MODELLING THE RELATIONSHIP BETWEEN TREE CANOPY PROJECTION AREA AND ABOVE GROUND CARBON STOCK USING HIGH RESOLUTION GEOEYE SATELLITE IMAGES

SHYAM KUMAR SHAH
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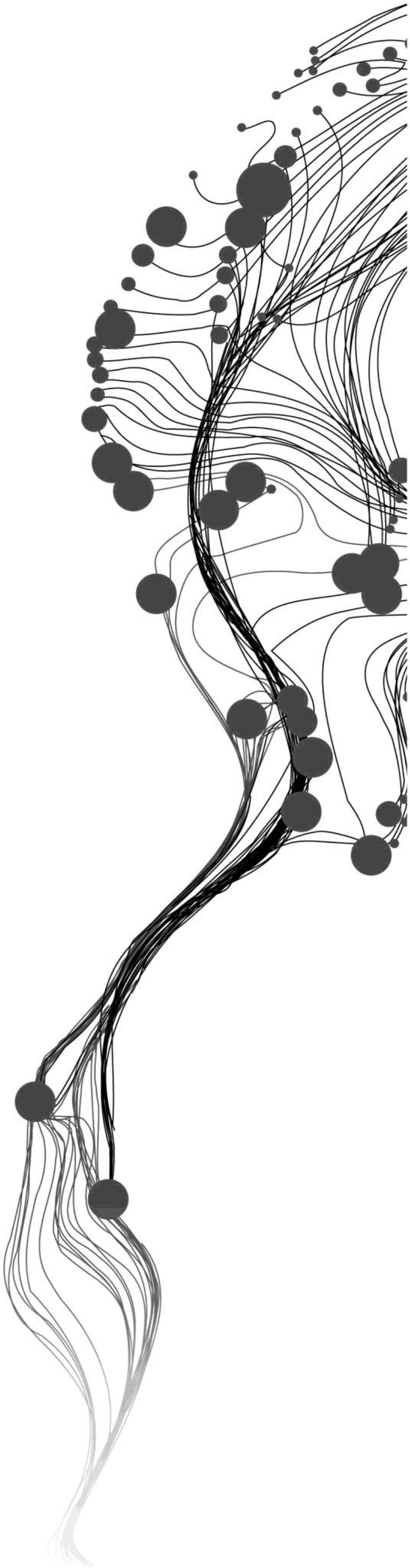

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Enschede, The Netherlands, February, 2011

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resources Management

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DISCLAIMER

This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the Faculty.

Dedicated to my parents,

The ultimate source of my inspiration!

ABSTRACT

Carbon stock estimation of above ground tree biomass is important for 'reducing emission from deforestation and forest degradation' (REDD) credit to mitigate climate change due to anthropogenic causes. Automatic delineation of individual tree crown (ITC) techniques results in a substantial error due to presence of intermingled canopy trees in the estimation of above ground carbon stock. The aim of this study was to establish regression models for the relationship of canopy projection area (CPA) with forest tree parameters, i.e., diameter at breast height (DBH), basal area (BA), biomass and carbon stock of standalone and intermingled canopy trees of dominant species for the prediction of above ground carbon stock. This study was carried out in subtropical broadleaf forest in Chitwan, Nepal. High resolution GeoEye satellite image was used for manual delineation of CPA of standalone and intermingled canopy trees of the dominant species. DBH of trees was measured in the field in 56 sample plots. Above ground tree dry biomass was calculated from the field measured DBH using allometric equation. Above ground tree carbon stock was obtained by multiplying their dry biomass with the factor 0.47. Individual basal area of intermingled canopy trees was calculated separately and was summed up (ΣBA) along with the summation of their carbon stock (Σcarbon). Correlation analysis was carried out to assess the linear relationship between CPA, DBH, BA, biomass, and carbon stock. Four types of functions, i.e., simple linear, quadratic, logarithmic and power, were used to fit the data using least square regression method. *Shorea robusta, Schima wallichii* and *Terminalia alata* were found dominant tree species in the study area forest. The relationship of CPA with DBH of standalone trees was found linear with coefficient of determination (R^2) ranging from 0.63 for *Schima wallichii* to 0.69 for *Shorea robusta* and 0.74 for *Terminalia alata*. The relationship of CPA with biomass or carbon stock of standalone trees was also revealed linear with R^2 ranging from 0.53 for *Schima wallichii* to 0.62 for *Terminalia alata* and 0.65 for *Shorea robusta*. The relationship of CPA with ΣBA and Σcarbon of intermingled canopy trees of *Shorea robusta* was also found linear with R^2 of 0.29 and 0.25 respectively. Simple linear regression model resulted in the least error for the prediction of carbon stock of standalone and intermingled canopy trees. Root mean square error (RMSE) for the prediction of carbon stock was ranging from 58.90% for *Shorea robusta* to 61.97% for *Terminalia alata* and 73.11% for *Schima wallichii* of standalone trees. RMSE for the prediction of carbon stock of intermingled canopy trees of *Shorea robusta* was 58.52%. Manually delineated CPA from GeoEye image which is intended to be used to predict above ground tree carbon stock of subtropical broadleaf forest is not having high R^2 to the level that the CPA can be utilized to model or predict carbon stock on an operational base. However, the approach to predict above ground tree carbon stock using CPA is still need to be improved.

Keywords: Crown projection area, standalone trees, intermingled canopy trees, diameter at breast height, basal area, biomass, above ground carbon stock, GeoEye satellite image

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Shyam Kumar Shah
Enschede, the Netherlands
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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Global context of forest carbon

The United Nations Framework Convention on Climate Change (UNFCCC), held in June 1992, has been marked the global commitment on climate change. The objective of the Convention is to stabilize greenhouse gas (GHG) concentrations, which is the main anthropogenic cause to climate change, in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system (UNFCCC, 2010). The Kyoto protocol, a binding protocol to UNFCCC, requires party countries to limit or reduce GHG emission (Gibbs *et al.*, 2007).

Forests, which occupy 31% of the total land area of the world (FAO, 2011), play a significant role in the global carbon cycle. They are the large carbon pool and acts as both carbon source and sink according to their management. Growing vegetation absorbs CO_2 from the atmosphere for the photosynthesis process and stores it in the form of carbon in their biomass. Biomass is defined as "organic material both aboveground and belowground, and both living and dead, e.g., trees, grasses, tree litter, roots. Above ground biomass of trees is the all living biomass above the soil including stem, stump, branches, bark, seeds, and foliage (IPCC, 2006)." When biomass is burned or decayed it release CO_2, an important GHG, back into the atmosphere. Deforestation is a major contributor to the release of CO_2 that leads to climate change (CIFOR *et al.*, 2009). Emissions from deforestation and forest degradation in developing countries constitute some 15-25% of the total global emission of GHGs annually (Gibbs *et al.*, 2007). Deforestation mainly for agricultural land has continued at approximately 13 million hectares per year (for the period 1990-2005) which resulted in the release of carbon as CO_2 originally stored in trees (CIFOR *et al.*, 2009). Nevertheless, forests store 289 gigatonnes of carbon in their biomass alone globally (FAO, 2010).

REDD stands for 'reducing emission from deforestation and forest degradation' was first introduced into the Conference of the Parties (CoP) agenda of UNFCCC at its eleventh session in Montreal in 2005 (UNFCCC, 2010). It provides financial incentives to developing countries that reduce GHG emissions from forests. Credit from reduced emissions would be quantified and sold in an emerging international carbon market (Gibbs *et al.*, 2007). Furthermore, it extends the opportunities of getting fund from developed countries. The initiative has commonly been accepted as a low cost option to deliver significant climate change mitigation benefits along with co-benefits such as biodiversity conservation and poverty alleviation that leads to win - win situation to all parties.

Nepal is a developing country with a forest cover of about 5.83 million hectares or 39.6% of the total geographical area of the country. Community forestry is the top priority programme for the forestry sector in the country. Community forest management forms an integral part of the rural subsistence economy in many parts of Nepal (Karky & Skutsch, 2010). More than 1 million hectares of forestland or about one quarter of the country's forest are being managed by local communities (DoF, 2010). However, according to Ministry of Forests and Soil Conservation (2009), deforestation rate is 1.7 %. Deforestation and forest degradation have been a great concern for Nepal as well for biodiversity conservation, livelihood of people and to address global commitment of mitigating impacts of climate change. Moreover, Nepal is a party country for UNFCCC and the Kyoto Protocol that requires reporting carbon balance of the country.

1.2. Carbon stock estimation

The carbon pools in forest ecosystem are comprised of above ground biomass, below ground biomass, deadwood, litter and peat soil (IPCC, 2006). Of them, above ground biomass (hereafter above ground biomass is referred to as biomass) of trees contains the largest carbon pool and is the most directly impacted by deforestation and forest degradation. Biomass estimation is the primary step in quantifying carbon stock of a forest as dry biomass contains about 47 % carbon (IPCC, 2006).

Biomass of trees can be derived directly by measuring sample tree attributes in the field or indirectly by transforming available volume data from forest inventory (IPCC, 2006). Although the direct way to quantify biomass is accurate for a particular location, it is too time consuming, expensive, destructive and impractical for country level analysis. There is no methodology to measure biomass of trees across a large area directly. Remote sensing (RS) provides alternatives to conventional forest inventory to estimate biomass and carbon stock across a large area (Gibbs *et al.*, 2007).

1.3. Overview of RS techniques to estimate biomass

RS has been used as an important technique to estimate biomass at a larger scale. It acquires data using different sensors, e.g., Optical or Radio Detection and Ranging (Radar) or Light Detection and Ranging (LiDAR) on board satellite or installed in aircraft. The strengths of the techniques are to provide spatially explicit information and repeated coverage including the possibility of covering large areas as well as remote areas that may be difficult to access. Three major RS techniques have evolved to estimate forest carbon: optical RS, Radar RS, LiDAR RS. In all cases, the airborne acquisition of RS data is too expensive at country level.

Optical data are widely available at various spatial and temporal resolutions and have been successfully used for land cover classification. It provides two-dimensional views of forest canopy surfaces. **Coarse resolution** optical data, for example, National Oceanic and Atmospheric Administration (NOAA), Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS) and SPOT satellite provide information at regional and continental scale. These data could not be used for biomass estimation of tropical forest with certainty and are very limited application for biomass estimation (Lu, 2006). This is because they have the problem of mixed pixels and the integration of sample data with the image derived variables (Lu, 2006).

Medium resolution optical data, for example, Landsat Enhanced Thematic Mapper (ETM+) spectral responses are more suitable for biomass estimation of simple forest stand structure. They are unsuitable for complicated forest stand structure where textures appear more important than spectral response (Lu, 2005). The predictive models of tropical forest biomass from Landsat Thematic Mapper (TM) data based on vegetation indices, multiple regression and neural networks were found the problem of spatial transferability (Foody *et al.*, 2003). This study further demonstrated that spectral response mostly related to biomass differ greatly between sites (Foody *et al.*, 2003). The strength of the relationship between biomass and canopy reflectance is largely contextual. In other words, the accuracy in deriving forest biomass from the medium resolution optical data has been inconsistent and varies across case studies. It underestimates carbon stock particularly for the most carbon rich and structurally complex forest ecosystem as the signals from remote sensing equipment saturate quickly. Its applicability is further limited by cloud cover in the tropics. However, optical remote sensing systems are operational at global level and many more are expected to launch in future (Gibbs *et al.*, 2007).

Synthetic Aperture Radar (SAR) can penetrate into forest canopies and provides three-dimensional information on canopy architecture and structure. The spaceborne SAR estimates biomass accurately of relatively young and open conifer forests but its signal saturates at low level of biomass (100Mgha-1). Whereas most forests supports greater than this biomass (Gonzalez *et al.*, 2010). Undulating topography or mountain also limits its applicability to estimate forest carbon at larger scale.

LiDAR can measure the three-dimensional vertical structure of vegetation in great detail. Its capabilities to estimate carbon far exceed Radar and optical sensor system, early saturation of tree height but continue accumulation of carbon pose some challenges. It also requires extensive field data for calibration. Although LiDAR has been claimed to give the highest level of accuracy and the lowest level of uncertainty for biomass estimation, it is not an option because no LiDAR is in operation from a satellite platform (Patenaude *et al.*, 2005) especially for vegetation characterisation. Airborne LiDAR system is too costly and not practical for large area.

1.4. Problem statement

Accurate estimation of forest carbon is still a challenging task. Unlike medium resolutions, high resolution satellites such as QuickBird, IKONOS and WorldView are capable of sensing biophysical parameters of trees such as crown dimension which correlate directly with biomass (Gonzalez *et al.*, 2010). High resolution satellite data have become available anywhere in the world because of rapid advances and decreasing cost (Asner, 2009). The cost is further justifiable for the initial carbon stock estimation and to meet Intergovernmental Panel on Climate Change (IPCC) 'Tier 3' standard which ensures the higher level of accuracy and lower level of uncertainty (Patenaude *et al.*, 2005). It has potential to higher financial returns for monitoring and verifying carbon stock and emissions. Unlike 'Tier 1' which use national forest cover and IPCC default value for carbon stock estimation, 'Tier 2 and Tier 3' provide details on carbon stock estimation and emission at regional and national level using plot inventory, satellite mapping and carbon modelling (Gibbs *et al.*, 2007).

Among the biophysical parameters of trees, DBH is an important predictive variable (Leboeuf *et al.*, 2007) which alone explains more than 95 % variation in biomass (Gibbs *et al.*, 2007). Studies have shown significant relationship between DBH and crown dimension (Anderson *et al.*, 2000; Bartelink, 1996). A linear relationship was found between stem diameter and crown diameter in all sets of observations for different broadleaf species (Hemery *et al.*, 2005). Highly significant correlation has demonstrated between CPA and all components of biomass of a tree such as foliage mass, branch mass and stem mass (Kuuluvainen, 1991).

The identification of relationship between DBH and CPA (derived from satellite image) allow predicting above ground tree biomass at a larger scale. Allometric equations can be used to estimate biomass that relate with the tree parameter, i.e., DBH (Basuki *et al.*, 2009; Chave *et al.*, 2005). Allometry means the relative growth. Tree allometry describes the relationship between its different diamentions. Allometric equations are developed on the basis of destructive sampling (Basuki *et al.*, 2009).

Individual tree crown (ITC) or CPA has been extracted from very high resolution (VHR) satellite image using ITC software and object oriented image analysis for forest stand information (Culvenor, 2003; Katoh *et al.*, 2009; Leckie *et al.*, 2005). Object oriented image analysis can make full use of image information which combine spatial as well as spectral information and extract objects at multiple scales. Whereas conventional pixel based image analysis, mainly focus on spectral information, is irrelevant using VHR satellite data as the target object size, for instance, tree crown is larger than a pixel (Greenberg *et al.*, 2005).

Individual tree crown delineation using high resolution imagery and ITC software technique is appropriate and consistent for conifer forests with abundant shade between trees that provides a crown outline (Katoh *et al.*, 2009; Leckie *et al.*, 2005). Indistinct or absence of valley of shade between trees in broadleaf forest stand makes it difficult to delineate individual tree crown using ITC software (Chubey *et al.*, 2006). Automatic delineation of individual tree crown techniques such as valley following and pattern matching has wide variation in their accuracy. Their accuracy varies from 50 to 80 % (Bunting & Lucas, 2006). They all have poor accuracy attributed largely to overtopping of smaller crowns and presence of intermingled crowns or overlapped canopy in complex forest (Bunting & Lucas, 2006). Tree crown identification algorithm (TIDA) cannot separate overlapping or adjacent intermingled tree crowns, which is common in natural forest, and computation is very intensive that cannot be applied over a large area (Asner *et al.*, 2002; Palace *et al.*, 2008; Song *et al.*, 1997).

Automatic ITC delineation techniques have been unable to separate canopies seen as one canopy in the image but in fact intermingled of two or more canopies, which causes substantial error for biomass estimation (Browning *et al.*, 2009; Hirata *et al.*, 2009 ; Palace *et al.*, 2008). Study has not yet explained the relationship between canopy delineated from the image, which are seen as one canopy in the image but in reality formed from two or three or sometimes more crowns of trees, and their corresponding DBH, BA, biomass and carbon. In this context, CPA of standalone as well as intermingled canopy trees was manually delineated from GeoEye satellite image. The relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees was investigated using correlation and regression analysis.

1.5. Research objective

The aim of this study was to establish regression models for the relationship of CPA delineated from the high resolution GeoEye satellite image with forest tree parameters, i.e., DBH, BA, biomass and carbon stock, of standalone and intermingled canopy trees of the dominant species for the prediction of above ground tree carbon stock. Hereafter carbon stock is referred to as carbon.

Specific objectives

1. To analyse the relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species.

2. To analyse the relationship between CPA, summed BA (ΣBA), summed biomass (Σbiomass) and summed carbon (Σcarbon) of intermingled canopy trees of the dominant species.

3. To develop and identify the best fit regression models (simple linear, quadratic, logarithmic, power functions) for the relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees of the dominant species.

1.6. Research questions

1. Is there any relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species?

2. Is there any relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of the dominant species?

3. Which regression models best explain the relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees of the dominant species?

1.7. Research hypotheses

1. H_0: There is no significant (95% confidence level) relationship between CPA, DBH, biomass and carbon of standalone trees.

   H_1: There is a significant (95% confidence level) relationship between CPA, DBH, biomass and carbon of standalone trees.

2. H_0: There is no significant (95% confidence level) relationship between CPA, ΣBA, Σbiomass and Σcarbon of two or more intermingled canopy trees.

   H_1: There is a significant (95% confidence level) relationship between CPA, ΣBA, Σbiomass and Σcarbon of two or more intermingled canopy trees.

1.8. Definition of terms

The **crown projection area** (CPA) of a tree is the area of vertical projection of the outermost perimeter of the crown on horizontal plane. Crown size, which is closely related to the photosynthetic capacity of tree, is an important parameter to characterize tree biomass.

The **standalone trees**: literally the word standalone means an entity that has no dependencies; it can "stand alone". Conceptually, standalone tree can be defined as the tree whose branches are not touched with branches of other trees. Standalone trees have no competition for space for canopy growth from surrounding trees.

The **intermingled canopy trees**: According to the Concise Oxford English Dictionary, the word 'intermingled' means mix or mingle together (Fowler *et al.*, 1976).The intermingled canopy trees can also be defined as the group of trees whose branches or canopies mix together. Individual tree in intermingled canopies has the competition for crown expansion from the branches of adjoining trees.

The **breast height** of a tree is 1.3 m from the base point along the axis of the stem.

The **basal area** (BA) is defined as the cross-sectional area of a stem of a tree at its breast height assuming cylindrical stem.

The **diameter of a tree at breast height** (DBH) is over bark standing tree stem diameter measured perpendicular to the stem axis at breast height.

2. METHODS AND MATERIALS

2.1. Study area

The study area, covering 2374.67 ha, is located in Chitwan district of the Central Development Region of Nepal (Figure 2-1). There are forty village development committees in the district. Of them, study area is limited to four village development committees, namely, Shiddi, Shaktikhor, Chainpur and Pithuwa.

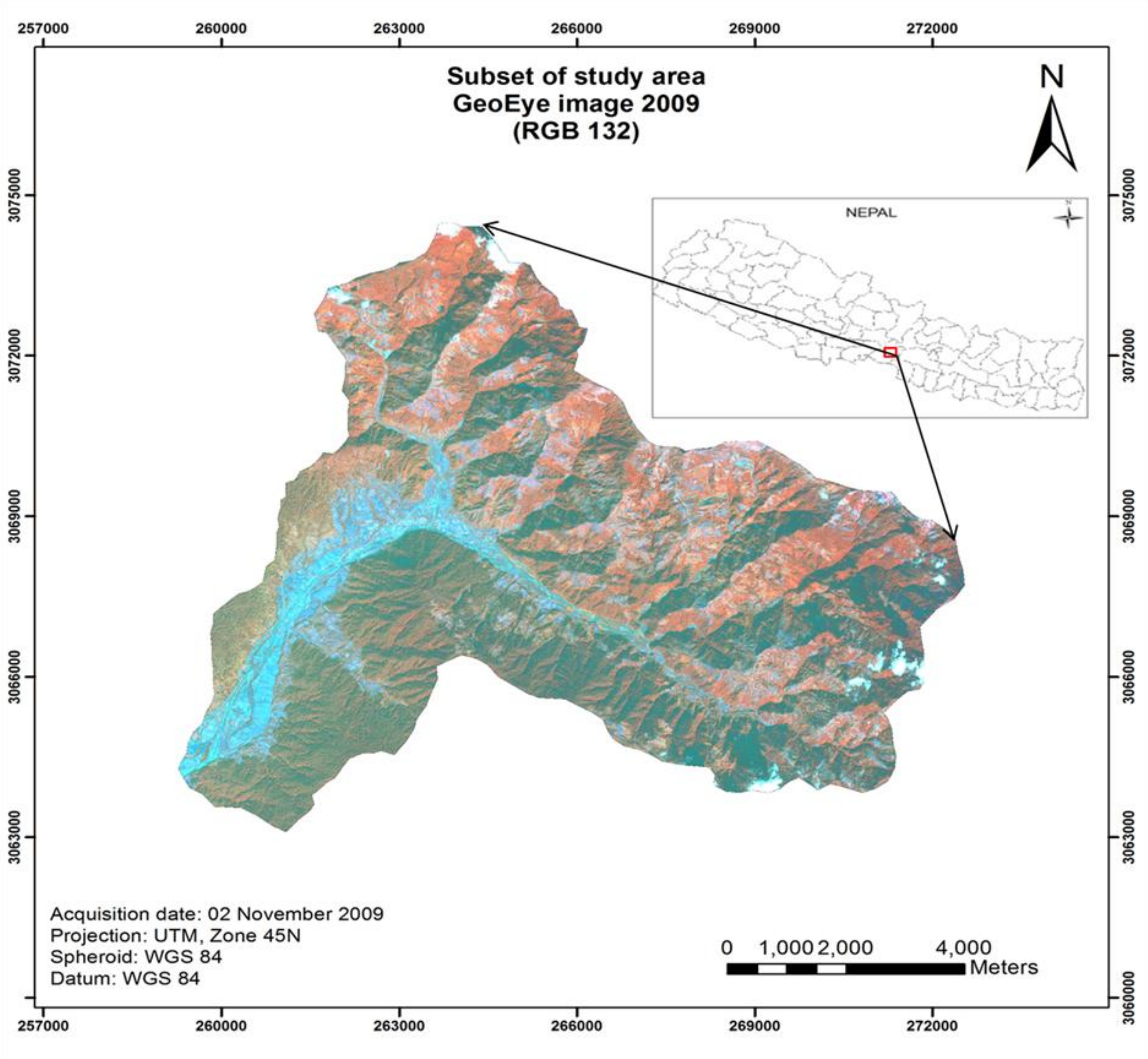


Figure 2-1 The Study area, Chitwan district, Nepal

Reason for selection of the area

First, community forest user groups (CFUGs) have been managing the forest in the study area. CFUG is a group of local people, recognized as autonomous corporate institution by the country's law, to whom certain area of national forest is handed over for conservation, management and utilization based on their capacity and willingness (Pokharel, 2009). There are a total of 15 CFUGs in the area in 4 different Village Development Committees (VDCs). These forest user groups are mainly comprised of indigenous Chepang and Tamang communities. They are highly dependent on forest for their livelihood such as livestock grazing, fuel wood collection and edible tuber collection. These communities are one of the most marginalized ethnic groups in the country. Second, the area is selected as one of the pilot project areas for the REDD program. The project has been funded by Norwegian government under UN REDD program. Third, high resolution satellite images of the study area as well as several other types of spatial and non-spatial data were made available from International Centre for Integrated Mountain Development (ICIMOD) organization. Fourth, the study area is fully accessible. Moreover, we received full help and support from the CFUGs and the Asia network for Sustainable Agriculture and Bioresources (ANSAB) organization to collect the field data and measurements.

2.1.1. Forest

The natural subtropical forest with broadleaf species is dominating the study area. *Shorea robusta* is the dominant tree species (Figure 2-2). The main associated tree species are *Terminalia alata, Terminalia bellirica, Lagerstromia parviflora, Schima wallichii, Semicarpus anacardium, Mallotus phillippensis, Cassia fistula, Cleistocalyx operculatus, Careya arborea, Holarrhena pubescens, Adina cordifolia, Syzygium cumini, Aesandra butyracea, Terminalia bellirica.*

Figure 2-2 Example of the forest and topography in the study area

2.1.2. Climate

The area lies in the central climatic zone of the Himalayas. The subtropical monsoon climate exists in the area. Usually monsoon rain starts in mid-June and last till late September. During the period, most of the annual precipitation falls in the form of rain. Annual average precipitation is 1830mm that varies from 1584 to 2287mm. Annual mean temperature is 24^{o}C that ranges from 36^{o}C to 18^{o}C (Panta *et al.*, 2008).

2.1.3. Topography

The area is mountainous with highly undulating terrain (Figure 2-2). The altitude varies from 300m to 1200m above sea level. The land is characterized by many steep gorges and slope varies from 30% to more than 100%. The area is drained by Khayarkhola stream having many small tributaries feeding into it**.**

2.2. Materials

- **Satellite data**

GeoEye – 1 images acquired on 02 November 2009 were used for this study. Orthorectified images were provided by ICIMOD. They were geo-registered in the Universal Transverse Mercator (UTM) coordinate system (WGS 84, Zone 45 N). The characteristics of satellite data are shown in Table 2-1.

Table 2-1 Characteristics of GeoEye satellite images used in this research

Image	Spectral range	Spatial resolution
Panchromatic	450–800 nm	0.5 m
MSS blue	450–510 nm	2.0 m
MSS green	510–580 nm	2.0 m
MSS red	655–690 nm	2.0 m
MSS near infrared	780–920 nm	2.0 m
Nominal collection elevation	75.92^{o}	
Sun angle elevation	45.67^{o}	

There was about 10-11 months lag between image acquisition and field work data collection in the study area. Data was collected in September-October, 2010. It was assumed that DBH of the tree (≥10cm) would not have increased significantly in the period.

- **Software**

ERDAS IMAGINE 2010, ArcGIS 2010, statistical software (R package, SPSS, XLSTAT 2010, and DTREG) and office software (MS Word, MS Excel, MS Visio) were software packages used for this study.

- **Equipment**

GPS and iPAQ were used in the field for navigation, sample plot location and recording coordinates. 10m diameter tape was used to measure DBH of trees and 30m surveyor tape was used to measure ground distance. Clinometer was also used to measure slope of sample plot location.

2.3. Methods

General flow diagram of research methods is presented in Figure 2-3. It mainly consists of image processing (violet colour block), field data collection especially DBH of trees (blue colour block) and data analysis, i.e., correlation and regression analysis (green colour block). RQ 1, RQ 2 and RQ 3 in the diagram refer to research question 1, 2 and 3 respectively.

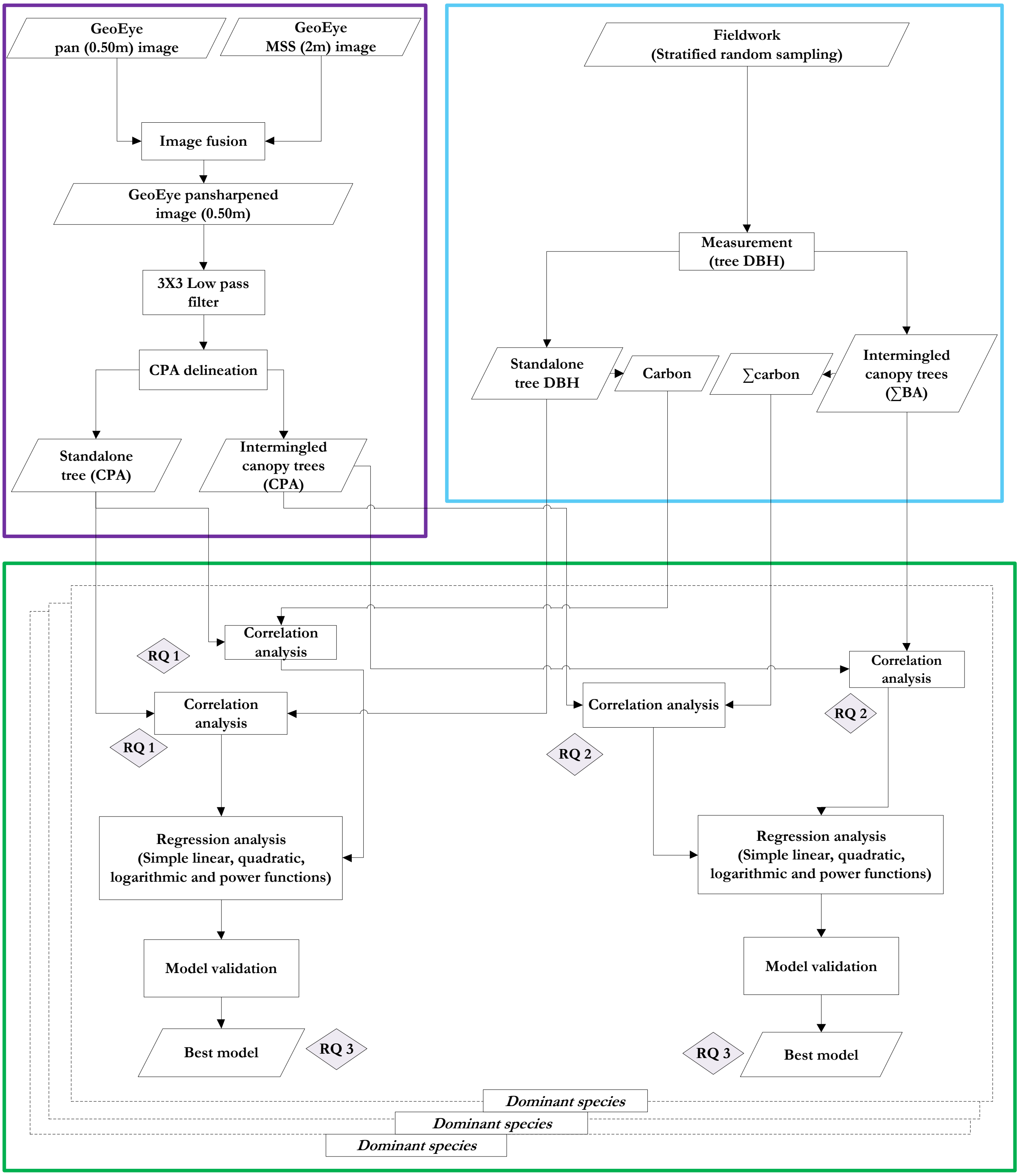


Figure 2-3 Flow diagram of research methods

2.4. Pre-fieldwork

2.4.1. Image pre-processing

Orthoimages of GeoEye -1 satellite were used for this study. Panchromatic band and four multispectral bands, i.e., blue, green, red and near IR, were in tagged image file format (TIFF) format. The panchromatic as well as four multispectral bands were imported to IMG file format. The images were set in WGS 84 spheroid projection system. The projection system was adopted as such because the system is currently used in the study area, Nepal. As the images were of single date acquisition and most part cloud free, no radiometric correction was applied. Topographic map (1992) with river and road was used to check the georeference of the orthoimages.

2.4.2. Image fusion

Pansharpening fusion technique was used to increase the spatial resolution of multispectral images by combining it with a fine spatial resolution panchromatic image, while preserving the spectral information in the multispectral images. Because colour images are easier to interpret than panchromatic and also higher resolution images are easier to interpret than lower resolution. For this, green, red and near infrared bands were layer stacked. Blue band was not used because spatial information is more important than spectral information for manual tree crown delineation. Including blue band, spatial information of the image was found less interpretable visually for digitising purpose. In the layer stack dialog box of ERDAS IMAGINE 2010 software, unsigned 16 bit output data type was assigned and union output option was chosen. The layer stacked image of lower spatial resolution (2m) was fused with panchromatic image of higher spatial resolution (0.50m) using modified IHS option in ERDAS IMAGINE 2010. This resulted in pansharpened image with colour composite of spatial resolution 0.50m. Modified IHS fusion technique was chosen among other fusion techniques based on better visualisation of forest vegetation. In the modified IHS merge dialog box following options were checked: bilinear interpolation resampling technique, computation method single pass three layer RGB, true colour (RGB 321) layer combination and unsigned 16 bit output data type. The assigned layer combination was decided based on the visual interpretability of different combination results. Bilinear interpolation technique was assigned because it reduces the alteration of spatial information and lead to smoother image compared to nearest neighbour resampling.

Pansharpened colour composite image was too large (5593.94 MB) to upload in iPAQ for the field work. The image was exported to enhanced compressed wavelet (ECW) format that reduced file size to 46.25 MB. RGB 234 band combination was selected while exporting the image to ECW format so that output ECW image (Appendix 1) would be similar to pansharpened image (imagine format) in the same band combination.

2.4.3. Sampling design

Stratified random sampling was followed to design sample plot in the study area (Mitchell & Popovich, 1997). There were total 15 user group forests in the study area. Each user group forest was different from other in several aspects such as altitude, slope, aspect, species composition and stand structure. Stratification into blocks allowed the sample to spread over the whole study area, even if the study area forest appears to be homogeneous (Thompson, 1992). Each user group forest was considered as a stratum that resulted into total of 15 strata.

Stratified random sampling is used to estimate population parameter of interest (mean or total) more precisely than non-stratified sampling for a given sample size or cost. Conversely, it estimates population parameters as precise as simple random sampling or systematic sampling using a fewer plots for a lower cost (Shiver & Borders, 1996).

Total sample size was calculated using following formula and second hand data of tree parameters, i.e., DBH of trees of the study area. As determining sample size without having some kind of prior knowledge of the population is impossible, in that case preliminary survey might be necessary to establish reasonable information of population parameters (Husch *et al.*, 2003).

$$N = t^2 * (CV\ \%)^2 / (AE\ \%)^2$$

Where

N	=	minimum number of sample
t	=	t value associated with the desired probability
CV	=	coefficient of variation of DBH of trees to be sampled from secondary data (38.46%)
AE	=	allowable error or desired precision for DBH of trees to be sampled

The sample size became 60 at probability level of 5 % and allowable error of 10 %. The number of sample plots for each stratum was calculated in proportion to their area. Proportional allocation is the most basic and easily implemented sample allocation strategy (Shiver & Borders, 1996). While dividing total 60 sample plots to individual stratum (15 user group forests), sample plots for two of the strata were less than 2 and for another two strata even less than 1 (Appendix 2). In both cases, number of sample plots were maintained at 2 to optimize the sampling design while considering both stratification and sample size (Dalenius & Cochran, 2006) that resulted in total of 63 sample plots.

Sample plots to each stratum were located randomly using ArcGIS 2010 (Appendix 3). For this, polygon shapefile for each 15 user group forest was made separately. The number of random points (sample size) for each polygon were generated and made point shapefile to be used in iPAQ for fieldwork.

2.5. Field work

DBH of trees were measured and species were noted (see data sheet Appendix 4) in 56 sample plots out of the total 63 sample plots as mentioned in sampling design section. Remaining sample plots could not be reached due to inaccessible terrain and time limitation. At sample plot location, circular plot of radius 12.62m (500m^2 area) were demarcated. Sample plot radius was extended up to 15m as the slope of the area increased more than 5 % using slope correction factor (Appendix 5).

The circular plot is widely used. As a single dimension, radius is used to define the perimeter. It has minimum perimeter for a given area and no predetermined orientation. And small circular plots are more efficient than large ones (Husch *et al.*, 2003). Within the circular plot, DBH $\geq$ 10cm of standalone as well as intermingled canopy trees (recognizable in the image) were measured and their species were noted. DBH of trees equal and above 10cm is usually taken for above ground biomass estimation (Brown, 2002; Clark & Clark, 2000). If standalone trees were not found within the plot, standalone trees around the plot were looked and measured. This strategy was also followed for intermingled canopy trees. As many as possible number of trees (standalone and intermingled canopy) were measured and recorded in the data collection sheet considering time and feasibility.

To identify exactly the same trees on the image and in the field, the following strategy was adopted. Pansharpened image was exported to ECW format (Appendix 1) and uploaded in iPAQ. Print outs of the pansharpened image (RGB 132) rotated 180^o at 1:1000 scale in JPEG format (Figure 2-4) were made for each sample plot and used in the field. The trees which were measured in and around the sample plot were marked with outlines and numeric notation in JPEG image print out. The numeric notations were recorded in the data sheet as well. And the coordinates of trees were also recorded in iPAQ.

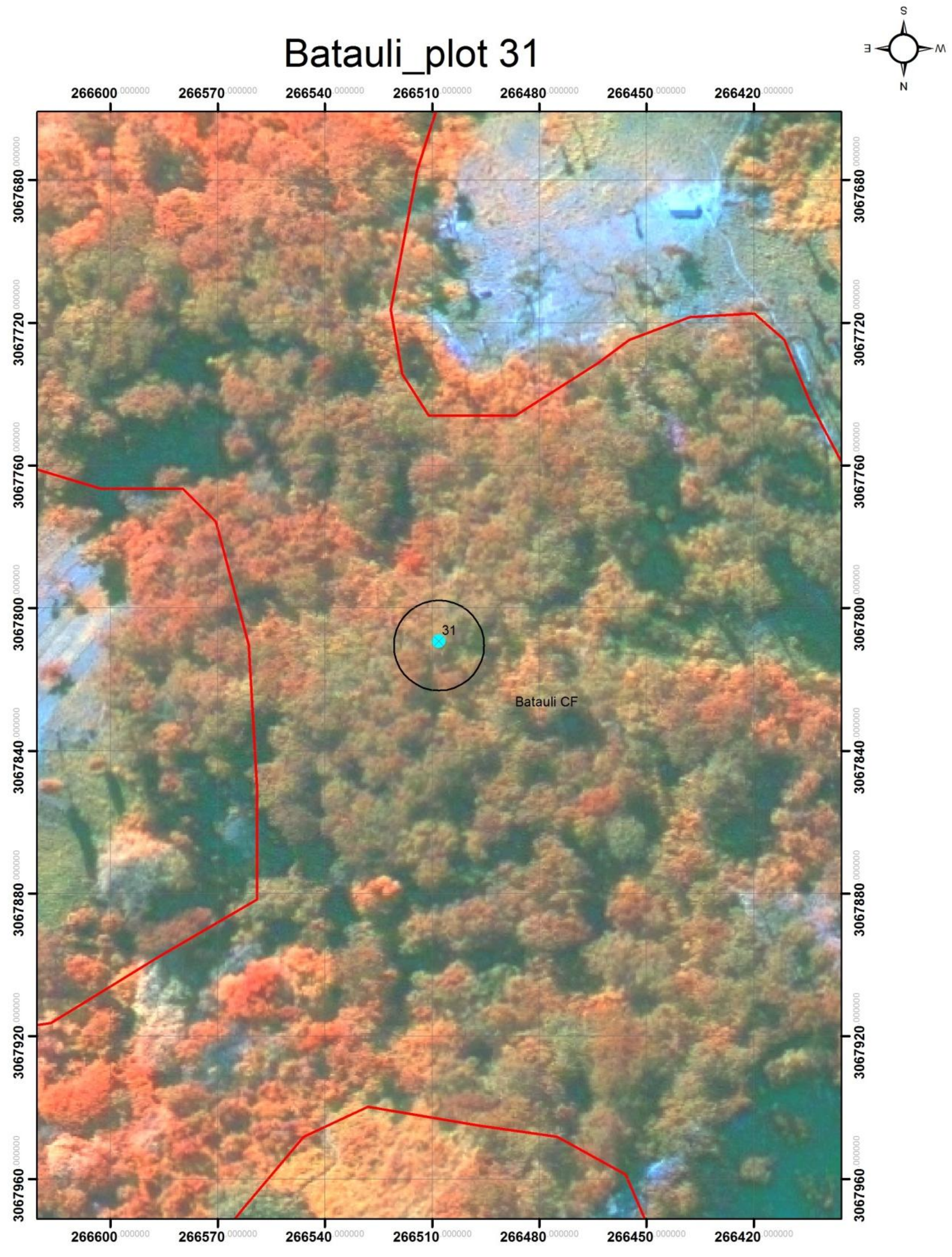


Figure 2-4 Pansharpened image rotated 180° at 1:1000 scale showing a sample plot (31)

In some cases, where actual sample plot was not reachable due to inaccessible terrain condition or actual sample plot laid in gorges, stream or walking tracks, sample plots were taken at some nearby location. In such cases, canopy of the trees, which were measured for DBH, was outlined on the back of the datasheet. Coordinates of trees were also recorded in iPAQ.

2.6. CPA delineation from GeoEye image

- **3X3 low pass filter**

Spatial filter was applied to the pansharpened GeoEye image using ERDAS IMAGINE 2010. The purpose was to enhance image information content and thus improve image interpretability. 3X3 low pass filter was applied to the image. This filter reduces the effect of high and medium frequency features and emphasizes low frequency features. Consequently, the filtered image appears smooth. In the convolution dialog box, 3x3 low pass kernel was assigned and handle edge by reflection were checked to preserve tree edges.

- **Image visualisation and CPA delineation**

Both filtered and unfiltered pansharpened image were opened in RGB 132 combination in ArcGIS 2010. Images were rotated 180^{o} to have better view of tree crown (Figure 2-4 and Figure 2-5). The opened images were observed alternatively at several scales to get better view of tree crown. Finally, visualisation of images at 1: 250 scale was found suitable for delineation of tree crown as shown in Figure 2-6. Sample plot shapefile and tree point shapefile were overlaid in the image. The pansharpened image was kept unchecked and canopy digitisation was carried out on filtered pansharpened image at 1:250 scale (Figure 2-6) consistently. Where there was confusion about the edge of tree canopy, the pansharpened image (without filter) was checked and compared. Standalone as well as intermingled canopy of trees (CPA) were digitised manually using polygon construction tool in ArcGIS 2010.

Vertical projection of crown perimeter

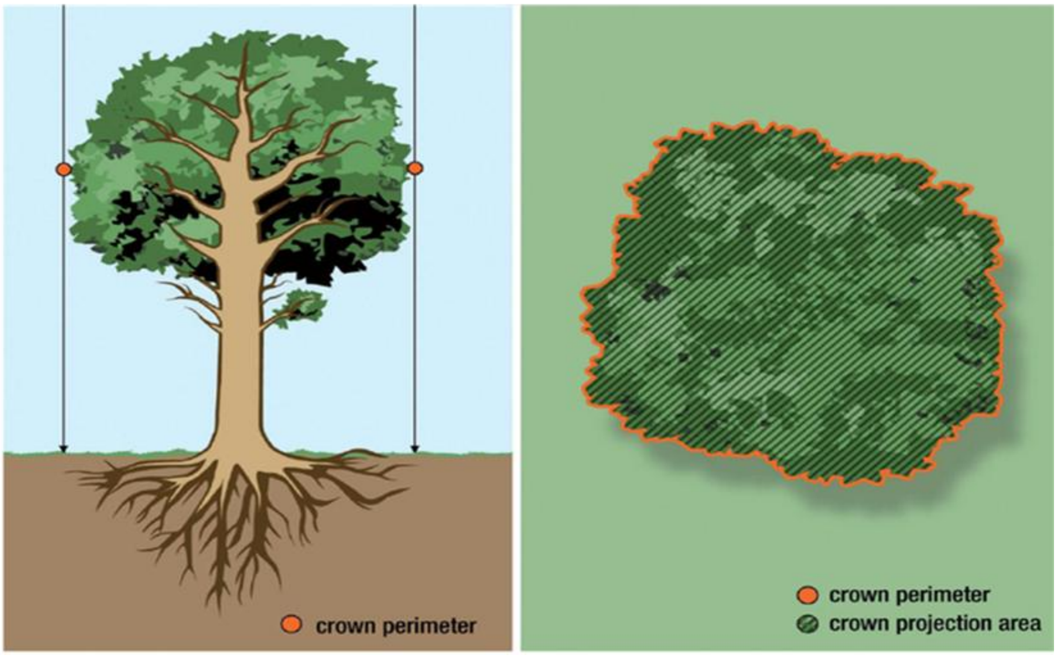
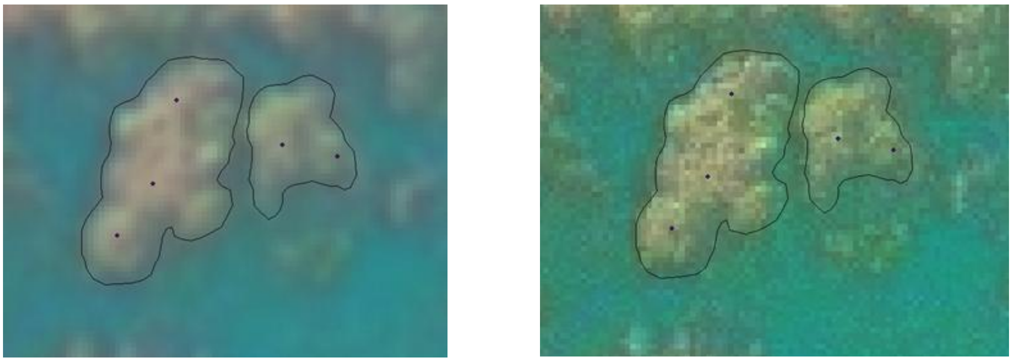


Figure 2-5 CPA of standalone tree; Source: (Gschwantner *et al.*, 2009)



(a) (b)

Figure 2-6 (a) CPA of two and three-intermingled canopy trees digitised on filtered image (b) The CPA on unfiltered image

2.7. Calculation of carbon from DBH

Dominant tree species were identified based on sample plot field data. Biomass and carbon of the dominant tree species were calculated including basal area of intermingled canopy trees.

- **Standalone trees**

Biomass of standalone trees (defined in section1.8) of the dominant species was calulated from field measured DBH using allometric equations. Allometric equations are used to estimate the biomass and carbon stock of forest (Basuki *et al.*, 2009; Chave *et al.*, 2005). Allometric equation was selected among the available ones based on the characteristics of the selected dominant tree species such as wood density and closeness of climatic parameters of the forest site. However, site and species specific allometric equation is is required for higher level accuracy (Basuki *et al.*, 2009). The calculated dry biomass was converted to carbon using the factor 0.47 (IPCC, 2006). The CPA, DBH, biomass and carbon data were compiled species-wise.

- **Intermingled canopy trees**

Biomass of intermingled canopy trees (defined in section1.8) of the dominant species was calculated from field measured DBH using allometric equation. Biomass of all trees in one intermingled canopy group was summed up (Σbiomass). The total carbon (Σcarbon) of intermingled canopy trees was calculated from Σbiomass using conversion the factor 0.47 (IPCC, 2006). Individual basal area of interminlged canopy trees of the dominant species were calculated from their DBHs separately using the formulae[$BA = \pi(DBH)^2/4$] (Hedl *et al.*, 2009). Basal area of all trees in one intermingled group was summed up (ΣBA). The reason was that it is more sensible to add two dimensional BA of individual trees of intermingled canopy group; and relate with two dimensional intermingled CPA instead of one dimension DBH particularly in intermingled canopy situation. The CPA, ΣBA, Σbiomass and Σcarbon data were compiled.

2.8. Data analysis

2.8.1. Graphical data analysis

The data were analysed using CPA as the predictor and DBH, biomass, carbon as response variables subsequently for standalone trees. Similarly, the data were analysed using CPA as the predictor and ΣBA, Σbiomass, Σcarbon as response variables subsequently for intermingled canopy trees. Pairs of continuous variables: (CPA and DBH) and (CPA and carbon) of standalone tree were examined in scatter plot for the form, direction and strength of relationship between them. Scatter plots can reveal nonlinearity, suspected outlier and unequal variance. Pair of continuous variables: (CPA and ΣBA) and (CPA and Σcarbon) of intermingled canopy trees were also observed in the scatter plot. The data (CPA and Σbiomass) were not presented in scatter plot as carbon was calculated from biomass using conversion factor (0.47). The pattern of scatter plot will not be different from (CPA and Σcarbon). The response variables: DBH of standalone and ΣBA of intermingled canopy trees, were also examined in box plot for suspected outliers.

2.8.2. Correlation analysis

Pearson's product-moment correlation coefficient (r) was computed between the pairs of continuous variables: (CPA and DBH), (CPA and biomass) and (CPA and carbon), for standalone trees. The correlation coefficient was also computed between the pairs of variables: (CPA and ΣBA), (CPA and Σbiomass) and (CPA and Σcarbon), for intermingled canopy trees.
The correlation measures the strength and direction of linear relationship between two quantitative variables. Suppose, a sample of paired continuous variables (X_i, Y_i), the sample Pearson's correlation coefficient is

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}.$$

Where $\overline{X}$ and $\overline{Y}$ are the mean of X and Y respectively.

2.8.3. Regression analysis

Regression technique was used to summarize the relationship between pairs of continuous variables: (CPA and DBH), (CPA and biomass) and (CPA and carbon), for standalone trees and between pairs of variables: (CPA and ΣBA), (CPA and Σbiomass) and (CPA and Σcarbon), for intermingled canopy trees. The significances of regression coefficients were assessed by t – statistic and the significance of regression models were assessed by F – statistic at 95% confidence level.

Regression analysis describes how a response variable y changes as explanatory variables x changes. The term regression of y on x is analogous to y is the function of x in mathematics. Often y is called dependent and x independent without any causal suggestion. Important purpose of regression analysis is to estimate the change in y from a given change in x that aims to predict y from given x. The developed models were predictive and fixed variable model that is only response had error and the explanatory variable (CPA) was assumed to be measured without error.

Linear and nonlinear functions, i.e., simple linear ($y = a + b.x$), quadratic ($y = a + b.x + c.x^2$), logarithmic ($y = a + b.Lnx$) and power ($y = a.x^b$) functions, were used to develop regression models for the relationship of CPA with DBH, BA, biomass and carbon. These functions were selected based on higher explanation of variables (R^2) to fit the data using least square regression method. Since graphic evaluation (scatter plot) of empirical relation between the variables is difficult, add trend line options in MS Excel 2010, which includes exponential, linear, logarithmic, polynomial and power, were used to observe higher value of R^2.

Studies have demonstrated linear as well as nonlinear relationship between tree parameters in the context of different species, site, condition (competition or crowding), natural and plantation stand. For example, Quadratic and piecewise linear models were found better fit of data (basal area and canopy cover) in the Ponderosa pine forests (Mitchell & Popovich, 1997). The straight-line relationship between basal area and overstory canopy in Ponderosa pine was found broke down above 60 % canopy cover (Mitchell & Popovich, 1997). Power function allometric model was used to study the influence of stand variables on allometric model parameters for the relationship between CPA delineated from QuickBird panchromatic data and field measured DBH of *Cryptomeria japonica* and *Chamaecyparis obtusa* tree in plantation forest using nonlinear regression analysis. Study found that parameter of power function model affected by stand variables (Hirata *et al.*, 2009). In addition to linear and quadratic models, most studies have been applied power function (Mohns *et al.*, 1988) which is widely used in biology (Huxley, 1932). Quadratic function has the disadvantage that the shape could be biologically unreasonable. Moreover, it is important to emphasize that these are empirical relationships chosen based on goodness of fit (R^2).

2.8.4. Model comparison

Significant regression models were compared for their predictive accuracy. Root mean square error (RMSE) was used for the comparison of predictive accuracy of the models (Gill *et al.*, 2000). RMSE is the reasonable and reliable measure of predictive accuracy of a model (Leboeuf *et al.*, 2007; Tedeschi, 2006; Wallach & Goffinet, 1989). RMSE was calculated using the formulae mentioned in Table 2-2. The larger dataset were divided randomly into two sets: 60% for model calibration and another 40% for model validation (Gill *et al.*, 2000). The identified significance model based on F – statistics were validated using 40% independent dataset for the calculation of RMSE.

Leave One Out Cross Validation (LOOCV) method was used to calculate RMSE for small dataset where splitting for calibration and validation were no choice for statistical inference. This method runs regression in iterations equal to number of samples. In each iteration, it leaves one data for validation and the rest for model development. This cross validation method provides unbiased estimation of prediction error for model selection (Cawley & Talbot, 2008; Efron & Gong, 1983). The most accurate model was identified based on the lowest value of RMSE for the prediction.

Table 2-2 Statistics used to compare models

Statistics	Formulae	Remarks
R^2	1- RSS/TSS	RSS= $\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$ and TSS $= \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2$ are residual sum and total sum of squares respectively
RMSE	$\sqrt{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 / n}$	Y_i is the measured value and $\hat{Y}_i$ is the predicted value by the model
RMSE in %	$\frac{RMSE}{\overline{Y}} * 100$ %	$\overline{Y}$ is the mean of validation dataset

3. RESULTS

3.1. Relationship between CPA, DBH, biomass and carbon in standalone trees

- **Standalone tree species**

A total of 237 trees of 26 different species were found standalone (Appendix 6). Of them, Figure 3-1 shows standalone trees of 17 different species which were found at least 1% in the sampled plots. Remaining 9 trees species of the total 26 were found less than 1 % in the sampled plots. *Shorea robusta* was the dominant species covering 54% followed by *Schima wallichii* 10 % and *Terminalia alata* 7 %.

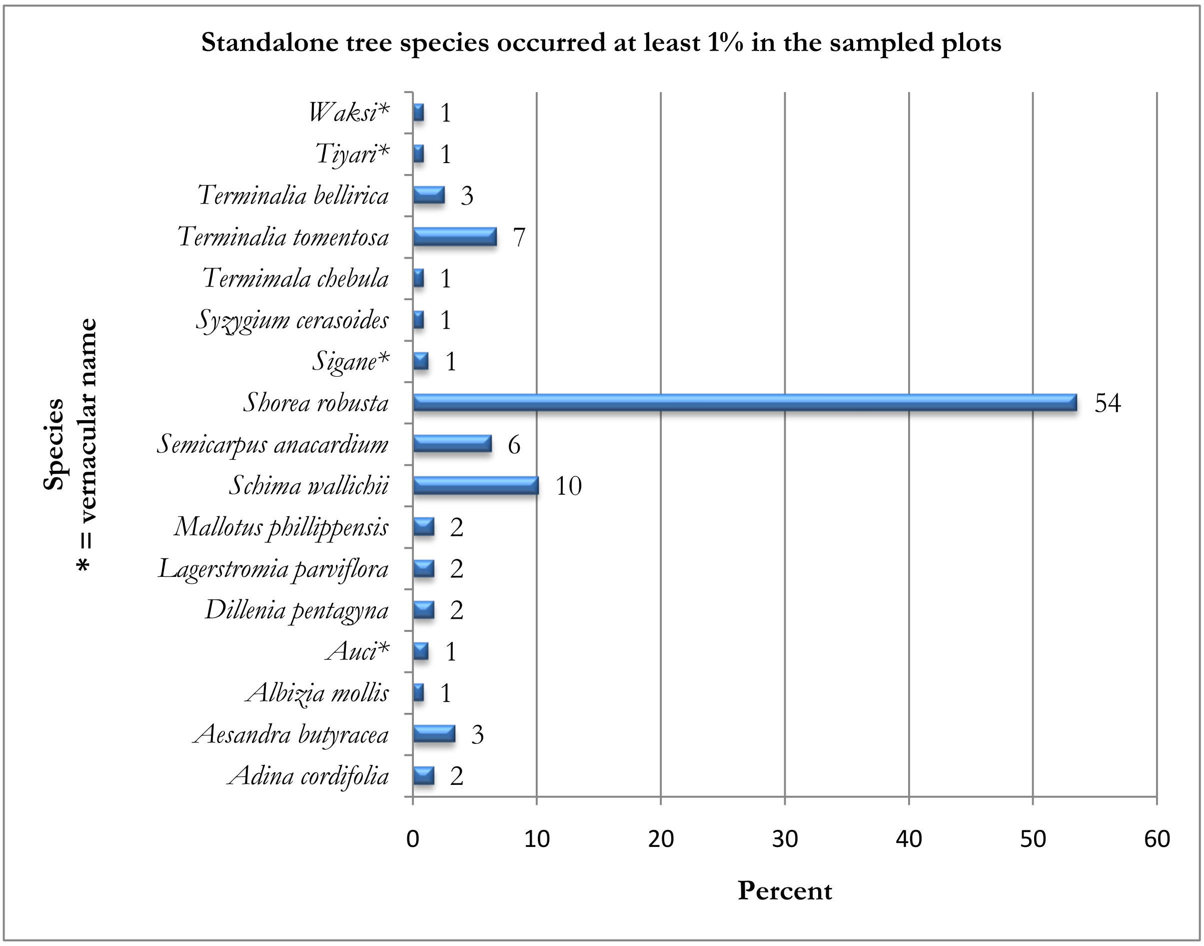


Figure 3-1 Standalone tree species in the sampled plots

- **Application of allometric equations for biomass calculation**

The three dominant tree species, namely, *Shorea robusta, Schima wallichii* and *Terminalia alata* were selected to analyse the relationship between CPA, DBH, BA, biomass and carbon. Other species were relatively few for statistical analysis. The biomass of *Shorea robusta* trees was calculated using species specific allometric equation (Table 3-1). The biomass of the other two species: *Schima wallichii* and *Terminalia alata* were calculated using the allometric equation developed for commercial species (Table 3-1). These two species are commercially valuable and largely used for timber locally. Both the equations were developed for tropical lowland dipterocarp forests in Indonesia. Although, site specific allometric equation is recommended for higher level of accuracy (Basuki *et al.*, 2009), the equations were not available for the study site, Nepal. Moreover, climate parameter of the study site of Indonesia is similar to this study site in Chitwan, Nepal. The mean annual rainfall is 2000mm and the temperature ranges from 21^0c to 34^0c with mean 26^0c in the study site of Indonesia. Carbon stock of above ground biomass of the trees was obtained by multiplying their dry biomass with the factor 0.47.

Table 3-1 Allometric equations adopted from Basuki *et al.,* (2009)

Allometric equations	R^2	**Standard error of residual**	**Correction factor**	**DBH(cm) range**
Shorea robusta				
Ln (TAGB) = -2.193 +2.371*Ln (DBH)	0.984	0.2601	1.034	5 – 200
Schima wallichii and Terminalia alata (Commercial species)				
Ln (TAGB) = -1.498 +2.234*Ln (DBH)	0.981	0.252	1.032	5 - 200

TAGB dry weight of the total above ground biomass in kilogram
DBH over bark diameter of tree at breast height in centimetre
Ln Natural logarithm

3.1.1. Exploratory data analysis

Descriptive statistics of DBH, biomass, carbon and CPA of standalone *Shorea robusta, Schima wallichii* and *Terminalia alata* species are presented in Table 3-2, 3-3 and 3-4 respectively. The range of DBH was found the highest for *Shorea robusta* and the mean DBH was found the largest for *Terminalia alata*. The statistics shows that there was not much difference in the standard deviation of DBH between three species. The mean and the range of delineated CPA followed the similar trend as the DBH, i.e., the range of CPA was the largest in *Shorea robusta* and the mean and standard deviation of CPA was the largest in *Terminalia alata*. The standard error of DBH for *Shorea robusta* was found smaller compared to *Terminalia alata* and *Schima wallichii*. The dataset of DBH, carbon and CPA of *Shorea robusta, Schima wallichii,* and *Terminalia alata* are presented in Appendix 7 and Appendix 8.

Table 3-2 Descriptive statistics of DBH, biomass, carbon and CPA of standalone trees of *Shorea robusta*

Species	Number	Minimum	Maximum	Mean	Std. deviation	Std. error
DBH (cm)	127	13	129	54.61	21.02	1.87
Biomass (kg)	127	50.50	11649.87	1887.81	1741.28	154.51
Carbon (kg)	127	23.73	5475.43	887.27	818.40	72.62
CPA (m^2)	127	19.70	147.39	58.90	20.76	1.84

Table 3-3 Descriptive statistics of DBH, biomass, carbon and CPA of standalone trees of *Schima wallichii*

Species	Number	Minimum	Maximum	Mean	Std. deviation	Std. error
DBH (cm)	24	14	93	46.92	23.24	4.74
Biomass (kg)	24	83.86	5763.65	1659.28	1657.75	338.39
Carbon (kg)	24	39.41	2708.92	779.86	779.14	159.04
CPA (m^2)	24	22.71	99.88	57.46	22.26	4.54

Table 3-4 Descriptive statistics of DBH, biomass, carbon and CPA of standalone trees of *Terminalia alata*

Species	Number	Minimum	Maximum	Mean	Std. deviation	Std. error
DBH (cm)	16	30	119	63.38	23.49	5.87
Biomass (kg)	16	460.25	9997.20	2888.16	2468.23	617.06
Carbon (kg)	16	216.32	4698.69	1357.43	1160.07	290.02
CPA (m^2)	16	34.21	125.84	83.28	27.46	6.86

- **Graphical analysis of the relationship between CPA, DBH, biomass and carbon using scatter plot**

The scatter plot of explanatory variable CPA with response variables DBH and carbon of the three species is shown in Figure 3-2. Overall pattern of the scatter plot show that there was positive linear relationship of CPA with DBH and carbon in all three species. The scatter plots do not show any well-defined nonlinear pattern. The strength of relationship between them would be confirmed by calculating correlation coefficient.

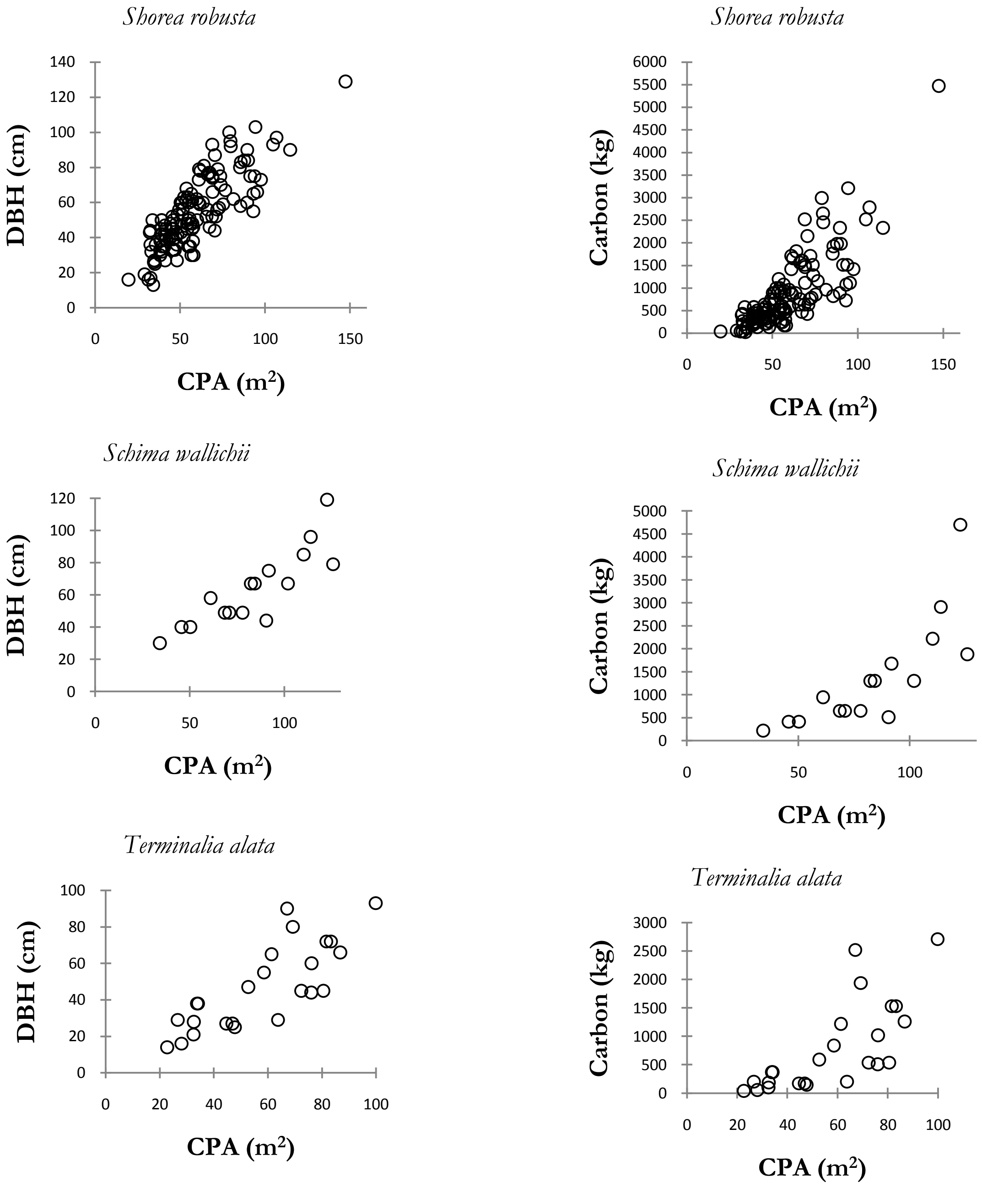


Figure 3-2 Scatter plots of CPA with DBH and carbon of standalone trees of *Shorea robusta, Schima wallichii* and *Terminalia alata*

- **Graphical analysis of DBH data in box plot**

Figure 3-3 shows the box plot graph of DBH of *Shorea robusta*, *Schima wallichii,* and *Teminalia alata*. The box plot of DBH of *Shorea robusta* based on 1.5 X IQR (inter quartile range) criterion for outlier reveals that there was a possible outlier in dataset of *Shorea robusta*. This outlier was removed for correlation and regression analysis.

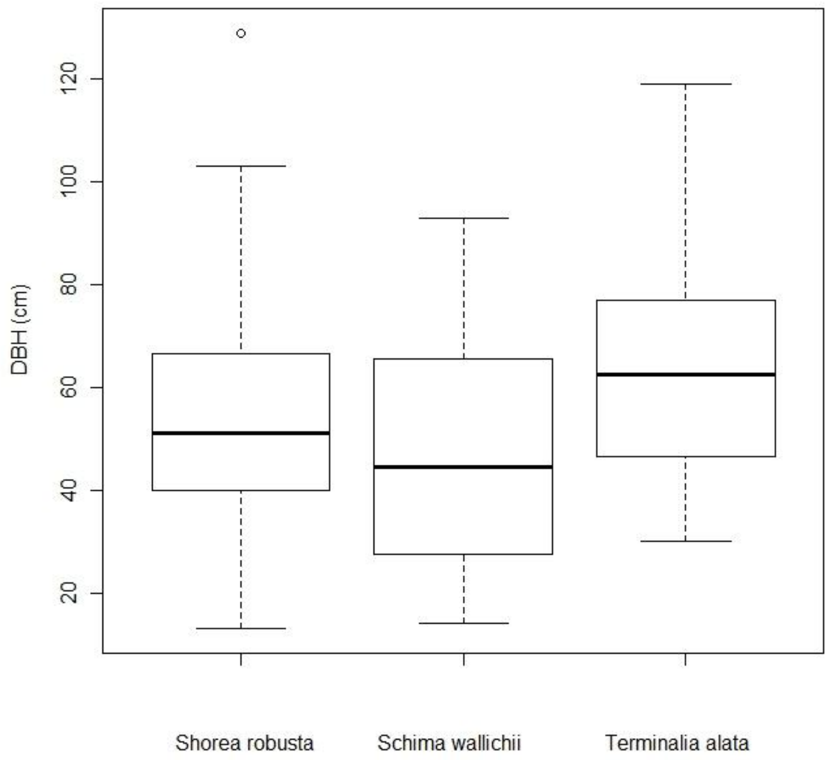


Figure 3-3 Box plot of DBH of standalone trees of *Shorea robusta*, *Schima wallichii* and *Terminalia alata*

3.1.2. Correlation analysis

Pearson's product-moment correlation coefficient was calculated using R software to analyse the strength of linear relationship between the variables. Randomly divided 60% dataset were used to calculate the correlation coefficient for *Shorea robusta* as these 60% data would be used for model development and rest 40% dataset was kept for independent validation. The whole dataset were used for other two species, i.e., *Schima wallichii* and *Terminalia alata*. These two species dataset were less than 30 and could not be spitted for reliable statistical inferences. The calculated correlation of CPA with DBH, biomass and carbon are shown in Table 3-5. There are strong positive correlations (>0.70) of CPA with DBH, biomass and carbon in all three species. The correlation between them are highly significant (P<0.001). In general, the correlation coefficient of CPA with biomass and carbon was found less than that of CPA with DBH. Specifically, differences were 0.03, 0.07 and 0.07 in the case of *Shorea robusta, Schima wallichii* and *Terminalia alata* respectively.

Table 3-5 Pearson's correlation between CPA, DBH, biomass and carbon of standalone trees of *Shorea robusta*, *Schima wallichii* and *Terminalia alata*

Species	Variables	t	df	r	95 % confidence interval		P-value
Shorea robusta	CPA and DBH	12.729	74	0.83	0.742	0.888	<0.001
	CPA and Biomass	11.667	74	0.80	0.708	0.872	<0.001
	CPA and Carbon	11.667	74	0.80	0.708	0.872	<0.001
Schima wallichii	CPA and DBH	6.175	22	0.80	0.578	0.908	<0.001
	CPA and Biomass	4.941	22	0.73	0.455	0.873	<0.001
	CPA and Carbon	4.941	22	0.73	0.455	0.873	<0.001
Terminalia alata	CPA and DBH	6.370	14	0.86	0.640	0.951	<0.001
	CPA and Biomass	4.745	14	0.79	0.474	0.922	<0.001
	CPA and Carbon	4.745	14	0.79	0.474	0.922	<0.001

The correlation results rejected the null hypothesis - Ho: There is no significant (95% confidence level) relationship between CPA, DBH, biomass and carbon of standalone trees.

3.1.3. Regression analysis

- ***Shorea robusta***

Table 3-6 shows the regression models for the relationship of CPA with DBH, biomass and carbon of *Shorea robusta*. Least square regression method was used to fit the data using four different functions – linear, quadratic, logarithmic and power. 60% dataset were used for model fitting and 40% for model validation. The simple linear, quadratic, and logarithmic function models were developed using SPSS software. The power function model was developed using XLSTAT 2010 software. Regression coefficients were found significant ($P<0.05$) in simple linear, quadratic and logarithmic function models. The regression coefficient of power function model was found not significant. It was not taken for further analysis. The simple linear, quadratic and logarithmic models were found statistically significant ($P< 0.05$) (see Appendix 9) based on F test. The simple linear model was found to have the least error for the prediction of carbon compared to the other models. However, RMSE was 58.90% which means model accuracy was 47.10%.

Table 3-6 Regression models with the calibration and validation statistics for the relationship of CPA with DBH, biomass and carbon of standalone trees of *Shorea robusta*

Regression models	**Constants**			**Calibration (N = 76)**	**Validation (N=50)**	
	a	**b**	**c**	**R^2**	**RMSE**	**RMSE %**
DBH = a +b.CPA	4.510	.853***		0.69	13.73	25.20
DBH = a+b.CPA+c.CPA^2	-19.45	1.671***	-.006*	0.70	13.87	25.45
DBH = a+b.ln(CPA)	-145.54***	49.79***		0.70	13.73	25.20
DBH =a.CPA^b	1.453	0.892*		coefficient not significant (p>0.05)		
Biomass = a +b.CPA	-1772.83***	61.476***		0.65	1101.45	58.90
Biomass = a+b.CPA+c.CPA^2	-1538.67	53.481*	.062	0.64	1101.63	58.91
Biomass = a+b.ln(CPA)	-11875.75***	3410.62***		0.60	1118.58	59.82
Biomass =a.CPA^b	1.072	1.813*		coefficient not significant (p>0.05)		
Carbon = a +b.CPA	-833.401***	28.900***		0.65	517.78	58.90
Carbon = a+b.CPA+c.CPA^2	-723.324	25.141	.029	0.64	517.86	58.91
Carbon = a+b.ln(CPA)	-5582.720	1603.313		0.60	525.84	59.82
Carbon =a.CPA^b	0.504	1.813*		coefficient not significant (p>0.05)		

For quadratic function model, adjusted R^2 is mentioned because R^2 get inflated by increasing the parameters in the model. In the other models, R^2 is mentioned since they have only one parameter. Significance levels are $P < 0.05$*, $P < 0.01$**, and $P < 0.001$***. Regression coefficients were tested for significance ($P<0.05$) using t test. Note: validation R^2 of simple linear and logarithmic model was compared, which were found 56.41% and 56.32% respectively, for the selection of the model. Because their RMSE values found equals.

- **Scatter plots with the linear regression equations**

Regression equations with coefficients of determination are shown in scatter plots in Figure 3-4 for the selected simple linear models. The strength of relationship of CPA with DBH was the highest, with intercept more than zero. This suggested that the equation is suitable to predict outside the range of delineated CPA (Anderson *et al.*, 2000). However, the intercept terms in the regression equations of CPA with biomass and carbon were found less than zero and unsuitable to predict outside the range of delineated CPA.

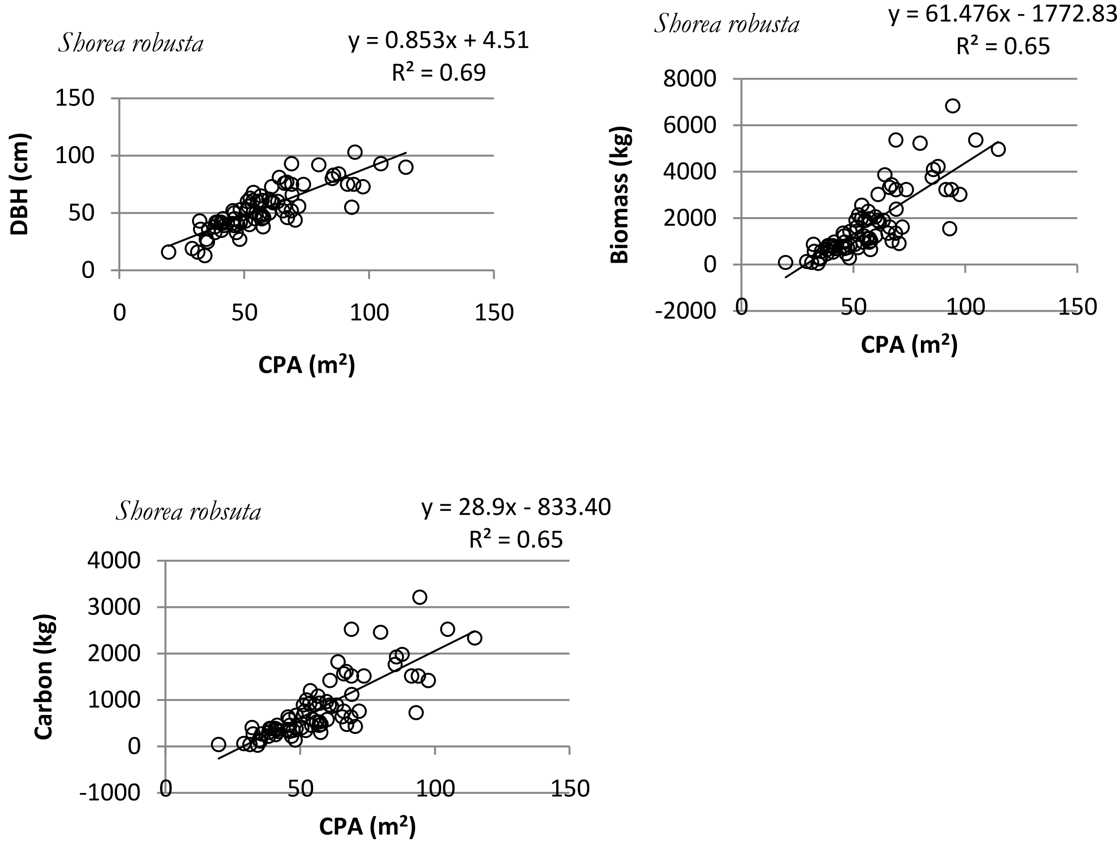


Figure 3-4 Linear regressions of DBH, biomass and carbon on CPA of standalone trees of *Shorea robusta*

- ***Schima wallichii***

Table 3-7 shows the regression models for the relationship of CPA with DBH, biomass and carbon of *Schima wallichii*. The whole 24 dataset were used to develop the models. The results of the regression models of this species were found similar to above mentioned species (*Shorea robusta*). The regression coefficients of quadratic and power function models were found not significant. The power function was not taken for further analysis. Quadratic function model was taken because of deliberate introduction of collinearity between CPA and CPA^2. LOOCV RMSEs were computed using DTREG software. The models – simple linear, quadratic and logarithmic were found significant ($P<0.05$) (see Appendix 10). Among these significant models, the simple linear model was found to have the least error (55.88%) for the prediction of carbon.

Table 3-7 Regression models with the calibration and validation statistics for the relationship of CPA with DBH, biomass and carbon of standalone trees of *Schima wallichii*

Regression models	**Constants**			**Calibration (N = 24)**	**LOOCV**	
	a	**b**	**c**	**R^2**	**RMSE**	**RMSE %**
DBH = a +b.CPA	-.850	.831***		0.63	14.73	31.39
DBH = a+b.CPA+c.CPA^2	3.543	.654	.002	0.60	15.54	33.12
DBH = a+b.ln(CPA)	-119.987***	42.056***		0.61	15.28	32.56
DBH =a.CPA^b	0.729	1.027*		coefficient not significant (p>0.05)		
Biomass = a +b.CPA	-1444.540*	54.014***		0.53	1213.18	73.11
Biomass = a+b.CPA+c.CPA^2	206.053	-12.651	.577	0.51	1274.35	76.80
Biomass = a+b.ln(CPA)	- 8866.397***	2652.227***		0.48	1274.12	76.79
Biomass =a.CPA^b	0.159	2.238*		coefficient not significant (p>0.05)		
Carbon = a +b.CPA	-678.934*	25.387***		.53	570.19	73.11
Carbon = a+b.CPA+c.CPA^2	96.845	-5.946	.271	.51	598.95	76.80
Carbon = a+b.ln(CPA)	- 4167.207***	1246.547***		.48	598.84	76.79
Carbon =a.CPA^b	0.075	2.238*		coefficient not significant (p>0.05)		

For quadratic function model, adjusted R^2 is mentioned because R^2 get inflated by increasing the parameters in the model. In the other models, R^2 is mentioned since they have only one parameter. Significance levels are $P < 0.05$*, $P < 0.01$**, and $P < 0.001$***. Regression coefficients were tested for significance ($P<0.05$) using t test.

- **Scatter plots with the linear regression equations**

Regression equations with coefficients of determination are shown in scatter plots (Figure 3-5) for the selected simple linear models. The strength of relationship of CPA with DBH was found the highest. The y- intercepts in all cases were found less than zero. It implied that the equations are not suitable to predict outside the range of delineated CPA (Anderson *et al.*, 2000).

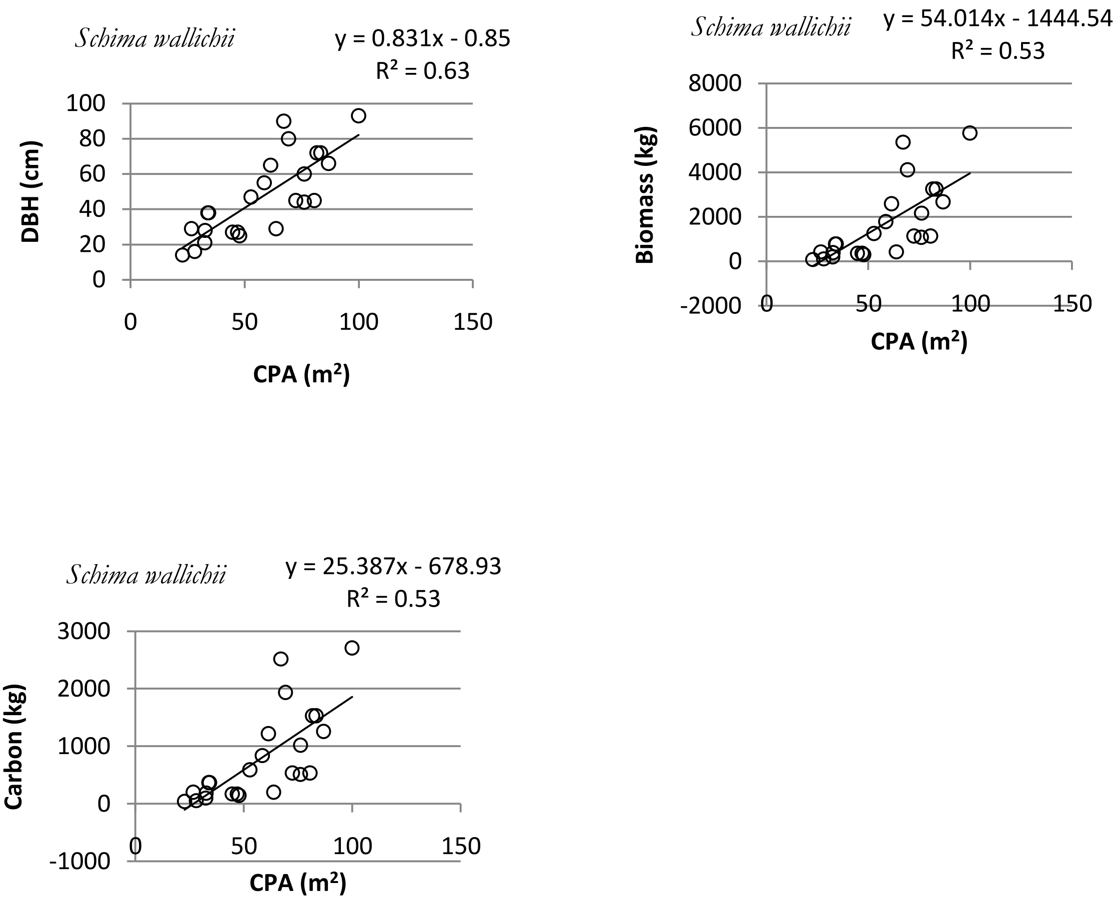


Figure 3-5 Linear regressions of DBH, biomass and carbon on CPA of standalone trees of *Schima wallichii*

- ***Terminalia alata***

The regression models for the relationship between CPA, DBH, biomass and carbon of *Terminalia alata* are presented in Table 3-8. The whole 16 dataset were used to fit the models. LOOCV RMSEs were computed using DTREG software. In general, results were found similar to *Shorea robusta* and *Schima wallichii*. The models summaries with ANOVA are presented in Appendix 11. Simple linear model was found to have the least error in comparison with the other models for the prediction of dependent variables. The accuracy of the simple linear model was 64.82% for the prediction of DBH and 43.91% for the prediction of biomass and carbon.

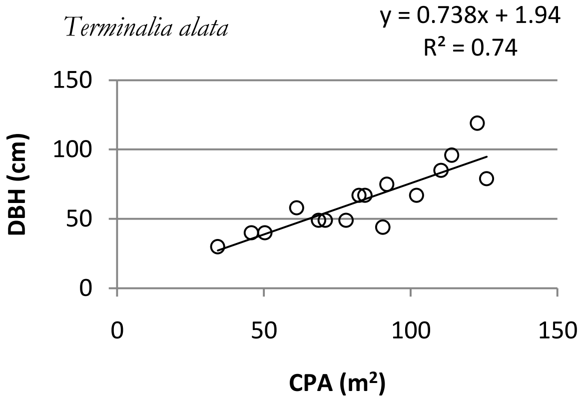
Table 3-8 Regression models with the calibration and validation statistics for the relationship of CPA with DBH, biomass and carbon of standalone trees of *Terminalia alata*

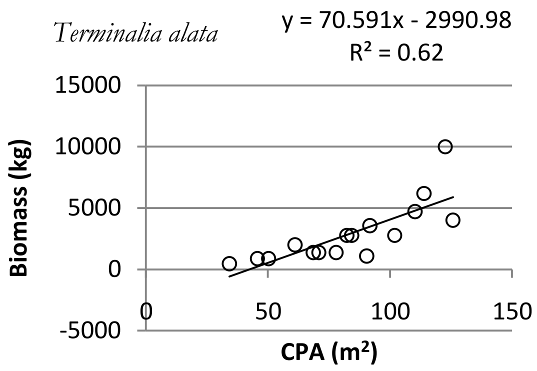
Regression models	**Constants**			**Calibration (N = 16)**	**LOOCV**	
	a	**b**	**c**	**R^2**	**RMSE**	**RMSE %**
DBH = a +b.CPA	1.940	.738***		0.74	13.49	21.29
DBH = a+b.CPA+c.CPA^2	27.822	.032	.004	0.73	15.08	23.79
DBH = a+b.ln(CPA)	-163.911**	52.092***		0.68	14.95	23.58
DBH =a.CPA^b	0.750	1.003*		coefficient not significant (p>0.05)		
Biomass = a +b.CPA	-2990.981*	70.591***		0.62	1789.84	61.97
Biomass = a+b.CPA+c.CPA^2	2364.886	-75.421	.890	0.64	1927.64	66.74
Biomass = a+b.ln(CPA)	.523**	4806.264**		0.52	1962.57	67.95
Biomass =a.CPA^b	0.034	2.528*		coefficient not significant (p>0.05)		
Carbon = a +b.CPA	-1405.761*	33.178***		0.62	841.22	61.97
Carbon = a+b.CPA+c.CPA^2	1111.496	-35.448	.418	0.64	905.99	66.74
Carbon = a+b.ln(CPA)	-8498.686**	2258.944**		0.52	922.41	67.95
Carbon =a.CPA^b	0.016	2.528*		coefficient not significant (p>0.05)		

For quadratic function model, adjusted R^2 is mentioned because R^2 get inflated by increasing the parameters in the model. In the other models, R^2 is mentioned since they have only one parameter. Significance levels are P < 0.05*, P < 0.01**, and P < 0.001***. Regression coefficients were tested for significance (P<0.05) using t test.

- **Scatter plots with the linear regression equations**

Regression equations with coefficients of determination are presented in scatter plots (Figure 3-6) for the selected simple linear models. The strength of relationship of CPA with DBH was found the highest. The y-intercept in the regression equation of CPA with DBH was more than zero. It implied that the equation is suitable to predict outside the range of delineated CPA. However, the y-intercept in the regression equations of CPA with biomass and carbon were found less than zero. These equations are not suitable to predict outside the range of delineated CPA.





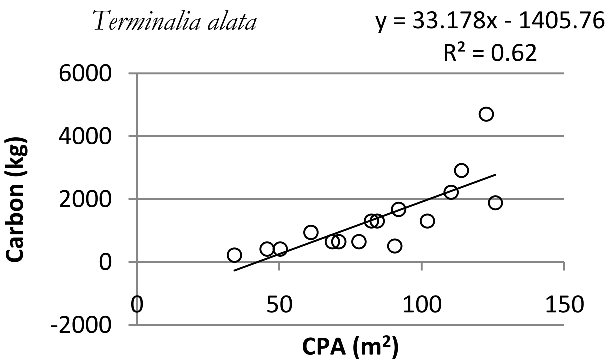


Figure 3-6 Linear regressions of DBH, biomass and carbon on CPA of standalone trees of *Terminalia alata*

3.2. Relationship between CPA, BA, biomass and carbon in intermingled canopy trees

- **Intermingled canopy tree species**

A total of 146 trees of 12 different species (Appendix 12) were found in a two-intermingled canopy situation. Figure 3-7 shows pure and mixed two-intermingled canopy trees of different species. Out of total two-intermingled canopy trees, 122 were pure intermingled canopy trees and rest 24 were mixed intermingled canopy trees. A total of 6 species, namely, *Adina cordifolia, Lagerstromia parviflora, Schima wallichii, Semicarpus anacardium, Shorea robusta and Terminalia alata* were occurred in pure intermingled canopy situation (Figure 3-7). The other 6 species (see Appendix 12) were intermingled with different species. In the category two-intermingled, *Shorea robusta* species had the largest number followed by *Schima wallichii* and *Terminalia alata.*

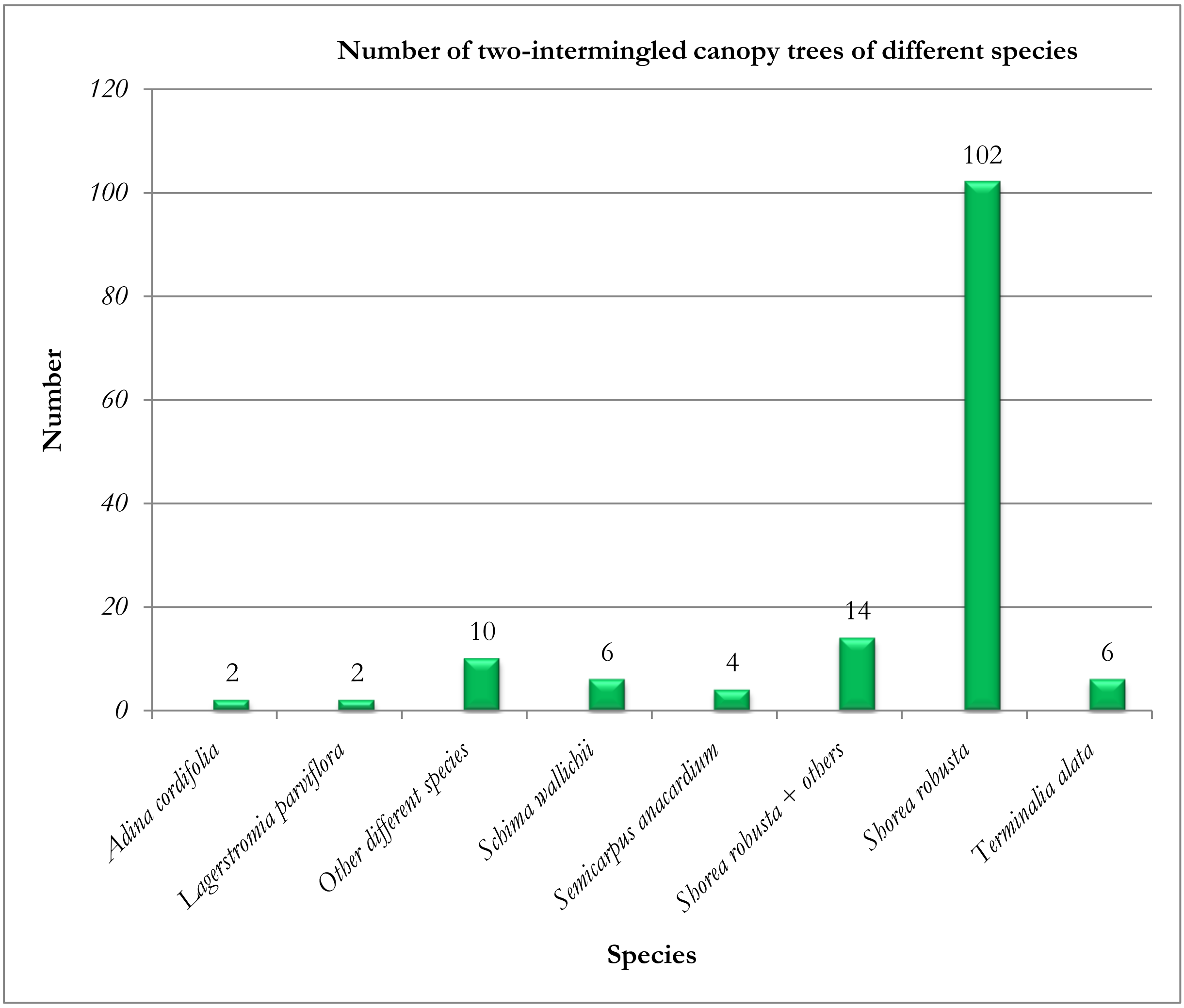


Figure 3-7 Number of two-intermingled canopy trees of different species

The dominant *Shorea robusta* were found pure intermingled canopy situation with two trees, three trees and four trees (Figure 3-8). The numbers of two, three, and four intermingled canopy were 51, 23 and 2 respectively. The total number of trees resulted in 102, 69 and 8 trees with two, three and four intermingled canopy situation respectively. No other species found pure intermingled canopy situation especially with more than two trees. The two and three intermingled trees of *Shorea robusta* was the only trees taken for analysis. The two and three intermingled canopy trees were treated together as it was not possible to differentiate between two and three intermingled canopy situation in satellite image.

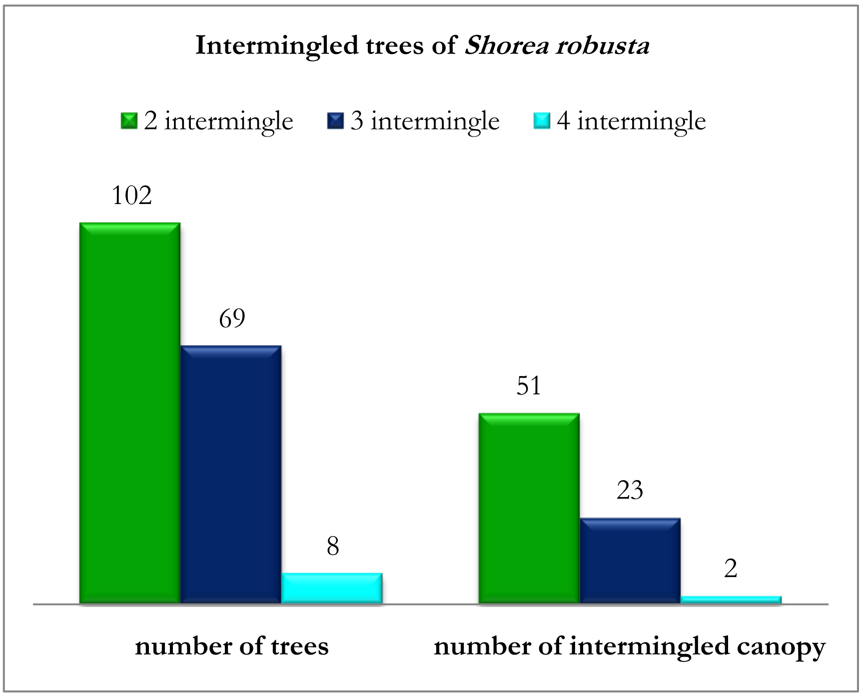


Figure 3-8 Number of intermingled canopy trees of *Shorea robusta*

3.2.1. Exploratory data analysis

The descriptive statistics of ΣBA, Σbiomass, Σcarbon and CPA of intermingled (two and three together) canopy trees of *Shorea robusta* are presented in Table 3-9. The data (with field measurement of DBH) of two, three and four intermingled canopy are presented in Appendix 13 and Appendix 14. The data under intermingled category (two and three-intermingled canopy trees together) are presented in Appendix 15.

Table 3-9 Descriptive statistics of ΣBA, Σbiomass, Σcarbon and CPA of intermingled canopy trees of *Shorea robusta*

Species	Number	Minimum	Maximum	Mean	Std. deviation	Std. error
Basal area (cm^2)	74	733.91	14950.75	4559.42	2424.87	281.88
Biomass (kg)	74	335.56	12117.83	2966.26	1913.55	222.45
Carbon (kg)	74	157.72	5695.38	1394.14	899.37	104.55
CPA (m^2)	74	48.10	252.53	122.87	46.316	5.38

- **Graphical analysis of the relationship between CPA, BA, biomass and carbon using scatter plot**

The scatter plots of explanatory variable CPA with response variables ΣBA and Σcarbon of two and three intermingled trees of *Shorea robusta* is shown in Figure 3-9. Overall pattern of the scatter plots show that there was positive linear relationship of CPA with ΣBA and Σcarbon. Nonlinear pattern was not found distinctly. The strength of relationship between them would be confirmed by calculating correlation coefficient.

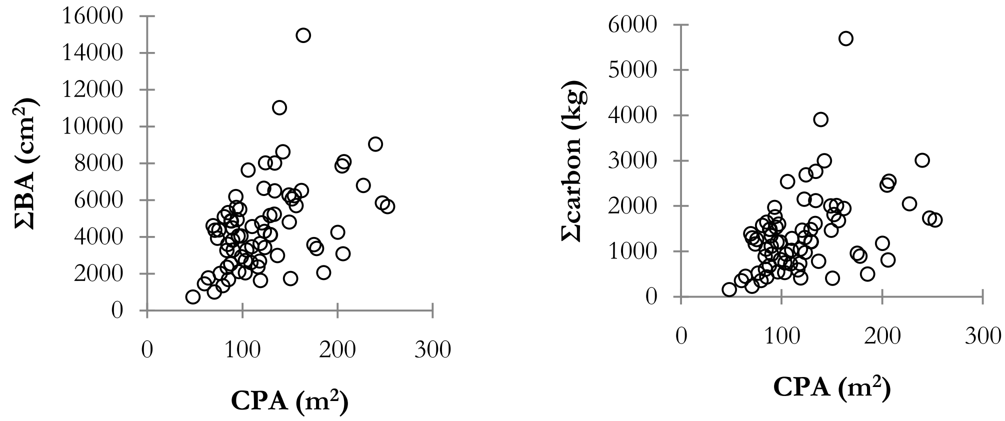


Figure 3-9 Scatter plot of CPA with ΣBA and Σcarbon of intermingled canopy trees of *Shorea robusta*

- **Graphical analysis of ΣBA data in box plot**

The box plot of ΣBA of intermingled canopy trees of *Shorea robusta* is shown in Figure 3-10. It reveals that there were two possible outliers in the dataset. The rule of thumb for identifying suspected outlier is the 1.5 X IQR where IQR is the inter quartile range. These outliers were excluded for correlation and regression analysis. The removal of these outliers was found to improve the model development.

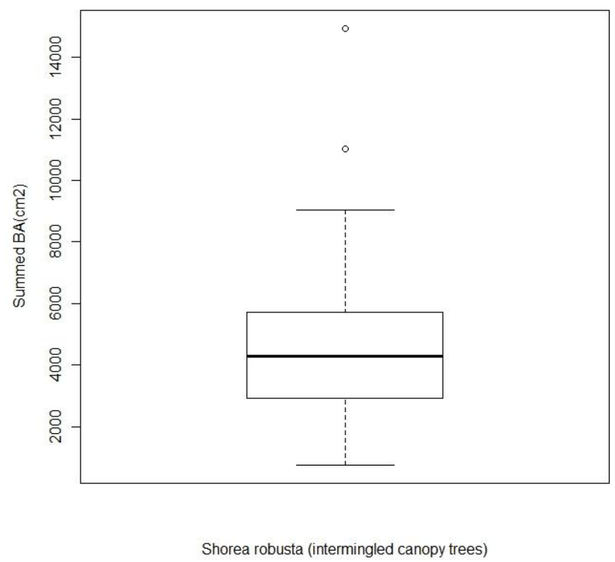


Figure 3-10 Box plot of ΣBA of intermingled canopy trees of *Shorea robusta*

3.2.2. Correlation analysis

Pearson's correlation coefficient was calculated using R software to analyse the strength of linear relationship of ΣBA with Σbiomass and Σcarbon. Randomly divided 60% dataset were used to calculate the correlation coefficient as these 60% data would be used for model development and rest 40% dataset was kept for independent validation. The correlation of ΣBA with Σbiomass and Σcarbon are presented in Table 3-10. The correlation of ΣBA with Σbiomass and Σcarbon are highly significant ($P < 0.001$). However, the strength of linear relationship between them are not that strong (<0.7).

Table 3-10 Pearson's correlation between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*

Species	Variables	t	df	r	95 % confidence interval		P-value
Shorea robusta **(Intermingled canopy trees)**	CPA and ΣBA	4.096	41	0.54	0.285	0.722	<0.001
	CPA and Σbiomass	3.673	41	0.50	0.234	0.694	<0.001
	CPA and Σcarbon	3.673	41	0.50	0.234	0.694	<0.001

The correlation results rejected the null hypothesis - Ho: There is no significant (95% confidence level) relationship between CPA, ΣBA, Σbiomass and Σcarbon of two and three- intermingled canopy trees.

3.2.3. Regression analysis

Table 3-11 shows the regression models for the relationship of ΣBA with Σbiomass and Σcarbon of *Shorea robusta*. The randomly divided 60% dataset were used to fit linear, quadratic and logarithmic function regression models using SPSS software. Similarly, power function regression model was developed from the data using XLSTAT 2010 software. The regression models were validated using 40 % independent dataset. The models summaries with ANOVA are presented in Appendix 16.

The regression coefficients of quadratic and power function models were found not significant. The power function was not taken for further analysis. Whereas, the quadratic function model was taken because of deliberate introduction of collinearity between CPA and CPA^2. The simple linear, quadratic and logarithmic models were found significant ($P< 0.05$) (See Appendix 16) based on F statistics. The simple linear model was found to have the least error for prediction of carbon compared to the other function models.

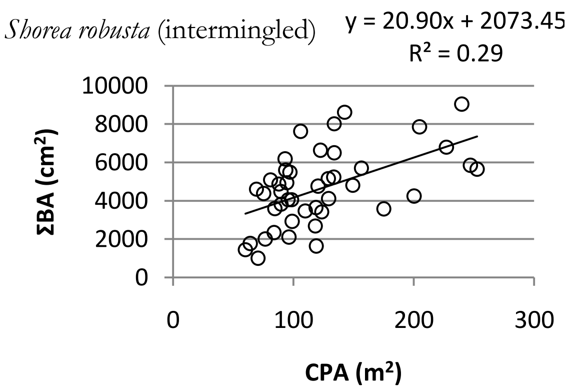
Table 3-11 Regression models with the calibration and validation statistics for the relationship of CPA with ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*

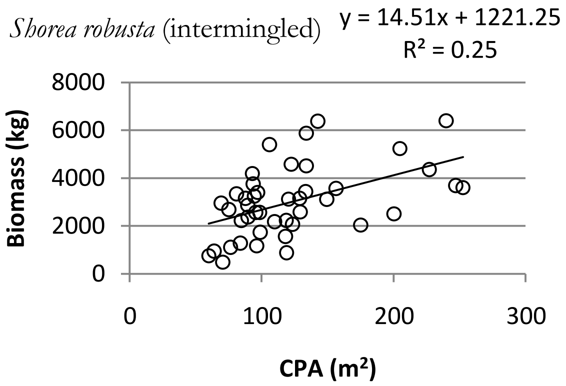
Regression models	Constants			Calibration (N = 43)	Validation (N = 29)	
	a	b	c	R^2	RMSE	RMSE %
BA = a +b.CPA	2073.45**	20.90***		0.29	1896.28	49.25
BA = a+b.CPA+c.CPA^2	-747.32	63.80*	-.14	0.29	1940.80	50.40
BA = a+b.ln(CPA)	-9700.66**	3025.203***		0.33	1902.23	49.40
BA=a.CPA^b	298.27	0.57*		coefficient not significant (p>0.05)		
Biomass = a +b.CPA	1221.25*	14.51***		0.25	1407.18	58.52
Biomass = a+b.CPA+c.CPA^2	-985.447	48.074*	-.109	0.25	1453.34	60.62
Biomass = a+b.ln(CPA)	-7048.59**	2120.59***		0.28	1415.22	58.85
Biomass =a.CPA^b	163.223	0.6095*		coefficient not significant (p>0.05)		
Carbon = a +b.CPA	573.99*	6.82***		0.25	661.39	58.52
Carbon = a+b.CPA+c.CPA^2	-463.16	22.595*	-.051	0.25	685.25	60.62
Carbon = a+b.ln(CPA)	-3312.839**	996.675***		0.28	665.15	58.85
Carbon = a.CPA^b	76.715	0.610*		coefficient not significant (p>0.05)		

For quadratic function model, adjusted R^2 is mentioned because R^2 get inflated by increasing the parameters in the model. In the other models, R^2 is mentioned since they have only one parameter. Significance levels are P < 0.05*, P < 0.01**, and P < 0.001***. Regression coefficients were tested for significance (P<0.05) using t test.

- **Scatter plots with the linear regression equations**

Regression equations with coefficients of determination are shown in scatter plots (Figure 3-11) for the selected simple linear models. The scatter plots reveal that relationships between the parameters were weak. These plots do not show any distinct nonlinear pattern.





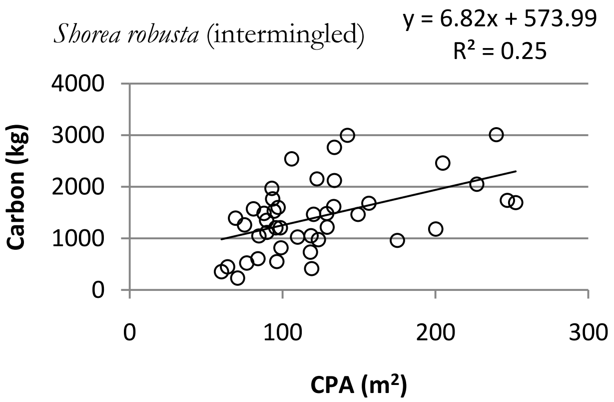


Figure 3-11 Linear regressions of ΣBA, Σbiomass and Σcarbon on CPA of intermingled canopy trees of *Shorea robusta*

3.3. Summary of results

Research question 1:

Is there any relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species?

Table 3-12 shows Pearson's correlation of CPA with DBH, biomass and carbon of standalone trees. Results rejected the null hypothesis and concluded that there is a significant (95% confidence level) relationship between CPA, DBH, biomass and carbon of the standalone trees.

Table 3-12 Pearson's correlation between CPA, DBH, biomass and carbon of standalone trees of *Shorea robusta, Schima wallichii* and *Terminalia alata*

Species (variables)	df	Pearson's correlation
Shorea robusta		
CPA and DBH	74	0.83 (P<0.001)
CPA and biomass / carbon	74	0.80 (P<0.001)
Schima wallichii		
CPA and DBH	22	0.80 (P<0.001)
CPA and biomass / carbon	22	0.73 (P<0.001)
Terminalia alata		
CPA and DBH	14	0.86 (P<0.001)
CPA and biomass / carbon	14	0.79 (P<0.001)

Research question 2:

Is there any relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of the dominant species?

Table 3-13 presents the results of correlation coefficient of CPA with ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of dominant *Shorea robusta*. The results rejected null hypothesis and concluded that there is a significant (95% confidence level) relationship between CPA, ΣBA, Σbiomass and Σcarbon of two and three-intermingled canopy trees.

Table 3-13 Pearson's correlation between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*

Variables	df	Pearson's correlation
CPA and ΣBA	41	0.54 (P<0.001)
CPA and Σbiomass / Σcarbon	41	0.50 (P<0.001)

Research question 3:

Which regression models best explain the relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees of the dominant species?

Table 3-14 presents the models having the least error for prediction of DBH, biomass and carbon of standalone trees of the dominant species. These models are the best explaining the relationship between CPA, DBH, biomass and carbon in standalone trees of the dominant *Shorea robusta, Schima wallichii and Terminalia alata.*

Table 3-14 Regression models (with the least error) for the prediction of DBH, biomass and carbon of standalone trees of *Shorea robusta, Schima wallichii and Terminalia alata*

Regression models	Calibration R^2	Validation RMSE	RMSE (%)
Shorea robusta	N=76	N=50	
DBH = 4.51 + 0.85 CPA	0.69	13.73	25.20
Biomass = -1772.84 + 61.48 CPA	0.65	1101.45	58.90
Carbon = -833.40 + 28.90 CPA	0.65	517.78	58.90
Schima wallichii	N = 24	LOOCV	
DBH = -0.85 + 0.83 CPA	0.63	14.73	31.39
Biomass = -1444.54 + 54.01 CPA	0.53	1213.18	73.11
Carbon = -678.93 + 25.39 CPA	0.53	570.19	73.11
Terminalia alata	N = 16	LOOCV	
DBH = 1.94 + .74 CPA	0.74	13.49	21.29
Biomass = -2990.98 + 70.59 CPA	0.62	1789.84	61.97
Carbon = -1405.76 + 33.18 CPA	0.62	841.22	61.97

Table 3-15 shows the models having the least error for the prediction of ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of the dominant *Shorea robusta*. These models are the best explaining the relationship between CPA, BA, biomass and carbon of intermingled canopy trees of the dominant *Shorea robusta*.

Table 3-15 Regression models (with the least error) for the prediction of ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*

Regression models	Calibration R^2	Validation RMSE	RMSE (%)
	N = 43	N = 29	
BA = 2073.45 + 20.90 CPA	0.29	1896.28	49.25
Biomass = 1221.25 + 14.51 CPA	0.25	1407.18	58.52
Carbon = 573.99 + 6.82 CPA	0.25	661.39	58.52

4. DISCUSSION

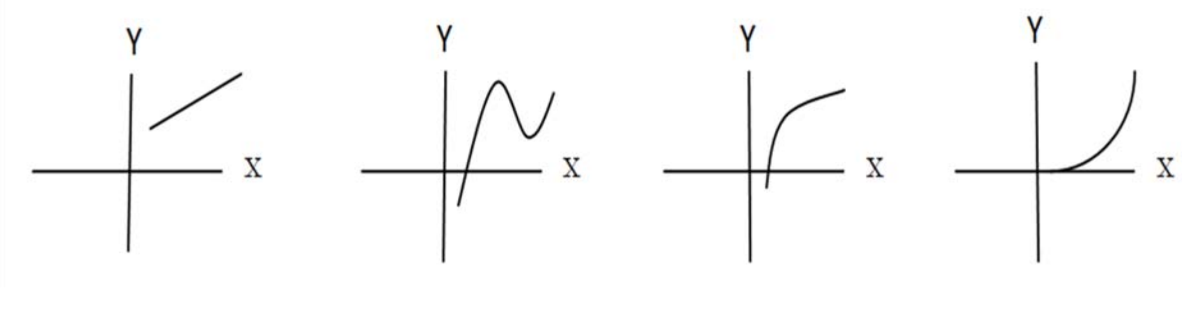
4.1. Relationship between tree biophysical parameters

A tree is a woody perennial species typically forming a single self-supporting main stem and having a definite crown. There is an allometric relationship among different parts of trees, i.e., stem dimension, crown dimension, foliage area and biomass. The relationship originates from their physiological function and interrelations. The crown is the photosynthetic part that produces glucose results in biomass of the whole tree. The stem conducts water and mineral and provides mechanical support to the tree. The allometric relationship differs between species and site and climate condition (Mencuccini and Grace 1985) cited from (Bartelink, 1996). There are studies on allometric relationship between different parts of tree. For example, Wang (2006) found DBH and height allometry controlled by climate across large scale. Aboal (2005) demonstrated DBH and biomass relationships varied significantly among the slopes and elevations considering each species separately.

Bertelink (1996) studied the relation between tree parameter and found that there was strong stand-independent correlations between stem and crown dimensions; DBH nonlinearly related to tree height and linearly related to crown radius; tree biomass generally increased with increasing DBH; and stem biomass and DBH found stand-independent; but crown biomass and DBH relation found differed between stands. Similarly, DBH and height relation found significantly varied between plot to plot (Fang & Bailey, 1998). The relationship between crown diameter and stem diameters from 20 to 50cm DBH was found very close to linear, with R^2 value higher than 0.8 for different species of broadleaf trees (Hemery *et al.*, 2005).
These evidences provide support for the expectation of significant and strong CPA – biomass relation of dominant tree species, where CPA delineated from GeoEye image. Satellite sensor only sees dominant trees from above not many of the suppressed or intermediate trees (Leckie *et al.*, 2003).

- **Functions used to study the relationship**

Simple linear, quadratic, logarithmic and power functions are commonly used to study the relationship between the tree parameters. Figure 4-1 shows the nature of graphs of these functions. The power function graph could be convex, i.e., the reverse the pattern what is shown in Figure 4-1 (d) depends upon the power of parameters. Mohns *et al.,* (1988) reported that power function model is applied mostly to describes relationship between tree parameters besides the linear and quadratic functions.



(a) (b) (c) (d)

Figure 4-1 Graphs of (a) Simple linear (b) Quadratic (c) Logarithmic (d) Power function

Logarithmic transformation is usually followed for linearising power functions and comparing the models. The transformation has the following disadvantages:
1) There is multiplicative error in the model,
2) The evaluation of the goodness of fit (R^2) and standard error of the estimate is difficult,
3) It provides biased estimate when data are retransformed to arithmetic units

On the other hand, this transformed model has nil or less heteroscedasticity compared to linear and quadratic model. It somehow deforms the original data. A bias correction factor has to be applied for retransforming (Basuki *et al.*, 2009; Chave *et al.*, 2005). Several procedures have been suggested for correcting bias in the logarithmic regression estimate (Zianis & Mencuccini, 2004). There is no standard correction procedures (Chave *et al.*, 2005; Cienciala *et al.*, 2006). Moreover, high value of coefficient of determination (R^2) and low value of standard error of estimates (usually obtained in log transformed regression models) do not guarantee the precision of estimate when values are back transformed to linear scale (Zianis & Mencuccini, 2004).

Ketterings *et al.,* (2001) reported that polynomial and power functions are the most commonly used for the allometric relationship between tree parameters. He further mentioned that the shape of polynomial functions (Figure 4-1: b) might be biologically unreasonable. Moreover, he concluded that the emphasis is to be given to the empirical relationship chosen based on goodness of fit. This statement further supported by Chave *et al.*, (2005) who used goodness of fit, parsimony and mathematical simplicity as the criteria for the selection of regression models for prediction of above ground tree biomass. And the predictive power of these models depends on how well they are validated using independent dataset (Chave *et al.*, 2005).

4.2. CPA – DBH / biomas / carbon relation in standalone trees

4.2.1. Correlation Analysis

The correlation results demonstrated that the strength of linear relationship between CPA and DBH were strong (>0.7) and highly significant ($P<0.001$) in all three species. The correlation coefficient (Table 3-5) of CPA with DBH were 0.83 ($t = 12.73$, $P<0.001$), 0.80 ($t = 6.17$, $P<0.001$) and 0.86 ($t = 6.37$, $P<0.001$) of *Shorea robusta*, *Schima wallichii* and *Terminalia alata* respectively. The confidence interval (Table 3-5) of correlation coefficient was less (0.15) for *Shorea robusta* than the other two species which were 0.33 and 0.31 for *Schima wallichii* and *Terminalia alata* respectively. It showed that the precision of correlation coefficient was higher for *Shorea robusta* in comparison to the other two species. In other words, the tree distribution of *Shorea robusta* is more homogeneous comparatively.

The statistical significance test of correlation coefficient merely shows that there is a linear relationship between the variables with nonzero slope but nothing about causal relationship between them. The correlation coefficient near zero indicates that there is no linear relationship between two variables. That does not mean that they are unrelated, for there may be a high nonlinear correlation between them. The correlation coefficient of >0.70 or <-0.70 is usually considered strong relationship between the variables (Reimann *et al.*, 2008).

The correlation coefficient of CPA with biomass and carbon were also strong (>0.7) and highly significant ($P<0.001$) in all three species. The correlation coefficient (Table 3-5) of CPA with biomass were 0.80 ($t = 11.67$, $P<0.001$), 0.73 ($t = 4.94$, $P<0.001$) and 0.79 ($t = 4.75$, $P<0.001$) of *Shorea robusta*, *Schima wallichii* and *Terminalia alata* respectively. The confidence interval (Table 3-5) of the correlation coefficient was less (0.16) for *Shorea robusta* than the other two species which were 0.42 and 0.45 for *Schima wallichii* and

Terminalia alata respectively. Similarly, the correlation coefficient of CPA with carbon was exactly same with all statistics as with biomass. Because the carbon was the result of multiplicative (factor = 0.47) derivation of biomass.

In general, the correlation coefficient of CPA with biomass and carbon was found less than that of CPA with DBH. Specifically, differences were 0.03, 0.07 and 0.07 for *Shorea robusta*, *Schima wallichii* and *Terminalia alata* respectively. Important reason for this difference was the use of log transformed allometric equation (see Table 3 -1) for the calculation of biomass and carbon. Non-site specific allometric equation and associated error with the equation caused to reduce the correlation. The difference was lower for *Shorea robusta* and higher and equal for the other two species. Because species specific allometric equation was used for biomass calculation for *Shorea robusta* while for the other two species, the same allometric equation, developed for commercial species by (Basuki *et al.*, 2009), was used because of unavailability of species specific allometric equations.

Correlation coefficients could not be compared between species because of different sample sizes (Reimann *et al.*, 2008). In addition, the sample correlation coefficient is quite variable, if sample size is small, and highly vulnerable to data outliers (Reimann *et al.*, 2008).

4.2.2. Regression analysis

Results show that regression coefficient of power function models in all three species was not significant (see Table 3-6, 3-7 and 3-8). This suggested that there were not significant and strong power function relationship between the parameters. The model summary statistics of this function are referred to Appendix 9, Appendix 10 and Appendix 11 for *Shorea robusta*, *Schima wallichii* and *Terminalia alata* respectively. The regression coefficients in simple linear and logarithmic function models were found significant ($P<0.05$) in all three species (see Table 3-6, Table 3-7 and Table 3-8). The regression coefficients in quadratic function model were found not significant in *Schima wallichii* and *Terminalia alata*. This could be because of the deliberate introduction of collinearity between CPA and CPA^2. The variation of the data explained by the parameters is divided between them. And the models were found significant.

In *Shorea robusta*, the calibration R^2 and validation RMSE were not much different between different models. The RMSE values were found equal between simple linear and logarithmic while validation R^2 value was slightly higher in simple linear model. Considering higher precision and simplicity of model, simple linear model could be preferred. This was further supported by the results of CPA versus carbon model; where simple linear model R^2 was higher and RMSE was lower (Table 3-6). The scatter plot of the regression model (Figure 3-4) do not show well defined logarithmic pattern.

Similarly, simple linear models were found better performance for the relationship between CPA, DBH, biomass and carbon of *Schima wallichii* and *Terminalia alata* as well (Table 3-7 and Table 3-8). The scatter plots of regression models do not show any distinct nonlinear pattern (Figure 3-5 and Figure 3-6). Moreover, small dataset of *Schima wallichii* and *Terminalia alata* was a limitation to draw a conclusion from the scatter plots.

The linear relationship between tree parameters are in agreement with Anderson *et al.*, (2000) who found highly significant ($P<0.001$) relationship between DBH and crown area with R^2 ranging from 0.37 for *Ulmus crassifolia* to nearly 0.80 for *Quercus nuttallii* and *Taxodium distichum* species. He estimated crown area of trees subjectively choosing the longest axis of crown and the longest axis perpendicular to the first axis.

Hirata *et al.*, (2009) described the relationship between DBH and CPA and stand variables such as stand age, stand density, mean stand DBH on even-aged plantation stands using power function. He demonstrated that the stand variables affected parameters of allometric models of CPA (derived from QuickBird panchromatic data) versus DBH. Followings are comparable points:

First, CPA derived from high resolution satellite data was used as the predictor for the allometric models of CPA with DBH. Second, power function was used as a descriptive model unlike the comparison of predictive accuracy of models of this study. Thirdly, the study was carried out in plantation stands of *Cryptomeria japonica* and C*hamaecyparis obtusa* coniferous species while this study was carried out in natural broadleaf forest. Reason for power function relation could be competition, whereas in case of standalone trees, there is no competition for canopy expansion.

Shimano (1997) reported that the functional relationship between CPA and DBH in deciduous broadleaved as well as in coniferous trees could be analysed effectively using power sigmoid function. He used field measured CPA and DBH in natural deciduous broadleaved and coniferous forest in the cool-temperate zone. But, he did not confirm the power sigmoid characteristic between the parameters statistically. Since the functional relations and regression model coincide only if the independent variables do not have error Lindley (1947) cited from (Mark & Church, 1977). Moreover, the situation of the trees in his study could be different from standalone trees of the dominant species.

In this research, the relationship of CPA with biomass was found linear with R^2 ranging from 0.53 for *Schima wallichii* to 0.62 for *Terminalia alata* and 0.65 for *Shorea robusta*. Kuuluvainen *et al*., (1991) demonstrated nonlinear relationship between CPA (calculated from maximum crown diameter by assuming a circular crown projection) and above ground biomass in Norway spruce trees using log transformed allometric equation in even-aged stands. This contradicted the present findings. Noteworthy reasons could be as follows:

First, it was observed that the tree crown size of the broadleaf species, *Schima wallichii, Shorea robusta and Terminalia alata,* are larger than needleleaf, Norway spruce, having the same stem size. Second, the competition between tree canopies in even-aged mature stand is assumed to be effective, whereas it is not applicable to natural forest particularly in standalone situation. Consequently, rate of increase of CPA in even-aged stand is diminishing with respect to DBH. This could be one of the important reasons to explain nonlinearity between CPA and biomass in even-aged mature stands.

Studies investigated DBH and crown radius relation. These are comparable to DBH and CPA relation assuming the crown of trees circular. Betelink (1996) found linear relationship between DBH and crown radius in even-aged mono-species stands of Douglas fir. Hemery *et al*., (2005) reported very close to linear relationship with R^2 value higher than 0.8 between crown diameter and stem diameter ranging from 20cm to 50cm for different species of broadleaf trees. These two studies further supported present study findings.

4.3. CPA – BA / biomass / carbon relation in intermingled canopy trees

A total of 12 species were found in two-intermingled canopy situation (Figure 3-7). Of them, 6 species were found pure intermingled canopy trees situation. Besides, *Shorea robusta*, the other species were found few for statistical analysis. The dominant *Shorea robusta* were found in two, three and four-intermingled canopy situation (Figure 3-8). The two and three-intermingled canopy trees were only taken for analysis and treated together. There were only two dataset in four-intermingled canopy situation. These dataset were found unusual (possible outliers) in the whole dataset that caused a problem for development of regression models. Since the individual canopy of tree in intermingled canopy situation could not be identified separately in the satellite image, the intermingled canopy trees were treated together. Biomass and carbon of all individual trees in the intermingled canopy situation were summed up including basal area to regress against their common intermingled CPA.

4.3.1. Correlation analysis

The correlation between CPA and ΣBA was found highly significant ($P<0.001$) but weak (<0.7). The correlation coefficient (Table 3-10) of CPA with ΣBA were 0.54 ($t = 4.0956$, $P<0.001$). The confidence interval of correlation coefficient was (0.44). The correlation coefficient (Table 3-10) of CPA with biomass and carbon were also highly significant ($P<0.001$) but further getting weak (<0.7). The correlation coefficient of CPA with biomass were 0.50 ($t = 3.67$, $P<0.001$). The confidence interval of correlation coefficient was (0.46). It means the precision of correlation coefficient became low compared to correlation of CPA with ΣBA. Similarly, the correlation coefficient of CPA with carbon was exactly same with all statistics as with biomass. Because the carbon was the result of multiplicative (factor = 0.47) derivation of biomass.

4.3.2. Regression analysis

The regression coefficients of power function models were found not significant ($P<0.05$). The model summary statistics of this function are referred to Appendix 16. This suggested that there was no significant and strong power function relation between the parameters. The regression coefficients in simple linear and logarithmic were found significant ($P<0.05$). However, the coefficients in quadratic model were not significant. This could be because of deliberate introduction of collinearity between CPA and CPA^2. Based on the lowest value of RMSE, the regression results suggested simple linear relationship between CPA, ΣBA, Σbiomass and Σcarbon separately (Table 3-11). The scatter plots of regression equations do not show any distinct nonlinear pattern between the parameters (Figure 3-11).

The CPA and ΣBA relation was found in agreement and comparable with a study done by Mitchell & Popovich (1997). He analysed the relationship between basal area of trees per unit land area and canopy cover (%) in Ponderosa pine forest and demonstrated a straight line relationship between them below 60% canopy. Bartelink (1996) also found the linear relationship between CPA and BA of Douglas fir in single tree situation, whereas this study found a linear relationship between CPA and ΣBA in intermingled canopy trees. Simple linear relationship was shown applicable to the above ground biomass estimation (ton/ha) of forest stands using BA (m^2/ha) of forest stands (Chiba, 1998).

However, there is no literature available that investigated the relationship between CPA, ΣBA and Σbiomass or Σcarbon in intermingled canopy situation.

In order to explain the result, why linear relationship was found between ΣBA and CPA in intermingled canopy situation? We strengthen our understanding based on field experiences and some logic. It is important to understand standalone and intermingled canopy trees situation in the field. The standalone and two-intermingled trees are shown in Figure 4-2. The degree of intermingle has not been taken into account. Once tree canopies were not visibly as standalone (completely separated canopy from any other canopies surrounding it), it was taken as intermingle even without their branches considerably intermixed together like the situation of Figure 4-2 (b). This degree of intermingle affects the CPA considerably but has no effect on the DBH.

Another important factor could be the competition or crowding between the trees. Trees crown development found negatively affected by competition from neighbouring tree crowns (Larocque, 2000). It is reasonable to assume that a group of intermingled canopy trees is similar to a standalone in terms of competition and CPA. When branches of trees touch or intermingled one another, they fall under intermingled group. Since the forest in the current study area do not have 100% canopy cover, most of intermingled trees were isolated as a group without competition from surrounding trees. It can be assumed that due to the intra competition within intermingled canopy trees for canopy expansion, they start extending canopy on edges in order to compensate for the overlap area. This is shown in Figure 4-2 (c) where they are extending their canopy even with larger area than the overlapped one. It is thus plausible that canopy area is still growing without diminishing the rate of growth when we consider CPA of intermingled group as a whole.

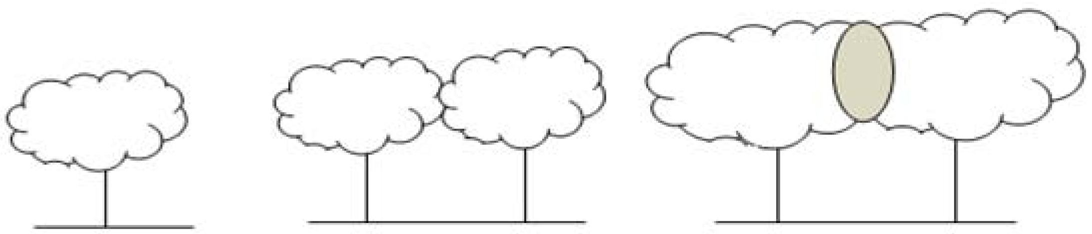


Figure 4-2 (a) Standalone trees (b) and (c) Two-intermingled canopy trees

Following the logic mentioned in above paragraph for CPA and ΣBA relation, the linear relationship between CPA and Σbiomass or Σcarbon is also maintained. Further, it appears that intra-competition in intermingled situation affects individual canopy area as well as diameter of trees. As a result, different sizes (DBH) of trees are found in the intermingled group. Therefore, the sum of carbon of all individual trees relate linearly with their intermingled canopy area. Despite the intermingled canopy, the intermingled CPA is not largely decreased as the intermingled group had no competition from surrounding trees. CPA and carbon relation still maintains linear. In this case, two third of the dataset used were two-intermingled canopy trees and one third dataset were three-intermingled canopy trees. In case of two-intermingled canopy trees, the competition for space in the intermingled zone might cause even higher reactive growth in the edges. In three-intermingled canopy trees, the chance of decreasing canopy area depends on their relative positions. However, the decrease of canopy area could be compensated by responsive growth in the periphery of intermingled canopies as the intermingled canopy trees as a group had no competition for canopy expansion from surrounding trees. Furthermore, these taller dominant trees are less sensitive to crowding than the shorter understory trees (Thorpe *et al.*, 2010). The forest is uneven-aged with lots of understory vegetation and very sparse overstory trees (Figure 2-2).

4.4. Model comparison and error in prediction of carbon

- **Standalone trees**

RMSE was used as a measure for model comparison and selection. There were not much differences of RMSE between the three regression models, i.e., simple linear, quadratic and logarithmic in standalone trees of *Shorea robusta*, *Schima wallichii* and *Terminalia alata.* Nevertheless, simple linear regression model was found to predict response variables, i.e., DBH, biomass or carbon with the least error.

In case of *Schima wallichii* and *Terminalia alata*, the sample sizes were 24 and 16 respectively. Because of small sample size, results were considered as indicative only (Austin *et al.*, 2003). Further studies using large sample is necessary to suggest the linear relationship between CPA, DBH, biomass and carbon. Furthermore, these predictive models were evaluated using cross validation RMSE because of the small sample sizes. Whereas predictive model need to be evaluated with independent dataset (Zianis & Mencuccini, 2004).

Table 4-1 Predictive accuracy of different models for standalone trees of *Shorea robusta, Schima wallichii and Terminalia alata*

Models	*Shorea robusta*		*Schima wallichii*		*Teminalia alata*	
	R^2 (N=76)	(N=50) RMSE%	R^2 (N=24)	LOOCV RMSE%	R^2 (N =16)	LOOCV RMSE%
CPA versus DBH						
Simple linear	0.69	25.20	0.63	31.39	0.74	21.29
Quadratic	0.70	25.45	0.60	33.12	0.73	23.79
Logarithmic	0.70	25.20	0.61	32.56	0.68	23.58
CPA versus Carbon						
Simple linear	0.65	58.90	0.53	73.11	0.62	61.97
Quadratic	0.64	58.91	0.51	76.80	0.64	66.74
Logarithmic	0.64	59.82	0.48	76.79	0.52	67.95

In this Table, the models for CPA versus biomass are not mentioned as R^2 and RMSE% value are same with the models of CPA versus carbon.

The R^2 and RMSE statistics of three different species could not be compared independently because of different sample sizes (Table 4-1). Being biologically different species, relationship between the tree parameters of three tree species could be different. Moreover, higher the R^2 lower is the RMSE was found to be followed in all three species, if we observe the species separately. But, why this trend was not found to be followed between species? For example, with the same R^2 value in quadratic function model, the RMSE value was found to be large in *Terminalia alata* as compared to *Shorea robusta* (Table 4-1). The descriptive statistics (Table 3-2, Table 3-3 and Table 3-4), scatter plots (Figure 3-2) and correlation coefficient (Table 3-5) of these species provides some insights to answer it. First, standard error of the carbon dataset of *Terminalia alata* was found large compared to *Shorea robusta*. Second, scatter plot of *Terminalia alata* show more heterogeneous nature of data compared to *Shorea robusta*. Third, the confidence interval of the correlation coefficient was found 0.45 for *Terminalia alata* while it was 0.16 for *Shorea robusta*. In other words, the precision of correlation coefficient for *Shorea robusta* was higher than that of *Terminalia alata*.

Remarkably, the prediction of carbon from CPA was found to have high error with RMSE ranging from 58.9% for *Shorea robusta* to 61.97% for *Terminalia alata* and 73.11 % for *Schima wallichii*. When DBH was converted to carbon using allometric equation, the error increased from 34 to 42% for the prediction of carbon. It becomes clear that allometric equation is the main cause for this incremental error. Moreover, the allometric equation is log transformed one which introduces multiplicative errors, if we compare with linear one which causes additive error. In this study, non-site specific but species specific allometric equation was used for *Shorea robusta*. Non-site as well as non-species specific allometric equation was used for *Schima wallichii* and *Terminalia alata*. To reduce the model error, we need to calibrate these allometric equations for the study site (Ketterings *et al.*, 2001) which is again impractical and expensive as we need to cut several trees for the calibration. The use of species specific allometric equation is preferred because tree of different species differ in their architecture and wood density. Trees of same species also differ in their growth between sites where climate parameters differ considerably. Taking into account of these variation, site specific as well as species specific allometric equation need to be used for higher accuracy of biomass estimation (Basuki *et al.*, 2009).

The RMSE of predictive models regressing DBH on CPA were considerably different between species ranging from 21.29% for *Terminalia alata,* to 25.20% for *Shorea robusta*, and 31.39% for *Schima wallichii.* This could be because of the difference of variance of the data between the species as shown in scatter plot (Figure 3-2). The important fact that even without using allometric equation and going from DBH to biomass or carbon, the predictive models error were more than 20%. This could be because of the accumulation of error in CPA delineation and error in vertical projection area of canopy in the image.

- **Intermingled trees**

As found in standalone trees, the difference of RMSE between the three regression models, i.e., simple linear, quadratic and logarithmic in intermingled canopy trees of *Shorea robusta* was not large. Nonetheless, simple linear regression model was found to predict, i.e., ΣBA, Σbiomass / or Σcarbon with the least error (Table 4-2).

Table 4-2 Predictive accuracy of different models for intermingled canopy trees of *Shorea robusta*

Models	CPA versus ΣBA		CPA versus Σcarbon	
	R^2 (N=43)	RMSE% (N=29)	R^2 (N=43)	RMSE% (N=29)
Simple linear	0.29	49.25	0.25	58.52
Quadratic	0.29	50.40	0.25	60.62
Logarithmic	0.33	49.40	0.28	58.85

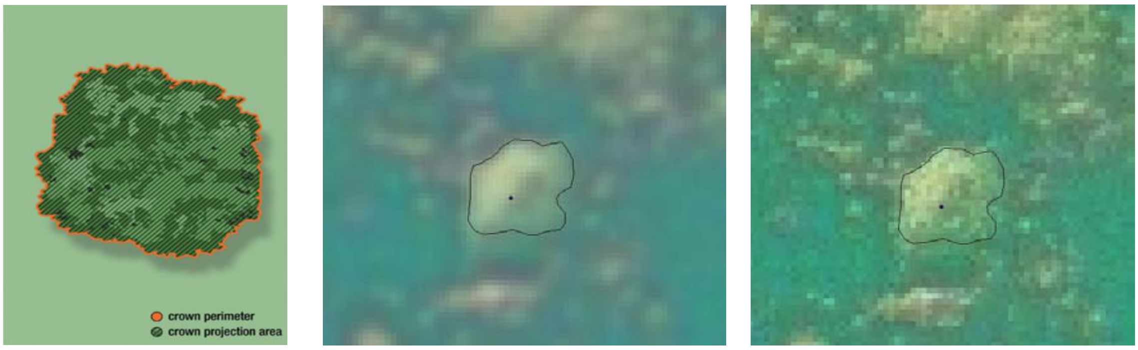
In this Table, the models for CPA versus biomass are not mentioned as R^2 and RMSE% value are same with the models of CPA versus carbon.

If we compared the regression of ΣBA on CPA with regression of DBH on CPA as shown in Table 4-1 and Table 4-2 respectively, the error in former case was considerably high. First, BA was calculated from DBH assuming cylindrical shape of stem. This is not true. BA of tree at any height is only approximately close to ideal objects. Second, summed up BA of individual trees of intermingled canopy were regressed against common CPA, in later case, individual tree DBH was regressed against its CPA.

Again, the prediction of carbon from CPA was found to have high error with RMSE 58.52% (Table 4-2). This error increased substantially compared to the prediction of basal area, i.e., from 49.25% to 58.52% (Table 4-2). It is further evident that the use of allometric equation for the calculation of biomass is an important factor for this incremental error including the error in the vertical projection area of CPA in the image and CPA delineation.

4.5. Error in CPA delineation

A set of rule, i.e., rotating image 180°, visualized in RGB 132, fixing scale at 1:250 was followed consistently for the manual delineation of CPA on low pass filtered pansharpened image. But precise digitisation also depends on canopy architecture (Browning *et al.*, 2009). The shape of crown of the broadleaf species (Figure 4-3: a) is very irregular compared to needleleaf trees. Because of irregular pattern, manual digitisation becomes too difficult to avoid error.



(a) (b) (c)

Figure 4-3 (a) CPA (b) Standalone tree CPA digitised on filtered image (c) The standalone tree CPA on unfiltered image

In intermingled canopy situation, where crowns of two or more individual trees met or overlapped, it was found difficult to identify from a top-down perspective whether the image object represent two, three or more tree crowns. This problem was handled with the help of information of sample plot location, intermingled canopy trees outline in the JPEG print out of image and the coordinates of the measured trees.

Another important point that caused error in CPA delineation is the fuzziness of boundary of the canopy (Figure 4-3: b, c) in the image. In the forest, reflectance of other vegetation, i.e., ground cover, understory shrubs, trees further creates noise for the reflectance of top canopy dominant trees. The boundary of the dominant trees is no longer remained crisp. We can imagine the crisp boundary of tree crown in the case of roadside plantation where trees are usually lopped, well trained and surrounded with man-made geographic objects.

The month of image acquisition also contributed to fuzziness of the boundary of dominant tree canopy. The image was acquired in November when the selected dominant species, which are semi-deciduous, starts leaf shedding. As the amount of leaves in the tree crown decreases, understory vegetation reflectance get space to appear in the scene. This further exacerbates the fuzziness of tree crown edges.

The third important point is the presence of shadow in the image (Figure 4-4: b). Mountainous topography further causes to increase the shadow in the scene. Shadow particularly obscured canopy area (Wulder *et al.*, 2004) as shown in Figure 4-4 (a) and (b).

(a) (b)

Figure 4-4 (a) CPA of two and three-intermingled canopy trees on filtered image (b) Shadow covered image

4.6. Error in vertical projection area of tree canopy in the satellite image

Remote sensing image is the record of reflected electromagnetic radiation from objects of the earth surface. Several factors influence the properties of the image such as, atmospheric conditions, meteorological condition, illumination, sensor property and its viewing angle (Culvenor, 2002). Sun angle and viewing angle of the sensor are the important factors for the true vertical projection area of canopy assuming other factors favourable.

For the true vertical projection area of tree canopy, ideally, sun should be straight up and sensor should be looking vertically down (nadir view). In other words, the sun elevation angle with respect to zenith should be 0^o or 90^o with respect to horizan. The viewing angle of sensor should also be 0^o with respect to zenith, that is nadir view. It becomes clear from image acquisition geometry (Figure 4-5). Sensor view angle of $\pm 14^o$ provides nearly true vertical projection area of tree crown (Wang *et al.*, 2004). Lower the sun elevation angle and higher off-nadir view result in oblique image. Figure 4-6 shows shape of the tree crown from three different view. The tree crown is seen different from assumed circular one in the oblique image (Figure 4-6). In this study, GeoEye image acquired on 09 November, 2009 was used. The sun elevation angle at the time of image acquisition was 45.67^o. Sensor elevation angle was 75.92^o. In other words, off-nadir was 14.08^o. Because of sun angle lower than 90^o, canopy projection area assumed to be circular became elongated (Figure 4-6) and caused to error (Wulder *et al.*, 2004). At lower sun angle, more shadow result in the scene. Further, topography constribute to forming the shadow (Gonzalez *et al.*, 2010) especially in hilly terrain like this study area. Where trees were visible in the scene, their crown edges were obscured because of shadow (Figure 4-4:b).

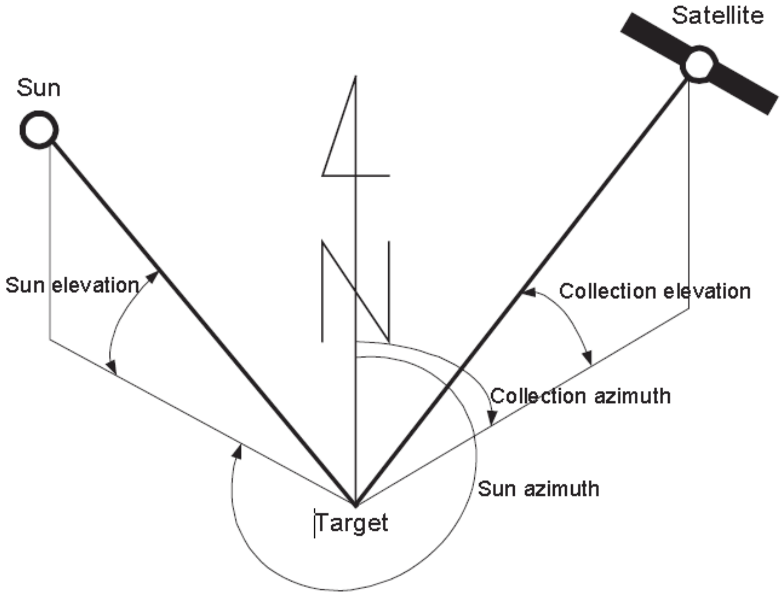


Figure 4-5 Image acquisition geometry, Source: (Dial *et al.*, 2003)

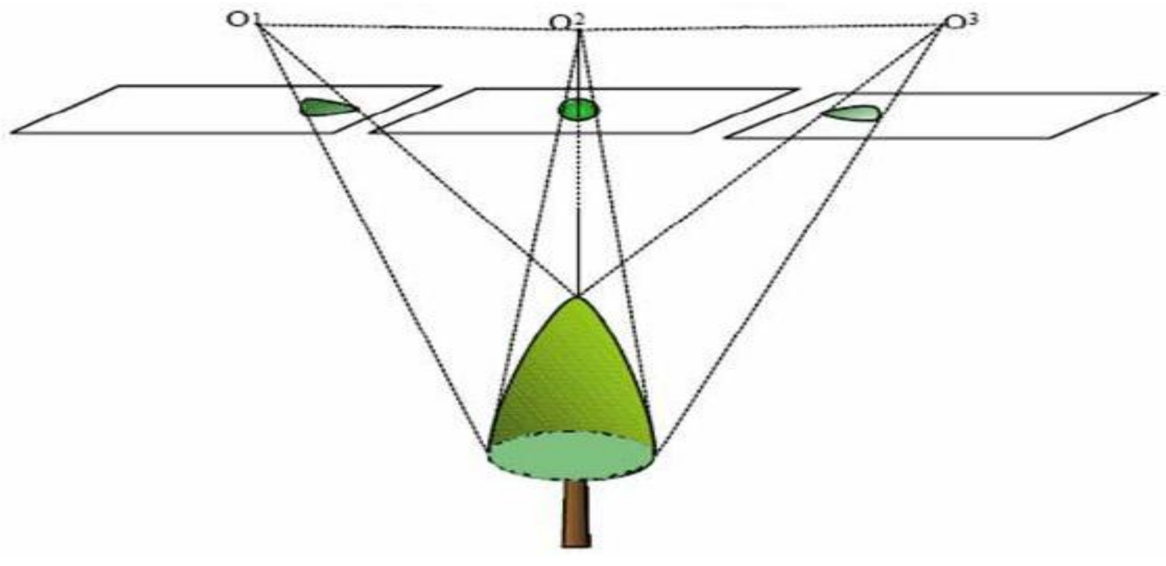


Figure 4-6 Tree crown shape from three different view, Source: (Li *et al.*, 2008)

4.7. Sources of error and its influence on modelling steps

Table 4-3 shows the sources of error in different steps of modelling the relationship between CPA and above ground tree carbon. Propagation of error in modelling steps from different sources causes poor prediction of carbon from CPA.

Table 4-3 Sources of error and its influence on modelling steps

Modelling steps	Sources of error and its influence on the modelling steps			
Image acquisition	High sun angle	Shadow (oblique image)	Shadow (mountain topography)	
CPA delineation	Irregular crown shape	Understory vegetation / fuzziness of canopy boundary	Shadow	Satellite image
CPA versus DBH	Satellite image	CPA delineation		
CPA versus Carbon	Allometric equation	CPA versus DBH		

4.8. Limitations of this study

- Non-site specific and non-species specific allometric equations: If local allometric equation was used for calculation of above ground tree biomass, the findings would be largely narrow down the uncertainty of this approach for the prediction of above ground tree carbon.

- Small dataset of standalone trees of *Schima wallichii, Terminalia alata* and intermingled canopy trees of *Shorea robusta:* The statistical inference using small dataset could not be reliable particularly if less than 30. It would also be difficult to draw conclusion by looking scatter plot with small dataset. If large dataset was used, scatter plot would reveal well defined pattern. Moreover, statistical inference would be reliable and might be differed between different functions notably.

- Acquisition of image on leaf shedding time also left a ground of uncertainty of this method. The reflectance of underground vegetation in the image would have more influenced in this period because of the opening space in the tree canopy. This contributes to the problem for CPA delineation from the image. Furthermore, delineated CPA might be underestimated, if leaves at the crown edges or boundary already fell.

5. CONCLUSIONS AND RECOMMENDATIONS

Manually delineated CPA from GeoEye satellite image which is intended to be used to predict above ground tree carbon stock of subtropical broadleaf forest is not having high R^2 to the level that the CPA can be utilized to model or predict carbon stock on an operational base. The identified simple linear regression models having the least error are not applicable for the prediction of above ground tree carbon stock of broadleaf forest in hilly terrain. The vertical projection area of tree canopy is subject to error because of low sun angle and shadow in the scene. This is further exacerbated by the mountain topography of the study area. In addition, manual delineation of CPA has been affected by the fuzziness tree crown boundary in the image.

- **Nevertheless, all the research questions are well answered as follows:**

Is there any relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species?

There is a linear relationship between CPA, DBH, biomass and carbon of standalone trees of the dominant species. The Pearson's correlation between CPA and DBH was 0.83, 0.80, and 0.86 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between CPA and biomass was 0.80, 0.73 and 0.79 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between CPA and carbon was also 0.80, 0.73 and 0.79 for *Shorea robusta, Schima wallichii and Terminalia alata* respectively. The correlation between them were highly significant ($P<0.001$).

Is there any relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of the dominant species?

There is a linear relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta.* The Pearson's correlation of CPA with ΣBA, Σbiomass and Σcarbon was 0.54, 0.50 and 0.50 respectively. The correlation between them were highly significant ($P<0.001$).

Which regression models best explain the relationship between CPA, DBH, BA, biomass and carbon of standalone and intermingled canopy trees of the dominant species?

Simple linear regression models best explain the relationship between CPA, DBH, biomass and carbon in standalone trees of *Shorea robusta*, *Schima wallichii,* and *Terminalia alata*. Similarly, simple linear regression models best explain the relationship between CPA, ΣBA, Σbiomass and Σcarbon of intermingled canopy trees of *Shorea robusta*. The precision and predictive accuracy of the selected simple linear models were not high enough to predict carbon.

Recommendations:

- Local species specific allometric equation could be useful to improve model accuracy for the prediction of above ground tree carbon.

- It is recommended to validate CPA (delineated from very high resolution satellite images) using field measured CPA.

- Large dataset of tree parameters need to be collected for the development of reliable regression models.

- Further studies are required to estimate above ground tree carbon accurately using other remote sensing method like airborne LiDAR. Currently it is not operational from the satellite platform for vegetation characterisation.

LIST OF REFERENCES

Aboal, J. R. ,Arévalo, J. R. & Fernández, Á. (2005). Allometric relationships of different tree species and stand above ground biomass in the Gomera laurel forest (Canary Islands). *Flora - Morphology, Distribution, Functional Ecology of Plants, 200*(3), 264-274.

Anderson, S. C. ,Kupfer, J. A. ,Wilson, R. R. & Cooper, R. J. (2000). Estimating forest crown area removed by selection cutting: a linked regression-GIS approach based on stump diameters. *Forest Ecology and Management, 137*(1-3), 171-177.

Asner, G. P. (2009). Tropical forest carbon assessment: integrating satellite and airborne mapping approaches. *Environmental Research Letters, 4*(3), 2-12.

Asner, G. P. ,Palace, M. ,Keller, M. ,Jr., R. P. ,Silva, J. N. M. & Zweede, J. C. (2002). Estimating Canopy Structure in an Amazon Forest from Laser Range Finder and IKONOS Satellite Observations. *Biotropica, 34*(4), 483-492.

Austin, J. M. ,Mackey, B. G. & Van Niel, K. P. (2003). Estimating forest biomass using satellite radar: an exploratory study in a temperate Australian Eucalyptus forest. *Forest Ecology and Management, 176*(1-3), 575-583.

Bartelink, H. H. (1996). Allometric relationships on biomass and needle area of Douglas-fir. *Forest Ecology and Management, 86*(1-3), 193-203.

Basuki, T. M. ,van Laake, P. E. ,Skidmore, A. K. & Hussin, Y. A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management, 257*(8), 1684-1694.

Brown, S. (2002). Measuring carbon in forests: current status and future challenges. *Environmental Pollution, 116*(3), 363-372.

Browning, D. M. ,Archer, S. R. & Byrne, A. T. (2009). Field validation of 1930s aerial photography: What are we missing? *Journal of Arid Environments, 73*(9), 844-853.

Bunting, P. & Lucas, R. (2006). The delineation of tree crowns in Australian mixed species forests using hyperspectral Compact Airborne Spectrographic Imager (CASI) data. *Remote Sensing of Environment, 101*(2), 230-248.

Cawley, G. & Talbot, N. (2008). Efficient approximate leave-one-out cross-validation for kernel logistic regression. *Machine Learning, 71*(2), 243-264.

Chave, J. ,Andalo, C. & Brown, S. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia, 145*(1), 87-99.

Chiba, Y. (1998). Architectural analysis of relationship between biomass and basal area based on pipe model theory. *Ecological Modelling, 108*(1-3), 219-225.

Chubey, M. S. ,Franklin, S. E. & Wulder, M. A. (2006). Object-based analysis of Ikonos-2 imagery for extraction of forest inventory parameters. *Photogrammetric Engineering and Remote Sensing, 72*(4), 383-394.

Cienciala, E. ,Černý, M. ,Tatarinov, F. ,Apltauer, J. & Exnerová, Z. (2006). Biomass functions applicable to Scots pine. *Trees - Structure and Function, 20*(4), 483-495.

CIFOR ,FAO ,UNDP & UNEP (2009). *Reporting REDD: A journalist's guide to the role of forests in combating global climate change*. UK.

Clark, D. B. & Clark, D. A. (2000). Landscape-scale variation in forest structure and biomass in a tropical rain forest. *Forest Ecology and Management, 137*(1-3), 185-198.

Culvenor, D. S. (2002). TIDA: an algorithm for the delineation of tree crowns in high spatial resolution remotely sensed imagery. *Computers & Geosciences, 28*(1), 33-44.

Culvenor, D. S. (2003). Extracting individual tree information : A Survey of Techniques for Very High Sspatial Resolution Imagery. In M. A. Wulder & Steven E. Franklin (Eds.), *Remote sensing of forest environments: concepts and case studies*. Kluwer Academic Publishers.Boston. 255-265p.

Dalenius & Cochran. (2006). Sampling in Forest Surveys *Sampling Methods, Remote Sensing and GIS Multiresource Forest Inventory*. Springer-Verlag Berlin Heidelberg.New York. 106p.

Dial, G. ,Bowen, H. ,Gerlach, F. ,Grodecki, J. & Oleszczuk, R. (2003). IKONOS satellite, imagery, and products. *Remote Sensing of Environment, 88*(1-2), 23-36.

DoF (2010). *Management Information System. Department of Forests. Kathmandu, Nepal.* . Retrieved from http://www.dof.gov.np/.

Efron, B. & Gong, G. (1983). A Leisurely Look at the Bootstrap, the Jackknife, and Cross-Validation. *The American Statistician, 37*(1), 36-48.

Fang, Z. & Bailey, R. L. (1998). Height-diameter models for tropical forests on Hainan Island in southern China. *Forest Ecology and Management, 110*(1-3), 315-327.

FAO (2010). *Communicating the role of Forests in Sustainable Development: The International Year of Forests (2011).* Rome, Italy.

FAO (2011). Media Centre, Official webpage of FAO. Retrieved 07-02-2011, from http://www.fao.org/news/story/pt/item/40893/icode/en/

Foody, G. M. ,Boyd, D. S. & Cutler, M. E. J. (2003). Predictive relations of tropical forest biomass from Landsat TM data and their transferability between regions. *Remote Sensing of Environment, 85*(4), 463-474.

Fowler, H. W. e. ,Fowler, F. G. e. & Sykes, J. B. e. (1976). *concise Oxford dictionary of current English : based on the Oxford English dictionary and its supplements* (Sixth edition). Oxford: Clarendon Press. 1368 p.

Gibbs, H. K. ,Brown, S. ,Niles, J. O. & Foley, J. A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters, 2*(4), 1-13.

Gill, S. J. ,Biging, G. S. & Murphy, E. C. (2000). Modeling conifer tree crown radius and estimating canopy cover. *Forest Ecology and Management, 126*(3), 405-416.

Gonzalez, P. ,Asner, G. P. ,Battles, J. ,Lefsky, M. A. ,Waring, K. M. & Palace, M. (2010). Forest carbon densities and uncertainties from Lidar, QuickBird, and field measurements in California. *Remote Sensing of Environment, 114*(7), 1561-1575.

Greenberg, J. A. ,Dobrowski, S. Z. & Ustin, S. L. (2005). Shadow allometry: Estimating tree structural parameters using hyperspatial image analysis. *Remote Sensing of Environment, 97*(1), 15-25.

Gschwantner, T. ,Schadauer, K. ,Vidal, C. ,Lanz, A. ,Tomppo, E. ,di Cosmo, L. ,Robert, N. ,Duursma, D. & Lawrence, M. (2009). Common tree definitions for national forest inventories in Europe. *Silva Fennica, 43*(2), 303-321.

Hedl, R. ,Svatek, M. ,Dancak, M. ,Rodzay, A. W. ,Salleh, A. B. M. & Kamariah, A. S. (2009). A new technique for inventory of permanent plots in tropical forests: a case study from lowland dipterocarp forest in Kuala Belalong, Brunei Darussalam. *Blumea, 54*(1-3), 124-130.

Hemery, G. E. ,Savill, P. S. & Pryor, S. N. (2005). Applications of the crown diameter-stem diameter relationship for different species of broadleaved trees. *Forest Ecology and Management, 215*(1-3), 285-294.

Hirata, Y. ,Tsubotab, Y. & Sakaic, A. (2009). Allometric models of DBH and crown area derived from QuickBird panchromatic data in Cryptomeria japonica and Chamaecyparis obtusa stands *International Journal of Remote Sensing, , 30*(19), 5071 - 5088.

Husch, B. ,Beers, T. W. & Kershaw, J. A. (2003). *Forest mensuration* (Fourth edition). Hoboken: Wiley & Sons. 443 p.

Huxley, J. S. (1932). *Problems of Relative Growth*. London: Methuen And Company Limited. 276 p.

IPCC (2006). Good Practice Guidance for Land Use, Land-Use Change and Forestry. Official webpage of IPCC. Retrieved 08-02-2011, from http://www.ipcc-nggip.iges.or.jp/public/gpglulucf/gpglulucf_contents.html

IPCC (2006). Guidelines for National Greenhouse Gas Inventories. Official webpage of IPCC. Retrieved 6 Aug 2010, from http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/V4_04_Ch4_Forest_Land.pdf

Karky, B. S. & Skutsch, M. (2010). The cost of carbon abatement through community forest management in Nepal Himalaya. *Ecological Economics, 69*(3), 666-672.

Katoh, M. ,Gougeon, F. & Leckie, D. (2009). Application of high-resolution airborne data using individual tree crowns in Japanese conifer plantations. *Journal of Forest Research, 14*(1), 10-19.

Ketterings, Q. M. ,Coe, R. ,van Noordwijk, M. ,Ambagau, Y. & Palm, C. A. (2001). Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. *Forest Ecology and Management, 146*(1-3), 199-209.

Kuuluvainen, T. (1991). Relationships between crown projected area and components of above-ground biomass in Norway spruce trees in even-aged stands: Empirical results and their interpretation. *Forest Ecology and Management, 40*(3-4), 243-260.

Larocque, G. R. (2000). Performance of young jack pine trees originating from two different branch angle traits under different intensities of competition. *Annals of Forest Science, 57*(7), 635-649.

Leboeuf, A. ,Beaudoin, A. ,Fournier, R. A. ,Guindon, L. ,Luther, J. E. & Lambert, M. C. (2007). A shadow fraction method for mapping biomass of northern boreal black spruce forests using QuickBird imagery. *Remote Sensing of Environment, 110*(4), 488-500.

Leckie, D. G. ,Gougeon, F. A. ,Tinis, S. ,Nelson, T. ,Burnett, C. N. & Paradine, D. (2005). Automated tree recognition in old growth conifer stands with high resolution digital imagery. *Remote Sensing of Environment, 94*(3), 311-326.

Leckie, D. G. ,Gougeon, F. A. ,Walsworth, N. & Paradine, D. (2003). Stand delineation and composition estimation using semi-automated individual tree crown analysis. *Remote Sensing of Environment, 85*(3), 355-369.

Li, Z. ,Hayward, R. ,Zhang, J. & Liu, Y. (2008). Individual Tree Crown Delineation Techniques for Vegetation Management in Power Line Corridor. Retrieved 01-01-2011, from http://dx.doi.org/10.1109/DICTA.2008.21

Lu, D. (2005). Aboveground biomass estimation using Landsat TM data in the Brazilian Amazon. *International Journal of Remote Sensing, 26*(12), 2509-2525.

Lu, D. (2006). The potential and challenge of remote sensing-based biomass estimation *International Journal of Remote Sensing, 27* (7), 1297 - 1328

Mark, D. & Church, M. (1977). On the misuse of regression in earth science. *Mathematical Geology, 9*(1), 63-75.

MFSC (2009). REDD - forestry and climate change. Official webpage of MFSC. Retrieved 01-01-2011, from http://mofsc-redd.gov.np/

Mitchell, J. E. & Popovich, S. J. (1997). Effectiveness of basal area for estimating canopy cover of ponderosa pine. *Forest Ecology and Management, 95*(1), 45-51.

Mohns, B. ,Applegate, G. B. & Gilmour, D. A. (1988). Biomass and productivity estimations for community forest management: A case study from the hills of Nepal -- II. Dry matter production in mixed young stands of chir pine (Pinus roxburghii) and broad-leaved species. *Biomass, 17*(3), 165-184.

Palace, M. ,Keller, M. ,Asner, G. P. ,Hagen, S. & Braswell, B. (2008). Amazon forest structure from IKONOS satellite data and the automated characterization of forest canopy properties. *Biotropica, 40*(2), 141-150.

Panta, M. ,Kim, K. & Joshi, C. (2008). Temporal mapping of deforestation and forest degradation in Nepal: Applications to forest conservation. *Forest Ecology and Management, 256*(9), 1587-1595.

Patenaude, G. ,Milne, R. & Dawson, T. P. (2005). Synthesis of remote sensing approaches for forest carbon estimation: reporting to the Kyoto Protocol. *Environmental Science & Policy, 8*(2), 161-178.

Pokharel, R. K. (2009). Pro-Poor Programs Financed Through Nepal's Community Forestry Funds: Does Income Matter? *Mountain Research and Development, 29*(1), 67-74.

Reimann, C. ,Filzmoser, P. ,Garrett, R. & Dutter, R. (2008). *Statistical data analysis explained : applied environmental statistics with R : also e-book*. Chichester: Wiley & Sons. 341 p.

Shimano, K. (1997). Analysis of the relationship between DBH and crown projection area using a new model. *Journal of Forest Research, 2*(4), 237-242.

Shiver, B. D. & Borders, B. E. (1996). *Sampling techniques for forest resource inventory*. New York: Wiley & Sons. 356 p.

Song, B. ,Chen, J. ,Desander, P. V. ,Reed, D. D. ,Bradshaw, G. A. & Franklin, J. F. (1997). Modeling canopy structure and heterogeneity across scales: From crowns to canopy. *Forest Ecology and Management, 96*(3), 217-229.

Tedeschi, L. O. (2006). Assessment of the adequacy of mathematical models. *Agricultural Systems, 89*(2-3), 225-247.

Thompson, S. K. (1992). *Sampling*. New York: Wiley & Sons. 343 p.

Thorpe, H. C. ,Astrup, R. ,Trowbridge, A. & Coates, K. D. (2010). Competition and tree crowns: A neighborhood analysis of three boreal tree species. *Forest Ecology and Management, 259*(8), 1586-1596.

UNFCCC (2010). UNFCC. Official webpage of UNFCCC. Retrieved 50-08-2010, from http://unfccc.int/2860.php

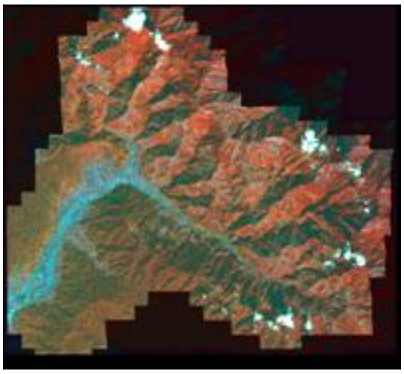
Wallach, D. & Goffinet, B. (1989). Mean squared error of prediction as a criterion for evaluating and comparing system models. *Ecological Modelling, 44*(3-4), 299-306.

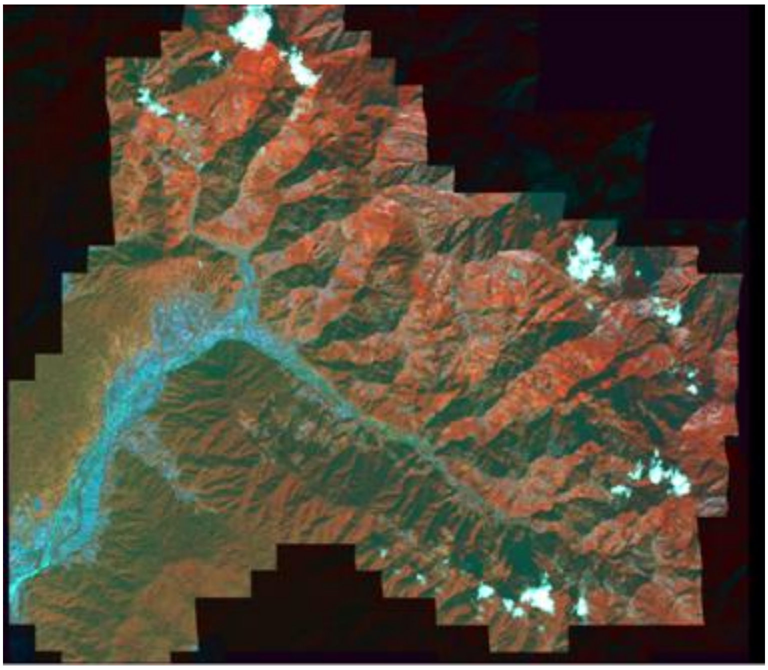
Wang, L. ,Gong., P. & Biging., G. S. (2004). Individual tree crown delineation and treetop detection in high-spatial resolution aerial imagery. *Photogrammetric Engineering and Remote Sensing 70*(3), 351-357.

Wang, X. ,Fang, J. ,Tang, Z. & Zhu, B. (2006). Climatic control of primary forest structure and DBH-height allometry in Northeast China. *Forest Ecology and Management, 234*(1-3), 264-274.
Wulder, M. A. ,Whitea, J. C. ,Niemannb, K. O. & Nelsonc, T. (2004). Comparison of airborne and satellite high spatial resolution data for the identification of individual trees with local maxima filtering *International Journal of Remote Sensing, 25*(11), 2225 - 2232.
Zianis, D. & Mencuccini, M. (2004). On simplifying allometric analyses of forest biomass. *Forest Ecology and Management, 187*(2-3), 311-332.

LIST OF APPENDICES

Appendix 1 IHS merge satellite image (img) in RGB 132 (bottom) and the image (ecw) in RGB 132 (top)



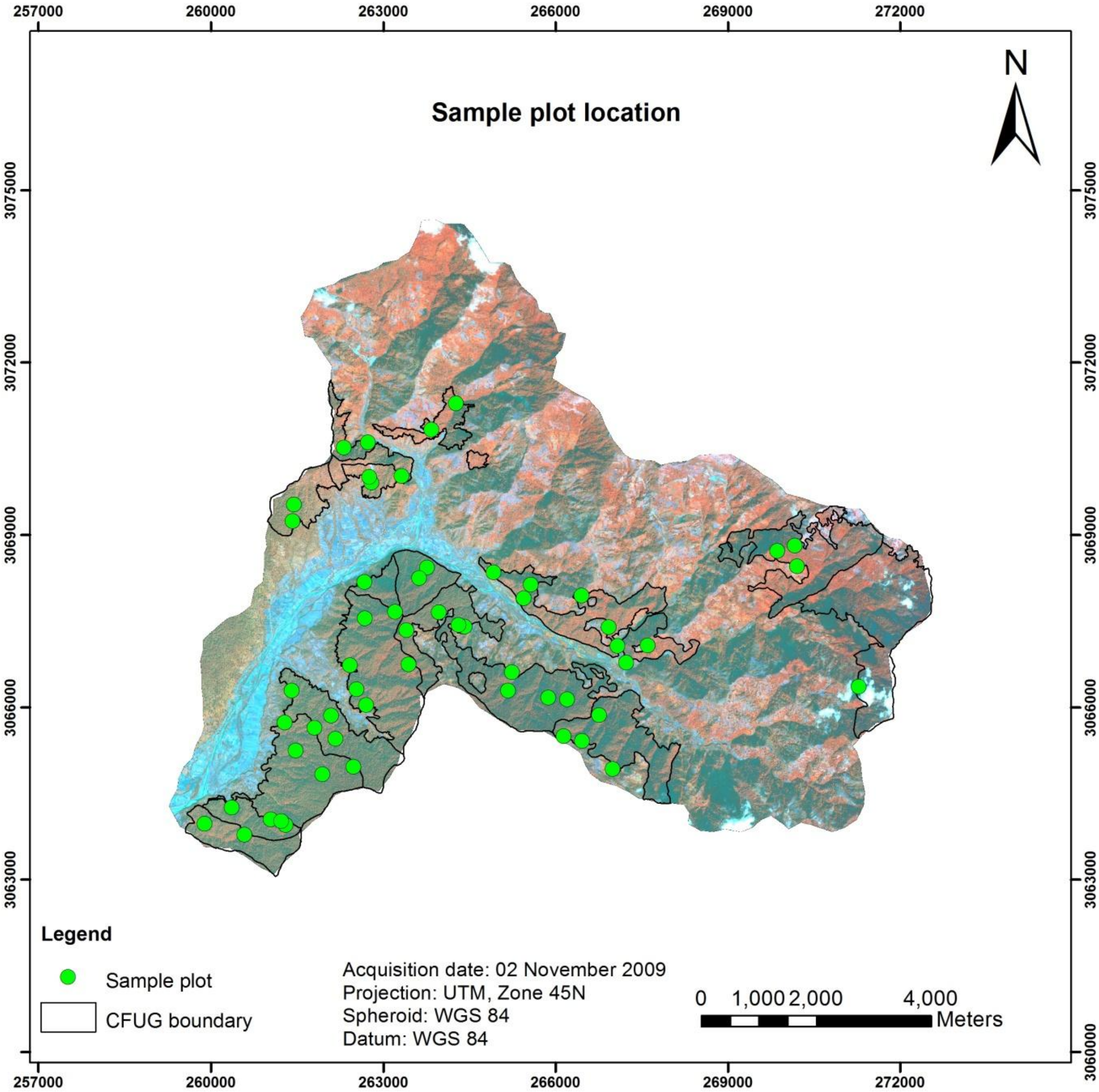


Appendix 2 Sample size for each 15 community forest (CF)

S.N.	Community Forest (CF)	Area (ha)	Calculated sample size (N)	Required sample size (N)
1	Batauli CF	155.77	3.94	4
2	Chitramkaminchuli CF	314.02	7.93	8
3	Deujar CF	271.56	6.86	7
4	Devidhunga CF	253.86	6.41	6
5	Dharapani CF	147.16	3.72	4
6	Indreni CF	171.06	4.32	4
7	Jamuna CF	34.53	0.87*	2
8	Janapragati CF	118.84	3.00	3
9	Jharana CF	34.54	0.87*	2
10	Kalika CF	150.23	3.80	4
11	Kankali CF	149.19	3.77	4
12	Nibuwatar CF	330.30	8.35	8
13	Pragati CF	115.48	2.92	3
14	Samfrang CF	63.90	1.61*	2
15	Satkanya CF	64.23	1.62*	2
	Total	**2374.67**	**60.00**	**63**

Note: * are maintained to 2.

Appendix 3 Sample plot location in each CFUG



Appendix 4 Data collection sheet

Data Collection Form

Name of recorder: Date:

Slope: aspect: altitude:

Stratum ID		Coordinates	X:
Sample plot ID			Y:

S.N.	DBH (cm)	Species	Standalone tree	Intermingled canopy trees			Remarks
				2 trees	3 trees	More trees	
1.							
2.							
3.							
4.							
5.							
6.							
7.							
8.							
9.							
10.							
11.							
12.							
13.							
14.							
15.							

Appendix 5 Slope correction factor

Plot size 500 m^2

Slope%	Radius(m)	Slope%	Radius(m)	Slope%	Radius(m)
0	12.62				
1	12.62	36	13.01	71	13.97
2	12.62	37	13.03	72	14.00
3	12.62	38	13.05	73	14.04
4	12.62	39	13.07	74	14.07
5	12.62	40	13.09	75	14.10
6	12.63	41	13.12	76	14.14
7	12.63	42	13.14	77	14.17
8	12.64	43	13.16	78	14.21
9	12.64	44	13.19	79	14.24
10	12.65	45	13.21	80	14.28
11	12.65	46	13.24	81	14.31
12	12.66	47	13.26	82	14.35
13	12.67	48	13.29	83	14.38
14	12.68	49	13.31	84	14.42
15	12.69	50	13.34	85	14.45
16	12.70	51	13.37	86	14.49
17	12.71	52	13.39	87	14.52
18	12.72	53	13.42	88	14.56
19	12.73	54	13.45	89	14.60
20	12.74	55	13.48	90	14.63
21	12.75	56	13.51	91	14.67
22	12.77	57	13.53	92	14.71
23	12.78	58	13.56	93	14.74
24	12.79	59	13.59	94	14.78
25	12.81	60	13.62	95	14.82
26	12.82	61	13.65	96	14.85
27	12.84	62	13.68	97	14.89
28	12.86	63	13.72	98	14.93
29	12.87	64	13.75	99	14.97
30	12.89	65	13.78	100	15.00
31	12.91	66	13.81	101	15.04
32	12.93	67	13.84	102	15.08
33	12.95	68	13.87	103	15.12
34	12.97	69	13.91	104	15.15
35	12.99	70	13.94	105	15.19

Source: A. De Gier (2000) from lecture note

Appendix 6 Standalone trees of different species

S.N.	Species	Number	%
1	*Adina cordifolia*	4	2
2	*Aesandra butyracea*	8	3
3	*Albizia lebbek*	1	0
4	*Albizia mollis*	2	1
5	*Auci**	3	1
6	*Bombax ceiba*	1	0
7	*Careya arborea*	1	0
8	*Casearia graveolens*	1	0
9	*Cassia fistula*	1	0
10	*Castonopsis indica*	1	0
11	*Crauci**	1	0
12	*Dillenia pentagyna*	4	2
13	*Diospyros embryopteris*	1	0
14	*Lagerstromia parviflora*	4	2
15	*Mallotus phillippensis*	4	2
16	*Schima wallachia*	24	10
17	*Semicarpus anacardium*	15	6
18	*Shorea robusta*	127	54
19	*Sigane**	3	1
20	*Syzygium cerasoides*	2	1
21	*Syzygium cumini*	1	0
22	*Termimala chebula*	2	1
23	*Terminalia alata*	16	7
24	*Terminalia bellirica*	6	3
25	*Tiyari**	2	1
26	*Waksi**	2	1
Total		**237**	**100**

Appendix 7 DBH, carbon and CPA of standalone trees of *Shorea robusta*

Shorea robusta (standalone)											
S.N.	**DBH**	**Carbon**	**CPA**	**S.N.**	**DBH**	**Carbon**	**CPA**	**S.N.**	**DBH**	**Carbon**	**CPA**
1	43	404.73	32.11	44	78	1660.99	62.08	86	52	635.12	68.83
2	35	248.43	54.83	45	50	578.72	33.79	87	129	5475.44	147.39
3	13	23.73	34.23	46	66	1117.76	69.15	88	56	757.12	71.86
4	84	1980.05	90.01	47	56	757.12	49.48	89	16	38.83	19.70
5	103	3211.05	94.37	48	40	340.95	52.07	90	26	122.78	34.59
6	60	891.68	51.23	49	58	822.81	85.60	91	30	172.37	56.69
7	73	1419.54	61.04	50	52	635.12	45.48	92	32	200.87	39.41
8	59	856.84	61.61	51	90	2331.95	89.53	93	33	216.08	46.84
9	50	578.72	39.23	52	79	1711.92	61.13	94	33	216.08	45.88
10	43	404.73	50.57	53	52	635.12	71.06	95	33	216.08	45.47
11	17	44.83	32.66	54	75	1513.49	91.38	96	35	248.43	39.24
12	55	725.46	93.04	55	60	891.68	60.86	97	36	265.59	48.11
13	57	789.57	73.01	56	84	1980.05	87.85	98	38	301.91	57.59
14	52	635.12	65.54	57	53	664.46	48.43	99	39	321.09	45.95
15	62	963.77	81.39	58	33	216.08	38.26	100	39	321.09	41.91
16	48	525.33	44.52	59	50	578.72	59.99	101	60	891.68	63.44
17	25	111.87	35.21	60	79	1711.92	72.26	102	40	340.95	47.39
18	50	578.72	45.93	61	93	2520.48	68.99	103	41	361.51	45.31
19	39	321.09	43.64	62	45	450.79	57.05	104	41	361.51	41.43
20	38	301.91	38.33	63	35	248.43	40.90	105	70	1285.10	73.90
21	45	450.79	38.96	64	66	1117.76	95.42	106	42	382.77	39.47
22	48	525.33	56.10	65	62	963.77	59.82	107	44	427.40	70.43
23	32	200.87	33.00	66	100	2993.72	78.92	108	45	450.79	41.48
24	50	578.72	39.10	67	83	1924.62	85.73	109	45	450.79	54.31
25	44	427.40	32.49	68	76	1561.78	66.16	110	63	1001.03	52.36
26	45	450.79	45.15	69	35	248.43	55.85	111	48	525.33	47.76
27	77	1610.94	67.05	70	16	38.83	31.36	112	48	525.33	54.06
28	75	1513.49	93.86	71	42	382.77	48.51	113	53	664.46	51.15
29	45	450.79	46.13	72	19	58.36	29.12	114	56	757.12	51.64
30	36	265.59	32.53	73	46	474.91	57.80	115	61	927.32	57.12
31	60	891.68	55.29	74	93	2520.48	104.73	116	63	1001.03	54.44
32	56	757.12	66.20	75	90	2331.95	114.77	117	65	1078.02	56.62
33	60	891.68	50.33	76	97	2785.14	106.80	118	65	1078.02	93.24
34	50	578.72	54.74	77	30	172.37	38.20	119	67	1158.33	76.62
35	48	525.33	57.19	78	81	1816.47	64.03	120	68	1199.75	53.74
36	75	1513.49	73.67	79	47	499.75	41.15	121	75	1513.49	69.01
37	36	265.59	35.68	80	27	134.27	48.16	122	73	1419.54	97.54
38	27	134.27	41.17	81	80	1763.75	85.23	123	74	1466.08	69.13
39	51	606.54	55.58	82	60	891.68	89.46	124	77	1610.94	67.46
40	42	382.77	40.75	83	61	927.32	53.54	125	87	2151.84	70.49

41	59	856.84	75.35	84	30	172.37	58.02	126	95	2650.90	79.60
42	42	382.77	38.66	85	92	2456.70	79.83	127	46	474.91	67.29
43	27	134.27	34.83								
Note: DBH, CPA and Carbon are in cm, m^2 and kg respectively. Data in grey colour are outliers.											

Appendix 8 DBH, carbon and CPA of standalone trees of *Schima wallichii* and *Terminalia alata*

Schima wallichii (standalone)					*Terminalia alata* (standalone)			
S.N.	DBH (cm)	Carbon (kg)	CPA (m^2)		S.N.	DBH (cm)	Carbon (kg)	CPA (m^2)
1	38	366.81	33.82		1	79	1881.50	125.84
2	14	39.41	22.71		2	30	216.32	34.22
3	29	200.54	63.73		3	67	1302.13	84.36
4	66	1259.12	86.74		4	49	647.30	77.96
5	28	185.42	32.62		5	85	2215.78	110.30
6	60	1017.64	76.13		6	96	2908.03	113.96
7	16	53.11	28.07		7	49	647.30	68.61
8	25	143.95	47.73		8	40	411.35	45.70
9	44	508.95	76.04		9	119	4698.69	122.66
10	38	366.81	34.18		10	67	1302.13	101.96
11	93	2708.91	99.88		11	58	943.41	61.11
12	45	535.16	80.53		12	49	647.30	70.88
13	72	1529.27	81.63		13	44	508.95	90.50
14	72	1529.27	83.30		14	40	411.35	50.29
15	21	97.51	32.46		15	75	1675.29	91.84
16	27	170.95	44.65		16	67	1302.13	82.36
17	27	170.95	46.91					
18	65	1216.89	61.36					
19	55	837.87	58.55					
20	80	1935.12	69.21					
21	45	535.16	72.36					
22	47	589.75	52.74					
23	29	200.54	26.66					
24	90	2517.57	67.09					

Appendix 9 Regression models (with ANOVA) of CPA with DBH, biomass and carbon separately of standalone trees of *Shorea robusta*

1. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.829	.687	.682	11.062

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19828.794	1	19828.794	162.048	2.544E-20
	Residual	9054.890	74	122.363		
	Total	28883.684	75			

b. Dependent Variable: DBH

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.510	4.062		1.110	.270
	CPA	.851	.067	.829	12.730	2.544E-20

c. Dependent Variable: DBH

2. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.843	.711	.703	10.699

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	20527.088	2	10263.544	89.658	2.189E-20
Residual	8356.596	73	114.474		
Total	28883.684	75			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	1.671	.338	1.623	4.950	4.619E-6
CPA^2	-.006	.003	-.810	-2.470	.016
(Constant)	-19.453	10.468		-1.858	.067

c. Dependent variable: DBH

3. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.839	.704	.700	10.743

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	20343.806	1	20343.806	176.284	2.878E-21
Residual	8539.878	74	115.404		
Total	28883.684	75			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	49.790	3.750	.839	13.277	2.878E-21
(Constant)	-145.549	15.052		-9.670	9.141E-15

c. Dependent variable: DBH

4. Model summary: Power

Goodness of fit statistics:

Observations	76.000
DF	74.000
R^2	0.692
SSE	8919.489
MSE	120.534
RMSE	10.979
Iterations	20.000

Model parameters:

Parameter	Value	Standard error	t
pr1	1.453	0.743	1.955141
pr2	0.892	0.072	12.42783

Equation of the model:

$DBH = 1.453*(CPA^{0.892})$

...Continued Appendix 9

5. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.805	.648	.643	870.072

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.030E8	1	1.030E8	136.110	1.941E-18[a]
	Residual	5.602E7	74	757024.837		
	Total	1.591E8	75			

b. Dependent Variable: biomass

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1772.838	319.504		-5.549	4.256E-7
	CPA	61.476	5.269	.805	11.667	1.941E-18

c. Dependent Variable: biomass

6. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.805	.648	.639	875.489

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.031E8	2	5.155E7	67.259	2.746E-17
Residual	5.595E7	73	766481.625		
Total	1.591E8	75			

b. Dependent variable: biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	53.481	27.622	.700	1.936	.057
CPA^2	.062	.209	.107	.295	.769
(Constant)	-1538.679	856.527		-1.796	.077

c. Dependent variable: biomass

7. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.775	.600	.595	927.068

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	9.546E7	1	9.546E7	111.069	2.204E-16
Residual	6.360E7	74	859455.098		
Total	1.591E8	75			

b. Dependent variable: biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	3410.622	323.621	.775	10.539	2.204E-16
(Constant)	-11875.752	1298.981		-9.142	8.961E-14

c. Dependent variable: biomass

8. Model summary: Power

Goodness of fit statistics:

Observations	76
DF	74
R^2	0.637
SSE	57988368.72
MSE	783626.604
RMSE	885.227
Iterations	68

Model parameters:

Parameter	Value	Standard error	t
pr1	1.072	0.798	1.343
pr2	1.813	0.171	10.602

Equation of the model:

Biomass = 1.072($CPA^{1.81}$)

...Continued Appendix 9

9. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.805	.648	.643	409.016

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.277E7	1	2.277E7	136.110	1.941E-18[a]
	Residual	1.238E7	74	167293.691		
	Total	3.515E7	75			

b. Dependent Variable: carbon

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-833.401	150.197		-5.549	4.256E-7
	CPA	28.900	2.477	.805	11.667	1.941E-18

c. Dependent Variable: carbon

10. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.805	.648	.639	411.562

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.279E7	2	1.139E7	67.259	2.746E-17
Residual	1.236E7	73	169383.531		
Total	3.515E7	75			

b. Dependent variable: carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	25.141	12.985	.700	1.936	.057
CPA^2	.029	.098	.107	.295	.769
(Constant)	-723.324	402.648		-1.796	.077

c. Dependent variable: carbon

11. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.775	.600	.595	435.809

Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.110E7	1	2.110E7	111.069	2.204E-16
Residual	1.405E7	74	189929.588		
Total	3.515E7	75			

b. Dependent variable : carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	1603.313	152.132	.775	10.539	2.204E-16
(Constant)	-5582.720	610.643		-9.142	8.961E-14

c. Dependent variable : carbon

12. Model summary: Power

Goodness of fit statistics:

Observations	76.000
DF	74.000
R^2	0.637
SSE	12814755.525
MSE	173172.372
RMSE	416.140
Iterations	67.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.504	0.375	1.342893
pr2	1.813	0.171	10.61365

Equation of the model:

Carbon = $0.50*(CPA^{1.81})$

Appendix 10 Regression models (with ANOVA) of CPA with DBH, biomass and carbon separately of standalone trees of *Schima wallichii*

1. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.796	.634	.618	14.371

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7876.131	1	7876.131	38.135	3.243E-6[a]
	Residual	4543.702	22	206.532		
	Total	12419.833	23			

b. Dependent Variable: DBH

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.850	8.273		-.103	.919
	CPA	.831	.135	.796	6.175	3.243E-6

a. Dependent Variable: DBH

2. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.797	.635	.600	14.692

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	7886.697	2	3943.348	18.268	2.535E-5
Residual	4533.137	21	215.864		
Total	12419.833	23			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	.654	.814	.626	.803	.431
CPA^2	.002	.007	.172	.221	.827
(Constant)	3.543	21.584		.164	.871

c. Dependent variable: DBH

3. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.781	.610	.592	14.847

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	7570.119	1	7570.119	34.341	6.760E-6
Residual	4849.714	22	220.442		
Total	12419.833	23			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
ln(CPA)	42.056	7.177	.781	5.860	6.760E-6
(Constant)	-119.987	28.642		-4.189	3.801E-4

b. Dependent variable: DBH

4. Model summary: power

Goodness of fit statistics:

Observations	24.000
DF	22.000
R^2	0.634
SSE	4541.913
MSE	206.451
RMSE	14.368
Iterations	21.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.729	0.610	1.193638
pr2	1.027	0.197	5.214981

Equation of the model:

DBH = 0.728($CPA^{1.027}$)

5. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.725	.526	.505	1.167E3

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3.325E7	1	3.325E7	24.425	6.061E-5
	Residual	2.995E7	22	1361477.042		
	Total	6.321E7	23			

b. Dependent Variable: biomass

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1444.540	671.673		-2.151	.043
	CPA	54.014	10.929	.725	4.942	6.061E-5

c. Dependent Variable: biomass

6. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.741	.550	.507	1164.169

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.475E7	2	1.737E7	12.819	2.299E-4
Residual	2.846E7	21	1355289.988		
Total	6.321E7	23			

b. Dependent variable: biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	-12.651	64.478	-.170	-.196	.846
CPA ^{2}	.577	.550	.908	1.049	.306
(Constant)	206.053	1710.235		.120	.905

c. Dependent variable: biomass

7. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.690	.476	.453	1226.591

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.011E7	1	3.011E7	20.011	1.898E-4
Residual	3.310E7	22	1504526.484		
Total	6.321E7	23			

b. Dependent variable : biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	2652.227	592.891	.690	4.473	1.898E-4
(Constant)	-8866.397	2366.242		-3.747	.001

c. Dependent variable: biomass

8. Model summary: Power

Goodness of fit statistics:

Observations	24.000
DF	22.000
R^2	0.550
SSE	28418064.816
MSE	1291730.219
RMSE	1136.543
Iterations	126.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.159	0.417	0.381933
pr2	2.238	0.597	3.745105

Equation of the model:

Biomass = 0.159(CPA $^{2.24}$)

...Continued Appendix 10

9. Model Summary: Linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.725	.526	.505	548.407

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7345889.114	1	7345889.114	24.425	6.061E-5
	Residual	6616506.131	22	300750.279		
	Total	1.396E7	23			

b. Dependent Variable: carbon

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-678.934	315.686		-2.151	.043
	CPA	25.387	5.137	.725	4.942	6.061E-5

c. Dependent Variable: carbon

10. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.741	.550	.507	547.160

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	7675340.518	2	3837670.259	12.819	2.299E-4
Residual	6287054.727	21	299383.558		
Total	1.396E7	23			

b. Dependent variable: carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	-5.946	30.305	-.170	-.196	.846
CPA ^{2}	.271	.259	.908	1.049	.306
(Constant)	96.845	803.810		.120	.905

c. Dependent variable: carbon

11. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.690	.476	.453	576.498

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	6650697.439	1	6650697.439	20.011	1.898E-4
Residual	7311697.806	22	332349.900		
Total	1.396E7	23			

b. Dependent variable: carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	1246.547	278.659	.690	4.473	1.898E-4
(Constant)	-4167.207	1112.134		-3.747	.001

c. Dependent variable: carbon

12. Model summary: Power

Goodness of fit statistics:

Observations	24.000
DF	22.000
R^2	0.550
SSE	6277550.518
MSE	285343.205
RMSE	534.175
Iterations	125.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.075	0.196	0.381933
pr2	2.238	0.597	3.745105

Equation of the model:

Carbon = 0.0074(CPA $^{2.237}$)

Appendix 11 Regression models (with ANOVA) of CPA with DBH, biomass and carbon separately of standalone trees of *Terminalia alata*

1. Model Summary: Simple Linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.862	.743	.725	12.314

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6152.787	1	6152.787	40.575	1.739721E-5
	Residual	2122.963	14	151.640		
	Total	8275.750	15			

b. Dependent Variable: DBH

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.940	10.124		.192	.851
	CPA	.738	.116	.862	6.370	1.740E-5

c. Dependent Variable: DBH

2. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.873	.762	.726	12.299

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	6309.348	2	3154.674	20.856	8.772E-5
Residual	1966.402	13	151.262		
Total	8275.750	15			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	.032	.703	.037	.046	.964
CPA^2	.004	.004	.836	1.017	.328
(Constant)	27.822	27.376		1.016	.328

c. Dependent variable: DBH

3. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.824	.678	.656	13.786

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5615.041	1	5615.041	29.545	8.781E-5
Residual	2660.709	14	190.051		
Total	8275.750	15			

b. Dependent variable: DBH

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	52.092	9.584	.824	5.436	8.781E-5
(Constant)	-163.911	41.957		-3.907	.002

b. Dependent variable: DBH

4. Model summary: Power

Goodness of fit statistics:

Observations	16.000
DF	14.000
R^2	0.744
SSE	2128.502
MSE	152.036
RMSE	12.330
Iterations	34.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.750	0.604	1.242236
pr2	1.003	0.176	5.686526

Equation of the model:

DBH = .750(CPA $^{1.003}$)

...Continued Appendix 11

5. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.785	.617	.589	1.582E3

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.635E7	1	5.635E7	22.515	3.134E-4
	Residual	3.504E7	14	2502576.948		
	Total	9.138E7	15			

b. Dependent variable: biomass

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2990.981	1300.595		-2.300	.037
	CPA	70.591	14.877	.785	4.745	3.134E-4

c. Dependent variable: biomass

6. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.831	.690	.642	1476.265

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	6.305E7	2	3.153E7	14.465	4.945E-4
Residual	2.833E7	13	2179358.875		
Total	9.138E7	15			

b. Dependent variable: biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	-75.421	84.398	-.839	-.894	.388
CPA^2	.890	.508	1.647	1.754	.103
(Constant)	2364.886	3285.973		.720	.484

c. Dependent variable: biomass

7. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.723	.523	.489	1764.394

Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	4.780E7	1	4.780E7	15.354	.002
Residual	4.358E7	14	3113085.986		
Total	9.138E7	15			

b. Dependent variable: biomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
ln(CPA)	4806.264	1226.568	.723	3.918	.002
(Constant)	.523	5369.851		-3.367	.005

b. Dependent variable: biomass

8. Model summary: Power

Goodness of fit statistics:

Observations	16.000
DF	14.000
R^2	0.685
SSE	28823753.853
MSE	2058839.561
RMSE	1434.866
Iterations	200.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.034	0.081	0.412111
pr2	2.528	0.634	3.985341

Equation of the model:

Biomass = $30.035(CPA^{2.528})$

9. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.785	.617	.589	743.518

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.245E7	1	1.245E7	22.515	3.134E-4
	Residual	7739469.471	14	552819.248		
	Total	2.019E7	15			

b. Dependent variable: carbon

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1405.761	611.280		-2.300	.037
	CPA	33.178	6.992	.785	4.745	3.134E-4

c. Dependent variable: carbon

10. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.831	.690	.642	693.845

a. Predictor: CPA
ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.393E7	2	6963986.291	14.465	4.945E-4
Residual	6258464.881	13	481420.375		
Total	2.019E7	15			

b. Dependent variable: carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	-35.448	39.667	-.839	-.894	.388
CPA^2	.418	.239	1.647	1.754	.103
(Constant)	1111.496	1544.407		.720	.484

c. Dependent variable: carbon

...Continued Appendix 11

11. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.723	.523	.489	829.265

a. Predictor : CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.056E7	1	1.056E7	15.354	.002
Residual	9627529.720	14	687680.694		
Total	2.019E7	15			

b. Dependent variable: carbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	2258.944	576.487	.723	3.918	.002
(Constant)	-8498.686	2523.830		-3.367	.005

c. Dependent variable: carbon

12. Model summary: Power

Goodness of fit statistics:

Observations	16.000
DF	14.000
R^2	0.685
SSE	6367167.226
MSE	454797.659
RMSE	674.387
Iterations	200.000

Model parameters:

Parameter	Value	Standard error	t
pr1	0.016	0.038	0.412111
pr2	2.528	0.634	3.985341

Equation of the model:

Carbon = 0.016(CPA $^{2.528}$)

Appendix 12 Species of two-intermingled canopy trees and their number

S.N.	Species	Number of intermingled canopy	Number of trees
1	*Adina cordifolia* with itself	1	2
2	*Adina cordifolia* and *Shorea robusta*	2	4
3	*Aesandra butyracea* and *Sigane**	1	2
4	*Lagerstromia parviflora* with itself	1	2
5	*Schima wallichii* with itself	3	6
6	*Schima wallichii* and *Semicarpus anacardium*	1	2
7	*Semicarpus anacardium* with itself	2	4
8	*Semicarpus anacardium* and *Tiyari**	1	2
9	*Shorea robusta* with itself	51	102
10	*Shorea robusta* and *Semicarpus anacardium*	1	2
12	*Shorea robusta* and *Terminalia bellirica*	1	2
13	*Shorea robusta* and *Tiyari**	1	2
14	*Shorea robusta* and *Tiyari**	1	2
15	*Terminalia alata* with itself	3	6
16	*Terminalia alata* and *Lagerstromia parviflora*	1	2
17	*Terminalia alata* and *Shorea robusta*	1	2
18	*Terminalia alata* and *Terminalia bellirica*	1	2
	Total	**73**	**146**

* Vernacular name

Appendix 13 DBH, ΣBA, Σcarbon and CPA of two-intermingled *Shorea robusta*

Two intermingled canopy trees of *Shorea robusta*							
S.N.	**DBH1**	**DBH2**	**BA 1**	**BA2**	**ΣBA (cm^2)**	**Σcarbon (kg)**	**CPA (m^2)**
1	35	37	967.75	1081.51	2049.26	531.84	102.98
2	39	41	1201.59	1327.99	2529.58	682.60	87.69
3	55	39	2389.75	1201.59	3591.34	1046.54	84.61
4	48	48	1820.16	1820.16	3640.32	1050.66	118.71
5	63	63	3135.51	3135.51	6271.02	2002.06	148.97
6	53	49	2219.11	1896.79	4115.9	1216.11	129.23
7	45	37	1599.75	1081.51	2681.26	734.20	118.17
8	51	67	2054.79	3546.31	5601.1	1764.87	93.56
9	23	20	417.91	316	733.91	157.72	48.10
10	32	39	808.96	1201.59	2010.55	521.96	76.58
11	33	34	860.31	913.24	1773.55	448.00	64.13
12	42	58	1393.56	2657.56	4051.12	1205.57	98.57
13	51	59	2054.79	2749.99	4804.78	1463.38	149.34
14	51	75	2054.79	4443.75	6498.54	2120.03	133.90
15	38	35	1140.76	967.75	2108.51	550.34	96.25
16	49	36	1896.79	1023.84	2920.63	817.24	98.97
17	52	50	2136.16	1975	4111.16	1213.84	129.53
18	40	62	1264	3036.76	4300.76	1304.72	123.19
19	10	40	79	1264	1343	353.69	79.42
20	52	38	2136.16	1140.76	3276.92	937.03	90.18
21	22	28	382.36	619.36	1001.72	228.98	70.64
22	38	52	1140.76	2136.16	3276.92	937.03	104.59
23	58	32	2657.56	808.96	3466.52	1023.68	109.87
24	58	40	2657.56	1264	3921.56	1163.76	73.80
25	64	44	3235.84	1529.44	4765.28	1466.52	120.38
26	38	25	1140.76	493.75	1634.51	413.78	119.00
27	48	45	1820.16	1599.75	3419.91	976.12	123.49
28	58	58	2657.56	2657.56	5315.12	1645.62	85.12
29	77	114	4683.91	10266.84	14950.75	5695.38	163.94
30	51	62	2054.79	3036.76	5091.55	1570.31	80.97
31	65	60	3337.75	2844	6181.75	1969.70	93.01
32	81	86	5183.19	5842.84	11026.03	3910.13	138.99
33	30	49	711	1896.79	2607.79	724.02	108.94
34	52	72	2136.16	4095.36	6231.52	2008.99	154.57
35	65	77	3337.75	4683.91	8021.66	2688.97	124.17
36	56	59	2477.44	2749.99	5227.43	1613.96	133.43
37	62	48	3036.76	1820.16	4856.92	1489.10	88.48
38	48	58	1820.16	2657.56	4477.72	1348.14	89.56
39	34	26	913.24	534.04	1447.28	354.70	60.06

40	45	65	1599.75	3337.75	4937.5	1528.82	94.50
41	58	42	2657.56	1393.56	4051.12	1205.57	95.62
42	58	71	2657.56	3982.39	6639.95	2151.87	122.49
43	53	90	2219.11	6399	8618.11	2996.41	142.54
44	88	49	6117.76	1896.79	8014.55	2762.60	133.92
45	45	53	1599.75	2219.11	3818.86	1115.25	89.77
46	47	35	1745.11	967.75	2712.86	748.18	103.20
47	54	54	2303.64	2303.64	4607.28	1389.14	69.32
48	51	54	2054.79	2303.64	4358.43	1301.11	71.02
49	54	57	2303.64	2566.71	4870.35	1484.14	87.89
50	41	21	1327.99	348.39	1676.38	435.50	85.33
51	61	77	2939.59	4683.91	7623.5	2538.26	105.98
Note: Data in grey shade are outliers							

Appendix 14 DBH, ΣBA, Σcarbon and CPA of three-intermingled canopy trees of *Shorea robusta*

Three intermingled canopy trees of *Shorea robusta*									
S.N.	DBH1	DBH2	DBH3	BA1	BA2	BA3	ΣBA(cm²)	Σcarbon (kg)	CPA (m²)
1	42	36	29	1393.56	1023.84	664.39	3081.79	807.41	205.74
2	44	20	25	1529.44	316.00	493.75	2339.19	605.19	83.88
3	43	43	57	1460.71	1460.71	2566.71	5488.13	1599.03	97.04
4	49	71	50	1896.79	3982.39	1975.00	7854.18	2459.43	204.75
5	44	71	57	1529.44	3982.39	2566.71	8078.54	2546.03	206.79
6	35	43	48	967.75	1460.71	1820.16	4248.62	1178.49	200.21
7	33	43	29	860.31	1460.71	664.39	2985.41	779.86	136.77
8	25	27	29	493.75	575.91	664.39	1734.05	405.20	150.65
9	44	35	37	1529.44	967.75	1081.51	3578.7	959.24	175.14
10	34	30	59	913.24	711.00	2749.99	4374.23	1261.14	75.17
11	42	30	40	1393.56	711.00	1264.00	3368.56	896.09	178.01
12	60	43	42	2844	1460.71	1393.56	5698.27	1679.17	156.46
13	47	58	55	1745.11	2657.56	2389.75	6792.42	2048.01	227.05
14	30	27	37	711.00	575.91	1081.51	2368.42	590.05	116.21
15	65	34	42	3337.75	913.24	1393.56	5644.55	1692.72	252.53
16	55	48	54	2389.75	1820.16	2303.64	6513.55	1945.36	161.95
17	31	26	50	759.19	534.04	1975.00	3268.23	887.80	83.67
18	45	43	87	1599.75	1460.71	5979.51	9039.97	3007.37	239.84
19	48	39	52	1820.16	1201.59	2136.16	5157.91	1481.54	128.93
20	34	50	46	913.24	1975.00	1671.64	4559.88	1285.55	110.25
21	44	63	42	1529.44	3135.51	1393.56	6058.51	1811.20	152.09
22	58	53	35	2657.56	2219.11	967.75	5844.42	1735.69	247.04
23	28	27	33	619.36	575.91	860.31	2055.58	496.70	185.43

Four-intermingled canopy trees of *Shorea robusta*										
S.N.	D1	D2	D3	D4	C1	C2	C3	C4	Carbon (kg)	CPA (m²)
1	63	54	53	71	1001.03	694.57	664.46	1329.06	3689.12	115.29
2	55	76	67	47	725.46	1561.78	1158.33	499.75	3945.32	277.83
Note: C1, C2, C3, C4 are calculated carbon of trees of the corresponding DBH (D1, D2, D3, D4).										

Appendix 15 ΣBA, Σcarbon and CPA of intermingled canopy trees (two and three intermingled canopy trees together) of *Shorea robusta*

Shorea robusta (intermingled)							
S.N.	ΣBA (cm2)	Σcarbon (kg)	CPA (m^2)	S.N.	ΣBA (cm^2)	Σcarbon (kg)	CPA (m^2)
1	2049.26	531.84	102.98	38	4477.72	1348.14	89.56
2	2529.58	682.60	87.69	39	1447.28	354.70	60.06
3	3591.34	1046.54	84.61	40	4937.5	1528.82	94.50
4	3640.32	1050.66	118.71	41	4051.12	1205.57	95.62
5	6271.02	2002.06	148.97	42	6639.95	2151.87	122.49
6	4115.9	1216.11	129.23	43	8618.11	2996.41	142.54
7	2681.26	734.20	118.17	44	8014.55	2762.60	133.92
8	5601.1	1764.87	93.56	45	3818.86	1115.25	89.77
9	733.91	157.72	48.10	46	2712.86	748.18	103.20
10	2010.55	521.96	76.58	47	4607.28	1389.14	69.32
11	1773.55	448.00	64.13	48	4358.43	1301.11	71.02
12	4051.12	1205.57	98.57	49	4870.35	1484.14	87.89
13	4804.78	1463.38	149.34	50	1676.38	435.50	85.33
14	6498.54	2120.03	133.90	51	7623.5	2538.26	105.98
15	2108.51	550.34	96.25	52	3081.79	807.41	205.74
16	2920.63	817.24	98.97	53	2339.19	605.19	83.88
17	4111.16	1213.84	129.53	54	5488.13	1599.03	97.04
18	4300.76	1304.72	123.19	55	7854.18	2459.43	204.75
19	1343	353.69	79.42	56	8078.54	2546.03	206.79
20	3276.92	937.03	90.18	57	4248.62	1178.49	200.21
21	1001.72	228.98	70.64	58	2985.41	779.86	136.77
22	3276.92	937.03	104.59	59	1734.05	405.20	150.65
23	3466.52	1023.68	109.87	60	3578.7	959.24	175.14
24	3921.56	1163.76	73.80	61	4374.23	1261.14	75.17
25	4765.28	1466.52	120.38	62	3368.56	896.09	178.01
26	1634.51	413.78	119.00	63	5698.27	1679.17	156.46
27	3419.91	976.12	123.49	64	6792.42	2048.01	227.05
28	5315.12	1645.62	85.12	65	2368.42	590.05	116.21
29	14950.75	5695.38	163.94	66	5644.55	1692.72	252.53
30	5091.55	1570.31	80.97	67	6513.55	1945.36	161.95
31	6181.75	1969.70	93.01	68	3268.23	887.80	83.67
32	11026.03	3910.13	138.99	69	9039.97	3007.37	239.84
33	2607.79	724.02	108.94	70	5157.91	1481.54	128.93
34	6231.52	2008.99	154.57	71	4559.88	1285.55	110.25
35	8021.66	2688.97	124.17	72	6058.51	1811.20	152.09
36	5227.43	1613.96	133.43	73	5844.42	1735.69	247.04
37	4856.92	1489.10	88.48	74	2055.58	496.70	185.43
Note: Data in grey colour are outliers.							

Appendix 16 Regression models (with ANOVA) of CPA with ΣBA, Σbiomass and Σcarbon separately of intermingled canoy trees of *Shorea robusta*

1. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.539	.290	.273	1667.095

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.662E7	1	4.662E7	16.774	1.932E-4
	Residual	1.139E8	41	2779204.600		
	Total	1.606E8	42			

b. Dependent variable: ΣBA

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2073.445	677.493		3.060	.004
	CPA	20.897	5.102	.539	4.096	1.932E-4

a. Dependent variable: ΣBA

2. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.573	.328	.294	1642.349

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5.267E7	2	2.634E7	9.764	3.522E-4
Residual	1.079E8	40	2697311.173		
Total	1.606E8	42			

b. Dependent variable: ΣBA

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	63.795	29.070	1.645	2.195	.034
CPA ^{2}	-.139	.093	-1.123	-1.498	.142
(Constant)	-747.318	1997.490		-.374	.710

c. Dependent Variable: ΣBA

...Continued Appendix 16

3. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.572	.327	.310	1623.715

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5.247E7	1	5.247E7	19.902	6.223E-5
Residual	1.081E8	41	2636450.722		
Total	1.606E8	42			

b. Dependent variable: ΣBA

Coeficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	3025.203	678.115	.572	4.461	6.223E-5
(Constant)	-9700.656	3225.267		-3.008	.004

c. Dependent variable: ΣBA

4. Model summary: Power

Goodness of fit statistics:

Observations	43.000
DF	41.000
R^2	0.308
SSE	111229137.925
MSE	2712905.803
RMSE	1647.090
Iterations	17.000

Model parameters:

Parameter	Value	Standard error	t
pr1	298.269	196.550	1.517519
pr2	0.575	0.134	4.294616

Equation of the model:

$\Sigma BA = 298.269*(CPA^{0.574})$

5. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.498	.248	.229	1291.069

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.249E7	1	2.249E7	13.492	.001
	Residual	6.834E7	41	1666860.291		
	Total	9.083E7	42			

b. Dependent Variable: Σbiomass

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1221.252	524.679		2.328	.025
	CPA	14.514	3.951	.498	3.673	.001

c. Dependent Variable: Σbiomass

6. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.537	.288	.253	1271.177

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.619E7	2	1.310E7	8.105	.001
Residual	6.464E7	40	1615890.877		
Total	9.083E7	42			

b. Dependent variable: Σbiomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	48.074	22.500	1.648	2.137	.039
CPA ^{2}	-.109	.072	-1.168	-1.514	.138
(Constant)	-985.447	1546.056		-.637	.527

b. Dependent variable: Σbiomass

...Continued Appendix 16

7. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.533	.284	.266	1259.573

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.578E7	1	2.578E7	16.251	2.351E-4
Residual	6.505E7	41	1586523.069		
Total	9.083E7	42			

b. Dependent variable: Σbiomass

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	2120.585	526.038	.533	4.031	2.351E-4
(Constant)	-7048.594	2501.953		-2.817	.007

c. Dependent variable: Σbiomass

8. Model summary: Power

Goodness of fit statistics:

Observations	43.000
DF	41.000
R^2	0.263
SSE	66977248.444
MSE	1633591.425
RMSE	1278.120
Iterations	6.000

Model parameters:

Parameter	Value	Standard error	t
pr1	163.223	128.505	1.270168
pr2	0.610	0.159	3.821967

Equation of the model:

Σbiomass = 163.223(CPA $^{0.609}$)

9. Model Summary: Simple linear

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.498	.248	.229	606.802

a. Predictor: CPA

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4967736.321	1	4967736.321	13.492	.001[a]
	Residual	1.510E7	41	368209.438		
	Total	2.006E7	42			

b. Dependent variable: Σcarbon

Coefficients

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	573.989	246.599		2.328	.025
	CPA	6.821	1.857	.498	3.673	.001

c. Dependent variable: Σcarbon

10. Model Summary: Quadratic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.537	.288	.253	597.453

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5786311.495	2	2893155.748	8.105	.001
Residual	1.428E7	40	356950.295		
Total	2.006E7	42			

b. Dependent variable: Σcarbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	22.595	10.575	1.648	2.137	.039
CPA ^{2}	-.051	.034	-1.168	-1.514	.138
(Constant)	-463.160	726.646		-.637	.527

c. Dependent variable: Σcarbon

...Continued Appendix 16

11. Model Summary: Logarithmic

R	R Square	Adjusted R Square	Std. Error of the Estimate
.533	.284	.266	591.999

a. Predictor: CPA

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	5695342.508	1	5695342.508	16.251	2.351E-4
Residual	1.437E7	41	350462.946		
Total	2.006E7	42			

b. Dependent variable : Σcarbon

Coefficients

	Unstandardised Coefficients		Standardised Coefficients		
	B	Std. Error	Beta	t	Sig.
ln(CPA)	996.675	247.238	.533	4.031	2.351E-4
(Constant)	-3312.839	1175.918		-2.817	.007

c. Dependent variable: Σcarbon

12. Model summary: Power

Goodness of fit statistics:

Observations	43.000
DF	41.000
R^2	0.263
SSE	14795274.181
MSE	360860.346
RMSE	600.717
Iterations	6.000

Model parameters:

Parameter	Value	Standard error	t
pr1	76.715	60.397	1.270168
pr2	0.610	0.159	3.821967

Equation of the model:

$\Sigma carbon = 76.715(CPA^{0.609})$