maintaining biodiversity and carbon storage in human modified landscapes

Maintenance of forest fragments and riparian vegetation zones within an oil palm dominated matrix allows for the retention of biodiversity and ecosystem functioning across a wide variety of disturbances (Turner et al., 2011). Research by Turner and Corlett (1996) indicates that isolated forest fragments (<100ha) can often provide a refuge for species and act as seeds from which the rainforest may recolonize a deforested landscape. While a significant amount of research has been done on examining how the maintenance of riparian forests can help in biodiversity conservation (Pardini et al., 2005, Sekercioglu, 2009). Additionally, riparian zones can provide vital ecosystem services, including carbon storage (Salemi et al., 2012). However, very little research has been done on examining how the presence of riparian corridors might influence the biomass dynamics of a landscape.

Chave et al. (2003) carried out an evaluation of different habitat types such as dry forests, forests on slopes, riparian forests in a 50 hectare plot in Panama. Their research indicated that riparian margins are dominated with tress having a smaller basal area and their AGB is lower than that of the other land use types. Another research by Williams- Linera et al. (1997) evaluated the impact of edge effects on riparian margins located in fragmented tropical ecosystems. Their research argued that while riparian margins are vulnerable to edge effects, they have a significant potential to maintain ecological diversity in disturbed landscapes. Restoring and reforesting riparian zones can both increase carbon storage and water quality in agricultural landscapes (Reinhardt et al., 2012). These studies have been carried out in the Neotropics and indicate that the biomass and structural dynamics of riparian forests can differ from non-riparian zones. Most of the research on tropical riparian forests has been restricted to Neotropics and no research has been undertaken to examine the structural and biomass dynamics of riparian forests in Borneo. Forests of Borneo face the unique challenge of oil palm conversion and several rounds of logging. It is therefore vital to evaluate how forest structure and AGB stocks in respond to varying levels of disturbance along with an evaluation of how a disturbance gradient ranging from light logging to oil palm plantations influences the AGB and forest structure in the riparian margins.

4.1.3 Aims and objectives

This study seeks to examine above ground biomass, forest structure and tree species richness of riparian margins located in areas of different disturbance intensities, ranging from primary old growth forests, logged forests (varying logging intensities) and OP plantations. The study has three main objectives: (1) to examine how the forest structure varies between riparian and non-riparian zones across a variety of land use types which have been exposed to different levels of disturbance; (2) to examine the implications of variation in forest structure on the AGB of riparian and non-riparian zones; and (3) to examine how the tree species diversity varies across the riparian margins of different land use types. The basic hypotheses of the research are: (a) biomass of riparian forests is greater and more diverse compared to non-riparian zones; (b) disturbances (such as those caused by logging and conversion to OP) influence these variables in both riparian and non-riparian areas; and (c) differences in tree diversity are related to forest structure.

4.2 MATERIALS AND METHODS

4.2.1 Study area

This research was undertaken at the Stability of Altered Forest Ecosystems [SAFE] Project (SAFE Project, 2011; Ewers et al., 2011) in Sabah, Malaysia. The area is comprised of a mixed landscape that includes areas of a) twice logged forest (LF), b) virgin jungle reserve (VJR), c) OP plantations (which covers 45,016 hectares and contains palm trees of varying ages) d) 7200 ha heavily logged area known as the experimental area (EA), which has been ear-marked for conversion to OP beginning in December 2011 d) undisturbed, old growth, lowland primary forests in the Maliau Basin Conservation Area (MBCA). Figure 4.1 A shows the layout of the MBCA where the OG forests are located and figure 4.1 B shows the layout of the mixed forests in the SAFE area.

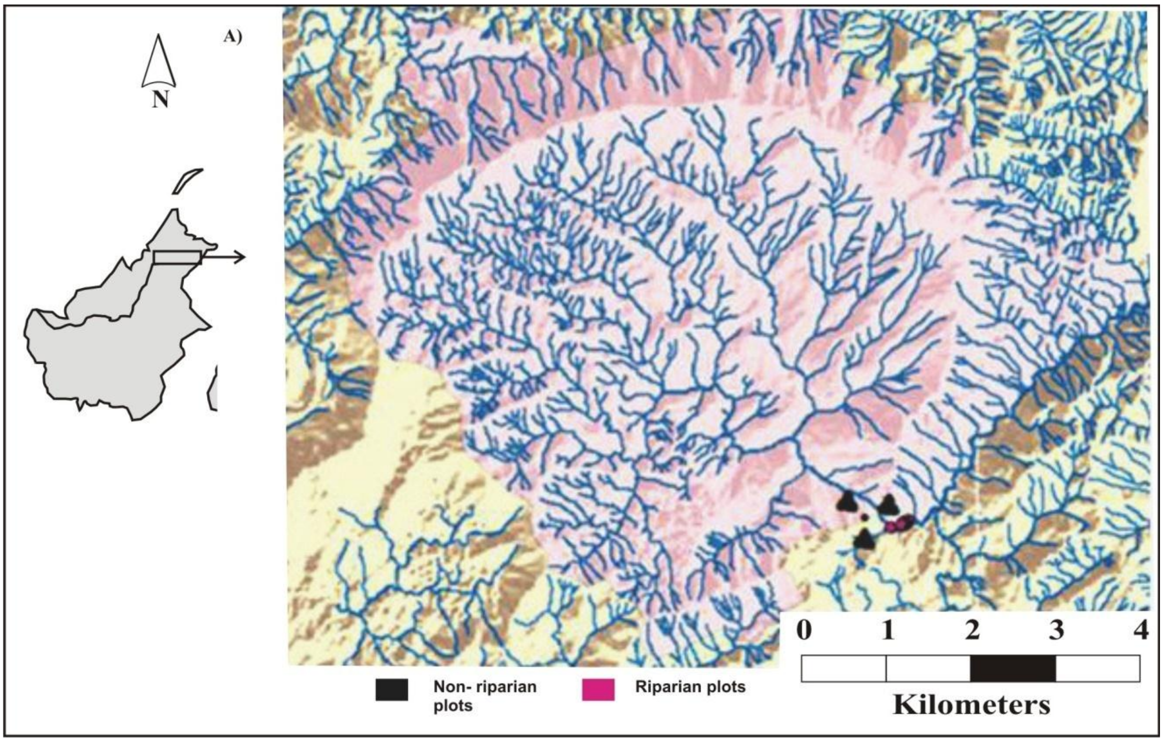

Figure 4.1 A: Layout of the Maliau Basin Conservation Area (MBCA) and the Old Growth (OG) forests

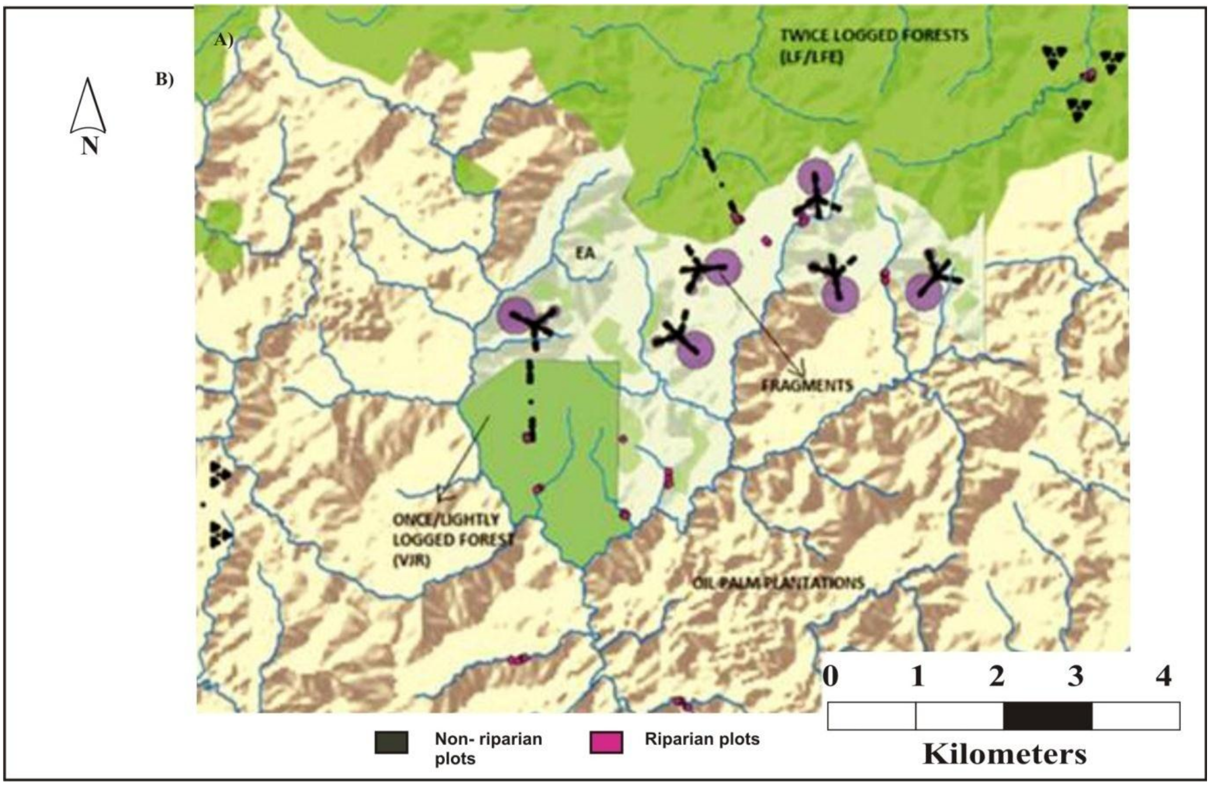

Figure 4.1 B Layout of the SAFE area comprising of plots of the Oil Palm plantations (OP), Twice logged forests (LF/LFE), Heavily logged forests (EA) and Once/slightly logged forests (VJR).

In the proposed OP concession, 800 ha of forest will be spared clearance, and these will be maintained in an arrangement of circular fragments together with the maintenance of a few riparian vegetation zones as shown in figure 4.1 A. In addition to the riparian zones present in the EA, a number of riparian margins are present in the other land use types, including OP plantations.

4.2.2 Data collection

In order to collect forest mensuration data, riparian plots measuring 10m × 50m were set up in the riparian zones of each of the different land use types. From these plots, forest mensuration data, namely DBH and height were recorded using the RAINFOR protocols (RAINFOR, 2011). All trees with DBH>= 2cm were recorded. In order to compare the functioning of the riparian margin with the surrounding land use type, the study also made use of the vegetation plots set up earlier as a part of the SAFE project. These plots measure

25m × 25m and are distributed across the different land use types (SAFE, 2011). A subset of these was included in the research, and the height, species information and DBH of trees measuring 2-10cm for the selected subset of plots was collected. Only species information for the trees of riparian zone was collected. Bray-Curtis similarity index was used to compare the tree species across all the riparian margins. This was done with the view of capturing the magnitude of tree species difference in the riparian margins across a disturbance gradient (Barlow et al., 2006).

4.2.3 Computing the AGB of trees in riparian margins

The AGB of the trees in the riparian margins was calculated using the biomass equation recommended by Chave et al. (2005):

$$Above\ Ground\ Biomass(AGB) = 0.0776 \times (\rho \times DBH^2 \times H) \qquad (4.1)$$

In the equation, H refers to the tree height and ρ refers to the wood specific gravity. The value of the latter for the study of this region was obtained from Brown (1997) and the value of ρ for individual tree species was taken from Reyes et al. (1992). Given the difference in the physiology of OP trees and trees in the forest, specific biomass equations needed to be applied in order to calculate the AGB of OP plantations. The AGB of OP trees was calculated using the biomass equation recommended by Morel et al. (2012):

$$AGB_{Trunk} = 100 \times \Pi \times (r \times z)^2 \times h \times \rho \qquad (4.2)$$

Where *r* is the radius of the trunk (in cm) without frond bases, *z* is the ratio of the trunk diameter below the frond bases to the measured diameter above the frond bases (estimated to be 0.777 from the sampled trunks), and *h* is the height of the trunk (in m) to the base of the fronds. ρ, the trunk density (in kgm^{-3})is defined as follows:

$$\rho = \frac{0.0076x + 0.083}{100} \qquad (4.3)$$

A number of studies have been undertaken for developing allometric equations for different regions, specific species or even for tropical forest biomes located in broad climatic classes. Many allometric equations, such as those recommended for the Asian moist forests by Brown

(1997) use only DBH as an input parameter (Morel et al., 2011). However, research by Morel (2010) indicated that it is very important to include height measurements for estimating ground AGB values for the Sabah region. Hence, equation 4.1 was used for the purpose of calculating AGB values.

4.2.4 Computing the height of non-riparian trees

In order to compare the AGB of riparian margins, DBH was collected for trees of the non-riparian zones. While the DBH data is available for trees in the non-riparian plots, no height data is available for these. Since equation 4.1 requires height data for the calculation of biomass, the height of the non-riparian plot trees has been estimated using the DBH-Height regression equations of Morel et al. (2011).

4.2.5 Evaluating canopy intactness

In addition to measuring the DBH of the trees in the plots, a qualitative evaluation of the intactness of the canopy structure was carried out. The intactness of the forest canopy may be evaluated in terms of percentage canopy cover where very dense forests have a canopy cover of up to 80% and highly degraded forests have a canopy cover of less than 50% (Wijaya et al., 2010).

4.3 RESULTS

4.3.1 Variations in forest structure across the riparian margins

The forest mensuration data was used to evaluate the above ground structure of the riparian forests. It was found on average, that trees in the riparian margin of OG forests had the highest basal area and maximum tree height while OP riparian margins hosted the largest number of trees (Table 4.1).

	$(OG)_{RF}$	**$(VJR)_{RF}$**	**$(LF)_{RF}$**	**$(EA)_{RF}$**	**$(OP)_{RF}$**
Basal Area (m^2/ha)	13.7±0.018	7.2±0.007	8.0±0096	3.4±0.0037	3.1±0.0024
Tree height (m)	19.7±0.83	18.9±1.31	22.7±1.44	9.2±0.33	9.7±0.25
Stemdensity (/ha)	602	644	567	757	996
DBH (cm)	26.58±1.31	21.91±0.83	22.42±0.96	15.01±0.53	14.79±0.42

Table 4.1: Above ground forest parameters across the riparian margins(n=18 riparian plots for each of the land use types).(OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

The riparian margins are exposed to a lot of disturbance owing both to the surrounding land use changes and their proximity to the river. Furthermore, a significant proportion of the trees found in the riparian zone have a DBH of less than 20cm. On average, the riparian margins of the OG forests have the highest DBH values and the riparian margins of the most disturbed land use types, the EA and OP plantations are dominated by trees having the lowest DBH values ranging from 2cm-10cm (Figure 4.2).

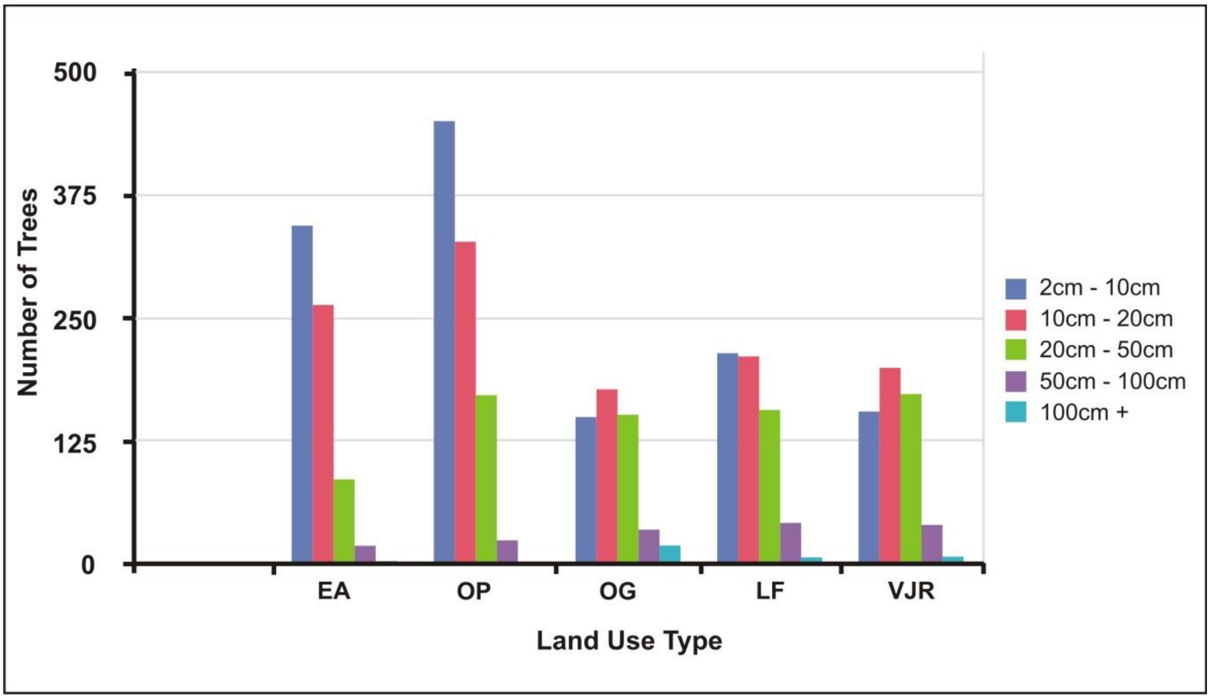

Figure 4.2: DBH of trees across the riparian margins(n=18 riparian plots for each of the land use types).(OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

The values of DBH in one of the riparian margins are statistically different from the carbon storage of other riparian margins. Moreover, no statistically significant difference was found between OG-VJR or OG-LF ($p>0.05$) in terms of DBH. On the other hand, statistically significant difference was identified between the DBH values of OG-OP and OG-EA ($p<0.05$). In addition, the variation in DBH between the riparian margins of the EA and LF areas was also found to be significant. A further examination of the DBH patterns in the riparian margins of different land use types indicated that the highest proportion of trees with a DBH>100cm are located in OG forests whereas OP plantations have the lowest proportion of trees with DBH >100cm (Figure 4.2).

An intact canopy with very few gaps was observed in the riparian zones of the OG forests and the VJR. These forests can be characterized as very dense forests with closed canopies (>80% canopy coverage), this means that tree crowns fill the canopy layer such that negligible light reaches the forest floor directly. Close canopied forests such as these also had thick understories. The LF/LFE region is also characterized by closed canopies where there were a few cleared areas in between the forests. The LF/LFE forests can be characterized as dense forests having a canopy cover of 50%-70%. However, the riparian margins in OP plantations and the EA comprised of a broken canopy along with areas which have negligible tree cover (<50% canopy cover). Photographs illustrating the difference in canopy intactness of some of the different forest types have been provided in Appendix I.

4.3.2 Comparison of DBH between riparian and non-riparian zones

According to the ANOVA analysis carried out between the DBH of trees in the riparian margin and the surrounding non riparian zones, the DBH of at least one of the riparian zones was statistically different from the surrounding non riparian zone ($F=132.038$, $p<0.001$). It was further identified that one of the riparian zones was statistically different from the others situated in the different land use types ($F=31.32$, $p<0.001$) and that one of the surrounding non riparian forest areas is statistically different from the others in terms of DBH ($F=24.38$, $p<0.001$). A Tukey test determined that there was no significant difference between the DBH of trees located in the non-riparian and riparian zones of OG,VJR and LF ($p>0.05$). However, DBH of trees in the non-riparian zones of LF vary significantly from that of OG and VJR non riparian zones ($p<0.05$). The difference between the DBH of trees in the non-riparian zones of LF areas and the EA was also found to be non-significant ($p>0.05$), whereas it was significant between the riparian margins of LF areas and the EA. The variation in forest structure, especially the DBH, has a significant influence on the biomass dynamics of a given area.

4.3.3 Above Ground Biomass Storage Value of the Riparian Margins

Another important objective of this study was to examine the impact of varying disturbance intensities on the AGB storage of riparian margins located in the different land use types. The Tukey test found that the value of AGB storage in one of the riparian margins was statistically different from that of other riparian margins. A Mann-Whitney test identified the riparian margins which have a statistically significant AGB value. This revealed no statistically significant difference between AGB values of OG-VJR or OG-LF ($p>0.05$) but there was a significant difference between OG-OP and OG-EA ($p<0.05$) (Figure 4.4). The AGB values do not vary significantly between the riparian margins of intact (OG), once/lightly logged (VJR) and twice logged (LF) forests (Figure 4.4). However there is a significant difference between the AGB of the riparian margins of LF areas as compared to the riparian margins of the EA and OP plantations. The difference in AGB storage values between the riparian margins of the EA and OP plantations is not significant either.

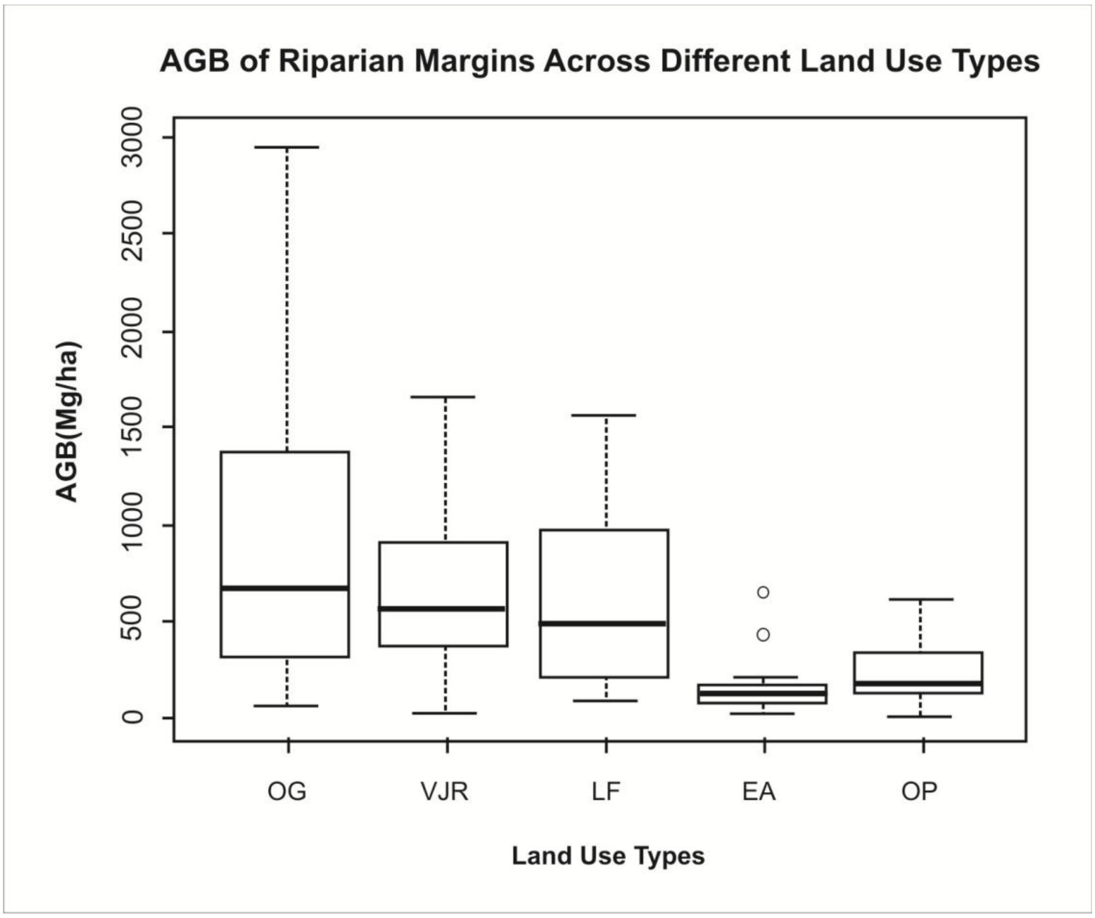

Figure 4.3: AGB of riparian margins located in different land use types (n=18 riparian plots for each of the land use types).(OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

The values of AGB drop sharply for the riparian margins of the EA (heavily logged forests) and OP plantations. Furthermore, it can be seen that OG forests have the highest AGB levels and this is reduced by 75% in OP plantations.

4.4 COMPARISON OF AGB STORAGE BETWEEN RIPARIAN AND NON-RIPARIAN ZONES

The first step in comparing the AGB values between non riparian and riparian zones was to calculate the AGB of OP plantations. As opposed to forests (including logged and degraded ones), OP plantations are characterized by a homogenous canopy structure. The OP possesses a single terminal bud located at the top of the tree, and its stem is crowned with drooping leaves (Jacquemard, 1998). It was found that the AGB of one of the riparian margins is significantly different from the surrounding land use type ($F=90.36$, $p<0.0001$). On the basis of a Tukey test it was determined that there was no statistically significant difference in the AGB between the riparian and non-riparian zones of OG forest, VJR and LF areas ($p>0.05$). However, there was a significant difference between the AGB of the riparian margins of LF areas and the EA ($p<0.001$), and the AGB declined sharply from riparian margins of LF areas to EA riparian margins. Furthermore, the riparian margins of LF have significantly higher AGB values than the surrounding non-riparian forest zones (Figure 4.5).

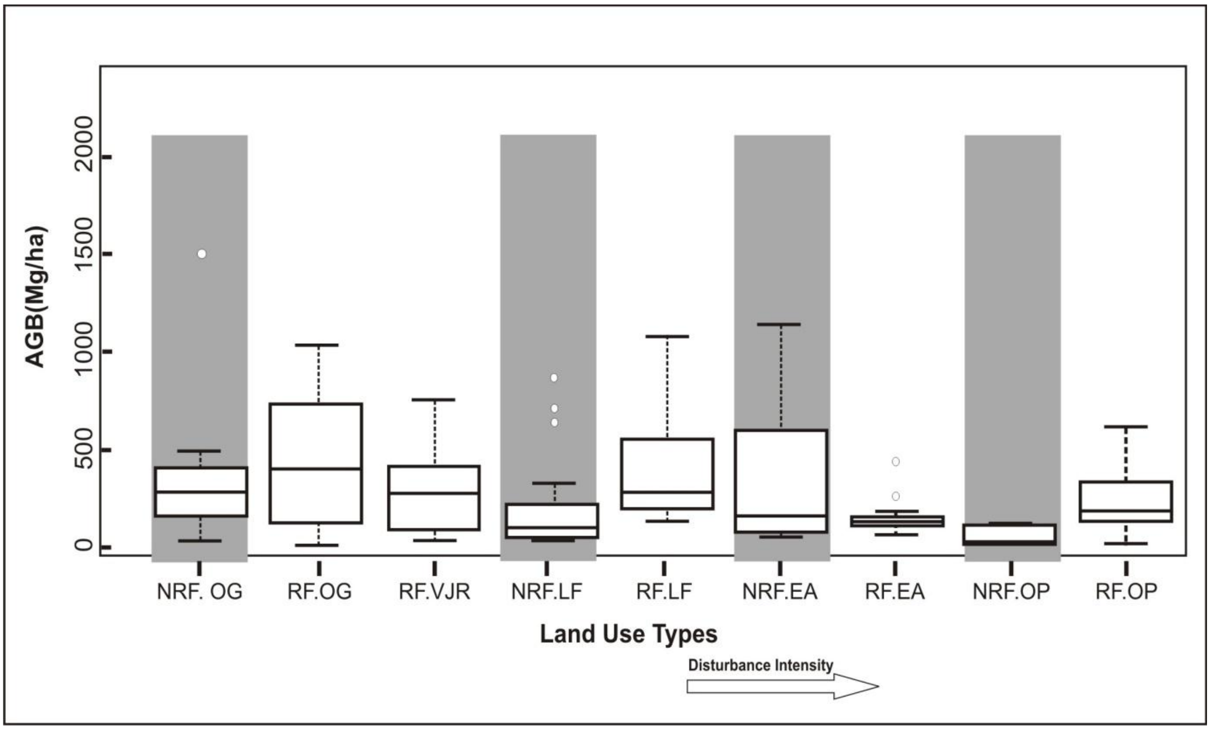

Figure 4.4: Comparison of AGB between riparian and non-riparian zones (n=18 riparian plots and n=12 non-riparian plots for each of the land use types). The grey stripes indicate non riparian forest zone. (OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations. RF-Riparian forests, NRF-Non Riparian Forests)

The difference between the AGB of the riparian margins of the EA and OP plantations was not found to be significant. The riparian margins of LF areas have a higher AGB storage value than OP plantation and EA riparian margins. The AGB of OP plantations and its riparian margins is significantly different, with the riparian margins exhibiting a much higher AGB as seen on Table 4.2:

	RIPARIAN FOREST ZONES	**NON-RIPARIAN FORST ZONES**
VJR (Virgin Jungle Reserve- once/lightly logged forests)	1)No significant variation between the DBH of the OG, VJR and LF of riparian zones 2)No significant variation in AGB between OG, VJR and LF of riparian zones	1) NO DATA AVAILABLE
LF (Logged Forests- twice logged forests)	1) No significant variation between the DBH and AGB of LF, OG and VJR.	1)DBH varies significantly between the non-riparian zones of LF and OG. 2) The AGB storage of LF is significantly lower as compared to non-riparian zones of OG 3) Non-riparian zones of LF have lower AGB storage value than that of riparian zones.
EA (Experimental area- heavily logged)	1)Sharp decline in DBH and AGB values from LF to EA	1)Significant decline in AGB value of EA as compared to OG and LF
OP (Oil Palm plantation)	1) No significant variation in AGB between EA and OP riparian margins 2) 75% AGB loss as compare to OG riparian margins	1) Dominated by oil palm monocultures 2) Significantly lower AGB value than riparian margins.

Table 4.2: Comparison between the riparian and non-riparian zones of different land use types

From this analysis it may arguably be inferred that the riparian margins and can withstand up to two logging rotations without undergoing any significant changes in AGB and DBH values. However this is not so in the case of non-riparian zones and the AGB values of the twice logged forest zone (LF) is significantly lower than that of OG. Heavy logging/degradation and conversion to OP plantations has a significant detrimental effect on the carbon storage of both the riparian and non-riparian zones. Heavy degradation and conversion to OP plantations induces a comparable level of decline in the AGB values of their riparian margins, i.e. the AGB values for these riparian margins do not vary significantly. Heavy logging causes a sharp decline in the DBH value of the riparian margins and this may in turn be seen as a having a domino effect on the AGB value of the riparian margins. In this scenario it would be worth examining to what extent the DBH values are influenced by changes in the surrounding land use and (illegal) logging operations within the riparian margins. However, this analysis is out of the scope of the present research. Riparian zones play a vital role in maintaining gamma diversity at a regional level and are known to harbour more species compared to the surrounding landscape (Sabo et al., 2004). The next section will examine the dynamics of species richness in the riparian margins.

4.5 SPECIES RICHNESS OF RIPARIAN MARGINS

In addition to collecting the forest mensuration data, the field research also focused on collecting species information which was used to assess the variation in species richness (the number of species in the study area) across the different riparian zones. On the basis of a Kruskal Wallis Test, it was identified that species richness in at least one of the riparian zones is statically different from the others. It was determined that the value of species richness also varies significantly across riparian margins of different land use types. There was no significant variation in the species richness of the riparian margins of OG forest and VJR but significant variation between OG-EA and OG-OP. These results are displayed in Figure 4.5.

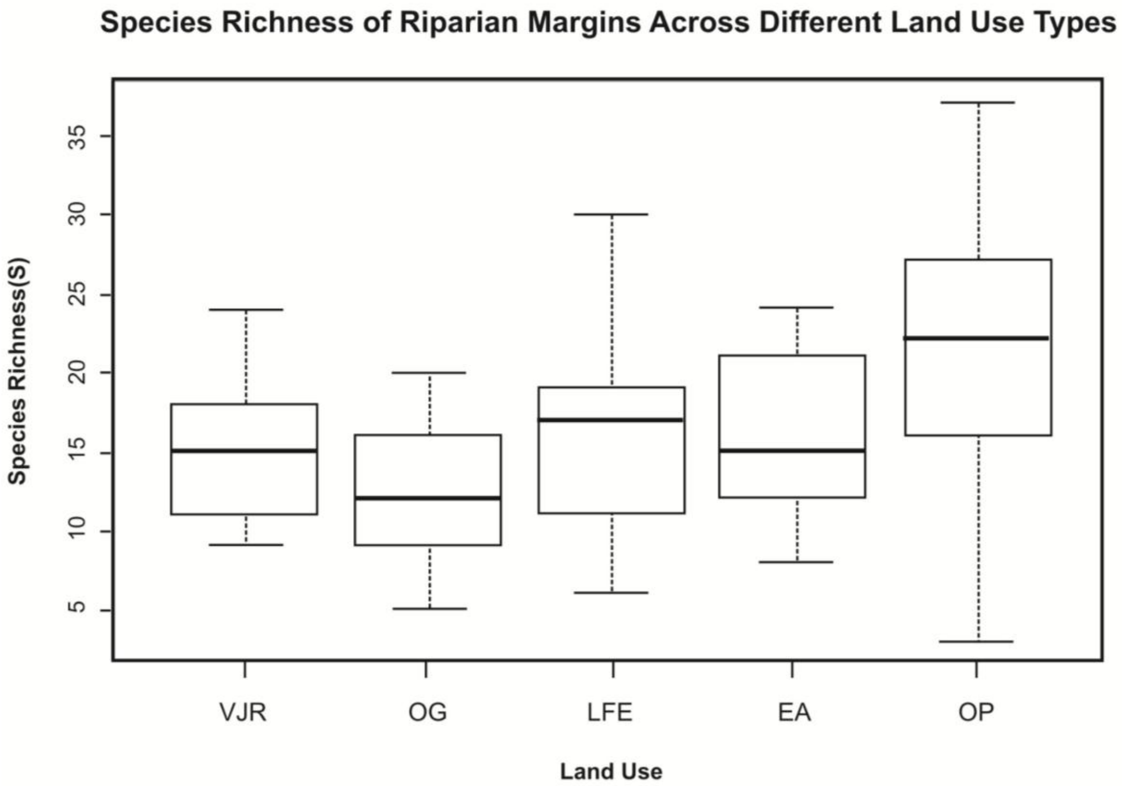

Figure 4.5: Species Richness (S) of the Riparian Margins across different land use types(n=18 riparian plots for each of the land use types).(OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

From figure 4.5 it can be seen that OP plantation riparian margins have the highest tree species richness. This result can be explained by the pattern of DBH classes prevalent in the different riparian zones. As seen in figure 4.2, trees which have DBH from 2cm-10cm dominate the OP plantation riparian margins. Further examination revealed that that species richness is highest in this DBH class.

4.6 SPECIES COMPOSITION OF RIPARIAN MARGINS

While the role of DBH in contributing to the AGB of a given area has been well established, it is equally important to examine the species composition in riparian margins (Kirby and Potvin, 2007). The species composition of riparian margins was examined by quantifying the percentage of a subset of tree species present (Table 4.3).

SPECIES	Percentage in $(OG)_{RF}$	Percentage in $(VJR)_{RF}$	Percentage in $(LF)_{RF}$	Percentage in $(EA)_{RF}$	Percentage in $(OP)_{RF}$
Glochidion borneensis	18.8%	11.16%	4%	2.429%	3.76%
Pternandra coerulescens	8.08%	0.63%	0.546%	0.135%	0%
Walsura pinnata	2.28%	4.46%	4.19%	3.64%	5.39%
Maccaranga beccariana	1.58%	3.18%	2.91%	14.3%	4.98%
Dryobalanops lanceolata	2.10%	3.98%	3.825%	4.45%	0.9155%
Nauclea subdita	0.35%	8.77%	1.82%	2.69%	2.23%
Dendrocnide elliptica	0%	0.955%	3.64%	3.64%	3.86%
Shorea johorensis	1.4%	0.79%	0.9%	0.135%	0.2%

Table 4.3: Variation in Species Composition of Trees Across Different Riparian Margins(n=18 riparian plots for each of the land use types).(OG-Old Growth forests, VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

Species composition of different tree species varies substantially across the different riparian margins. For instance, while *Pternandra coerulescens* comprises 8% of the total trees in the riparian margins of OG forests, no records of it were found in the riparian margins of OP plantation margins. Furthermore, the abundance based similarity index, Bray Curtis index was calculated and this gave an average of 0.577 across the different land use types. The highest similarity of species was found to be between the margins of OG forest and VJR (0.741) and the lowest similarity was between OG forest margins and LF area margins (0.59).

4.7 DISCUSSION

4.7.1 Variations in Biomass and Forest Structure

A significant feature of deforestation in Borneo is the removal of large Dipterocarp tree species (Hector et al., 2011).Large trees play a vital role in influencing AGB storage across a range of tropical ecosystems (Silva-Costa et al., 2012; Letcher and Chazdon, 2009; Paoli et al., 2008). Research carried out in the Brazilian Atlantic forest indicated that large trees contribute to 78% of the total AGB (Lindner, 2010). In addition to being a valuable timber producing species, Dipterocarps play an important role in the maintenance of AGB stocks in lowland tropical forests of Borneo (Hector et al., 2011; Gouvenain and Silander, 2003). Their removal significantly alters the biomass dynamics of the forests in the region (Saner, 2009). Berry et al. (2010) in their study quantified the impact of logging on the carbon storage and tree biodiversity on the lowland Dipterocarp forests of North Borneo. They found that a given area undergoes a significant loss of AGB (up to 53%) following logging.

From the analysis carried out in section 4.3.1-4.3.4 it may be inferred that riparian margins surrounded by undisturbed forests (such as OG) or lightly/once logged forests (such as VJR) have no significant difference in tree DBH or AGB either between each other or as compared to the surrounding land use type. In contrast, the tree DBH in the riparian margin of EA is significantly different from both the surrounding land use type and the riparian margins located in other land use types.AGB too falls sharply for the riparian margins of this land use type. The riparian margins of EA are characterized by a broken canopy structure (with the presence of significant gaps) and a significant removal of trees with large diameters. Similar structural patterns have been observed in the non-riparian zone of EA. Non-riparian zones of EA too display significantly lower AGB values than pristine or even twice logged forests. Arguably, structural parameters like these, especially DBH influence the AGB values in both riparian and non-riparian forest zones. Significant variation is present between the forest stand parameters (such as basal area) between primary forests and forests that have undergone logging. Basal area, which is directly proportional to DBH is significantly greater for unlogged forests in both South East Asian rainforests (Hertel et al., 2009) and South American rainforests (Lindner and Sattler, 2012). The riparian zones of OP plantations (which share the canopy and DBH characteristics of EA) have the lowest carbon storage as compared to other riparian zones (only 25% of the AGB of riparian margins located in pristine areas) although their AGB is significantly higher than the surrounding OP plantation. Low AGB values and high density of small stems (as observed in the OP riparian zones) would suggest significant past human disturbance (Alves et al., 2010).

In addition to DBH, these AGB variations may be explained on the basis of canopy structure and intactness. For instance, no significant variations were found between the DBH and AGB of the riparian and non-riparian zones of OG, which has an intact canopy structure compared to other land use types. Owing to this, dynamics of forest mensuration and biomass do not vary across the landscape and the riparian margins are protected from edge effects. Changes start emerging when riparian forests are no longer a part of a contiguous forest structure and instead are isolated in a logged/heavily degraded landscape, where they function as a remnant forest rather than as part of a contiguous forest.

4.7.2 Variations in species richness and composition

The species richness does not undergo any significant variation between the riparian margins of undisturbed and logged forests (both once/lightly logged and twice logged forests). However, it varies significantly between the old growth and heavily logged forests and between old growth and lightly logged forest and OP plantation riparian margins. OP plantation riparian margins have the highest species richness (as shown in figure 4.6) which has been attributed to the high species richness of trees which have a DBH between 2-10 cm. Trees of this DBH class are dominant in the OP plantation riparian margins. In contrast, the riparian margins of OG forests have the lowest level of species richness. This may be attributed to the fact that these riparian margins have the highest proportion of trees possessing a DBH>100cm and most of the other trees exhibit a DBH between 10-20cm. Similarly, the riparian margins of heavily logged forests and twice logged forests have higher species richness than pristine and lightly logged forests as seen in figure 4.6. Different logging regimes lead to a variation in species richness across different land use types (Imai et al., 2012; Clark and Covey, 2012). These results prove the third hypothesis of the research (see section 4.1.3), that the variation in species richness is related to the forest structure of different riparian zones.

These results are congruent with the body of literature that seeks to examine the impact of disturbance the removal of biomass from a community (Grime, 1977) - on species richness of a given area. The research of Berry et al. (2010) and Saner (2009) indicated that logged forests have higher faunal species richness than pristine forests. According to the Intermediate Disturbance Hypothesis (IDH), species diversity is low at low disturbance levels owing to competitive exclusion and high at intermediate levels owing to a mix of good competitors and colonizers (Hughes, 2010). This phenomenon has also been observed in the species richness of plant communities in riparian margins of a study area in Canada (Biswas and Mallick, 2011). In this study, both the OG forest and the VJR and their riparian margins have undergone very little disturbance. This in turn may account for their low species richness. In contrast, the riparian margins of the LF areas, the EA and the OP plantations have undergone a significant level of disturbance, although they still maintain sizeable canopy cover which explains their high species richness. The species composition also varies across the riparian margins of the different land use types. This can be explained on the basis that the species composition of riparian margins may be influenced by varying levels of disturbance (Shafroth et al., 2002).

4.7.3. Limitations of the study

The study has compared the AGB and DBH of trees among different riparian areas. It has also compared the AGB and DBH of trees from riparian areas and of those of trees from non-riparian areas. However, both the riparian and non–riparian plots are concentrated in the concession area rather than being spatially distributed (Figure 4.1b). It is expected that increasing the sampling intensity and including the areas between MBCA and SAFE area may help improve the accuracy of the results and provide deeper insights into the spatial variation of tree species composition. Secondly, while detailed measures of DBH and height were carried out, this research (like most other plot based studies) paid very little attention to quantifying the variation in canopy structure and intactness and how this may influence the biomass dynamics across the different forest types. Ground based evaluation of canopy structure parameters was difficult owing to the density of the forest and presence of very tall trees (Chambers et al., 2007). Remote sensing based methods offered a much more practical way of carrying out such an examination (discussed in Chapter 5 and Chapter 6).

4.8 CONCLUSIONS AND RECOMMENDATIONS

The research objective was to quantify the AGB of riparian margins and its variation across riparian margins of different land use types. We have been able to establish that riparian margins appear to be resilient to loss of biomass for up to two logging rotations. A decline in biomass values starts with heavy degradation/conversion to OP plantations in the surrounding landscape. However, the research has not been able to ascertain to what extent the fall in AGB values of the riparian margins of the EA could be attributed to (illegal) logging carried out in the past and the disturbance in the surrounding land use. The research has also been able to fulfil its objective of examining the variation in species richness across the riparian margins and how it may be influenced by varying disturbance intensities.

The research determined that the AGB value is much higher for riparian margins than for surrounding OP plantations. Hence the retention of riparian margins in OP plantations can yield significant carbon storage benefits which can help counteract some of the detrimental effects of OP plantations. However, it is vital to examine how the functioning of the riparian margins isolated in an OP matrix undergoes changes over time. In order to achieve this, regular carbon stock measurements and species surveys need to be carried out to evaluate the impact of edge effects and habitat fragmentation on the functioning of the riparian margins. Finally, the examination of the riparian margins and non-riparian zones in the heavily degraded areas indicates that these have undergone a significant loss in AGB storage. Hence, future OP plantation conversions could be directed towards heavily degraded forests as opposed to once or twice logged forests which retain a significant carbon storage and biodiversity value.

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Chapter 5: Evaluating Land Use and Above Ground Biomass Dynamics in a Tropical Forest-Oil Palm Dominated Landscape in Borneo Using Optical Remote Sensing

(In preparation for journal: *Journal of Forestry Research*)

ABSTRACT

This study explores the utility of optical remote sensing (RS) and field data in estimating variations in forest structure and above ground biomass (AGB) in East Sabah, Malaysia. The study area is a mixed landscape comprising of pristine old growth forests, forests that have undergone varying logging rotations (ranging from slight logging to heavily logging) and oil palm plantations. The field data pertaining to forest stand parameters and AGB were collected from 90 riparian and 60 non-riparian plots in the study region. RS data were used in conjunction with field data to evaluate the forest stand parameters and AGB dynamics. Multiple regression techniques were applied using band reflectance, vegetation indices and Grey Level Co-Occurrence Matrix (GLCM) texture features as predictor variables. The ability of these variables to distinguish between different land use types was examined. Variables based on spectral canopy reflectance have a limited ability to distinguish between different forest types in the study area and predict the biomass values. On the other hand, GLCM mean texture features showed a strong correlation with forest stand parameters and biomass of the different land use types. This research established the utility of texture analysis methods in distinguishing between different land use types and their AGB values in the tropical forests of Borneo.

Key words: Borneo, rainforests, vegetation indices, SPOT, Landsat, Grey Level Co-Occurrence Matrix, texture analysis, NDVI, AGB

5.1 INTRODUCTION

Over the past few years, optical remote sensing (RS) data has been widely used for evaluating changes in land use dynamics (Achard et al., 2002; Hansen et al., 2009), biomass dynamics

(Asner et al., 2010) and monitoring of degradation (Margono et al., 2012). At regional and national levels, vegetation indices have been commonly used for evaluations of forest biophysical properties. In Myanmar, SPOT derived NDVI has been used to assess canopy changes associated with forest harvesting in addition to identifying the role of logging roads in influencing the forest stand properties (Win et al., 2012). Matricardi et al. (2010) have used Landsat derived vegetation indices for evaluating forest degradation and recovery in Amazonia over a 13 year period. Tangki and Chappell (2008) evaluated the biomass variation in a selectively logged forest concession of Sabah by comparing field AGB data with NDVI measures obtained from Landsat TM data. Their research indicated NDVI explains only up to 58% variation in AGB. The spectral variables derived from Landsat TM and SPOT imagery have been utilized by de Wasseige and Defourny (2003) to distinguish between areas of different logging intensities in forests of Central African Republic. However, the use of variables derived from optical RS data have had limited success in Borneo in predicting biomass (Foody et al., 2001). Ten vegetation indices were used in conjunction with field data to generate predictive relation for biomass estimations for a number of tropical sites and these found that they have a weak correlation with field AGB measures (Foody et al., 2003). As opposed to methods based on exploiting the spectral characteristics of remote sensing data, texture based methods have provided valuable insights about the variation of forest structure, biophysical properties and biomass dynamics in tropical forests of both Malaysia and Thailand (Cutler et al., 2012). The research carried out by Cutler at al. (2012) and Kuplich et al. (2005) using high resolution radar data and the texture indices derived from these showed a high strength of association with the ground biomass values. Texture analysis of optical RS data too has been successfully used to quantify forest structural properties (Kayitakire et al., 2006). Wijaya et al. (2010) used a number of Landsat derived measures including vegetation indices and texture variables to examine the spatial variations in AGB and forest stand parameters in Kalimantan. Their research indicated that biomass and forest stand values had a significantly higher strength of association with variables such as texture measures derived using grey level co-occurrence (GLCF) matrices (Wijaya et al., 2010). These findings have been corroborated by research carried out by Castillo-Santiago et al. (2010) that used SPOT 5 data to derive spectral parameters and texture variables. Texture variables showed a stronger strength of association with forest stand parameters such as basal area, bole volume, canopy height than spectral parameters. Given the utility of RS data in evaluating biomass and forest structure dynamics at a landscape level, it is important to examine the extent up to which spectral and texture derived variables can predict AGB and forest stand parameters of the study area.

This paper has the following objectives: (a) To examine whether it is possible to distinguish between old growth primary forests, riparian forests of different logging intensities and oil palm from the spectral characteristics of Landsat TM and SPOT 5 data (b) To examine if texture based measures can provide insights into the spatial variation of forest structure and biomass dynamics across the different forest types (c) To generate biomass estimation models of the study area using remote sensing data. In order to achieve the aforementioned objectives, the paper uses several image processing techniques to enable the detection and mapping of land use/land cover patterns, as well as generating biomass estimation models for the different land use types.

5.2 MATERIALS AND METHODS

5.2.1 Study Area

The research was carried out at the Stability of Altered Forest Ecosystems [SAFE] Project (SAFE, 2011; Ewers et al., 2011) in Sabah, Malaysia. The area comprises of a mixed landscape that includes areas of a twice logged forest (LF/LFE), virgin jungle reserve/ VJR, oil palm plantation (OP) and a 7200 hectare heavily logged area known as the experimental area (EA) which have been ear-marked for conversion to oil palm beginning in December, 2011. The study area of the research extends to the Maliau Conservation Basin (116.87 E, 4.82 N). The location of the riparian and non-riparian plots is shown in Figure 5.1 (C):

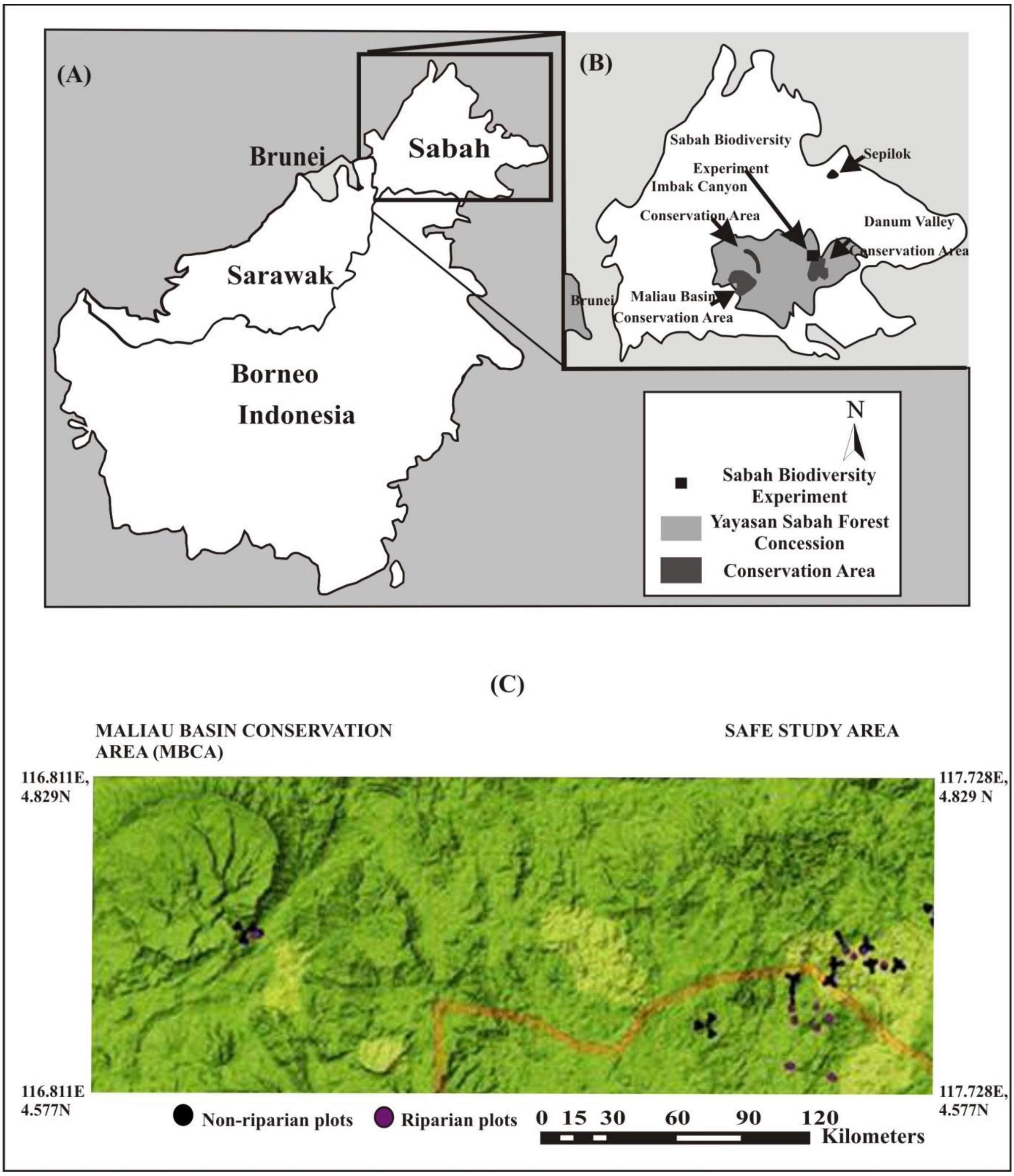

Figure 5.1: (A) and (B) Boundary of Borneo and Sabah (Hector et al., 2011) (C)Location of riparian and non-riparian plots in the study area

According to the ground truth data provided by SAFE, several different land use types are present (SAFE, 2011) in the study area. These include (a) old growth primary forests (b) disturbed forests (these have been exposed to slight anthropogenic disturbance, clearance) (c) virgin jungle reserve or once/lightly logged forests (d) twice logged forests (e) heavily logged forests which have undergone three rounds of logging and face severe degradation (f) riparian forests (g) oil palm plantations. These forest types have significant differences in their stand and canopy structure (table 5.1).

DIFFERENT LULCs	STRUCTURAL DIFFERENCES
Old Growth Forests: These are pristine lowland forests located in MBCA. The slope of the forest location did not exceed 20^0. These forests are characterized by a closed canopy and the presence of very large Dipterocarp trees. Some of the trees had heights >50m and DBH >80cm. A survey of the species carried out by the author revealed that OG forests also host IUCN Red listed Endangered Dipterocarp species such as *Shorea johorensis*. Further the forests also had a very thick understory.	
Oil Palm Plantations: The SAFE project site comprised of oil palm plantations of varying ages ranging from 5-8 years old. Oil Palm plantations are characterized by a homogenous canopy structure and negligible tree species diversity . The picture shows the air view of OP plantations in Sabah (Mongabay, 2012b).	

Heavily Logged Forests (EA): These are highly degraded forests which have undergone several rounds of logging. These are characterized by the presence of large open areas and broken canopy. Virtually no large trees were observed. Dominated by small successional trees and ginger shrubs.	
Riparian Forests (RF): These are forest zones adjacent to rivers and streams. These are dominated with slim and tall vegetation and trees of the Maccaranga genera. In some of the riparian zones, the evidence of illegal logging has been observed (owing to the presence of logging tracts). These are relatively intact compared to the surrounding heavily logged and twice logged forests.	

Table 5.1: Structure of the different forest types present in the study area (photographs taken by author at the SAFE Project Site, Sept 2011-December 2011).

The field data pertaining to forest stand parameters and ABG were collected from 90 riparian and 60 non-riparian plots which were distributed across all the different forest types in the study region. The riparian plots measured 10m by 50m and were established by the researcher in the riparian zones of each of the individual land use types. Forest mensuration data- diameter at breast height (DBH) and height were collected from these for tress having DBH>=2cm. The non-riparian plots too were distributed in all of the land use types and measured 25m by 25m. The researcher collected the height and DBH (<10cm) for a subset of these plots. These forest mensuration data were used to generate AGB values for the riparian and non-riparian zones of the individual land types in the study area (for details refer to chapter 4).

5.2.2 Satellite Data

Landsat TM and SPOT 5, both from 2009 have been used in this study. Landsat TM data has a spatial resolution of 30m and has six spectral bands. The SPOT 5 data was comprised of 10m multi-spectral bands (green, red, NIR) along with a 20m SWIR band which was resampled to 10m. Details have been provided in Chapter 3. Appropriate subsets covering the entire study area were clipped from the imagery data. These image subsets were co-registered and geo-referenced using appropriate ground control points. A Digital Elevation Model (DEM) data was obtained from Shuttle Radar Topography Mission (SRTM) data (USGS, 2011). The DEM was resampled to a 30m resolution using nearest neighbourhood algorithm and ortho-rectified with the Landsat TM data.

5.3 METHODOLOGY

5.3.1 Image Processing

A number of pre-processing and image processing remote sensing techniques have been applied on both Landsat TM and SPOT 5 datasets. For image pre-processing techniques both atmospheric and haze correction techniques have been applied (for details refer to chapter 3). Unsupervised classification is carried out to isolate non relevant features (such as clouds) in both the satellite datasets. Finally, supervised classification is carried out using the Maximum Likelihood Classification algorithm. On the basis of the field data obtained, the training samples have been created with the view of demarcating the different forest types in the study area (including oil palm plantations and riparian forests).

5.3.2 Vegetation Indices

The satellite data are converted to reflectance values and these have been used to calculate two vegetation indices-Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI). NDVI is a remote sensing based indicator of green vegetation in the study area. Soil adjusted vegetation Index (SAVI) is a modification of NDVI and corrects the influence of soil brightness when the vegetation cover is low (Huete, 1988).

$$NDVI = \frac{(\rho_{B4} - \rho_{B3})}{(\rho_{B4} + \rho_{B3})} \quad \text{----------} \ (5.1)$$

$$SAVI = \frac{1.5(\rho_{B4} - \rho_{B3})}{(\rho_{B4} + \rho_{B3} + 0.5)} \quad \text{----------} \ (5.2)$$

In addition to these two, the study makes use of normalized difference infrared index (NDII) for distinguishing between different land use/forest type classes (as recommended by Souza et al., 2005). The NDIIs are computed using the near infra-red and SWIR bands (Souza et al., 2005):

$$NDII5 = \frac{(\rho_{B4} - \rho_{B5})}{(\rho_{B4} + \rho_{B5})} \quad \text{----------} \ (5.3)$$

NDIIs such as NDII5 help distinguish forest disturbances on the basis of difference in water content.

5.3.3 Texture Measures: Grey Level Co-Occurrence Matrix

Texture analysis of an image can be carried out using statistical, spectral and spatial techniques (Ploton, 2010). In statistical based texture analysis methods, information is obtained by measuring the spatial variation in an image's tonal values (Jones and Vaughan, 2010). Image texture measures can be classified into two categories: 1) Occurrence, also known as first order statistics. This relates to the frequency of tonal values in a specified neighbourhood around each pixel (St-Louis et al., 2006). It takes no account of spatial relationships among pixels. 2) Co-occurrence, also known as second order statistics. It measures the frequency of associations between brightness value pairs within a given area (Estes et al.,2008; Jones and Vaughan, 2010). The statistical texture indices derived using the Grey Level Co-Occurrence Matrix (GLCM) algorithms are tabulated in Table 5.2:

Texture variable	Formula	Description
Mean	$\text{MEAN} = \sum_{ij=0}^{N-1} iP_{ij}$	Mean of the probability values from the GLCM. It is directly related to the image spectral heterogeneity.
Variance	$\text{VAR} = \sum_{ij=0}^{N-1} P_{ij\,(i - MEAN)}{}^{2}$	Measure of the global variation in the image. Large values denote high levels of spectral heterogeneity.
Correlation	$\text{COR} = \sum_{ij=0}^{N-1} P_{ij} \left[\frac{\text{ij - MEANij - MEAN)}}{\text{VAR}}\right]$	Measure of the linear dependency between neighbouring pixels.
Contrast	$\text{CONT} = \sum_{ij=0}^{N-1} P_{ij\,(i - j)}{}^{2}$	Quadratic measure of the local variation in the image. High values indicate large differences between neighbouring pixels.
Dissimilarity	$\text{DISS} = \sum_{ij=0}^{N-1} P_{ij\,(i - j)}$	Linear measure of the local variation in the image.
Homogeneity	$\text{HOM} = \sum_{ij=0}^{N-1} \text{P} \frac{P_{ij}}{1+(i-j)^2}$	Measure of the uniformity of tones in the image. A concentration of high values along the GLCM diagonal denotes to a high homogeneity,
Angular second moment	$\text{ASM} = \sum_{ij=0}^{N-1} P_{ij}{}^{2}$	Measure of the order in the image. It is related to the energy required for arranging the elements in the system.
Entropy	$\text{ENT} = \sum_{ij=0}^{N-1} \text{P}_{ij}\text{InP}_{ij}$	Measure of the disorder in the image. It is inversely related to ASM.

Table 5.2: Texture variables derived from GLCM (Gallardo-Cruz et al., 2012)

The texture variables are calculated on the basis of the red band (Eckert, 2012). According to extensive GLCM analysis carried out by Gallardo-Cruz et al. (2012), the texture variables derived from the red band of optical RS data serve as best explanatory variables for vegetation attributes. These derived texture variables, especially mean, standard deviation, contrast and entropy have the ability to provide vital information about the forest stand parameters and biomass dynamics and the variation and heterogeneity in these. As recommended by Lu et al. (2012), the textural variables which showed a high correlation with field biomass but low correlation with each other are utilized.

5.4. RESULTS

5.4.1 Land Use Land Cover (LULC) Map of the Study Area

LULC maps of the study area has been created using both Landsat TM and SPOT 5 data which clearly delineates the areas of different logging intensity in the study area (along with an identification of areas of primary forest, oil palm and upland clay forests) as shown in Figure 5.2. Riparian forests are difficult to distinguish from non-riparian zones through medium resolution Landsat TM data. For this purpose, information gleaned from high resolution satellite imagery (in this case SPOT 5) is used in conjunction with detailed hydrological vector data for the SAFE project for identifying training sites for the riparian zones in the Landsat TM imagery. DEM data has been used to refine the final land use classification.

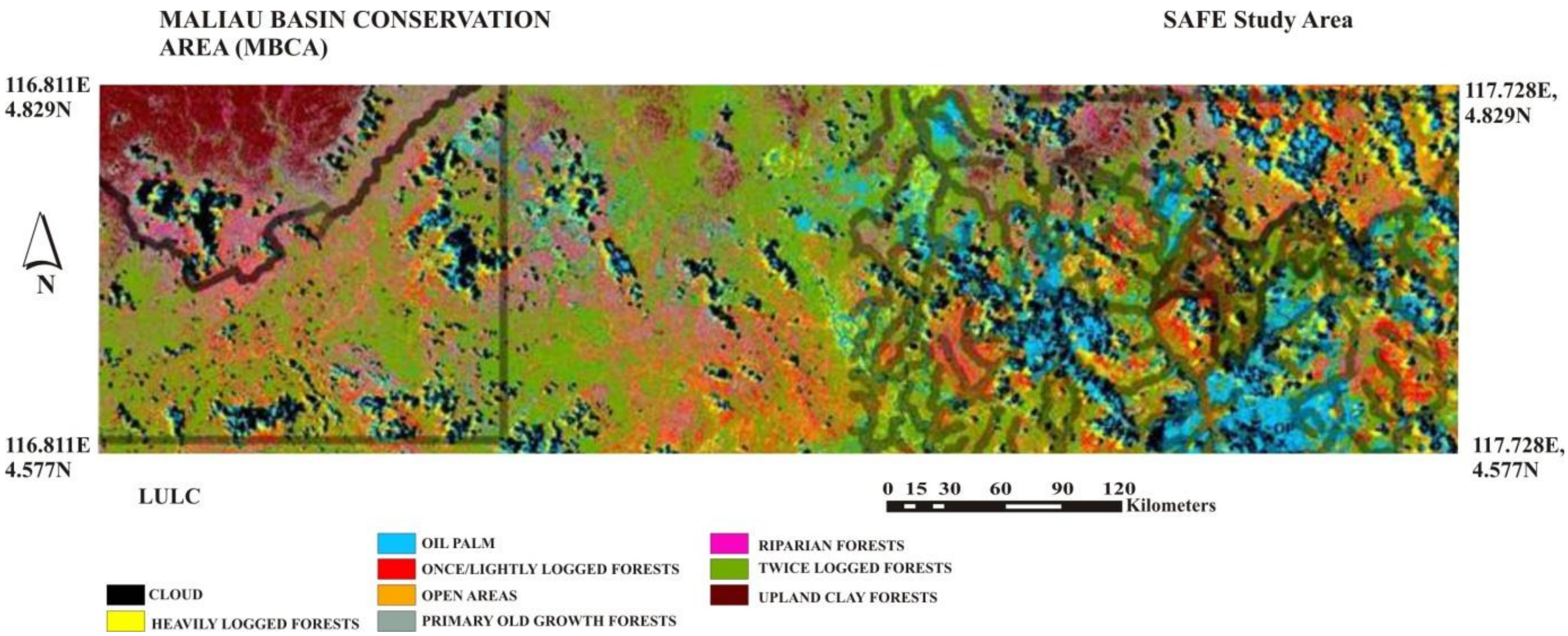

Figure 5.2: Landsat TM based map of the SAFE Area (The translucent black lines represent SAFE and MBCA boundaries)

While majority of the ground data is used for generating training pixels or regions of interest (ROIs), 30% of the ground truth data was kept aside for validation. Using the validation data and the classified data, a confusion matrix was generated which is a popular technique for post classification accuracy assessment (Foody, 2002). The classified Landsat image had a classification accuracy of 77% and κ (kappa coefficient) of 0.45.

5.4.2 Distinguishing Between Different Land Use Classes Using Reflectance and Vegetation Indices

5.4.2.1) Efficacy of SPOT 5 Based RS Data in Distinguishing between Different Land Use Types

Spectral characteristic derived values such as vegetation indices, band reflectances of SPOT 5 data have been used to distinguish between different land use types. Individual pixels from different classes are randomly selected for each of the bands. Tukey tests[3] are applied to the values obtained from the different LULC types in order to evaluate class seperability. All forest classes, ranging from old growth primary forests to the forests that have undergone different rounds of logging, riparian forests and oil palm plantations show significant difference in the shortwave band of the SPOT data. While the other bands, namely infrared and red bands can distinguish between the major forest classes, they cannot distinguish non-riparian zones from riparian zones and twice logged forests from heavily logged forests. All the three bands can distinguish oil palm from other forest types. However, in red and near infrared bands, the different logged forests show overlap. In addition to band reflectance's, spectral vegetation indices too have been used for the purpose of distinguishing between the different forest transitions systems (figure 5.3):

[3]Tukey tests perform a multi-comparison between the population means of the different land use types (Souza et al., 2005). In this study these range from intact forests, forests having different logging intensities and oil palm.

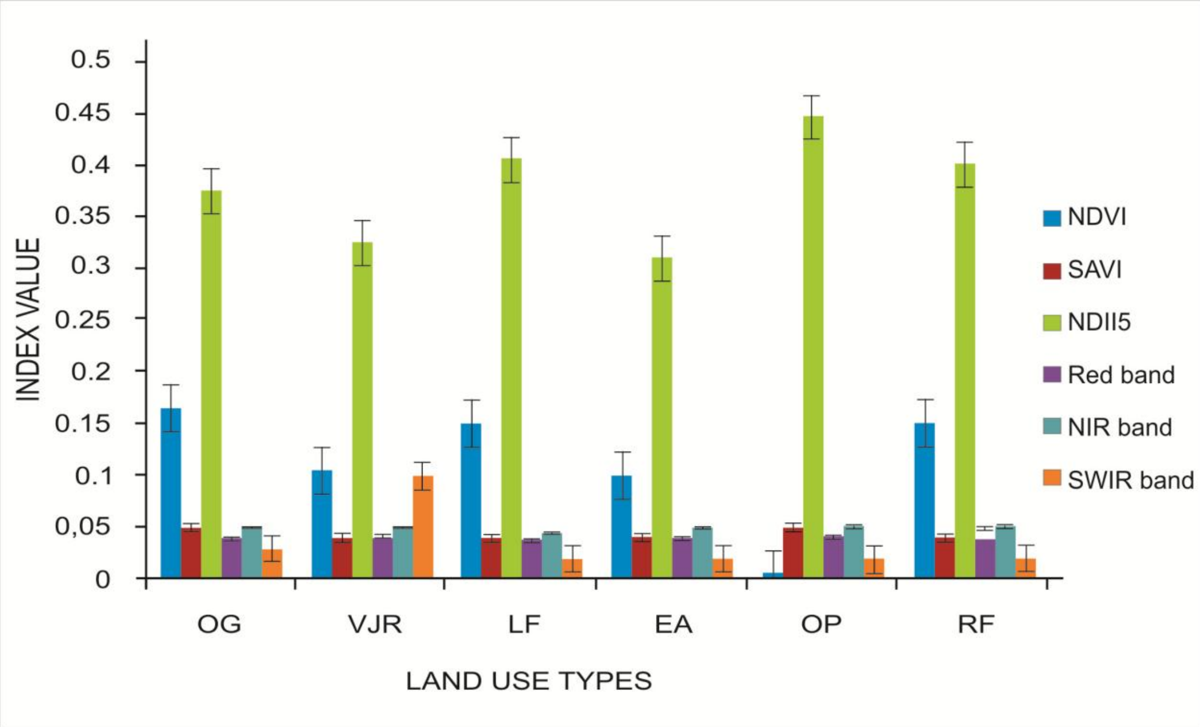

Figure 5.3: Behaviour of SPOT derived vegetation indices for different land use types (OG- Old Growth forests, OP-Oil Palm plantations, RF- Riparian forests, VJR-Virgin Jungle Reserve, EA-Experimental area, LF- Twice Logged forests)

Values of the different vegetation indices are selected from randomly selected pixels representing different land use types (Souza et al., 2005). Tukey tests are applied to the different vegetation indices obtained from the different LULC types in order to evaluate class seperability. It has been decided to use vegetation indices derived from higher resolution SPOT data to distinguish between different forests types present in the study area. Three vegetation indices are derived from SPOT data- NDVI, SAVI and NDII5.It is observed that the value of NDVI and NDII5 drops sharply between primary forests and once logged forests and rises from once logged to twice logged to heavily logged forests in this band. SPOT 5 derived NDVI is successfully able to distinguish between different forest types and forest transition systems in the study area. NDVI derived values varies significantly between old growth primary forests, once logged forests, twice logged and heavily logged forests. The oil palm plantations could also be distinguished from all the other land use types. However, the SPOT derived NDVI failed to distinguish between the riparian forests and the pristine, once logged and twice logged forests of the study region. The NDVI values vary significantly between heavily logged forests and oil palm plantation. However, SPOT derived SAVI has much less success in distinguishing between different forest types of the study area. SAVI values varied significantly between the old growth pristine forests and once/slightly logged forests and old growth forests and heavily logged forests. However, the SAVI values did not vary significantly between the once logged, twice logged and heavily logged forests. SAVI values (like NDVI) varied significantly between oil palm plantations and all the other forest transition systems. NDII5 could distinguish oil palm from other land use types.

5.4.2.2 Efficacy of Landsat TM Based RS data in Distinguishing Between Different Land Use Types in the Area

Landsat TM derived NDVI of different land use types is compared using Tukey tests. NDVI value is significantly different between OP and other land use types (disturbed forests, twice logged forests, OG and VJR). However, the Landsat derived NDVI values could not distinguish between forests that have undergone different logging intensities. These results can be attributed to saturation of the NDVI value at high biomass levels (Basuki et al., 2011; Sader et al., 1989) which limits their ability to predict biomass in tropical forests such as those present in Borneo.

5.4.3 Correlation between VIs and Field Measures of AGB

Predictive models of biomass have been generated using field AGB data in conjunction with Landsat TM and SPOT 5 data based remote sensing variables such as vegetation indices and band reflectances. The reflectance values of the green (band 1), red (band2), NIR (band 3) and SWIR (band 4) bands of the SPOT 5 data are correlated with field AGB data to derive remote sensing based biomass estimate models. With the exception of SWIR, all the variables displayed a high strength of association with field AGB values and the biomass estimate models that can be derived from these have been listed below:

$$(Biomass)_{SPOT} = 106.37 * (Band1) - 33.72 * (Band2) + 124.33 * (Band3) + 40.73 * (Band4) - 130.71 \text{----------------} \quad (5.4)$$

The values of field AGB values that were not used for equation generation were used for validation purposes. A strong strength of association was found between field AGB and SPOT band derived AGB values. It was also observed that the SPOT biomass model (equation 4) tends to underestimate the AGB values. The values that were not used in the model generation have been used for validation. The results of validation have been presented in Appendix II.A. A biomass estimate model comprising of all three bands- red, NIR and SWIR also displayed a high level of correlation (R^2=0.8512, p<0.001) with field AGB values. Single band biomass estimate models comprising of red and NIR bands had an R^2 value of 0.80 and 0.833 respectively and p<0.001.

However, for Landsat data, NDVI is found to have a very weak correlation (R^2=0.0562, p<0.01) with the field AGB measures of the study area. On the other hand, Landsat derived EVI just explain 2% of the variation in biomass of the study region. Other vegetation indices such as SAVI too showed an extremely weak correlation with field derived AGB values. On the other hand, the reflectance values of band 3 and band 4 in Landsat TM are strongly correlated with field AGB values. The reflectance values of band 3 showed a very strong strength of association with field AGB values (R^2= 0.85, p<0.01). On the other hand, the strength of association between the reflectance values of band 4 with field AGB are weaker (R^2=0.59, p<0.01). The band reflectance value based model of biomass for both the bands can be expressed as:

$$B_a = -2175.4\ (Band\ 4) + 2628.3 \text{---------------} \ (5.5)$$
$$B_a = -2776\ (Band\ 3) + 2817.4 \ \text{-----------------} \ (5.6)$$

Here Ba is the mean biomass of study area (in Mg/ha) which has been obtained from the reflectance values of band 3 and band 4.In addition to spectral parameters, texture variables have been used for examining the variation in forest stand parameters and generating biomass estimates of tropical forests from remote sensing indices and methods.

5.4.4 Use of Texture Based Variables in Evaluating Forest Stand Parameters and Biomass Dynamics

High resolution satellite data is better suited for calculation of texture indices than coarse and medium resolution data (Jones and Vaughan, 2010; Beguet et al., 2012). For this reason, high resolution SPOT data is used for obtaining the texture based variables. Two vegetation attributes are focus of this analysis-namely AGB and basal area. A statistical examination of AGB values in different land use types indicate that these values are affected by disturbance caused due to several rounds of logging and oil palm cultivation. Regression models are generated to describe relationships between these vegetation attributes and the texture variables described in table 5.2. The texture variables showed strong but different strength of association with the AGB and basal area of different forest types present in the study area (table 5.3).

	AGB	**Basal Area**
EA	R^2=0.86 (p<0.01)	R^2=0.92 (p<0.01)
LF	R^2=0.88 (p<0.01)	R^2=0.72 (p<0.01)
VJR	R^2=0.90 (p<0.01)	R^2=0.98 (p<0.01)
RF	R^2=0.91 (p<0.01)	R^2=0.84 (p<0.01)
OP	NA	NA

Table 5.3: Ability of texture based linear models to explain variation in vegetation attributes

Statistical texture measures have a strong (but varying) correlation with the AGB and basal area of the different forest types except OP plantations. Although strong strength of association was found between field AGB and the texture derived AGB values; texture based biomass estimate models underestimated the AGB values for all the land use types in question. The validation results for some of the land use types have been presented in Appendix II. B.

5.5 DISCUSSION

This paper presents an overview and comparison of the variety of remote sensing variable that may be applied for evaluation of the land use and biomass dynamics of the study area. The research has achieved two out of three of its objectives. The first objective was to use VIs and band reflectance values derived from Landsat and SPOT data to distinguish between different forest types present in the study area. The research established that vegetation indices derived from Landsat TM and SPOT 5 data have only a limited potential to distinguish the different land use types present in the study area. Vegetation indices derived from Landsat data (such as NDVI) can distinguish between major land use types such as old growth pristine forests and oil palm but not between forests having different logging intensities. NDVI derived from higher resolution SPOT data can distinguish between pristine forests, forests of different logging intensities and oil palm plantations (Souza et al., 2005). Other SPOT based vegetation indices too cannot distinguish between the forests of different logging intensities. Further, vegetation indices derived from both Landsat TM and SPOT 5(such as NDVI, EVI) do not have a strong correlation with field AGB. From these results it may be inferred that for the given study area, the vegetation indices based on Landsat TM and SPOT 5 data are insufficient for both distinguishing between the forests of different logging intensities and for generating biomass estimate models. These trends may be corroborated from the existing body of literature (Souza et al., 2005; Foody et al., 2003; Lu et al., 2004; Wijaya et al., 2010; Eckert, 2012; Castillo-Santiago et al., 2010). Landsat TM derived vegetation indices have been demonstrated to be insufficient for biomass estimation for mature forest, especially in the tropics as these data are fraught with data saturation problem caused by complex forest stand structure (Lu et al., 2012; Basuki et al., 2011).As opposed to the vegetation indices, reflectance values of band 3 and band 4 have a stronger correlation with the field AGB values. Similar strength of association between field AGB and reflectance values has been observed in a logging coupe- pristine forest study site located in Danum Valley Conservation Area which is close to the SAFE study area (Tangki and Chappell, 2008).

The second and third objectives were to use texture based variables to examine the structure and biomass parameters of different forest types in the study region and evaluate the possibility of developing biomass estimate models for the different forest types. The use of the GLCM based texture analysis method sheds light on both the biomass and structural dynamics across different land use types present in the study area. The texture analysis also helps to identify that different land use types, including forests having undergone different logging rotations vary in terms of their structure and optical remote sensing data can be used to identify (and demarcate) small fragmented areas such as riparian zones and forests having different logging intensities.Statistically based texture variables have been widely cited in literature for their strong association with variation forest structure/stand parameters and biomass dynamics (Eckert, 2012; Cutler et al., 2012; Wijaya et al., 2010;Tsuyushi et al., 2009). This fulfils the second objective of the research. Table 3 has clearly indicated that a regression model using texture variables as independent variables and field AGB values as independent variables showed different strength of association for different forest types. Hence it can be concluded that the use of texture analysis opens up the possibility of developing different biomass estimate models for different land use types, thereby fulfilling the third objective of the research.

5.6 CONCLUSION AND FUTURE DIRECTIONS

Remote sensing data offers the potential to study various forest properties including their structure, carbon dynamics and assessment of degradation. This paper provided a comprehensive overview of the different techniques that may be used to overcome the shortcomings of optical RS data. Most importantly, the efficacy of these different techniques in examining the structural and biomass dynamics of tropical forests, especially those comprising of a mixed land use type like the study area has been discussed in detail. There is a scope for applying this research to the management of lowland Dipterocarp forests and to evaluating both their carbon stocks and the temporal changes in these. It has been established that band reflectance, and texture measures derived from GLCM can be used to generate biomass estimate models that relate strongly to the field AGB. The biomass estimate models generated that can be derived from texture variables can be applied to similar mixed land use types comprising of logged forests, oil palm plantations along with pristine forests. Application of these biomass estimate models to the logging coupes, and to proposed and existing oil palm plantations within the study area could allow for the assessment of timber stocks, and for the assessment of the ecological status of the study area (and similar areas) in terms of forest recovery and variation in carbon stocks. Most importantly, use of biomass estimate models, especially those generated by using texture analysis based methods will make it possible to examine both the spatial variation in forest canopy structure and carbon stocks across a variety of different land use types and disturbance gradients. Texture analysis is a very promising technique for a study area like Borneo where optical remote sensing techniques is fraught with data saturation generates large uncertainty for sites with high biomass density or sites having complex forest stand structure (Lu et al., 2012). Therefore texture analysis (through application of different techniques) will be explored further in Chapter 6.

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Chapter 6:The Use of Fourier Transform Based Textural Approaches to Estimate Biomass of Intact, Degraded Forests and Oil Palm Plantations

(In preparation for journal: *Remote Sensing of the Environment*)

ABSTRACT

Assessment of forests structure parameters through the use of remote sensing data offers the possibility of carrying out an examination of stand parameters, detection of degradation and forest dynamics such as above ground biomass (AGB) stocks at a landscape scale. While much attention has focussed on spectrum based or radar backscatter approaches for assessing forest biomass, texture-based approaches show a strong promise in this regard. This paper explores the potential of Fourier transform approaches in estimating the different forest types, their stand structure and biomass dynamics in an oil palm-tropical forest landscape in Sabah, Malaysian Borneo. Specifically the research has made use of a novel approach of using texture oriented Fourier transform method known as Fourier transform textural ordination (FOTO). The FOTO method uses a combination of two different techniques- 2D Fast Fourier Transform (FFT) and ordination through Principal Component Analysis (PCA) for characterizing the structural and textural properties of vegetation. This method was applied to sub-samples of very high resolution (VHR) imagery representing the different forest types in the study area with the view of distinguishing between them. The use of FOTO has proved useful in distinguishing between the forest types and developing individual biomass estimate models for them. The first two axes obtained from the PCA evaluation (PC1 and PC2) allowed for distinguishing the different forest types across both a disturbance and fragmentation gradient respectively. For instance, this analysis was able to identify riparian forests as the most fragmented of all the forest types. The FOTO derived AGB values showed no evidence of saturation at high biomass values. Results of validation indicated that overall the FOTO derived AGB models predict biomass well for the different forest types.

Keywords: 2D Fourier analysis, Malaysian Borneo, SPOT, Landsat, AGB, oil palm, logged forests

6.1 INTRODUCTION

Ecological and field studies in tropical forests have been plagued by two major difficulties - the presence of large inaccessible regions where it was nearly impossible to carry out ground surveys (Gibbs et al., 2007; Pearson et al., 2005b) and the difficulty in sampling of some attributes of forest stand parameters, such as the crowns of large canopy trees (Chambers et al., 2007). Recent advances in remote sensing offer the possibility of overcoming some of these obstacles, and enable the landscape scale evaluation of forest parameters and dynamics (Ingram et al., 2005, Hawes et al., 2012; Helmer et al., 2012). Satellite remote sensing has long been considered an ideal technology for vegetation mapping and monitoring due to its ability to provide data beyond the local setting (i.e. at a landscape level) and repetitively at regular time intervals (Franklin and Wulder 2002). Retrieving tropical forest stand structure parameters from remotely sensed data is of primary importance for estimating global carbon stocks in above-ground biomass (Houghtonet al., 2001; Grace 2004; Eva et al., 2012). However, biomass prediction is a challenging task especially in dense and heterogeneous tropical forests (Huete et al., 2002). The challenges are mainly due to different forest structures possibly presenting similar AGB values. Hence the impact of the spatial variations of forest parameters on AGB values may not be accounted for.

A significant body of literature describes the use of spectral characteristics based methods such as vegetation indices and SMA derivatives in remote sensing based estimation of carbon stocks (Morel et al., 2011; Tangki and Chappell, 2008; Souza et al., 2005; Basuki et al., 2011). In addition to optical data, ALOS-PALSAR data was used for distinguishing oil palm plantations from other forest types in Sabah, Malaysian Borneo. These radar data were also used to generate AGB regression models (Morel et al., 2011). Landsat ETM+ was used in conjunction with ALOS-PASAR to improve the estimation accuracy of AGB in lowland mixed Dipterocarp forests in Borneo (Basuki, 2012). However, both optical (Nicol and Sarker, 2011; Lu, 2006) and radar (Woodhouse et al., 2012; Morel, 2010) data are fraught with the problem of saturation at high biomass values.

Over the past few years, texture based approaches have also been making inroads in generating remote sensing based estimates of AGB stocks in tropical ecosystems (Wijaya et al, 2010; Lu et al., 2004; Lu et al., 2012; Eckert, 2012). Texture has been used as a generic term to describe image properties such as smoothness, regularity and tonal variation (Jong and van der Meer, 2004). The research pertaining to above ground forest biomass estimation based on Landsat data has indicated that texture is an important variable for improving biomass estimation performance for the areas with complex forest stand structure. A number of different approaches ranging from statistical, to structural to spectral have been applied for the purpose of analysing texture (Jong and van der Meer, 2004).

The Fourier transform textural ordination (FOTO) uses a combination of two techniques, namely 2D Fast Fourier Transform (FFT) for converting spatial information into the frequency domain and ordination by Principal Component Analysis (PCA) (Proisy et al., 2007). 2D FFT was applied to sub-samples of very high resolution (VHR) imagery representing the different forest types in the study area with the view of obtaining the r-spectrum of the different forests types. PCA was applied to the r-spectrum of the different forest types. The most prominent components obtained from application of PCA were taken to be the texture indices (Proisy et al., 2011). The texture indices obtained from the FOTO method has been used to characterize the spatial structure and texture of vegetation, especially structural parameters that are connected to top canopy. FOTO results are further influenced by stand parameters such as basal area and diameter at breast height making it potentially useful for evaluating the AGB of a given area (Barbier et al., 2011). The first major research involving the use of FOTO methods for tropical forests was employed by Couteron et al. (2005). FOTO was used to estimate forest structural parameters and stand parameters of forests of French Guiana (Proisy et al., 2007; Proisy et al., 2011). The FOTO based model had a good explanatory power on several stand parameters such as basal area and did not suffer from the problem of saturation which is common for dense tropical forests (Ploton et al., 2012). Proisy et al. (2007) have used FOTO derived texture indices to generate a biomass model for the mangroves of French Guiana. Ploton et al. (2012) applied the same methodology to generate a FOTO texture indices based biomass estimate for Westerns Ghats (India). In both the cases, the FOTO generated AGB displayed a strong correlation to the field AGB measures, making FOTO a particularly useful tool for generating remote sensing based biomass models for tropical ecosystems.

This study explores the capabilities of textural approaches for high-resolution satellite imagery, namely that of Satellite Pour l'Observation de la Terre (SPOT)-5 images to evaluate the forest structure and estimate tree biomass of mixed land use forest landscape comprising of pristine forests, oil palm plantations and differently logged forests in Malaysian Borneo. Proisy et al (2007) suggested that while very-high (VHR) resolution imagery can provide valuable insights into the forest structure parameters the results can be improved by comparing high resolution images with coarser images. The paper has three main objectives, namely (1) to distinguish between different land-cover types, including forests of different logging intensities, oil palm plantations and pristine forests from one another using FOTO method, (2) to develop texture based biomass estimate models for different land use types, and (3) to examine the possibility of distinguishing a remnant/isolated forest ecosystem (in this case riparian forests) from surrounding contiguous forest types. The working hypothesis of the paper is that as forest types undergo different intensities of disturbances ranging from light logging to conversion to oil palm plantations, the canopy structure alters because of changes in the relative dominance of large diameter trees. We hypothesize that this change can be detected in the textural properties of the forest canopy. To the researcher's knowledge, this paper presents the first study on the use of SPOT data for distinguishing between the structural and biomass dynamics of forests that have undergone varying logging rotations, oil palm monoculture and a remnant/fragmented tropical forest ecosystem (in this case riparian forests) from the surrounding contiguous forests.

6.2 MATERIALS AND METHODS

6.2.1 Study Area and Ground Control Data

Remote-sensing instruments cannot measure forest carbon stocks and structural parameters directly (Gibbs et al., 2007). Use of remote sensing data for estimating forest biomass and structural parameters requires additional ground-based data collection and field inventory (Rosenqvist et al., 2003).

The study area was based at the Stability of Altered Forest Ecosystem (SAFE) project in Sabah, Malaysian Borneo (SAFE Project, 2011). The entire study area extended from the Maliau Basin Conservation Area that comprised of old growth lowland primary forests (OG) to the SAFE study area. The latter comprised of logged forests which have undergone varying logging rotations ranging from once/lightly logged (VJR), twice logged forests (LF) and heavily logged/degraded forests (EA). Additionally, the area was comprised of an oil palm plantation (OP) having palm trees of different ages. As shown in Figure 6.1A, these land use types have undergone different levels of disturbance and have vastly different canopy structures.

Figure 6.1A: Canopy Structure of the Different Forest Types in the Study Area. A: Canopy of OG Forests. B: Canopy of OP Plantation. C: Canopy of EA forests (SAFE Project, 2011)

Owing to the different levels of disturbance faced by the different land use types, their canopy structures varied from thick closed canopies of OG forests to open canopies of the heavily logged forests and the homogenous surface of the oil palm plantations as shown in figure 6.1A.

A total of 90 rectangular plots (10m by50m) were distributed over the riparian zones of the different land use types in the study area. From these plots, forest mensuration data was collected using the RAINFOR protocols (RAINFOR, 2011). The diameter at breast height (DBH) of trees having DBH > = 2cm was recorded. Height of all the trees was recorded as well along with the species information. The study also made use of the vegetation plots set up as a part of the SAFE project earlier on (figure 6.1B).

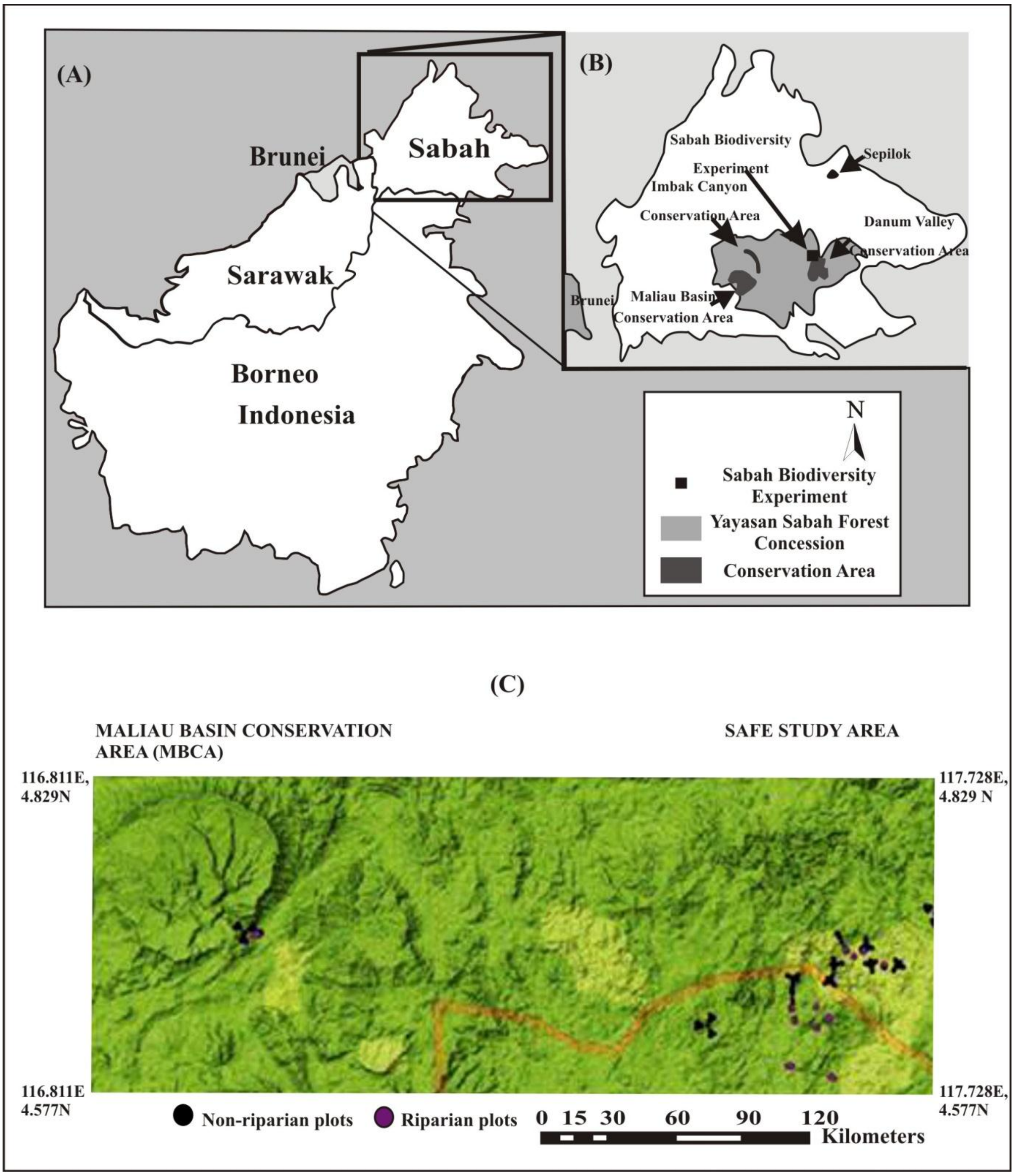


Figure 6.1 B: Location of Riparian and Non-Riparian Plots in the Given Study Area

The AGB of the trees in the riparian margins was calculated using the biomass equation recommended by Chave et al. (2005). Details were provided in Chapter 4.

6.2.2 Remote Sensing Data

6.2.2.1 SPOT Data

SPOT 5 data comprise three optical bands which have a resolution of 10m along with a panchromatic band which has a resolution of 2.5m. Data fusion of panchromatic band with optical bands had already been carried out as a way of providing multi-band SPOT data having a spatial resolution of 2.5m (Jones and Vaughan et al., 2010).

6.2.3 Fourier-based Textural Ordination (FOTO)

6.2.3.1 Background

Fourier based Textural ordination (FOTO) belongs to the family of spectral approaches which ordinates digital images (such as those obtained from satellite data) along coarseness-fineness texture gradients (Barbier et al., 2011). FOTO makes use of multivariate ordination of Fourier spectra to classify canopy images with respect to canopy grain. The latter is a combination of mean size and frequency of tree crowns per sampling window (Ploton et al., 2012). The Fourier-based Textural Ordination (FOTO) method is used to distinguish between pristine forests and varying logging intensities. The method is further applied for biomass prediction by from forest canopy parameters information obtained from remote sensing data (Couteron et al., 2006; Ploton et al., 2012). This method is well-known for analysing information that comes from digitised and visual data from remote sensing methods (Proisy et al., 2007; Ploton et al., 2012). Although this methodology can be applied for different purposes, it allows for constantly characterizing the canopy structure. The basic premise of the FOTO method is that frequency signatures relate well to components of the canopy grain size. Fourier transforms help representing/analyzing repetitive structure of the canopy by breaking the intensity signal into sinusoidal waves of different frequencies. It has been used as an effective way to analyse specific vegetation data from a wide range of frequencies obtained from VHR satellite data (Barbier et al., 2010). The SPOT data can be viewed using this ordination method to analyse spatial frequencies viewed within the images in order to quantify patterns and intensity of biomass and make predictions based on this information (Barbier et al., 2010a; Couteron et al., 2006). This is an ideal and efficient method for analysing specific patterns found in the forest amongst the existing biomass, including canopies and related textual vegetation (Ploton et al., 2012).

6.2.3.2 Obtaining r-spectra from a 2D Fourier Transform

This method first removed any aspects of the images that were not critical to the analysis, including images related to shadows, water features and manmade structures, which are not tied to biomass data. Then the specific areas, in this case the different land use types were delineated from the whole image. These images were input into window-sized segments. The method then proceeded with the specification of a square window size in which 2D-Fourier spectra were computed. To be clear, the window size *WS* is expressed in meters as (Proisy et al., 2011):

$$WS = N.S \text{---------------------} (6.1)$$

Where N is the number of pixels in the *X* or Y direction of the image and *S* is the pixel size in meters. *WS* may influence the FOTO results. The output of FOTO and subsequent biomass maps are influenced by WS; larger WS may lead to the generation of coarser biomass maps by the factor of N (Proisy et al., 2011). After windowing the forest images, the individual windows were subjected to a 2D Fourier transformation.

Fourier radial spectra were computed for each window image from the remote sensing data, setting the frequency versus the amplitude of each signal that has been retrieved from the data to assign a specific arrangement of the pixels. A two-dimensional Fourier transformation allows for the decomposition of the total image variance according to all possible integer pairs (p, q), of wave numbers along the two Cartesian geographical directions. When expressed in polar form (Mugglestone & Renshaw, 1998), these values are portions of image variance accounted for by a waveform having spatial frequency r. For each spatial frequency, summing values on all possible travelling directions yields an azimuthally cumulated 'radial' spectrum, which allows for the quantification of coarseness-related textural properties by studying the decomposition of variance among spatial frequencies. Images (which represent the individual land use types) with a coarse texture will yield a radial spectrum that is skewed towards small wave numbers, whilst fine-textured images are expected to produce more balanced spectra (Couteron et al., 2005). Figure 6.2 shows the different steps carried out sequentially to obtain the r-spectra of the different land use types.

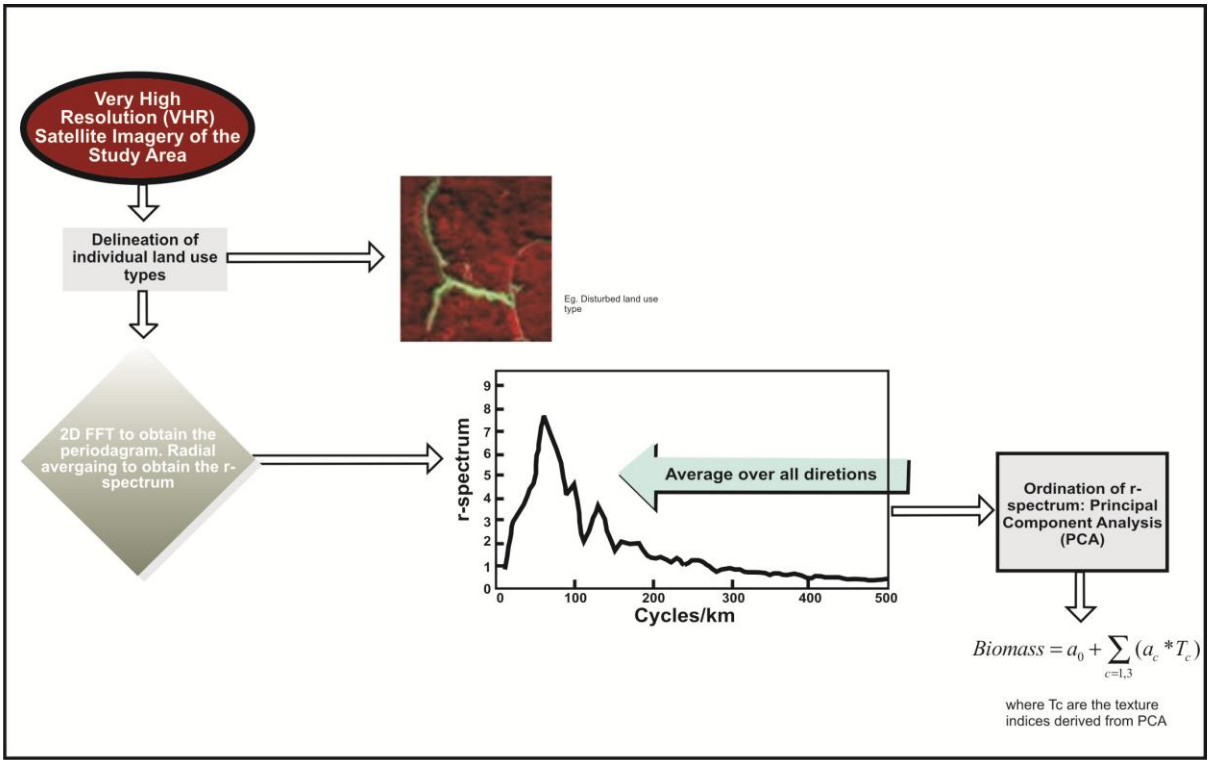


Figure 6.2: Obtaining radial spectra of individual land use classes by using the FOTO method (Adapted from Barbier et al., 2010b and Priosy et al., 2011).

The window images of individual land use types were subjected to 2D Fast Fourier Transform (FFT) using the ENVI software to obtain their power spectrum. This is the squared amplitude of the Fourier transform thus obtained. This is expressed by portioning the image variance or power into frequency bins along two Cartesian axes. The quantification of spatial frequencies (of images representing different land use types) is very effective in quantifying both the pattern scale and intensity, especially for repetitive patterns such as those formed by forest canopies. As a way of expressing this, the radial spectrum or r-spectra (which is the average of frequency information for across the azimuthal directions for space) is plotted with respect to frequencies which are expressed in cycles/km (Barbier et al., 2012).

6.2.3.3 Textural ordination of the r-spectra

A systematic textural analysis has been carried out on the power spectrum of the individual land use type images. For this purpose, the r spectra may be then stacked into a common matrix in which each row corresponds to the r spectrum of a given window., Each column on the other hand contains amplitude values. This table is then submitted to multivariate analysis techniques (ordinations/classifications). A body of literature indicates that these windows may be considered to be statistical observations characterized by their spectral profiles and may be subjected to ordination techniques such as principal component analysis or PCA (Priosy et al., 2007; Couteron et al., 2006; Barbier et al., 2010a; Ploton et al., 2012).

Spatial frequencies may be seen to be quantitative variables that are linearly combined to yield principal components (Couteron et al., 2005). In all the literature examined on FOTO methodology, the first three axes of the principal component analysis explained majority of the variability in the data. Each principal component (PC) image is a linear weighted combination of the original bands as shown in formula 6.2:

$$PC_i = {}_{k=1}^{m}\Sigma\, g_{ik} Band_k \text{---------------------}(6.2)$$

The first principal component concentrates the features common to all original image bands. The principal component variances started declining sharply with the increment in PC ranks. In case of satellite based vegetation analysis, bands up to PC3 highlight the vegetation changes. Hence, only the first three PC axes are retained for further analysis (Liu and Mason, 2011). For this research, these three axes have been used as texture indices, which are also known as the FOTO indices. The spatial resolutions from these align with the window-sized measurements mentioned earlier that segment each of the forested areas being analysed. Once these texture indices have been obtained, multiple linear regressions can be carried out to predict stand structure parameters and AGB (Ploton et al., 2012). For the purpose of this research, texture indices were obtained from the images representing the different land use types. The AGB data obtained from the plots located in the different land use types was correlated with these texture indices to obtain biomass estimate models for the different land use types.

6.3 RESULTS

Texture analysis was done by using Fast Fourier Transform (FFT) algorithm of ENVI (Couteron et al. 2006). The frequency signatures related effectively to the components of the canopy grain size. From the FFT output, the power spectrum of the different land use types was derived and it was discovered that the various land use types, including those that underwent varying rounds of logging, had different frequency signals expressed in cycles/km (Figure 6.3a).

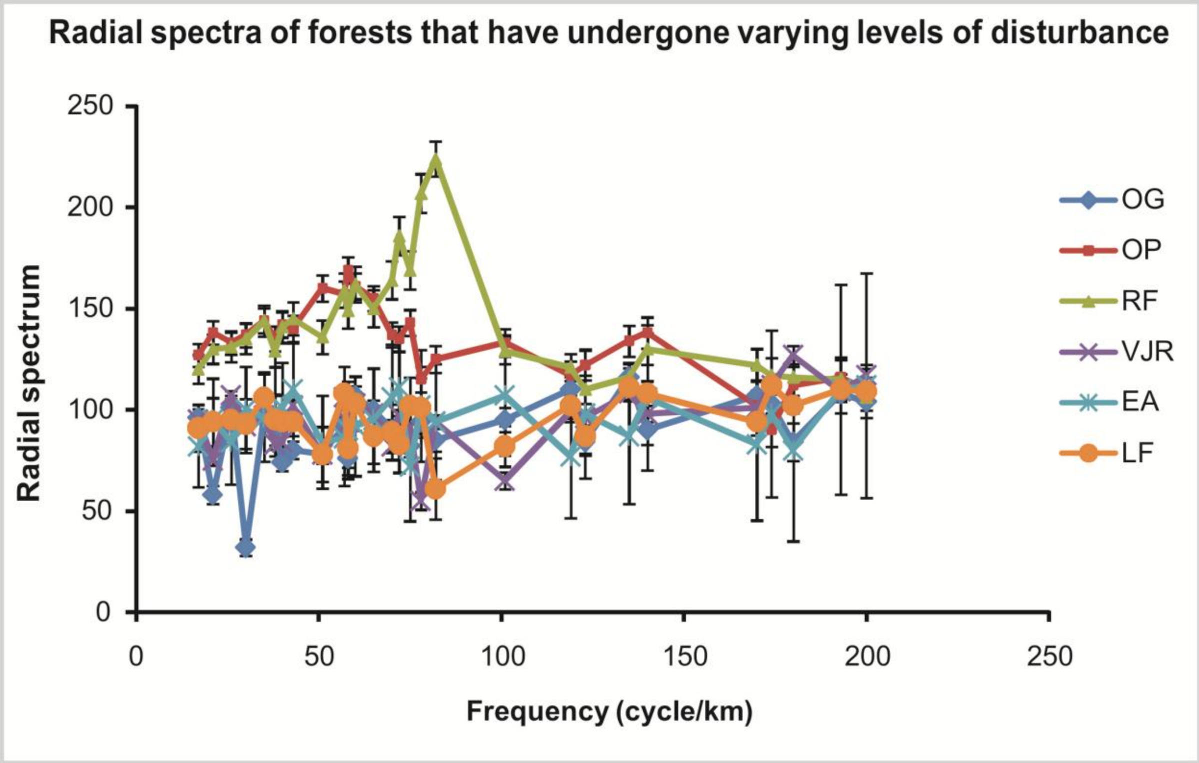


Figure 6.3a: Radial Spectrum of individual land use classes with respect to frequency (cycles/km).

(OG- Old Growth forests, OP-Oil Palm plantations, RF- Riparian forests, VJR-Virgin Jungle Reserve, EA-Experimental area, LF- Twice Logged forests)

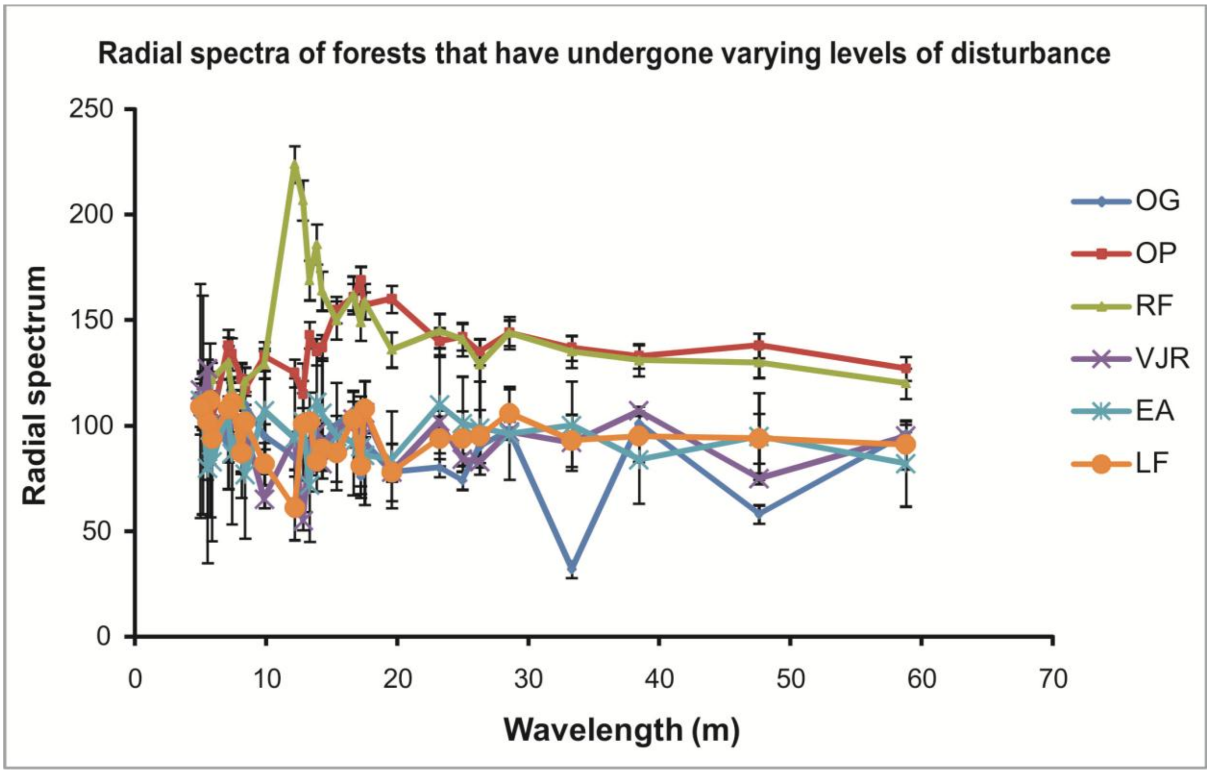


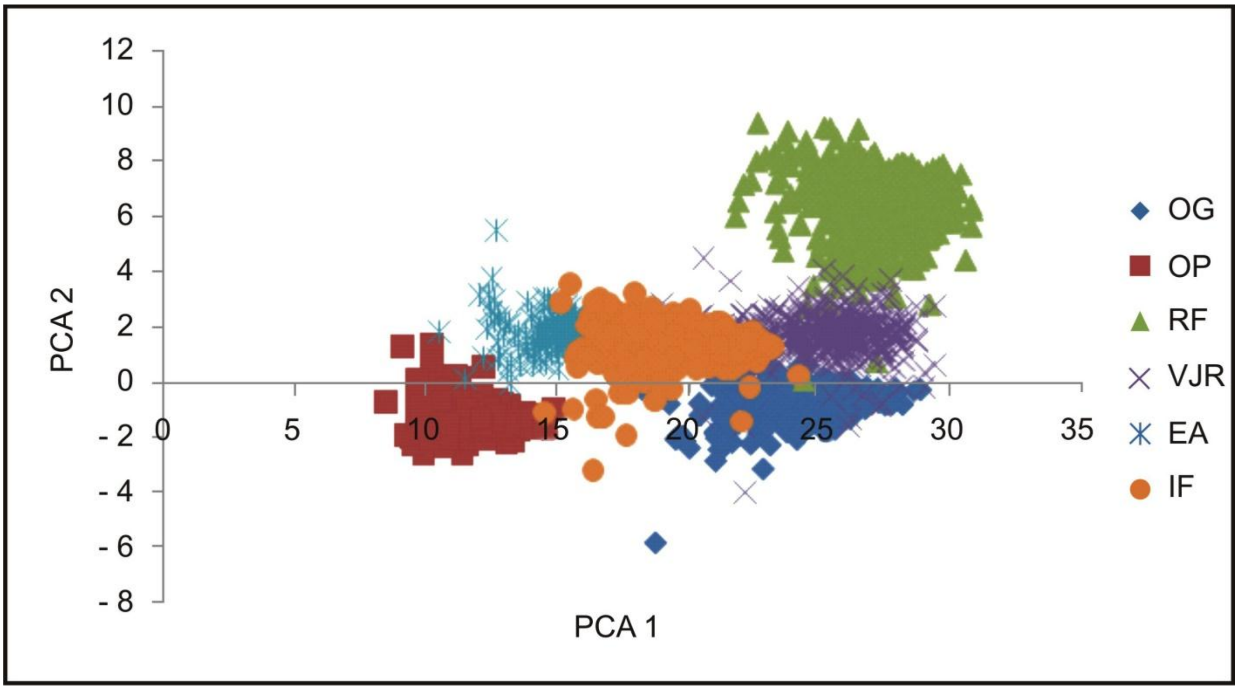
Figure 6.3b: Radial Spectrum of individual land use classes with respect to wavelength (metres).

(OG- Old Growth forests, OP-Oil Palm plantations, RF- Riparian forests, VJR-Virgin Jungle Reserve, EA-Experimental area, LF- Twice Logged forests)

Figure 6.3a demonstrates that different land use types show a different radial spectrum curve and peak frequencies. Further, r-spectra can capture the whole gradient of the canopy grain ranging from pristine old growth forests to logged forests to oil palm plantations. Across the different forest types, the dominant frequencies have varied from 57 cycles/ km (λ=17.5m) for oil palm to 82 cycles/km (λ=12.2m) for riparian forests to 135 cycles/km (λ=7.4m) for old growth forests to 180 cycles/km (λ=5.55m) for once/lightly logged forests (refer to figure 6.3a and 6.3b). This suggests that disturbance increased the dominant spatial dimensions of canopy texture.

Column-wise standardization was performed on r-spectra. Standardized PCA was performed on the unit window. PCA ordination allows for the interpretation of cloud of unit windows in terms of canopy grain variation ranging from fine scale to coarse scale. The results of the

PCA yielded three prominent axes which synthesized the majority of the variability in the data matrix. Out of these, the first PCA explains the maximum (in this case, 48%) of the variance and approximates the fineness-coarseness gradient of the canopy grain. This in turn is linked to the dominant crown size (Barbier et al., 2012). This corresponds to spatial frequencies of less than 80 cycles/km (wavelength=12.5m) for coarser textures to more than 180 cycles/km (wavelength=5.56m) for finer textures (Proisy et al., 2007).As shown in Figure 6, the fineness-coarseness gradient moves in the clockwise direction with oil palm plantations having the coarsest textures. Other PCA axes may point to a specific range of dominant spatial frequencies which in turn may be related to crown or gap sizes (Barbier et al., 2012). PCA1 is a representative of the disturbance gradient faced by the different land use types. It can be seen from Figure 6.4 that relatively homogenous/undisturbed forest types such as OG and OP have lower values of PCA1. On the other hand, it may be inferred that PCA2 explains the degree of fragmentation faced by the different land use types. Field studies revealed that riparian forests exist as fragmented patches throughout the landscape. In Figure 6.4 PCA2 has the highest value for riparian forests and lowest (negative) values for old growth and oil palm which have contiguous canopies.



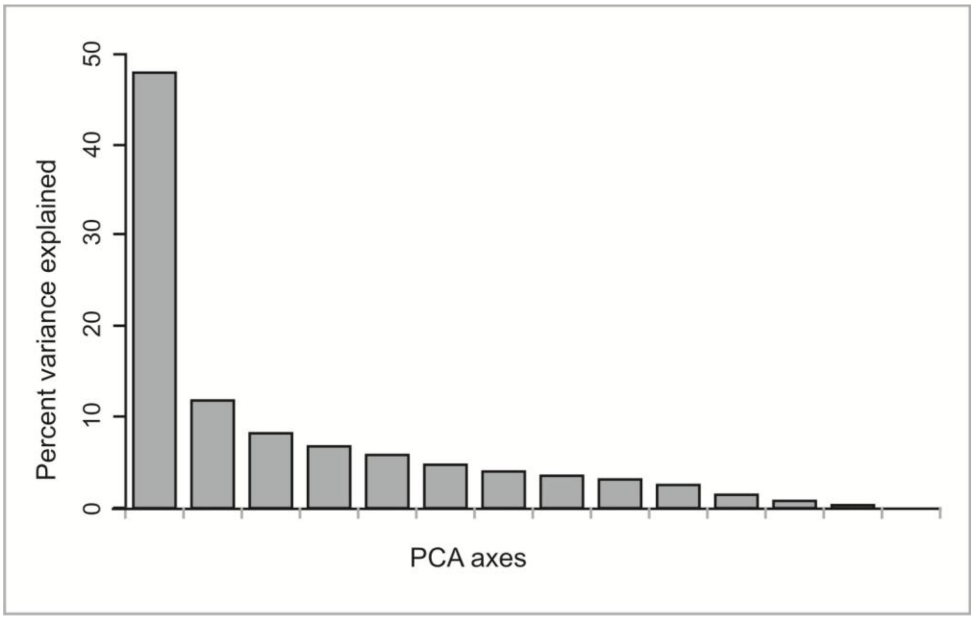


Figure 6.4:PCA on Fourier r-spectra obtained from FOTO method. Top: The PCA1 v/s PCA2 location of the r-spectrum of the different land use types. Bottom: Histogram of Eigen-values giving the percentage of variance explained by each PCA axis in sequence(OG- Old Growth forests, OP-Oil Palm plantations, RF- Riparian forests, VJR-Virgin Jungle Reserve, EA-Experimental area, LF- Twice Logged forests)

Most importantly, PCA1 and PCA2, when plotted together have indicated distinct patterns for different land use types along both the disturbance and fragmentation gradients. The principal component results can be in turn correlated with the forest stand and biomass parameters of the different land use types.

The first three principal axes were taken to be the texture indices. These in turn can be used for correlating with stand parameters and biomass dynamics of the different land use types. According to the research done by Couteron et al. (2005), the first principle component (PC1) also acts as a sound predictive variable to explain the variations in stand structure. This is the case in this research as well. For instance, in this research, PC1 explained approximately 30% of the variation in DBH of OG forest trees and 36.6% variation in basal area of OG. PC1 also explained 28% of the variation in DBH of heavily logged forests and 16% variation in basal area of this land use type.

For this paper, the main purpose of deriving texture indices is to use these for generating biomass estimate models for the different land use types in the study area. All three FOTO derived texture indices were related to field AGB values using multiple regressions in order to derive biomass estimate models for individual land use types. The FOTO derived biomass estimate equations for individual land use type have been detailed in table 6.1:

Land Use Type	**FOTO Texture Based Indices**	**R^2**
Old Growth (OG) forests	$-59.51 \times (PC1) - 45.551(PC2) - 4.936 \times (PC3) + 1743.287$	0.97
Once/Lightly logged forests (VJR)	$-493.51 \times (PC1) + 2792.2g(PC2) +2882(PC3) + 7653.62$	0.905
Twice logged forest (LF)	$-83.44 \times (PC1) + 1049.78g(PC2) -32.13.(PC3) + 289.1$	0.811
Heavily Logged Forest (EA)	$20.71(PC1) + 280.82\ (PC2) - 34.47 \times (PC3) - 222.1$	0.955
Riparian Forest (RF)	$-240.6 \times (PC1) - 632.66a(PC2) + 180.47 \times (PC3) + 3136.8$	0.84
Oil Palm Plantation (OP)	$-4773.26 \times (PC1) + 5171(PC2) -1817.546(PC3) + 61036.76$	0.83

Table 6.1: SPOT Texture Indices based Biomass Equation Derived using Field AGB

Besides contrasting stages of disturbance with distinct canopy textures, such as canopies where forests have undergone different logging intensities and pristine forest canopies stands may display similar biomass values (Proisy et al., 2002). Hence, a Tukey test was carried out for the purpose of examining if the canopy texture based biomass estimate models significantly vary across different land use types. It was found that the biomass estimate models varied significantly between the riparian forests, twice logged forests, once/slightly logged forests and oil palm. The biomass values derived from the canopy texture based biomass estimate model for oil palm was significantly different from all the other non-riparian land use texture based biomass model values. Further, it was ascertained that the texture based biomass values are significantly different for old growth pristine forests, once/slightly logged and heavily logged forests. A FOTO biomass map of the SAFE area was created using the equations mentioned in table 6.1 (Figure 6.5):

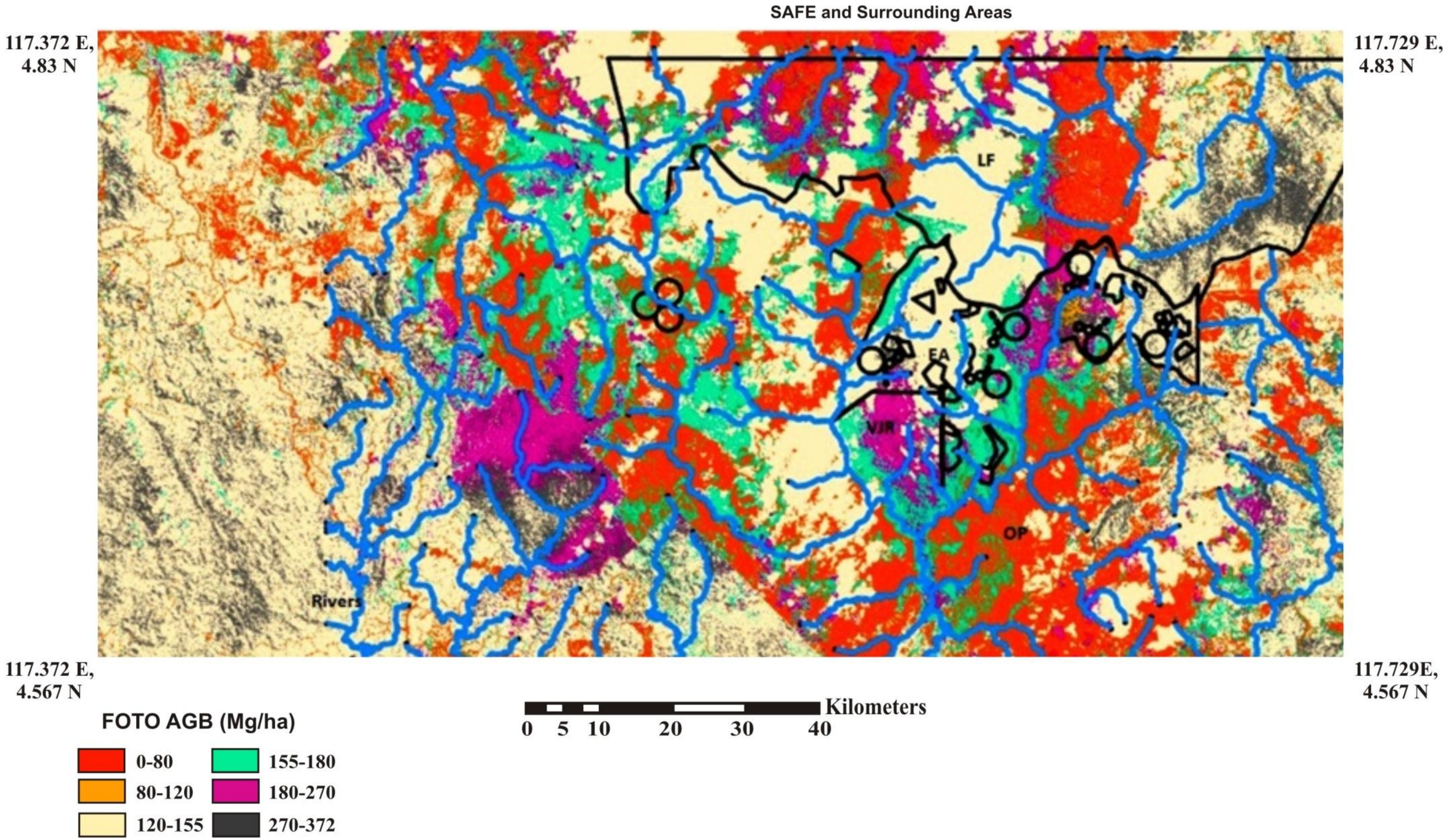


Figure 6.5: FOTO Generated Biomass Map of the SAFE area(VJR-Virgin Jungle Reserve, LF-Logged Forest, EA-Experimental area, OP-Oil palm plantations)

These values are cognizant with the field AGB values of these land use types found in the literature (Morel et al., 2011). The FOTO derived AGB values were validated against field AGB values (ones which were not used for generation of biomass estimate models). These values showed strong strength of association between the texture derived and field AGB values (figure 6.6).

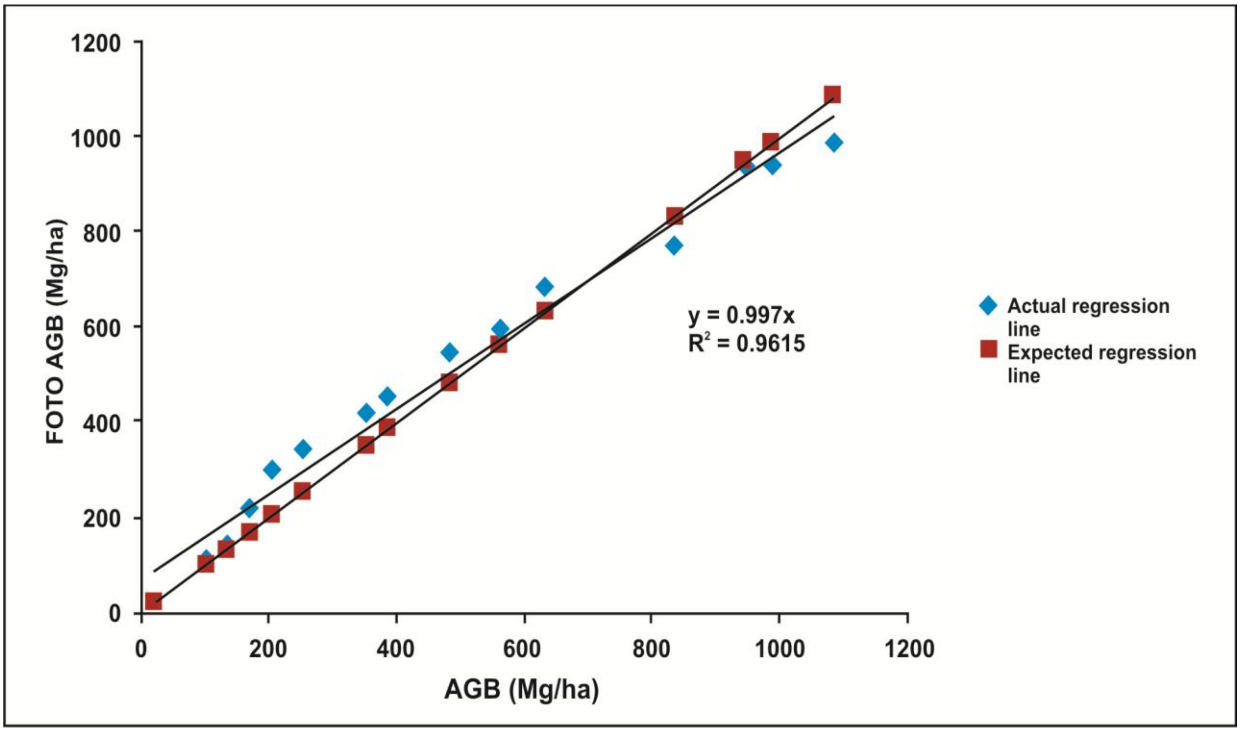


Figure 6.6: Comparison of FOTO vs. field AGB values for all the land use types

The FOTO derived AGB values show no evidence of saturation at high biomass values. FOTO derived AGB values for individual land use types too were validated against field AGB values (which were not used in the model generation). Results have been provided in Appendix III.

6.4 DISCUSSION

An estimation of AGB storage in tropical forests, especially in the context of large scale land use change and forest degradation is fraught with significant uncertainties (Grainger, 2010). One of the biggest challenges is the presence of a complex canopy structure and saturation at high biomass values (Williams et al., 2010; Malhi and Roman-Cuesta, 2008). Direct regressions with optical and radar data remain fraught with data saturation (Mitchard et al., 2011). However, FOTO allows for the discrimination of structural and biomass variation for different land use types and avoids undergoing saturation at high biomass values.

The use of Fourier transforms and subsequent ordination using PCA is at the core of the FOTO method. The frequency signatures relate effectively to the components of the canopy grain size (Couteron et al. 2006). The methodology has helped to represent and analyse the repetitive structure of the canopy. It may be inferred that radial spectra allows for distinguishing the different forests structures in the study area. For example, riparian forests display a markedly distinct radial spectrum profile from other land use types. Hence, it may be argued that structurally, riparian forests may be considered to be different from surrounding, non-riparian land use types. Similarly, other land use types display varying radial spectra and peak frequencies, indicating that the different forest types have different canopy structures which in turn are reflected in their frequency signals. The PCA ordination of the radial spectra of different land use types also allows for distinguishing between the different forest types and, potentially capturing the overall spatial variation in the texture of the different forest types in the study area. This in turn can be used to evaluate the degree of fragmentation and disturbance faced by the individual forest types. For instance, the PCA1 vs. PCA2 plot indicates that RF is the least homogenous of forest types and has faced very high levels of fragmentation. This has been verified from ground surveys. Similarly, the results of PCA have been useful in allowing for the examination of disturbance-fragmentation gradient of other land use types. For instance, OG and OP which have a fairly contiguous canopy structure are found at the lower end of the PCA1 vs. PCA2 plot. On an average for all the land use types combines, the FOTO derived estimate models predicted the biomass well However when the different forest types were taken into consideration individually, the FOTO derived estimate models underestimated by biomass by 22% for the EA forests.

Therefore, it can be seen that this methodology is useful in distinguishing between the different levels of logging and degradation across the land use types within the forest areas. This analysis achieves the first objective of the study and illustrated that the FOTO method has a significant potential in terms of being able to provide a system for predicting biomass changes among oil palm-tropical forest landscapes that can track the impact of various cycles of logging to better assess the current and future impact of such activity. As in other studies, FOTO has been seen to provide a strong potential ability to predict forest above ground biomass because it not only provides accurate structural information about the uppermost portions of the forest canopies, but it also can return this same level of information about sub-canopy characteristics and changes (Ploton et al., 2012), thus satisfying the second objective. No specific procedures exist for providing spatial and structural information about the conditions of riparian margins(Johansen and Phinn, 2006). However, the use of FOTO method in this study has allowed for assessing the structural and biomass dynamics of riparian margins, in addition to ascertaining that these variables vary between riparian and non-riparian zones. This satisfies the third objective of the research. The ability to discriminate the biomass and structural dynamics of riparian zones from non-riparian zones has significant implications for examining the impact of fragmentation and land use change on the structural and biomass dynamics of remnant ecosystems such as riparian forests. Forest fragmentation can lead to elevated tree mortality, micro-climatic changes at edges which in turn can lead to changes in structure, biomass stocks and carbon fluxes in the forest fragments (Nascimento and Laurance, 2004). The use of FOTO method can potentially allow for examining structural and biomass changes in isolated forest fragments and riparian zones.

6.5 CONCLUSION

The use of the FOTO method of canopy structure analysis provides a sound means of predicting biomass and developing the new insights necessary to understand the impact of logging and man-made changes to various forest landscapes. It is expected that the generation of maps of these forest landscapes based on the analysis of high resolution satellite data by the FOTO method in conjunction with ground data collection and experiments like those being undertaken the SAFE Project can provide some valuable insights. These insights can then provide the foundation for changing logging patterns and human activity in these valued forest landscapes, thereby reducing forest degradation and increasing ecological recovery. However, it must be kept in mind that the FOTO derived biomass estimate models are based on field AGB values. Hence, the inaccuracies and uncertainties in the allometric equations could influence the texture based AGB estimates.

Compared to methods based on spectral characteristics, texture based methods have the potential to avoid the problems faced by optical remote sensing datasets, including biomass saturation (Barbier et al., 2010b). Texture based methods such as FOTO along with the use of satellite and field data could also serve other uses in terms of the scope of which it could help more tropical forest countries and areas more effectively monitor their forest cover and track the on-going evolution and changes in the forest cover and related biomass.

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Chapter 7: Conclusions

7.1 REVIEW AND IMPLICATION OF THE MAIN FINDINGS

The overall aim of the research was to examine the impact of varying levels of degradation (ranging from light logging to oil palm conversion) on the riparian and non-riparian forest zones of a mixed forest area in Malaysian Borneo. This research encompassed a multidimensional assessment of forest canopy characteristics and the AGB dynamics in the study area through both extensive field data collection and remote sensing analysis. Through extensive ground truthing, the study succeeded in underlining the impact which varying levels of disturbance (ranging from light logging to large scale conversion to oil palm plantations) have on the forest structure and biomass dynamics of riparian and non-riparian forests. The research established thresholds for disturbances the riparian and non-riparian forest zones can take before undergoing a decline in AGB. The research established the AGB and forest structure differences between pristine forests, forests that have undergone varying logging rotations and plantations. Strategies for retaining ecosystem functioning (such as carbon storage, biodiversity conservation) in oil palm plantations were presented by specifically discussing role retention of riparian forests can have influencing AGB storage and tree species richness. The application of advanced image processing technologies has allowed for distinguishing different forest types and their AGB dynamics. Following sections will discuss the findings and their implications in detail, highlighting particular contributions to academic evidence in the field and the opportunities for applying these findings in future studies.

7.1.1 Impact of Disturbance on the AGB of Riparian and Non Riparian Zones

Statistical analysis of the ground tree mensuration and AGB data (carried out in chapter 4) revealed that whilst there is no significant variation in AGB amongst riparian margins located in unlogged, once/lightly logged, and twice logged forests, there was a sharp decline in the riparian margins for those areas located in heavily logged forests and oil palm plantations. In spite of these outcomes, it was determined that the riparian zones in oil palm plantations have a significantly higher AGB value than oil palm monocultures. An examination of species richness (of trees) in riparian margins located across the different land use types revealed that riparian margins located in oil palm plantations have the highest species richness. This analysis further helped estabilish the influence of disturbance on the species richness of riparian forest zones. However, the most important implication of this research is that it establishes the level of disturbance tropical forests can undertake before losing ecosystem functioning, in this case, the ability of store biomass. While a similar study had been carried out by Berry et al. (2010) that established the utility of logged forests in providing habitat to birds in Borneo, very little research has been done to establish the role logged forests and remnant forests (in this case riparian forests) in contributing to overall carbon storage in the landscape. In addition to quantifying the AGB storage potential of riparin margins, the research evaluated the impact land use changes in non-riparian forest zones have on the AGB storage of the riparian margins. In the long term, such research could help in the study of the impact of edge effects and fragmentation on the AGB storage of remnant forests such as the riparian zones. These findings have the potential to influence the management of human modified landscapes such as those found in Sabah. The field research establishes that less than pristine forests including logged forests and remnant riparian zones retain a significant AGB storage value. This can potentially have deep conservation ramifications. A significant body of literature argues that conservation efforts and funds should be directed to the preservation of forests which have the highest carbon storage potential (Venter et al., 2009; Putz and Redford, 2009). This puts the human modified forests such as logged forests at a risk of being converted to other land use types including oil palm. By establishing the AGB storage potential of the forest types that have undergone varying rounds of logging (as this research has done) case can be made for preserving logged forests and preventing their imminent conversion to oil palm. Moreover, based on the extensive study on biodiversity and AGB storage across the riparian margins of various land use types, it can be concluded that these may provide effective conservation services in oil palm plantations and heavily logged forests, yielding important carbon storage and biodiversity benefits. This is further substantiated by the argument presented by Turner et al. (2011) who have suggested that remnant forest types such as riparian vegetation zones within oil palm plantations can help maintain functional landscapes and provide a distinctive opportunity for reintroduction of diversity and sustain functions such as biomass retention.

7.1.2 Potential of Texture Based Methods in Examining Forest Stand Parameters

This research indicates that spectral characteristic based measures such as vegetation indices have limited utility in predicting and differentiating the forest stand and biomass parameters of the different forest use types in the study area. Optical remote sensing datasets have a limitation of undergoing saturation at high biomass levels (Barbier et al., 2010; Lu, 2006). This research then explored the efficacy of texture based analysis in distinguishing between the different forest types in the study area and predicting their biomass values. Two different texture based techniques were used, namely the Grey Level Co-Occurrence Matrix (GLCM) and FOTO. The latter only lends itself best to VHR imagery such as 1m panchromatic data (Barbier et al., 2011; Proisy et al., 2007). However the former can be applied to medium resolution imagery such as Landsat (Wijaya et al., 2010; Tsuyoshi et al., 2009) or 10m SPOT data used in this research. In both cases, the texture derived variables displayed strong (but varying) correlation with field AGB values. Texture analysis based methods such as GLCM, FOTO have the potential to overcome the shortcomings posed by optical remote sensing data.

Considering the significance of AGB storage within the Borneo tropical forests and the extensive impact of human activity on biodiversity and carbon sequestration characteristics (Curran et al., 2004), the techniques employed in this study provide next level tools for enhanced predictive modelling. Although traditional methodologies such as DBH measurements have provided in-situ assessment opportunities (See Hertel et al., 2009), compositional features of tropical forests and their relative inaccessibility make ground-based analysis localized and extremely difficult. The evidence captured through the application of texture analysis on optical remote sensing data has demonstrated that use of these analyses in conjunction with ground based data has potential to allow for the mapping of forest stand parameters and AGB dynamics at a landscape level. These analyses have significant relevance for landscape level management. They offer the potential to monitor varying levels of degradation in a given landscape and distinguish between the same. Furthermore, by allowing for the generation of biomass estimate models for different forest types it is possible to have more accurate estimated of AGB and structural dynamics for the different forest types at a landscape level.

7.1.3 Monitoring Degradation: Identifying Areas of Different Logging Intensity and Oil Palm Plantations

The application of remote sensing for spatial characteristic mapping and analysis is not a new concept; however, the complexity of tropical forests has continued to challenge researchers in this field (Norwana et al., 2010; Tsuyuki et al., 2011). Analyses of both the ground level and remote sensing data presented in this dissertation offer extensive value as monitoring tools, allowing analysts to identify and assess the net impact of logging intensity and oil palm plantations on AGB values and biodiversity. Future applications will further develop essential evidence that can be used to assess the net human impact and carbon sequestration variance over time.

7.2 CAN WE MEASURE AGB FROM SPACE?

Tropical forests such as those in Borneo are fraught with the problem of large inaccessible areas (Saatchi et al., 2011) and complex canopy structures (Chambers et al., 2007). Remote sensing plays a vital role in examining the various aspects of tropical forests ranging from examination of temporal land use changes (Meyfroidt and Lambin, 2008), evaluation of deforestation and degradation (Margono et al., 2012), forest structure and biomass stocks (Laporte-Bisquit, 2011; Asner et al., 2002). It must be specified that there are no remote sensing techniques that could measure AGB directly; remote sensing techniques need to be used in conjunction with ground data to produce biomass estimate models (Gibbs et al., 2007). Researchers such as Basuki et al. (2011) have argued that AGB estimation from Landsat based images may be inaccurate due to data saturation concerns. Radar data too are fraught with the problem of data saturation (Morel, 2010) and limited ability to predict AGB for tropical forests with closed canopies (Woodhouse et al., 2012). Both this research and a body of literature indicate that spectral parameters such as vegetation indices have a limited ability to predict biomass of tropical forests (Okuda et al., 2004). However texture analysis carried out using GLCM and FOTO have shown strong correlation with field AGB values. The FOTO method has the ability to distinguish between the different land use types present in the study area, including riparian margins. Most importantly, FOTO derived indices do not undergo saturation at high biomass values. It may be inferred from these analyses that the application of texture based methodologies such as Fourier-based FOTO analysis yields valuable outcomes and can be applied effectively to VHR optical RS datasets.

7.3 POLICY IMPLICATIONS OF THE PRESENT RESEARCH

An exhaustive analysis of the policy applications and implications of the present research is out of the purview of the dissertation. However, the most obvious policy application of this research is towards Reducing Emissions from Deforestation and Forest Degradation (REDD) projects and sustainable forest management. Remote sensing is increasingly being accepted as an essential component of monitoring, verification of carbon credits and evaluation of co-benefits under the REDD mechanism. Use of RS data can help in the examination of historical trends, evaluation of land use/land cover changes temporally and spatially, determining baseline deforestation rates and carbon density at a landscape scale (Holmgren, 2008; Goetz et al., 2009). Examination of these variables along with the collection of forest stand parameter data is an important cornerstone of any REDD project. Both the generation of LULC maps and examination of AGB dynamics of the different forest types at a landscape level have been covered in the dissertation. The application of texture analysis based techniques such as FOTO allows for distinguishing between different levels of degradation and generation of individual biomass estimate models for the different land use types. These outcomes can easily fulfil many of the requirements of REDD projects such as monitoring, estimation of AGB at a landscape scale. One of the biggest challenges that the inclusion of RS data in REDD mechanism is the availability of data, data quality and costs. Optical remote-sensing systems such as Landsat are operational at the global scale and provide a globally consistent record for the past three decades (Gibbs et al., 2007). However the use of these optical RS data is fraught with significant difficulties such as presence of thick canopies, data saturation (Barbier et al., 2010b), inability to calculate forest degradation rates (Gaveau et al., 2009) among others. However, research carried out in this dissertation indicates that the application of texture analysis techniques overcomes many of the shortcomings of optical RS data. For instance, the application of FOTO can help distinguish between land use types that have undergone varying levels of degradation and fragmentation. Additionally, FOTO can be used to generate biomass estimate models for individual land use types and these estimates do not suffer from biomass saturation at high values. GLCM analysis too can be applied to medium resolution imagery for distinguishing between different forest types.The analysis of the field data collected by the author provides a detailed overview of the AGB stocks in different forest types and the level of disturbance they can undertake before a loss in AGB stocks. These results can inform sustainable forest management by making a case for sparing logged forests from being converted to oil palm (as the former retain significant AGB) and by helping identify degraded lands with little AGB storage value which could be converted to oil palm.

7.4 STRENGTHS AND LIMITATIONS OF THE PRESENT RESEARCH

The biggest strength of this research lies in the fact that is has used advanced remote sensing techniques in conjunction with extensive ground data. This in turn has allowed for discrimination of the different forest types in the study area and generation of biomass estimate models that could estimate AGB storage of individual forest types at a landscape scale. This research has also established the biomass storage potential of logged forests and remnant forests.

The research has exclusively focused on quantifying the AGB storage of the different forest types and impact of disturbance on this. This is a limitation of the research. To understand carbon dynamics on the different forest types and impact of disturbance on them, it is important to take into account the full ecosystem carbon balance. This involves measuring the other variables of the carbon cycle such as below ground biomass (BGB) and carbon fluxes such as soil CO_2 fluxes, Net Primary Productivity (NPP) among others (Verwer et al., 2008).

7.5 FUTURE RESEARCH

The value of this particular study is largely linked to future research in the field of AGB stocks, carbon flux, and remote sensing technologies. Research and further understanding of the notion of carbon stocks and fluxes are not only of importance to environmental stability but also to economic benefits as tropical forest countries may accrue monetary value from the carbon reserves of their forests. Research into the carbon dynamics of different types of forests, especially those that have faced a varying disturbance gradient are important for developing sound conservation strategies for mixed land use human dominated landscapes such as those found in Malaysian Borneo.

It is important to design a system that allows for the systematic monitoring of the different carbon stocks and fluxes (Coomes et al., 2002). Hence, for future research field based measurements of carbon stocks (DBH, soil carbon, leaf litter) should be carried out and these should be based on RAINFOR Protocols (RAINFOR, 2011). In addition to this, the variables of carbon cycle such as NPP, respiration, gas exchange fluxes, mortality should be evaluated as well. In addition to this, respiration dynamics must be included in future studies as these are important components of the carbon balance of an ecosystem (Saner et al., 2012). It is proposed that these measurements be repeated at intervals of 12 to 14 months apart from each other.

In addition to the collection of detailed field data, future research must make use of very high resolution (VHR) remote sensing data such as those obtained from LiDAR. LiDAR data have been considered useful in mapping and characterizing the 3D structure of a forest, especially the vertical profile of the vegetation in a tropical forest (Zhao et al. 2009). LiDAR techniques, when used in combination with radar (Mitchardet al. 2011) or optical (Baccini et al. 2008) and field plot data, allows vegetation mapping over large areas, especially in tropical forests. Specifically, VHR RS data should be used for the characterization of vegetation structure of the study area and examined to see how accurately data such as LiDAR can predict parameters like height, canopy intactness and species richness forests of Malaysian Borneo. Such research has not been previously undertaken for this area. Furthermore, very little research has been done to correlate these remote sensing derived characterizations with carbon flux variables. Future research will aim to fill this gap in research and mapping by studying the different variables of carbon dynamics, such as NPP (Ibrahim, 2005) through the use of extensive field data and very high resolution satellite imagery.

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APPENDIX

APPENDIX I: MISCELLANEOUS INFORMATION ABOUT CHAPTER 4

I) CANOPY INTACTNESS OF OG FORESTS

Figure I: A-B: Different Views of the OG Canopy. (Photographs taken by the author at the SAFE site, September 2011-December 2011)

An aerial survey carried out over the OG forests of MBCA revealed the presence of a virtually unbroken canopy and a nearly contiguous canopy cover (Figure IA). Photos taken by the author (Figure IA-Figure IB) too indicate that the OG forests continue to enjoy a virtually impenetrable canopy cover (of more than 80%), large crown sizes and the presence of tall trees. A comparison of the tree heights of this forest type with the tree heights of other forest types revealed that on an average OG has the tallest trees (refer to table 4.1 in the chapter)

II) CANOPY INTACTNESS OF VJR


A

B

C

Figure II: A-C: Stand Structure of VJR (Photographs taken by the author at SAFE Sept 2011-December 2011)

Like the OG forests, VJR to has a virtually impenetrable canopy cover (>80%) with very few gaps. In addition to dense vegetation there, these forests also have a thick understory.

III) CANOPY INTACTNESS OF LF

A B

Figure III: A-B: Stand structure of LF forests (Photographs taken by the author at SAFE Sept 2011-December 2011)

Although LF forests have a significant canopy cover (varying from 50%-70%), in many places these forests are marred by canopy gaps as shown in figure III A and B.

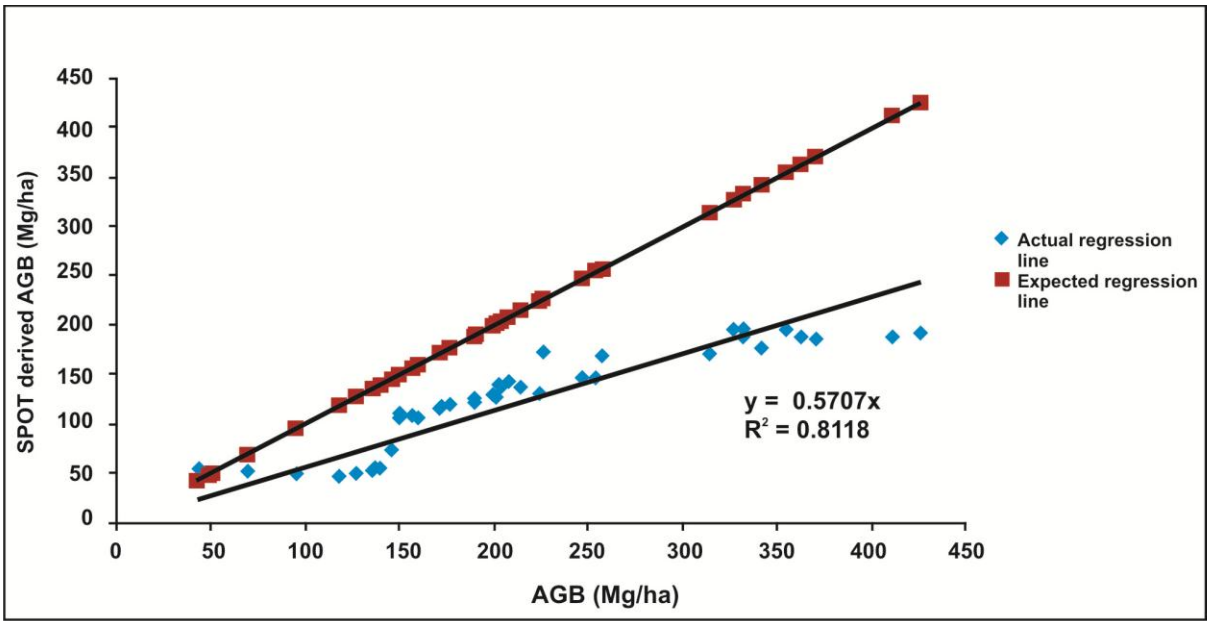
IV) CANOPY STRUCTURE OF OP

Figure IV: Oil Palm Canopy (SAFE Project, 2011).

APPENDIX II

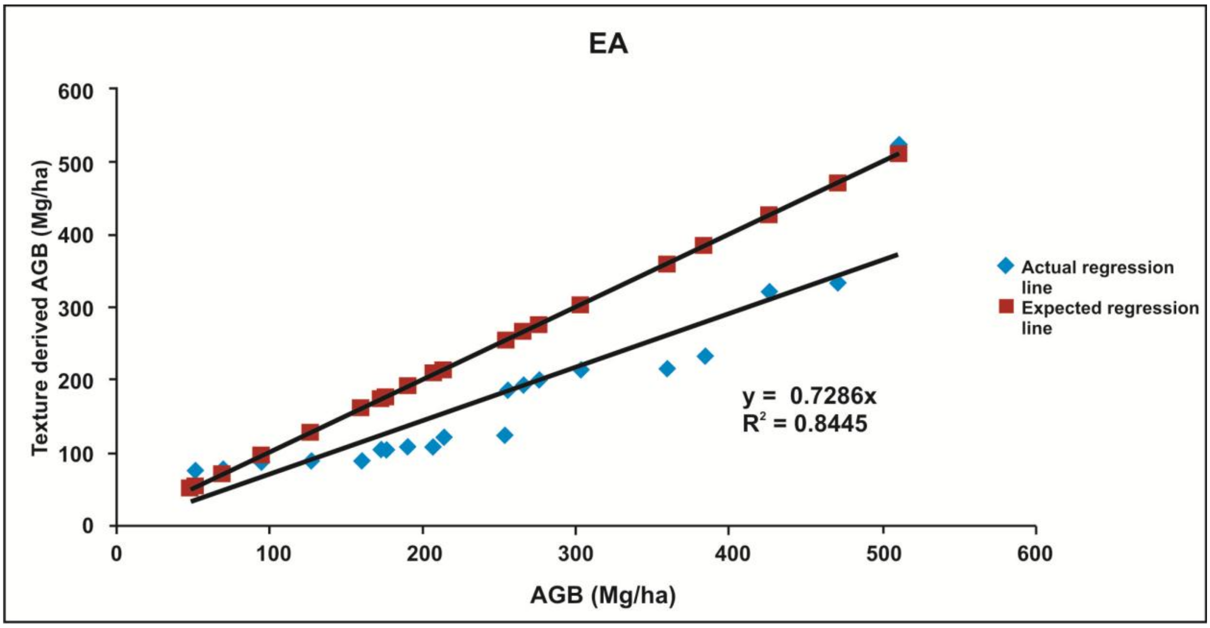
MISCELLANEOUS INFORMATION ABOUT CHAPTER 5

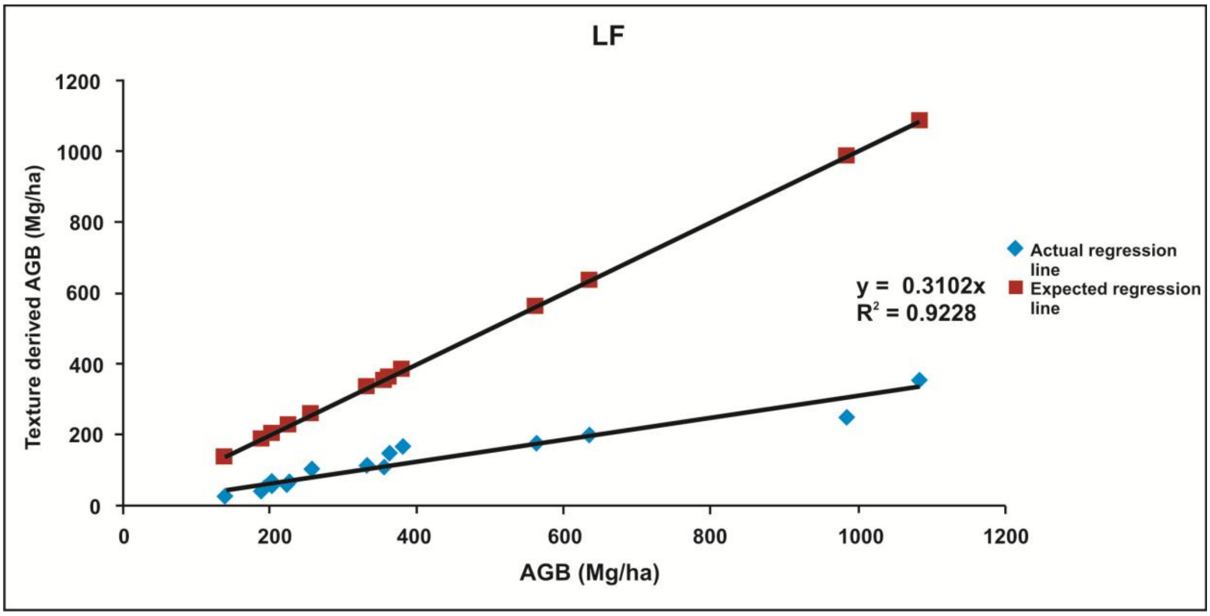
Appendix II.A: Validation of SPOT derived AGB with Field AGB



Appendix II.B: Validation of Texture Variables Derived AGB with Field AGB

The texture based AGB values derived for all the different land use types were validated with field AGB values. Significant correlation was present between the texture AGB and the field AGB values


EA
Texture derived AGB (Mg/ha)
AGB (Mg/ha)
Actual regression line
Expected regression line
y = 0.7286x
R^2 = 0.8445
0
100
200
300
400
500
600


LF
Texture derived AGB (Mg/ha)
AGB (Mg/ha)
Actual regression line
Expected regression line
y = 0.3102x
R^2 = 0.9228
0
200
400
600
800
1000
1200

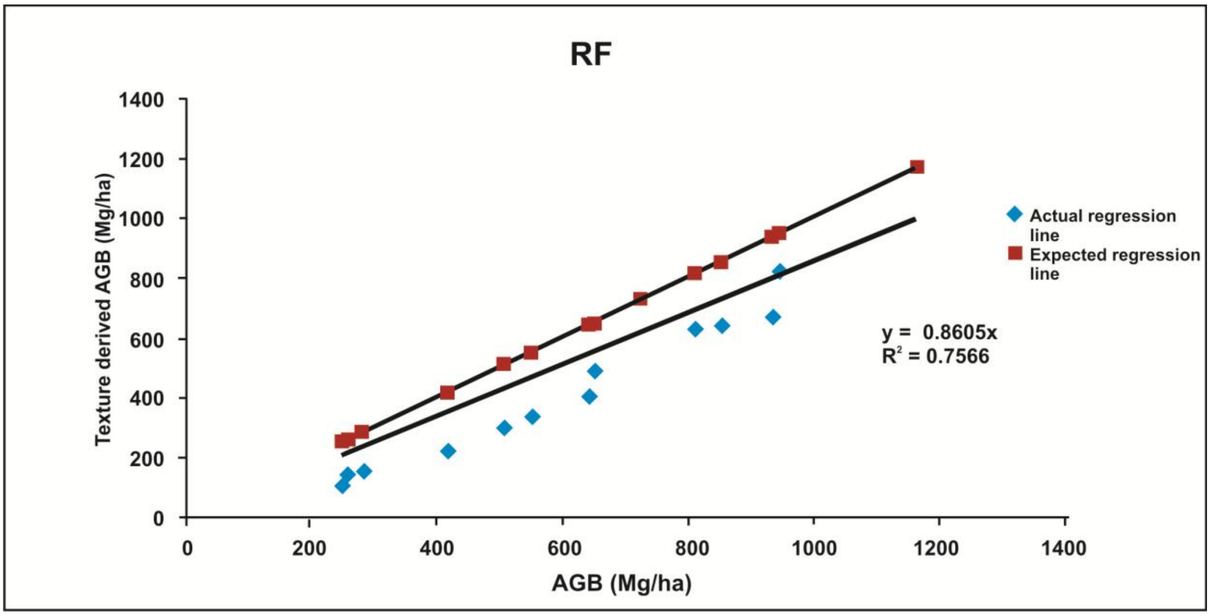
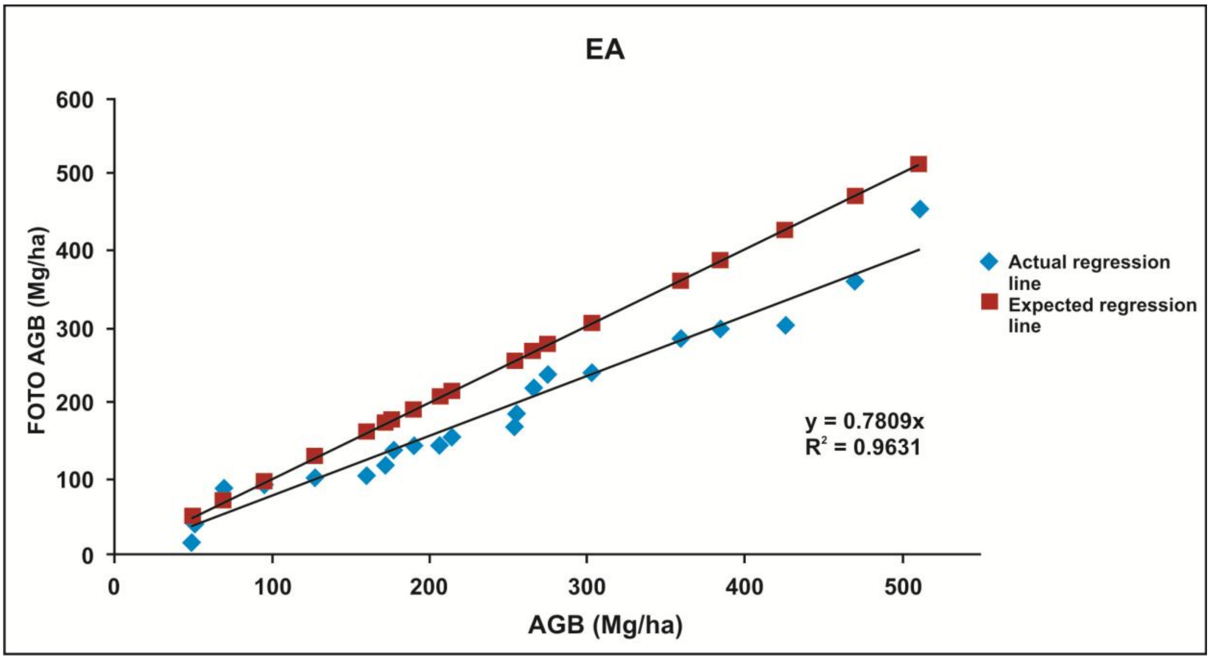


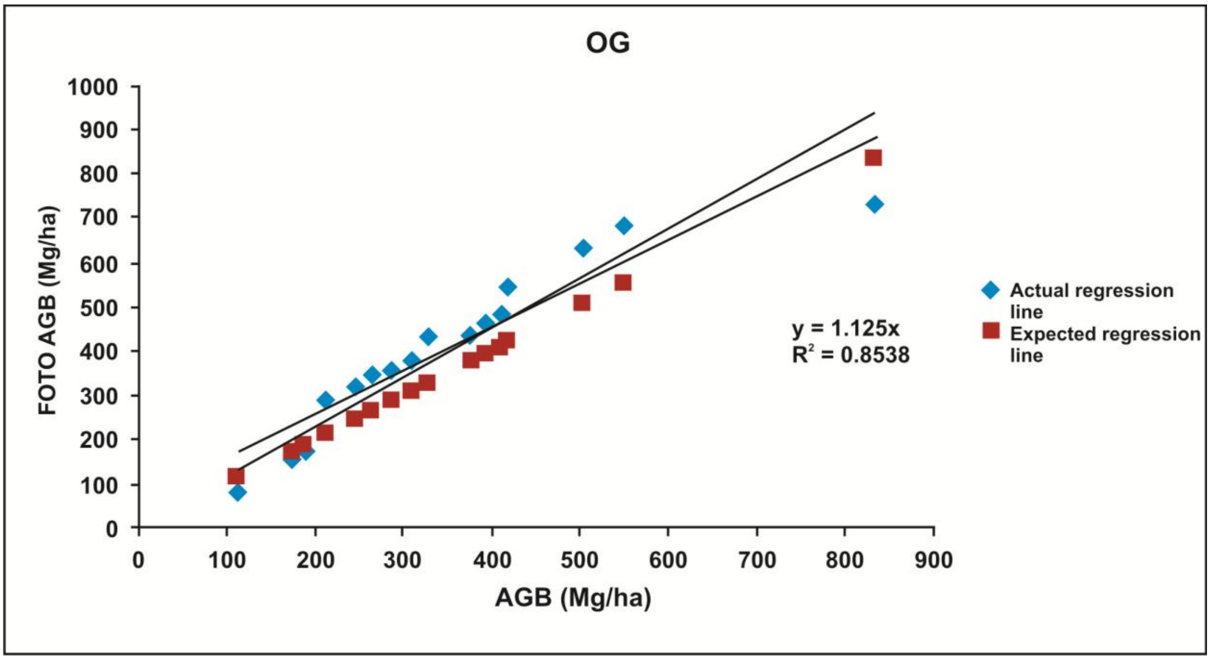
Figure II.I: The correlation between texture and field AGB for individual land use types

APPENDIX III

III.I) VALIDATION OF SPOT DERIVED FOTO AGB WITH FIELD AGB:

The comparison of the FOTO derived and field AGB values for a few of the individual land use types revealed that FOTO and field AGB derived values have a strong but varying correlation for different land use classes as shown in figure A III.I





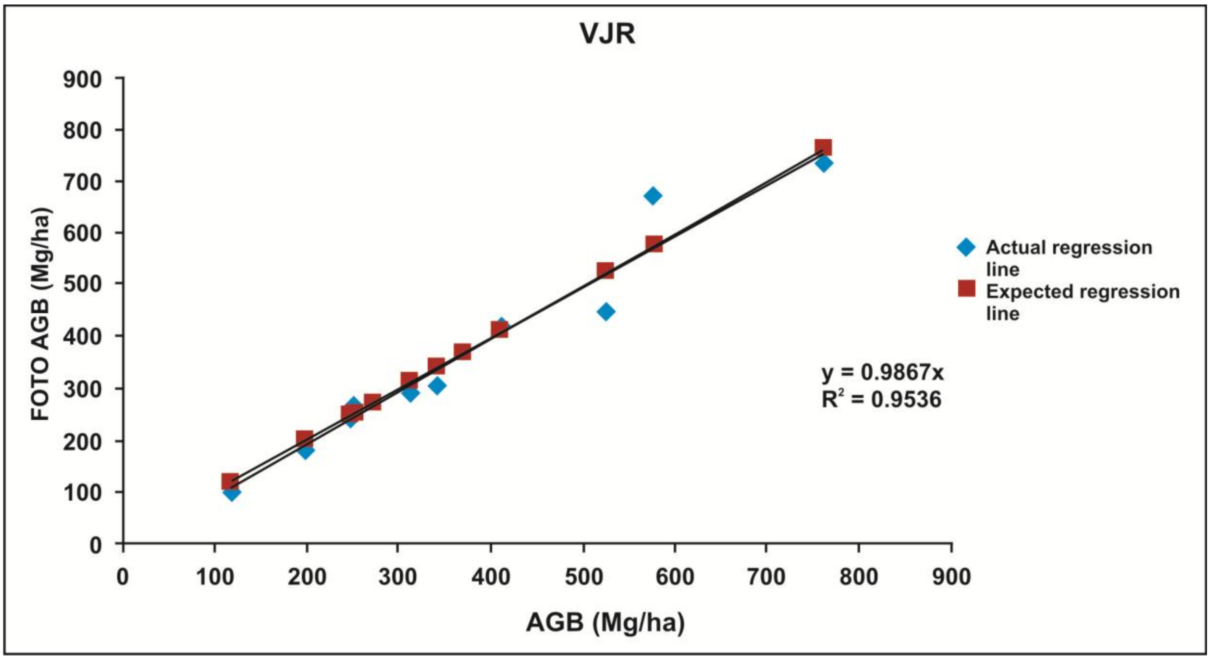


Figure III.I: The correlation between FOTO and field AGB for individual land use types

These regression relations were derived using the field AGB values that had not been utilized for the generation of biomass estimate models in table 6.1 of chapter 6.

APPENDIX IV: GUIDELINES FOR SUBMISSION OF CHAPTER 4 TO THE JOURNAL: FOREST ECOLOGY AND MANAGEMENT

Use of wordprocessing software

It is important that the file be saved in the native format of the wordprocessor used. The text should be in single-column format, and 1.5 line-spacing and line-numbering should be used throughout. Keep the layout of the text as simple as possible. Most formatting codes will be removed and replaced on processing the article. In particular, do not use the wordprocessor's options to justify text or to hyphenate words. However, do use bold face, italics, subscripts, superscripts etc. Do not embed "graphically designed" equations or tables, but prepare these using the wordprocessor's facility. When preparing tables, if you are using a table grid, use only one grid for each individual table and not a grid for each row. If no grid is used, use tabs, not spaces, to align columns. The electronic text should be prepared in a way very similar to that of conventional manuscripts (see also the Guide to Publishing with Elsevier: http://www.elsevier.com/guidepublication). Do not import the figures into the text file but, instead, indicate their approximate locations directly in the electronic text and on the manuscript. See also the section on Electronic illustrations. To avoid unnecessary errors you are strongly advised to use the "spell-check" and "grammar-check" functions of your wordprocessor.

Article structure

Subdivision

Divide your article into clearly defined and numbered sections. Subsections should be numbered 1.1 (then 1.1.1, 1.1.2, ..), 1.2, etc. (the abstract is not included in section numbering). Use this numbering also for internal cross-referencing: do not just refer to "the text". Any subsection may be given a brief heading. Each heading should appear on its own separate line.

Introduction

State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results.

Material and methods

Provide sufficient detail to allow the work to be reproduced. Methods already published should be indicated by a reference: only relevant modifications should be described.

Results

Results should be clear and concise.

Discussion

This should explore the significance of the results of the work, not repeat them. A combined Results and Discussion section is often appropriate. Avoid extensive citations and discussion of published literature.

Conclusions

The main conclusions of the study may be presented in a short Conclusions section, which may stand alone or form a subsection of a Discussion or Results and Discussion section.

Appendices

If there is more than one appendix, they should be identified as A, B, etc. Formulae and equations in appendices should be given separate numbering: Eq. (A.1), Eq. (A.2), etc.; in a subsequent appendix, Eq. (B.1) and so on. Similarly for tables and figures: Table A.1; Fig. A.1, etc.

Essential title page information

- ***Title.***Concise and informative. Titles are often used in information-retrieval systems. Avoid abbreviations and formulae where possible.

- ***Author names and affiliations.***Where the family name may be ambiguous (e.g., a double name), please indicate this clearly. Present the authors' affiliation addresses (where the actual work was done) below the names. Indicate all affiliations with a lower-case superscript letter immediately after the author's name and in front of the appropriate address. Provide the full postal address of each affiliation, including the country name and, if available, the e-mail address of each author.

- ***Corresponding author.*** Clearly indicate who will handle correspondence at all stages of refereeing and publication, also post-publication. **Ensure that telephone and fax numbers (with country and area code) are provided in addition to the e-mail address and the complete postal address. Contact details must be kept up to date by the corresponding author.**

- ***Present/permanent address.*** If an author has moved since the work described in the article was done, or was visiting at the time, a 'Present address' (or 'Permanent address') may be indicated as a footnote to that author's name. The address at which the author actually did the work must be retained as the main, affiliation address. Superscript Arabic numerals are used for such footnotes.

Abstract

A concise and factual abstract is required (not longer than 400 words). The abstract should state briefly the purpose of the research, the principal results and major conclusions. An abstract is often presented separately from the article, so it must be able to stand alone. For this reason, References should be avoided, but if essential, then cite the author(s) and year(s). Also, non-standard or uncommon abbreviations should be avoided, but if essential they must be defined at their first mention in the abstract itself

Graphical Abstract

A Graphical abstract is optional and should summarize the contents of the article in a concise, pictorial form designed to capture the attention of a wide readership online. Authors must provide images that clearly represent the work described in the article. Graphical abstracts should be submitted as a separate file in the online submission system. Image size: Please provide an image with a minimum of 531 × 1328 pixels (h × w) or proportionally more. The image should be readable at a size of 5 × 13 cm using a regular screen resolution of 96 dpi. Preferred file types: TIFF, EPS, PDF or MS Office files. Seehttp://www.elsevier.com/graphicalabstracts for examples. Authors can make use of Elsevier's Illustration and Enhancement service to ensure the best presentation of their images also in accordance with all technical requirements: Illustration Service.

Keywords

Immediately after the abstract, provide a maximum of 6 keywords, using American spelling and avoiding general and plural terms and multiple concepts (avoid, for example, 'and', 'of'). Be sparing with abbreviations: only abbreviations firmly established in the field may be eligible. These keywords will be used for indexing purposes.

Abbreviations

Define abbreviations that are not standard in this field in a footnote to be placed on the first page of the article. Such abbreviations that are unavoidable in the abstract must be defined at their first mention there, as well as in the footnote. Ensure consistency of abbreviations throughout the article.

Acknowledgements

Collate acknowledgements in a separate section at the end of the article before the references and do not, therefore, include them on the title page, as a footnote to the title or otherwise. List here those individuals who provided help during the research (e.g., providing language help, writing assistance or proof reading the article, etc.).

Units

SI (Système International d'unités) should be used for all units except where common usage dictates otherwise. Examples of non-SI that may be more appropriate (depending on context) in many ecological and forestry measurements are ha rather than m^2, year rather than second. Use Mg ha^{-1}, not tonnes ha^{-1}, and use μg g^{-1}, not ppm (or for volume, μL L^{-1} or equivalent). Tree diameter will generally be in cm (an approved SI unit) rather than m. Units should be in the following style: kg ha^{-1} $year^{-1}$, kg m^{-3}. Non-SI units should be spelled in full (e.g. year). Do not insert 'non-units' within compound units: for example, write 300 kg ha^{-1} of nitrogen (or N), not 300 kg N ha^{-1}.

Math formulae

Present simple formulae in the line of normal text where possible and use the solidus (/) instead of a horizontal line for small fractional terms, e.g., X/Y. In principle, variables are to be presented in italics. Powers of e are often more conveniently denoted by exp. Number consecutively any equations that have to be displayed separately from the text (if referred to explicitly in the text).

Footnotes

Footnotes should be used sparingly. Number them consecutively throughout the article, using superscript Arabic numbers. Many wordprocessors build footnotes into the text, and this feature may be used. Should this not be the case, indicate the position of footnotes in the text and present the footnotes themselves separately at the end of the article. Do not include footnotes in the Reference list.

Table footnotes

Indicate each footnote in a table with a superscript lowercase letter.

APPENDIX V: GUIDELINES FOR SUBMISSION OF CHAPTER 4 TO THE JOURNAL: JOURNAL OF FORESTRY RESEARCH

- **Title page**

  The first page of each paper must contain the following items: (1) the title of the paper, (2) the name(s) and address(es) of the author(s), (3) the full postal address with the telephone and fax numbers and e-mail address of the corresponding author, (4) article type, subject area, and field (see list of "Subject areas and fields" at the end of these instructions), (5) page count for the text, including abstract and references, (6) number(s) of tables and figures listed separately, and (7) any necessary footnotes.

- **Abstract**

  The abstract should be no longer than 250 words and should be followed by up to five key words.

- **Text**

  The text of the article should be divided into the following sections, if appropriate: Introduction, Materials and methods, Results, Discussion, Acknowledgments, References, tables, and figure legends.

- **Tables**

  Tables must be numbered with Arabic numerals according to their sequence in the text. Each table must be typewritten double-spaced on a separate page. Each table should have a brief and self-explanatory title. Any explanation essential to the understanding of the table should be given as a footnote below the table.

  Vertical lines should not be used to separate columns; additional space should be used to separate columns, if necessary.

- **Figures**

  Figures (drawings and photographs) must be numbered with Arabic numerals according to their sequence in the text. Each figure should be submitted on a separate page, each bearing the figure number, and the author's name, and the figure number written in the upper right corner. Figure legends should be brief and self-explanatory and should be placed at the end of the text.

Figures should be in the desired final size and should be match the size of either the column width (8.4 cm) or the printing area (17.4 × 23.4 cm). If reduction is necessary, the alternative scale desired should be stated. The publisher reserves the right to reduce or enlarge figures. Figure parts should be identified by lowercase roman letters (a, b, etc.). If illustrations are supplied with uppercase labelling, lowercase letters will still be used in the figure legends and citations.

APPENDIX VI: GUIDELINES FOR SUBMISSION OF CHAPTER 4 TO THE JOURNAL: REMOTE SENSING OF ENVIRONMENT

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It is important that the file be saved in the native format of the word-processor used. The text should be in single-column format. Keep the layout of the text as simple as possible. Most formatting codes will be removed and replaced on processing the article. In particular, do not use the word-processor's options to justify text or to hyphenate words. However, do use bold face, italics, subscripts, superscripts etc. When preparing tables, if you are using a table grid, use only one grid for each individual table and not a grid for each row. If no grid is used, use tabs, not spaces, to align columns. The electronic text should be prepared in a way very similar to that of conventional manuscripts (see also the Guide to Publishing with Elsevier: http://www.elsevier.com/guidepublication). Note that source files of figures, tables and text graphics will be required whether or not you embed your figures in the text. See also the section on Electronic artwork.

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All material should be typed, double-spaced, allowing ample margins using 8.5 x 11 paper size format. Pages must be numbered; in addition, line numbering is preferred. Flexibility of presentation is allowed, but authors are asked to arrange the subject matter clearly under headings such as Introduction, Methods, Results, Discussion, etc. All contributions should include a concise, informative **Abstract.** All **equations, tables,** and **figure legends** should be numbered consecutively and separately throughout the paper. The International System (SI) of units should be used. Language: Papers are to be submitted in and will be published in English. Table numbers and captions should be placed directly above each table. Figure numbers and legends, if possible, should be placed directly below each figure.

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Divide your article into clearly defined and numbered sections. Subsections should be numbered 1.1 (then 1.1.1, 1.1.2, ...), 1.2, etc. (the abstract is not included in section numbering). Use this numbering also for internal cross-referencing: do not just refer to 'the text'. Any subsection may be given a brief heading. Each heading should appear on its own separate line.

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State the objectives of the work and provide an adequate background, avoiding a detailed literature survey or a summary of the results.

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