Estimating and Mapping Aboveground Carbon Stocks in Cocoa Plantation Using Worldview-2 Satellite Image and Lidar Data

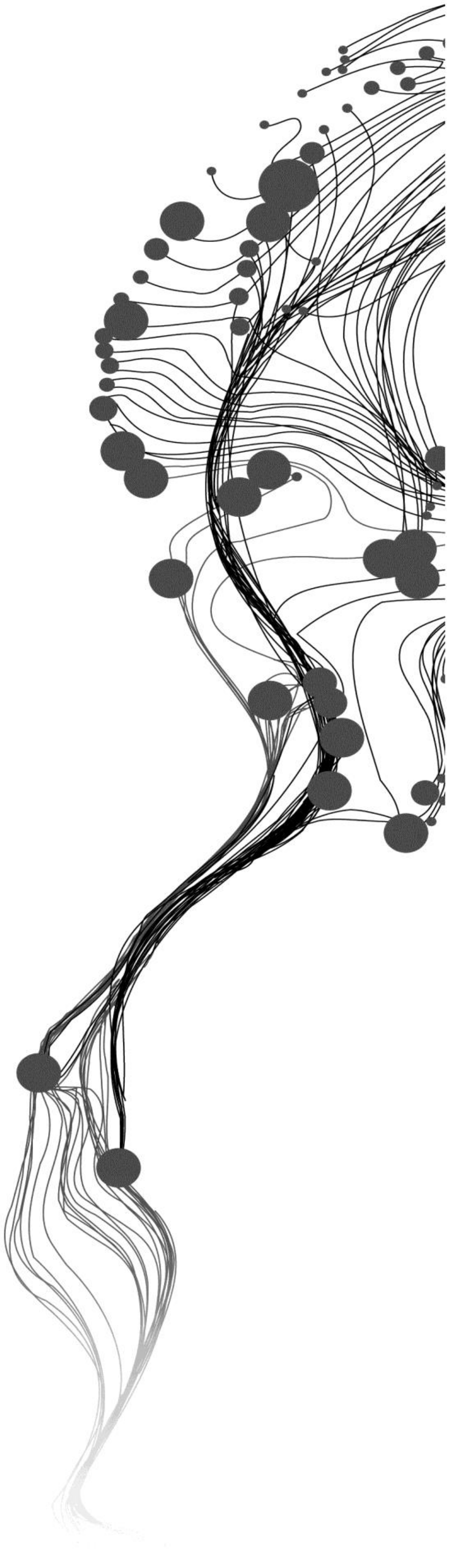
MALEDA ABEBE TESEMA

Enschede, The Netherlands, February, 2015

SUPERVISORS:

Ir. L. M. Van Leeuwen

Dr. R. Darvishzadeh (Roshanak)



Estimating and Mapping Aboveground Carbon Stocks in Cocoa Plantation Using Worldview-2 Satellite Image and Lidar Data

MALEDA ABEBE TESEMA

Enschede, The Netherlands, February, 2015

Thesis submitted to the Faculty of Geo- Information Science and Earth Observation of the University of Twente in partial fulfilment of the Requirements for Master of Science Degree in Geo-information Science and Earth Observation.

Specialization: Natural Resources Management

SUPERVISORS:

Ir. L. M. Van Leeuwen

Dr. R. Darvishzadeh (Roshanak)

THESIS ASSESSMENT BOARD:

Dr. Yousif Hussin (Chairman)

Dr. ir. J. G. P. W. Clevers (External Examiner,
Wageningen University)

DISCLAIMER

Abstract

Estimation of carbon stock has gained attention in the context of the United Nations Framework Convention on Climate Change (UNFCCC) and Kyoto Protocol. Estimating and mapping of carbon produced by cocoa plantation using field based data collection methods is both expensive and time consuming. Satellite remote sensing is a low cost alternative in estimating and mapping carbon stocks in large cocoa plantation areas. The overall aim of this study was to develop a method for estimating and mapping carbon stocks in cocoa plantation using Worldview-2 Imagery and Lidar data in Goaso district, Ghana. A total of 57 sample plots and 52 shade trees were considered in the field and several parameters such as DBH, height, and crown diameter of shade trees were measured. In case of cocoa carbon content estimation, total aboveground biomass (AGB) was estimated using allometric equation from height derived from Lidar data and DBH measured in the field work. Consequently the AGB were converted into carbon stock using a conversion factor. Regression model were developed using height derived from Lidar data and DBH measured from field work for predicted carbon. Pan-sharpened Worldview-2 image and Lidar derived height were used for CPA extract and height of the individual trees.

The Pan-sharpened Worldview-2 imagery and predicted carbon were used for cocoa carbon stock mapping. The relationships between calculated carbon and predicted carbon for cocoa trees were examined using coefficient determination (R^2) was found to be 79%. Object based image analysis was carried out in Worldview-2 image to obtain CPA. Non-linear regression model were developed using CPA for carbon estimation of shade trees. The correlation coefficient of CPA and predicted carbon, calculated carbon and predicted carbon was 74% and 84% respectively. The coefficient of determination (R^2) showed that Lidar derived tree height was able to explain 78% of variability in field measured height, which means that the 78% of the Lidar derived height was explained by field measured height.

Keywords: Cocoa Plantation, Worldview-2 image, Lidar data, Carbon stocks, Image Segmentation

Acknowledgements

I would like to take this opportunity to thank all the special peoples and organizations whose efforts and contributions are valuable for me to accomplish my study in Faculty of Geo-information Science and Earth Observation (ITC), University of Twente.

First and foremost I would like to express my sincere gratitude and appreciation to my first supervisor, Ms. Ir. L.M. Louise van Leeuwen for her creative guidance, constructive feedback and comments and words of encouragement from the very beginning till the completion of this research and for bringing ideas to shape up my work. Sincere thanks goes to my second supervisor Dr. R. Darvishzadeh (Roshanak) whose critical suggestions and continuous support to me from beginning till the end and the inspirations have added strength in me.

My deepest appreciation goes to Dr. Yousif Hussin for his comments and suggestions during my proposal and mid-term defense, which has added flavor in my research. I'm also thankful to NRM department faculty members who always supported my study.

I would like to acknowledges the sponsorship I received from the Government of the Netherlands under Netherlands Fellowship Programme (NFP) to make my dream come true. Thanks goes to Kwame Nkrumah University of Science and Technology (Faculty of Renewable Natural Resources and Goaso forest district for their support during the fieldwork and other logistics support.

Maleda Abebe

Enschede, The Netherlands

February, 2015

Table of Contents

List of Figures

List of Tables

List of Appendixes

List of Acronyms

AGB	Above Ground Biomass
CO_2	Carbon Dioxide
CPA	Crown Projection Area
DBH	Diameter at Base Height
DN	Digital Number
FAO	Food Agricultural Organization
GPS	Global Positioning System
IPCC	International Panel on Climate Change
OBIA	Object Based Image Analysis
REDD+	Reducing Emissions from Deforestation and Forest Degradation
RMSE	Root Mean Square Error
UNFCCC	United Nations Framework Convention on Climate Change
LiDAR	Light Detection and Ranging

1. Introduction

1. 1. Background

Forests play a key role in global warming and climate change through their unique nature of carbon storages capacity. Forests sequester and store more carbon compared than any other terrestrial ecosystem and it are considered as an important brake on climate change (Gibbs *et al.*, 2007). Tropical deforestation is estimated to have released on the order of 1-2 billion tons of carbon per year, these accounts about 15-20% of annual global fossil fuel emissions during the 1990s (Malhi & Grace, 2000; Earnside & Laurance, 2004). Increasing the amount of greenhouse gas in the atmosphere leads to rising temperature of the earth and to rising attention about global warming and climate change issues. In most of tropical countries deforestation and forest degradation are said to be the main sources of green house gas emission (Gibbs *et al.,* 2007). The conversion of tropical forests to agricultural land and pasture land has been a major cause of global carbon emission (Paustian *et al.,* 2000). The amount of carbon stock change varies with the land use changes (e.g. conversion of forest lands to agricultural lands), and with ecosystem types (moist tropical forest or dry tropical forest) (Moutinho & Schwartzman, 2005).

The United Nations Collaborative Programme on Reducing Emissions from Deforestation and Forest Degradation in Developing Countries (UN-REDD Programme) was produced in September 2008 to support developing countries to build capacity to reduce emission and to participate in a future REDD+ mechanism. (REDD+) refers to Reducing Emissions from Deforestation and Forest Degradation (REDD+). REDD+ is a global regime to mitigate carbon emissions and to recompense tropical forest countries for their efforts in forest conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries. Thus, REDD+ aims to reduce atmospheric greenhouse gas concentration and contribute to climate change mitigation through five main activities: (i) Reducing emissions from deforestation, (ii) Reducing emissions from degradation, (iii) Reducing emissions through the role of conservation, (iv) Sustainable forest management, and (v) Enhancement of carbon stock(Asare & Kwakye, 2013).

United Nations Framework Convention on Climate Change (UNFCCC) on December 1997 adopted the Kyoto Protocol, which sets a legally binding target to industrialized countries to reducing GHG emissions(UNFCC, 1998).The UNFCCC have established reduction of greenhouse gas emissions programs through credits for forest conservation, reforestation, and afforestation. Reduction of greenhouse gas emission programs require scientifically vigorous methods to compute forest carbon stock across different spatial and temporal scales(P. Gonzalez *et al.,* 2010).

The Cocoa(Theobroma cacao L) is an understory tree species which is developed in the Amazon(Motamayor *et al.,* 2008), but is currently grown by smallholder farmers in different humid tropical countries. Cocoa cultivation has played a significant role in the alteration of lowland tropical forest landscapes in Africa, Latin America and Asia over the past centuries and continues until now (Schroth & Harvey, 2007). Cocoa is the major important agricultural commodity crop in lowland forests in West Africa and it is produced largely by smallholder farmers. Cocoa trees mostly grow under thinned forest canopy of naturally regenerating or artificially planted canopy trees which typically produces fruits and timbers(Rice & Greenberg, 2000).

In Ghana, Cocoa farms were mainly established either by slashing and burning the original forest and then planting cocoa trees or by planting cocoa trees under a thinned forest over-story (Gockowski & Sonwa, 2011). Planted cocoa trees by slash and burn will typically have a higher carbon emissions over time than planted cocoa trees under a thinned forest over-story(Gockowski & Sonwa, 2011). According to (Asae *et al.,* 2008) reviewed, the higher cocoa yields in the un-shaded farms could be described by higher cocoa trees density and reduction in shaded trees. Un-shaded cocoa had a higher density of cocoa trees than shaded cocoa trees per plot and consequently productivity of un shaded cocoa farms higher than shaded cocoa farms by 73% (Asase *et al.,* 2008).

In Ghana, the climate smart agriculture (CSA) cocoa initiatives program has focused on building and supporting initiatives that reduce vulnerability, enhance food security, mitigate and adapt the impact of climate change through climate smart agriculture(cocoa) interventions within the context of national REDD+ Readiness activities (FAO, 2010).Therefore the capacity to accurately and precisely measure the amount of carbon stored or carbon sequestered by cocoa plantation is an important issues to increasing the gaining of global attention in recognition of the role of cocoa plantation in the global carbon cycle, particularly with respect to reducing carbon emissions.

1.2. Techniques for aboveground carbon estimation

There are different methods, approaches and techniques to estimate aboveground biomass and carbon stocks. The aboveground biomass can be accurately estimated by destructive methods of harvesting, weighting (Greenberg *et al.,* 2005), but this methods is not a practical approach because it is time consuming, extremely costly, and labour intensive, inappropriate for large scale biomass and carbon estimation (Brown, 2002). Using Worldview-2 multispectral satellite image is a low cost alternative for estimating and mapping carbon stock in large forest area. Aboveground biomass can be estimated using allometric equations based on field measurement of diameter at breast height(DBH) and tree height (Gibbs *et al.,* 2007) and consequently converted to carbon stocks. Carbon stocks estimation based on remote sensing approach consists of the set of all the knowledge and techniques to get information of the tree height and crown projection area of a tree from object, scene through the analysis of remote sensing data measurements.

The Intergovernmental Panel on Climate Change (IPCC) has provided different levels of methodology alternatives for estimating greenhouse gas (GHG) emission. These alternatives are specified at different Tiers, which relate to methodological complexity(IPCC, 2006). More accurate measurement means a higher compensation level for countries, as inaccurate measurement results in reduction of compensation. IPCC also recommends that carbon stocks in the most significant categories and pools area estimated according to the higher tiers. Tier 3 requires the most rigorous approach to directly measuring changes in forest biomass, and consequently changes in carbon stocks. However, tiers 3 estimates can be achieved and verified by adopting a high resolution satellites imagery based biomass and carbon assessments methods(IPCC, 2006). And therefore this info is also important for cocoa trees.

1.3. Image Segmentation

Image segmentation is a process that delineates an image into regions of neighbouring pixels that share some similar characteristics. Segmentation is the partitioning of a digital image into multiple regions or spatial clusters based on spectral and textural image information to simplify and/or change the representation of an image into building blocks which are useful for further analysis(Möller *et al.,* 2007; Drăguţ *et al.,* 2010; Gibbes *et al,* 2010;). Region based category will be used to generate objects according to a certain homogeneity criteria of colour, texture (compactness and smoothness), and shape properties. The expectation for a segmentation algorithm is that it will arrange the pixels into homogeneous related groups called as "object candidates" which can be further processed/classified into meaningful objects (Blaschke, 2010).

Object-based image segmentation is a recently developed technique, which involves the delineation of homogeneous image regions called segments and classifies them to individual objects by utilizing object level spectral information as well as additional auxiliary measures (Blaschke & Hay, 2001; Hay *et al.,* 2003).

In order to obtain image objects, object based classification starts by segmenting the whole image. The object-based classification approaches in remote sensing has suggested that the rule based classifier and the standard nearest neighbor classifier are among the most commonly employed image object classifiers, which is popularized by the availability of commercial software such as eCognition(Blaschke, 2010,) The rule-based classifier assign the objects to a particular class using a set of rules derived from human knowledge using spectral characteristics. The image object classification process is restricted by a human knowledge base that describes the characteristics of the output object classes(Darwish, *et al.,* 2003). For this research simple ratio, brightness and mean layer criteria were used for image object classification.

1.4. Extraction of Crown Projection Area (CPA) from Shade Trees

The crown projection area of a tree is the area of the vertical projection of the outermost perimeter of the crown on the horizontal plane(Gschwantner *et al.,* 2009)(see Figure: 1) Crown area or crown projection area is defined as the proportion of the forest floor that is covered by the vertical projection of the tree crowns (Jennings *et al.,*1999). Diameter at Breast Height (DBH) is very important in forest ecology, siliviculture and forest management (Shimano, 1997). CPA is calculated from the maximum crown diameter (Kuuluvainen, 1991) and DBH obtained from field measurement. Hirata *et al.,* (2009) established significant relationship between DBH measured from the field and CPA derived from Quick bird panchromatic data.

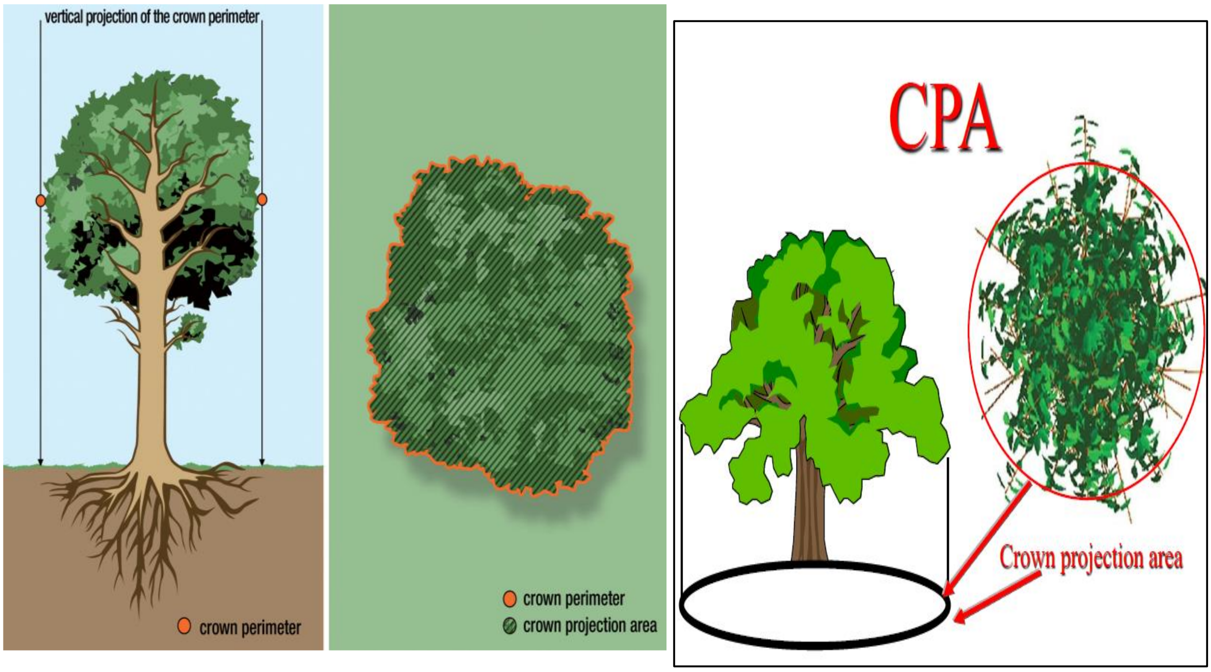


Figure 1. Crown Projection Area (CPA), Source:(Gschwantner *et al.,* 2009)

1.5. Operation of Lidar Remote Sensing

Lidar (Light Detection and Ranging) is an active remote sensing system and it is relatively new type of remote sensing that promises to provide accurate forest biomass estimation than other remote sensing techniques. The airborne sensor in a helicopter or an aero plane sends laser pulses towards the ground and records the time lapses between the launch of the beams and the return of the signals(Lefsky *et al.,* 2002). The greatest strength of Lidar lies in its capacity to monitor three-dimensional forest structure. Forest biomass and carbon content can be calculated from the information obtained from Lidar pulses. Lidar can be used to estimate tree height, aboveground biomass, timber volume, and crown properties(http://www.arbonaut.com/). This information makes it possible to estimate carbon content in all categories of forest, and to estimate forest degradation as well, which is represented as a reduction in vegetation height or density in Lidar point clouds.

The exact three dimensional locations of objects can be calculated using three factors: (i) the location of the sensor, (ii) the time beam takes to return to the sensor, and (iii) beam shooting direction. The tree separation from Lidar data is typically based on a canopy height model (CHM), which is the difference between canopy surface height and a digital elevation model (DEM) of the earth surface(Chen *et al.,* 2006). Digital Surface Model (DSM) and Digital Terrain Model (DTM) will be generated from Lidar point cloud data using lastools. DSM and DTM will be generated from elevation attribute of the first return of Lidar point and the last return of Lidar point cloud data respectively. Hence, Crown height model (CHM) was obtained by subtracting the digital terrain model (DTM) from digital surface model (DSM). Figure: 2 Shows that the different return signal wave forms of Lidar illumination.

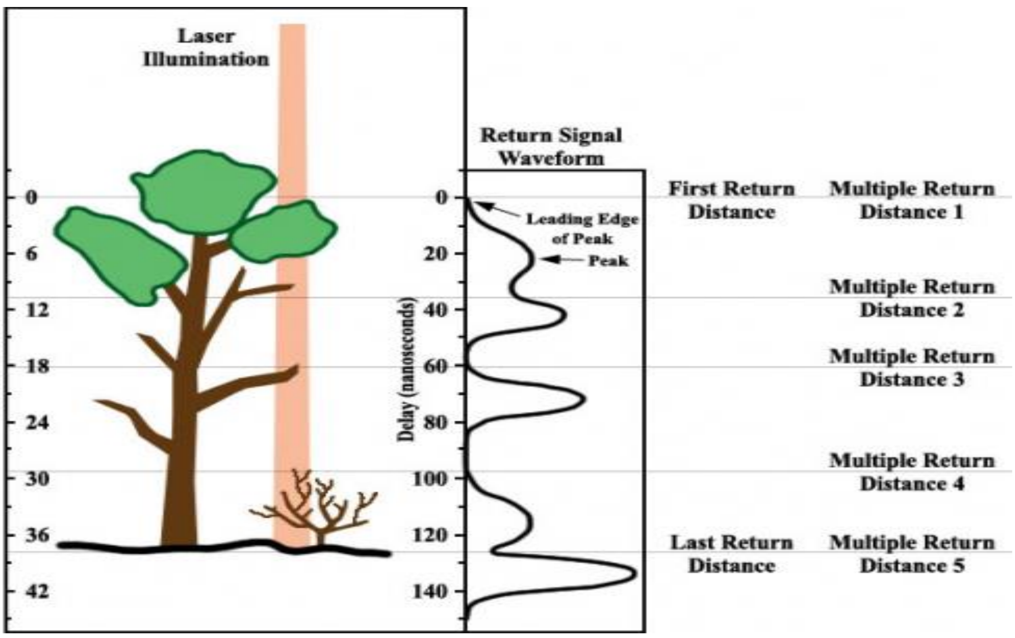


Figure 2. Different return signal wave form of Lidar illumination; Source: (Lim, *et al.,* 2003)

1.6. Problem Statement and Justification

Estimating and mapping aboveground carbon stock in cocoa plantation using conventional satellite based measurements is challenging due to the difficulty to identify the cocoa trees from forest within an images because the spectral signatures are similar, hence they look the same on an image, but are different in texture and shape. Cocoa trees in a plantation have smooth texture, uniform height, and canopy structure. On the other hand, forests have rough texture, different height, irregular multi-story canopy and structure. Estimates of aboveground carbon stocks in cocoa plantation have uncertainty because of the spatial heterogeneity in cocoa plantation and the inherent difficulty of producing field based inventories. Hence, a vigorous and consistent methodology is necessarily to overcome the uncertainty presents in cocoa plantation.

The current approach of tropical countries to forest inventory is both subjective and short of available datasets and also measuring of stand height or tree height by current manual photogrammetric or field survey techniques is time consuming and quite expensive (Popescu & Wynne, 2004). Satellite images alone are unable to map the vertical view of cocoa trees that is important for estimation of aboveground biomass and carbon stocks. Tropical forest canopies are multilayered, and structurally complex ecosystems with three dimensional arrangement of canopy components from the upper part of the canopy to the lower part of forest (Hernández-Stefanoni *et al.,* 2014). In this respect they are very similar to traditional cocoa plantations and it is very difficult to separate accurately the cocoa trees from shade trees when using optical remote sensing data.

The greater strength of Lidar data is the capacity to screen three dimensional forest structures. Individual tree and stand level physical attributes such as tree height, canopy height, canopy closure, and density can be generated from Lidar data(Zimble *et al.,* 2003). Worldview-2 satellite image analysis methods does not provide 3D structural forest information at either an individual tree or forest stand level for comprehensive biomass/ carbon estimation. WorldView-2 offers more wavebands (8 bands) and high spatial resolution; this can be used to separate cocoa from shade trees using object based image analysis techniques. A cocoa tree plantation, due to its horizontal canopy structure has a smoother texture than the irregular shade trees. Therefore, the combination of very high resolution satellites imagery and airborne Lidar data provides an accurate efficient measurement of carbon stock in a diversity multi-story forest types(Huda *et al.,* 2002).

The height and density distribution of Lidar points strongly correlates with the characteristics of underlying vegetation, which makes Lidar a powerful tool for accurate estimation of full spatial variability of forest carbon stocks (Lee & Lucas, 2007). Laser pulses penetrate in dense multilayered forest canopy, and for that reason there is a tendency of strong relationship between Lidar data and aboveground biomass(Cao *et al.,* 2014).Therefore, the combination of very high resolution imagery with airborne Lidar data at the individual tree level may provide a very useful inventory tools and provides a powerful suite of data for extracting the required tree parameters information (Leckie *et al.,* 2003) and also offered a significant advantages and greater accuracy for carbon estimation in tropical country(Gibbs *et al.,* 2007).

1.7. The General Objectives

- To develop a method for accurately estimating and mapping aboveground carbon stocks in cocoa plantations using worldview-2 satellite imagery and Lidar data.

1.7.1. The Specific Objectives

- To develop a method for separating cocoa trees from shade trees.
- To develop a model for estimation of the amount of carbon stocks in cocoa plantations using DBH and Lidar derived tree height.
- To develop a model for estimation of the amount of carbon stocks in coca plantations using Worldview-2 image and predicted carbon.
- To determine the relationship between crown projection area (CPA) and carbon stock of shade trees.

1.8. The Research Questions

- How can cocoa trees be separated from shade trees using remote sensing data
- What is the relationship between DBH, Lidar derived tree height and carbon stock in cocoa plantation?
- What is the relationship between the reflectance value of Worldview-2 image and predicted carbon?
- What is the relationship between crown projection area (CPA) and carbon stocks of shade trees
- How much aboveground carbon is stored by cocoa plantation in the study area?

1.9. The Research Hypothesis

- Ha: There is a significant difference between Lidar derived tree height and field measured tree height of shade trees.

2. Description of the study area

2.1. Location

The study area is located in south west of Goaso forest district in Brong Ahafo region, Ghana, West Africa. It is geographically located between latitudes 6°47'48" N and 7°06'44" and longitude 2°38'45"W and 2°17'53"W and it covers an area of approximately 29 km^2(see Figure: 3) The Goaso district has covered a land area of 2,187.5 km^2 out of which 592.99 km^2 under forest reserves (i.e. 27.11%)(Adhikari, 2005).

2.2. Climate

The climate in the region is hot and humid with mean annual rainfall ranging from 1500-1750mm. Mean annual temperature varies from 19 °C to 33 °C (Aduse-Poku et al., 2003). The study area has two distinct seasons, a wet season which starts from May/June to October/ November and a dry season starts from December/ January to April/ May(Adhikari, 2005).

2.3. Vegetation cover

Goaso district consists of a rural community where agriculture is the mainstay of the economy. The major land use is agriculture with cocoa trees, which is the major cash crop. There are other agricultural crops like oil palm, cassava, plantain, maize, cocoyam, citrus fruits but these crops are mainly for subsistence and not cultivated as the cash crop like cocoa. Farmers retaining trees in the farmland for the purpose of providing shade to the remaining old variety of cocoa plantation underneath. There is a wide variety of tree species in the study area. The forest type found in this area is moist semi-deciduous(Kotey *et al.,* 1998). Farmers prefer replacing old variety of cocoa by new improved cocoa variety, which gives higher yields and requires less shade trees once it is mature.

Much forest land outside forest reserves has been converted to agriculture through the course of this century. Today, the areas outside forest reserves are variety of agricultural fields, fallow lands, secondary forest patches and settlements. The farm and fallow areas also host substantial forest resources. Due to the nature of the dominant farming system in the high forest zone, trees on farms are gradually being removed by farmers because farmers don't benefit from them. The off-reserve forest resource provides much of the country's timber and is an important source of non-timber forest products.

Off-reserve forest resources, unlike those in the forest reserves, are not strictly under Forestry Department management, but under the control of individual and communal owners. The off-reserve lands are not managed for timber production, but for agriculture and other forms of land use by their owners(Kotey *et al.,* 1998).

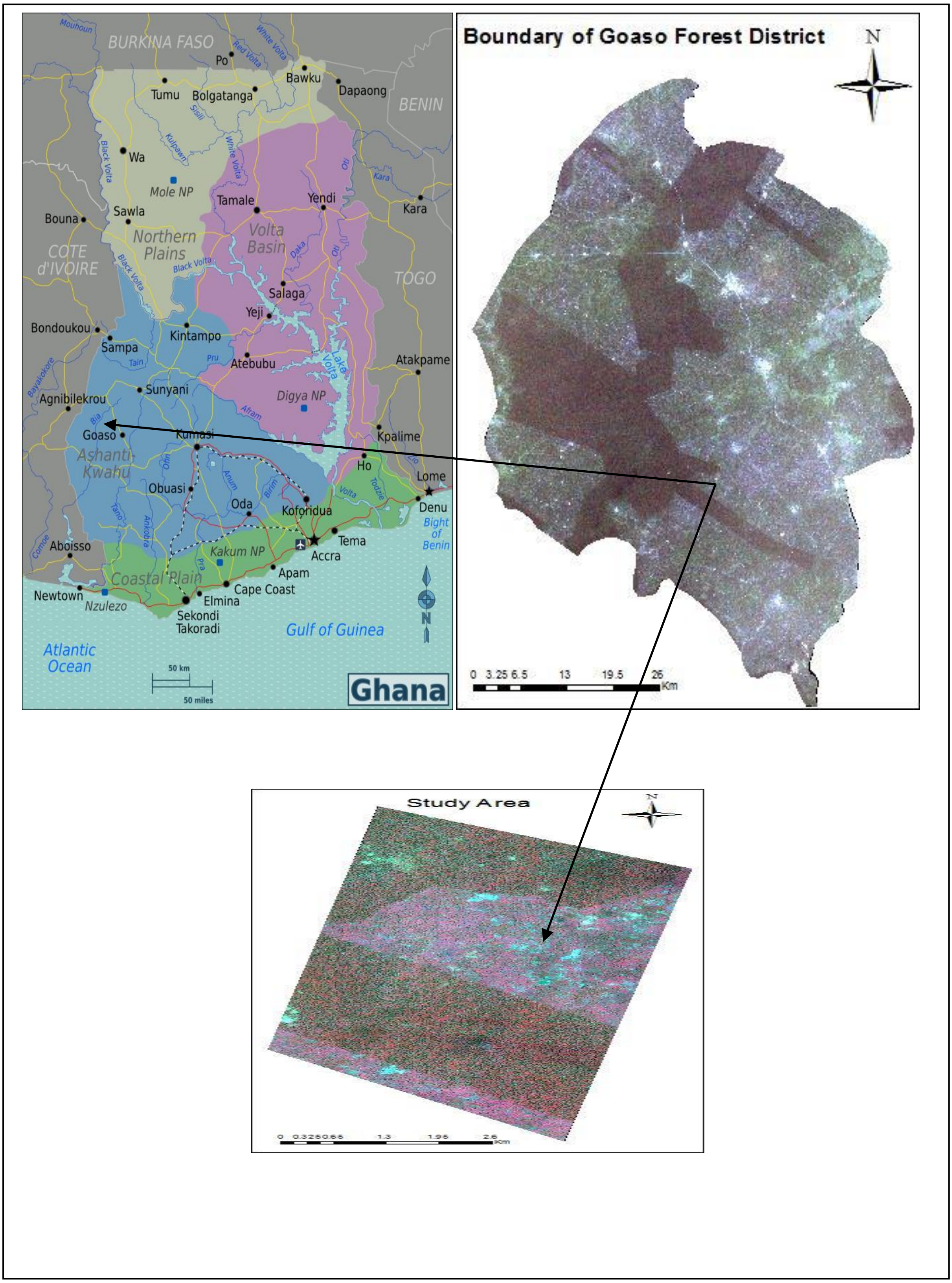


Figure 3. Location of the study area

3. Materials and Methods

3.1. Datasets and Materials

3.1.1. Satellite data

Two different satellite data of Goaso district were used in the study area. The high resolution satellite imagery of optical satellite sensor worldview-2 was acquired on January 2013, and covers an area of 2907 ha. The Worldview-2 satellite sensor provides panchromatic data at a spatial resolution of 0.5m as well as multispectral data divided into eight spectral bands at a spatial resolution 2m. For the purpose of this research four spectral bands are used 0.45–0.51 µm(band 2-blue), 0.51–0.58µm(band 3-green), 0.63–0.69µm(band 5-red), and 0.86–1.04µm(band 8-near-infrared2).

Airborne Lidar data where acquired on January 2013, and contains three classification codes, these are first return second return and return. The classification codes are used as a query filter for Lidar data points. The Lidar data obtained for the study was ortho-rectified and geo-referenced to the UTM WGS 84 coordinate system. The minimum and maximum value of Lidar data described in Table: 1.

Table 1. The minimum and maximum value of Lidar data information

Lidar points info	Minimum	Maximum
X	-245500915	54722854
Y	-26763464	73788360
Z	23638	129969
Intensity	0	255
Return number	1	2
Number of returns	1	3
Classification codes	1	3

3.1.2. Instruments used for field data collection

Various equipments were used during the fieldwork for data collection. GPS and iPAQ were used for navigation to the sample plot and recording the centre of sample plot. Height of the tree was measured using haga clinometer. DBH of a tree was measured using a diameter tape, percent of plot canopy closure were measured using a spherical densitometer; Compass Suunto was used for bearing/direction measurement. Table: 2 shows the various equipments used during the field work.

Table 2. Field equipments used for data collection in the field

No	Instrument	Purpose
1	Garmin GPS and iPAQ	Navigate sample plot location
2	Haga Altimeter	Tree height measurement
3	Diameter tape(5m)	DBH measurement
4	Suunto Clinometers	Slope and Aspect measurement
5	Spherical densitometer	Percent of plot canopy closure measurement
6	Compass Suunto	Bearing/direction measurement
7	Measuring tape (50 m)	Measuring the radius of sample plot
8	Digital Camera	Taking pictures of trees and other observations
9	Data sheet	Recording tree parameters

3.1.3. Software's and Tools

Various software's and tools were used for data preparation, processing and analysis(see Table:3). Erdas imagine 2013 and eCognition Developer 9 software were used for image analysis, object based image segmentations, and shade tree crown delineation. ArcGIS software 10.2 was used for mapping carbon stocks, and geospatial analysis. Lastools were used for Lidar data analysis. Microsoft office like Microsoft word, Microsoft excel and Microsoft power point were used for thesis writing, statistical analysis and report preparation respectively.

Table 3. Software's and tools used for data analysis

No	Software	Purpose
1	ERDAS imagine 2013	Satellite image analysis
2	eCognition Developer 9	Object based image segmentation
3	ArcGIS software 10.2	Mapping carbon stock and geospatial analysis
4	Lastools	Lidar data analysis
5	Microsoft Word	Thesis writing
6	Microsoft Excell	Statistical analysis
7	Microsoft Power point	Presentation of the report

3.2. Pre- field work

3.2.1. Pre-processing of remote sensing data

Image pre-processing of the raw data also called image restoration and rectification is usually done for further manipulation and analysis of the remote sensing data to obtain information (Lillesand & Kiefer, 1979). It is carried out to correct the sensor and platform specific geometric and radiometric distortion of the raw data and aims to correct the distorted or degradation of the image generated at the time of data acquisition. There are various sources of image distortions/ degradation namely radiometric corrections (to correct for uneven sensor response over the whole image) and geometric distortions (to correct for geometric distortion due to rotation of the Earth's and other the sensor conditions. The Worldview-2 images obtained were ortho-rectified.

The Worldview-2 image obtained from ITC was already pre-processed and geo-referenced using WGS 84 UTM Zone 30N projection system. The Lidar data was projected from Ghana_Metre_Grid Projection: Transverse_Mercator to World_1984_ World_Mercator; WGS 84 UTM Zone 30N projection system. This enables to overlap each other the two remote sensing images for data analysis.

3.2.2. Image Fusion

Image fusion refers to a technique to the acquisition, processing and synergistic of information provided by different remote sensors or by the same sensor but in many measuring context (Sarup & Singhai, 2011). It is the method of integration two or more images in such a way as to maintain the most advantageous characteristics of each.

Different fusion techniques like high pass filter (HPF) resolution and Intensity Hue Saturation (IHS) resolution merge algorithm were examined to obtain a better visual appearance and spectrally attractive image for object based image analysis in ERDAS imagine 2013.

Intensity Hue Saturation (IHS) algorithm has the advantage that the three components (red, green blue) are independent; therefore manipulating one components can not affect the other components. The intensity of IHS merge technique is a simple average of the three RGB(Red, Green and Blue) components(Padwick *et al.,* 2010). IHS gave better visual appearance while HPF was spectrally attractive.

High pass filter (HPF) resolution merge is applied to combine the high resolution panchromatic image with lower resolution multispectral data on pixel to pixel(Chavez *et al.,* 1991) resulting in higher spatial resolution and multi spectral resolution. The advantage of using HPF resolution merge that all the bands of original multispectral image are maintained in the spectral resolution of pan image. Therefore, High pass filter (HPF) was used to obtain a high resolution of World View-2 by combining the multispectral 2m image with the 0.50m panchromatic band.

3.2.3. Image filtering/ Convolution

Filtering is an image enhancement technique to reduce noise and/ or extract useful image structures which involves the varying of spatial or spectral features of an image(Leica Geosystems, 2011). Filtering was conducted in order to enhance the edges of pixels or features in the scene before the segmentation process. Pre-processing for segmentation of Worldview-12 image was done using ERDAS imagine. Convolution Gaussian filter was applied to the panchromatic image. The convolution filter uses a kernel which is a square matrix of a value that is applied to the image pixels and each pixel value is replaced by the average of the square area of the matrix centered on the pixel(Definiens., 2009a.) An average Kernel low pass filter and 7* 7 low pass filter were carried out for Worldview-2 image. Since the size of the 3*3 low pass filter gave better visualization, window size 3*3kernel low pass filter was applied to the Worldview-2 in ERDAS imagine 2013.

3.3. Field Work

3.3.1. Sampling design

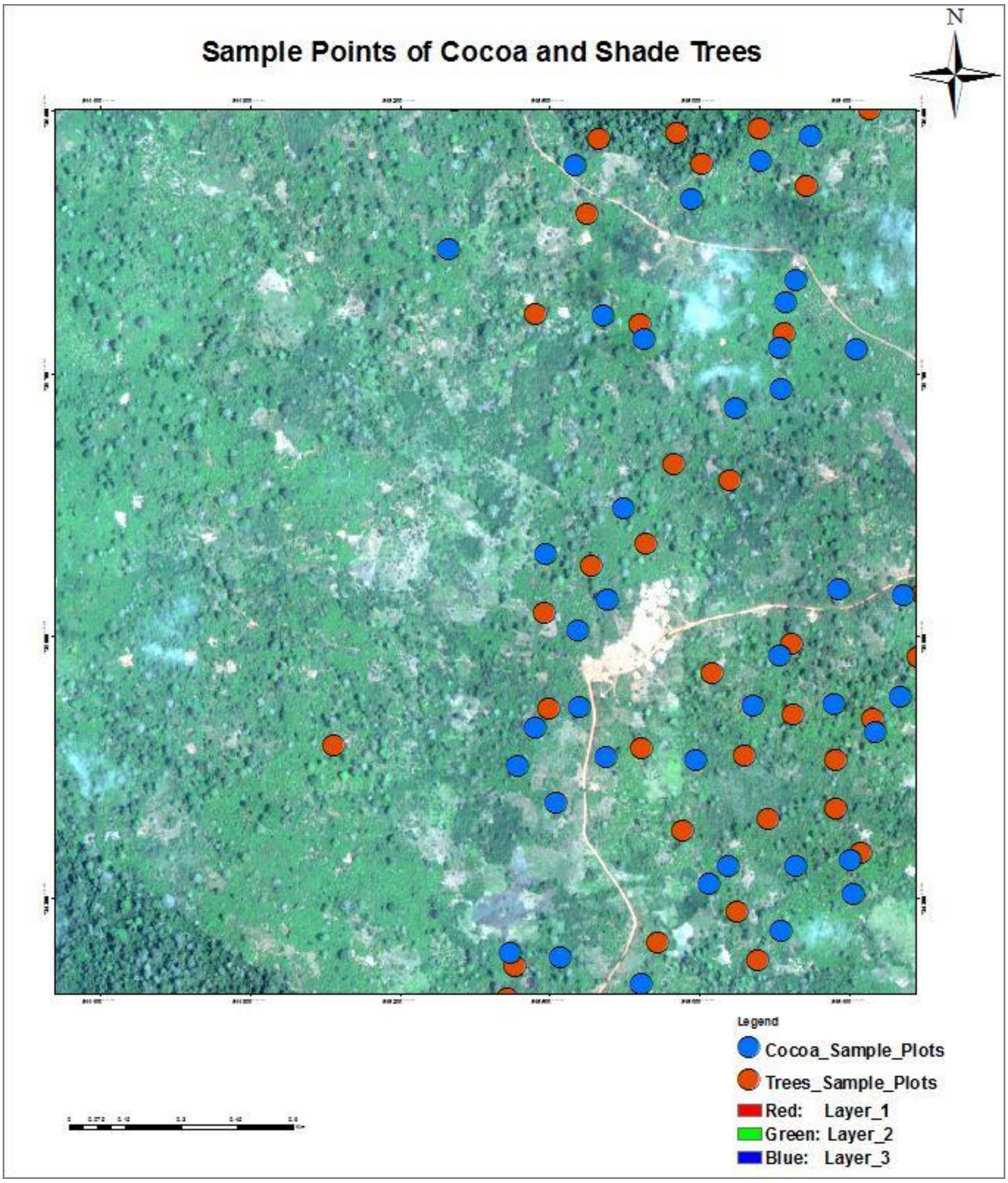
A well-planned sampling inventory can improve the efficiency of field data collection and the precision of the results. For forest parameter inventory, the use of random sampling methods for field data collection does not generally represent the entire population(Rana *et al.,* 2014). Stratified random sampling methods for broad leave forest types highly increase field survey efficiency by reducing unnecessary sampling and guaranteeing that major variations have been confined(Gibbs *et al.,* 2007).

Stratified random sampling methods often yields more precise estimate of the forest parameters than random sampling method of the same size (Husch, *et al.,* 2003). Hence, the study area is divided into 2 strata based on shade trees and cocoa trees. In each stratum random sampling methods were performed. A large number of sample plots increases the confidence in the carbon estimation and reduces the uncertainty due to spatial variability.

3.3.2. Sampling plots

Based on the accessibility of the sample points, a total of 57 plots were selected for cocoa trees. This sample plots were distributed across the whole study area. From a total of 57 plots, 48 plots were selected within Worldview-2 image and Lidar data coverage area while samples in 9 plots were selected from outside Lidar data coverage area which is but inside Worldview-2 images. Based on systematic random sampling method, a total of 52 shade trees were selected within Worldview-2 and Lidar data.

Circular plots were established in the field with a radius of 12.62 m (equivalent to an area of 500 m^2) were used(Rana *et al.,*2014). Circular plots area chosen because is simple for plot layout in the field. It is only requiring a single dimension of radius to define the area of circle. Figure: 4 show the location of the sample points of cocoa and shade trees.



Figures 4. Shows the location of the sample points of cocoa and shade trees

3.3.3. Data collection from field work

The field sample plot data were collected between September 25th and October 18th, 2014. Stratified random sampling method was used to layout sample plots in the study area. In the field circular plots were established with a radius of 12.62 m (equivalent to an area of 500 m^2) were used(Rana *et al.,* 2014) for measuring cocoa trees DBH, average plot height of cocoa trees, percent of plot canopy closure of cocoa tree, and plot age of cocoa were the measured parameters.

All living tree species (including both cocoa and shade trees) in each plot with DBH ≥ 5 cm were measured. (DBH) using a diameter tape. On each plot, average height of the cocoa trees was measured using a haga altimeter. The XY coordinates of the center of the sample plot and shade tree locations inside the plot (for shaded cocoa only) were recording using Global Positioning System (GPS). Percent of plot canopy closure were measured using a spherical densitometer and also age of cocoa plantation was recorded. A total of 52 shade tree crown diameter was estimated based on the average of four perpendicular crown radii measured with a meter tape from the tree bole towards each cardinal direction. The average value of crown diameter of shade trees was used to determinate the length factor in eCognition software for watershed transformation.

3.4. Post- Field Work

All the data collected from field were organized and compiled in Microsoft excel. Statistical analysis (descriptive statistics, regression and correlation) of the field data were done. The shade trees that were recognized on the image and measured during the field work were delineated using ArcGIS software 10.2. The delineated shade tree crown area was used for validation of image segmentation. Based on field data, aboveground biomass and carbon stock for cocoa tree and shade trees were calculated.

The overall research method consists of two major methodology parts. Part 1. Esimating and modelling the cocoa carbon stock per plot from the integration of Worldview-2, Lidar data and average field measured data using DBH and height as shown in Figure: 5. Part 2. Estimating and modelling the shade tree carbon stock per tree from the integration of Worldview-2, Lidar data and field mesured data as shown in Figure: 6. Calculated carbon for cocoa trees was obtained based on average field meaasured DBH and height of the plot. Similarly, calculated carbon for shade trees was calculated based on DBH and height from field. while remote sensing operations were needed to obtain spectral value of the cocoa trees, individual shade tree crown and tree height from Lidar data. Regression analysis was carried out to develop and validate the carbon stocks for cocoa trees and shade trees.

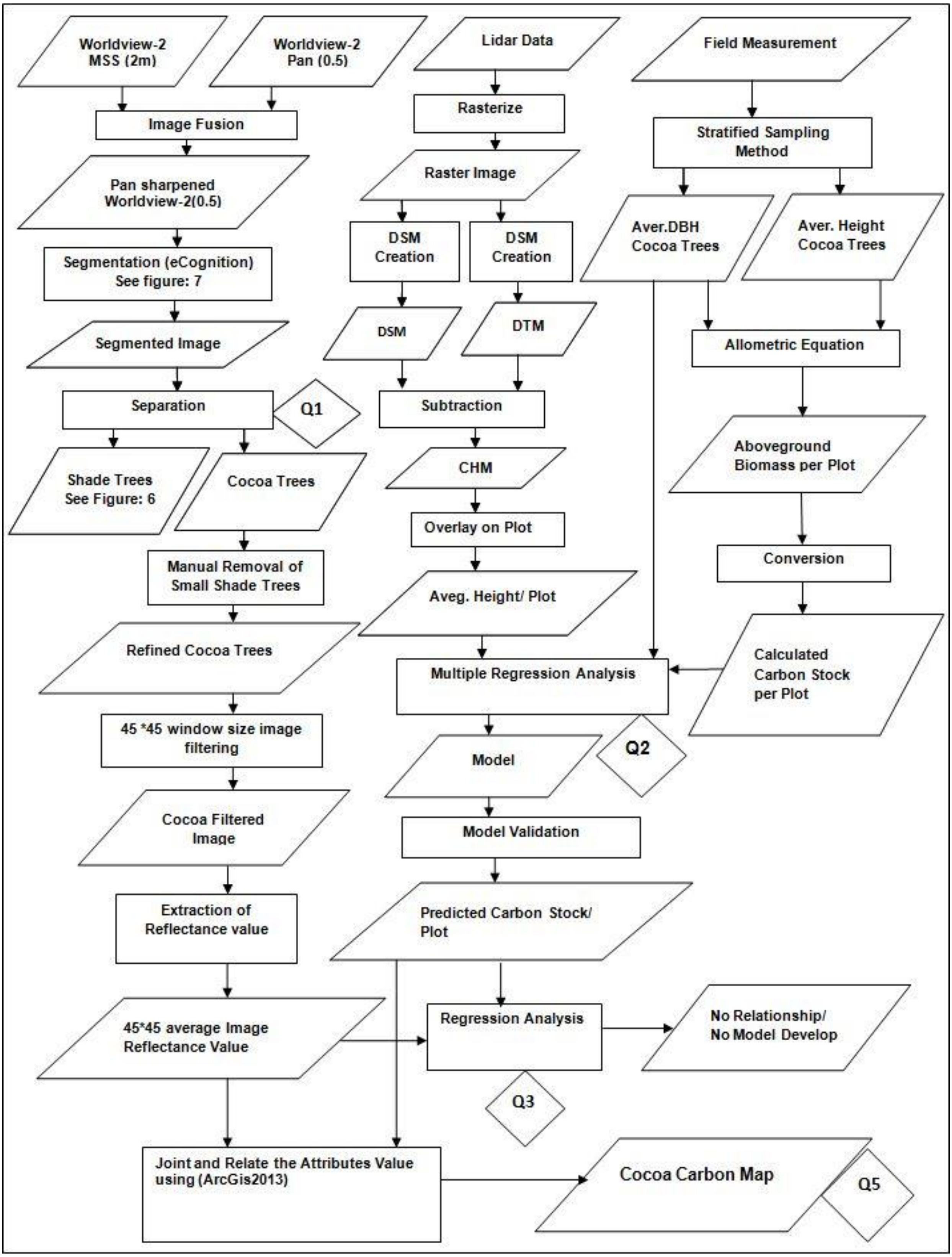


Figure 5. Flowchart of research methods for cocoa carbon mapping

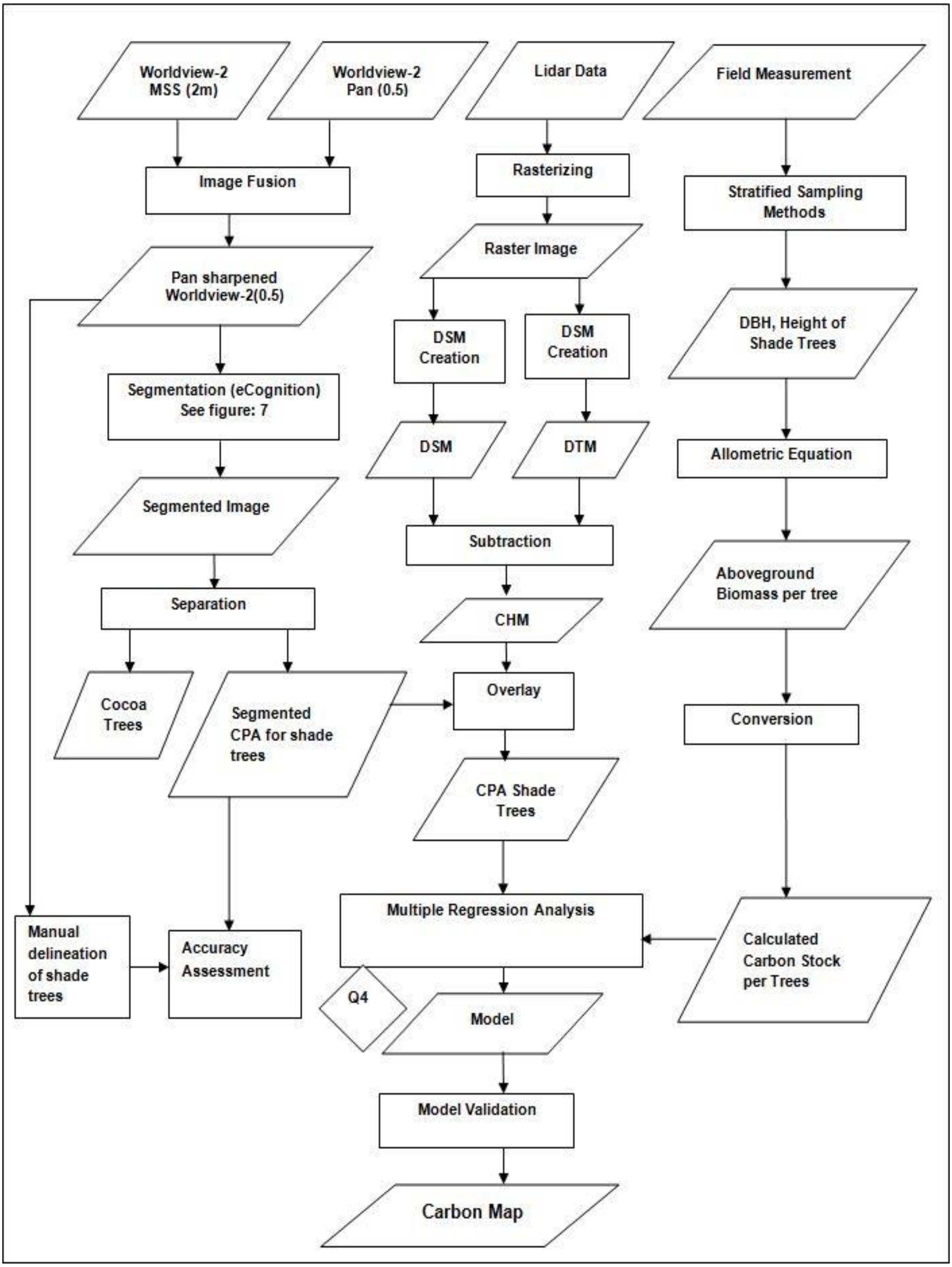


Figure 6. Flowchart of research methods for shade trees carbon mapping

3.5. Procedures for image segmentations Using Worldview-2

Pre-processing like pan-sharpening, image filtering and estimation of scale parameter was done before start segmentation. There are a series of steeps has been carried out for image segmentation and mapping cocoa trees as shown in Figure7. For mapping cocoa trees the following activates were done in sequence (extract cocoa shape files, mask cocoa image, integrate 45*45 window filtering with predicted carbon. Watershed segmentation, morphology and removal of undesired object operations were carried out to obtain an individual tree CPA. This process has been illustrated in Figure: 7.

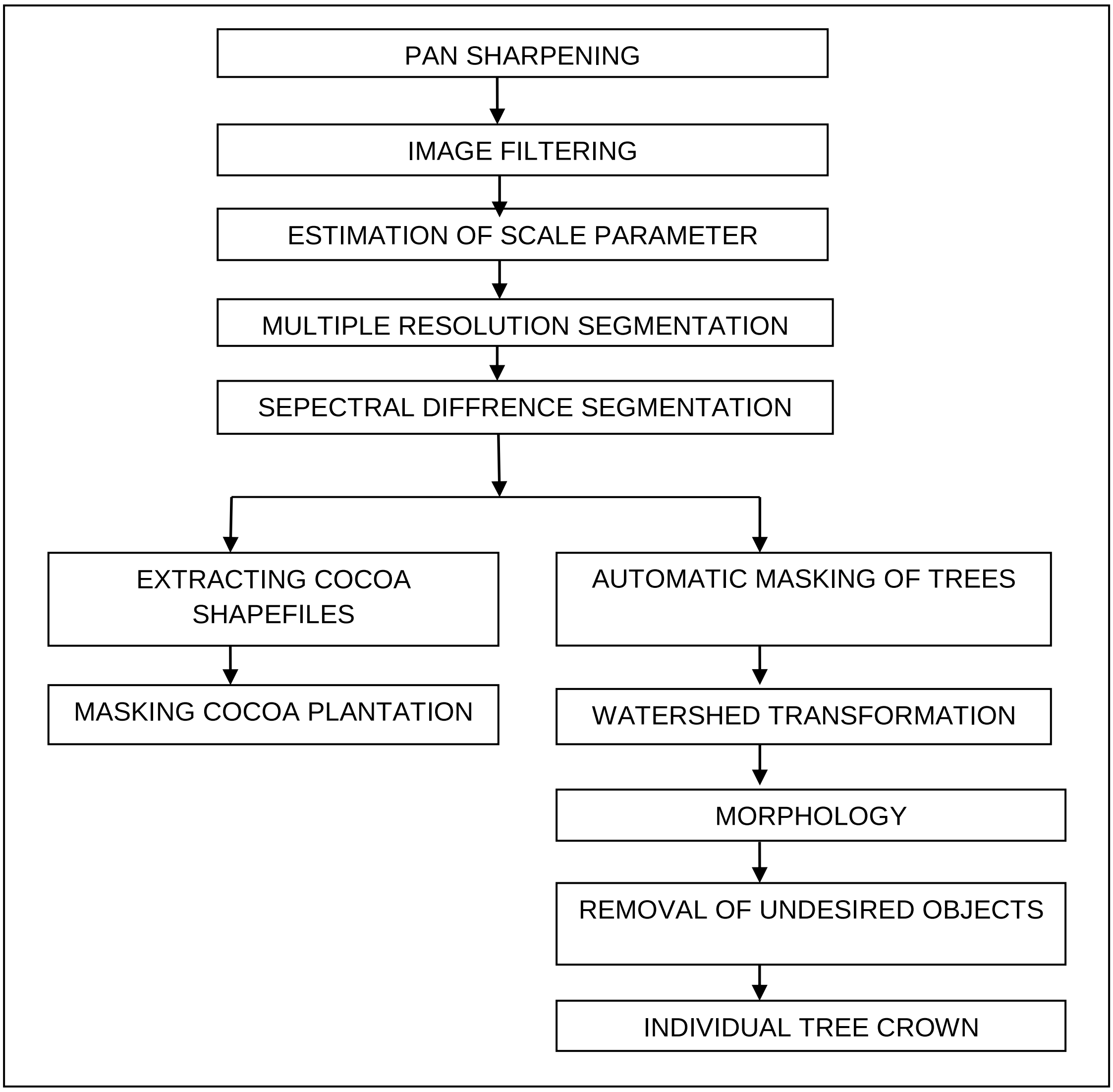


Figure 7. Segmentation processes of worldview-2 image

3.5.1. Pan Sharpening

Pan-sharpening is a type of data fusion technique that involves the combining of lower resolution multispectral spectral data with the higher resolution panchromatic data to produce a high resolution multispectral image (Padwick *et al;* 2010). Worldview-2 multispectral image of 2 m resolution was fused with world view-2 panchromatic image of spatial resolution 50 cm and a pan-sharpened image with spatial resolution of 50 cm was obtained.

3.5.2. Estimation of scale parameter (ESP) Determination

The degree of heterogeneity within an image-object is controlled by a subjective measure called the 'scale parameter'. Estimation of Scale Parameters (ESP) determines the size and shape of the object; hence a low scale parameter will result in small sized segments and vice versa. The homogeneity of the objects segmentation on which the scale parameter depends upon the homogeneity composition value of object colour, smoothness and compactness. The value of shape field is determined by the relationship between shape and colour criteria. Therefore, decreasing the shape value will increase the value of colour criteria. The compactness criteria are used to separate different image objects by compute relatively spectral contrast of object images.

The Estimation of Scale Parameters (ESP) tool builds on the idea of local variance (LV) of object heterogeneity within an image and generates image-objects at multiple scale levels in a bottom-up approach. ESP calculates the LV for each scale. Variation in heterogeneity is explored by evaluating the local variance plotted against each scale or average object size. In addition to the local variance the rates of change of local variance (ROC-LV) are calculated, which are found to decrease as the scale increases as opposed to local variance which is observed to increase as the scale increases(Drăguţ, *et al.,* 2010). The thresholds in rates of change of LV (ROC-LV) indicate the scale levels at which the image can be segmented at the most appropriate manner, relative to the data properties at the scene level. The ESP tool enables fast and objective parameterization when performing image segmentation and holds great potential for OBIA applications(Gibbs *et al.,* 2007). Rule set for multi-resolution segmentation was developed using ESP tool in eCognition software to get the optimum scale parameters for worldview_2 images. Therefore, a scale parameter of 26 was chosen in case of the WorldView-2 image segmentation as shown in Figure: 8.

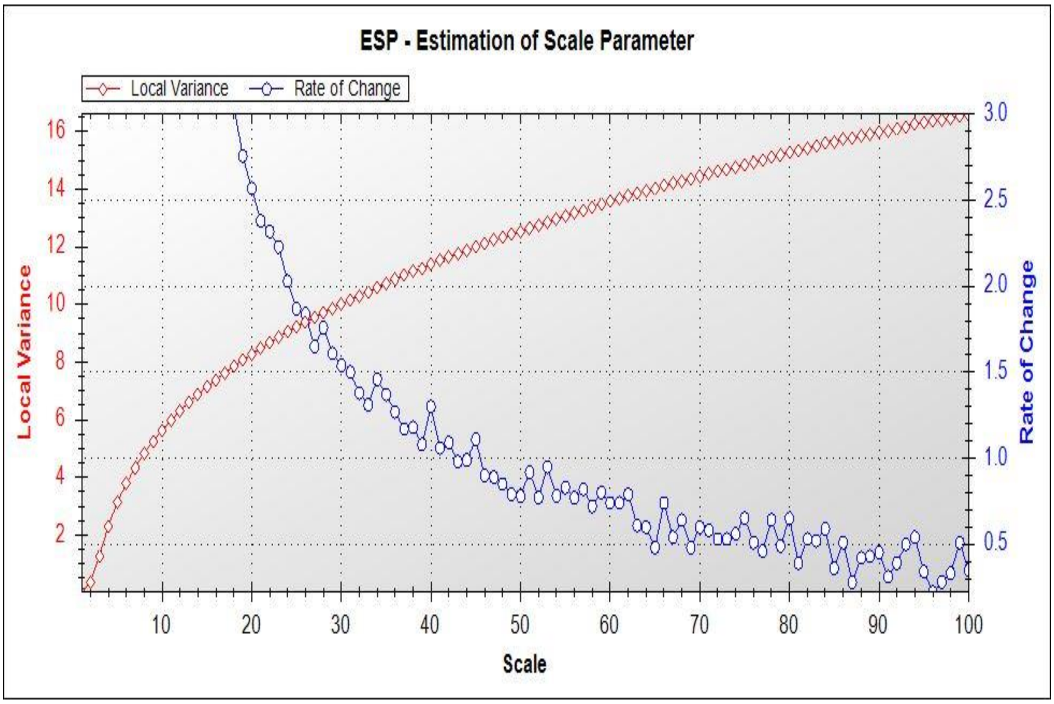


Figure 8. Estimation of scale parameter of worldview-2 image

3.5.3. Object based image analysis

Object-based image analysis (OBIA) is gaining rapid popularity in remote sensing science as a means of bridging very high spatial resolution (VHSR) imagery and GIS(Drăguţ *et al.,* 2010). The first step in object based image segmentation is therefore the grouping of spatially neighboring pixels with similar spectral characteristics into meaningful regions, a process often termed as segmentation. In order to derive these object-based image segments, a number of techniques have been developed in eCognition software, which can be broadly categorized into pixel, edge and region-based methods(Pekkarinen, 2002). For the purpose of this research multi-resolution and spectral difference segmentation algorithm was used to separate cocoa tree from shade trees and other land uses such as oil palm, bare lands and buildings. Once the image segmentation is carried out, the next step is assigning an appropriate image object class using a suitable classifier (threshold condition). The spectral difference segmentation algorithm was applied on the image segmentation to neighboring objects with a spectral mean value below the given threshold (maximum spectral difference). The spectral difference segmentation algorithm applied when after multi resolution segmentation produced.

3.5.4. Multi-resolution segmentation

Multi-resolution segmentation creates image objects in a bottom up approach where individual pixels are perceived as the initial regions, which are merged into larger ones with the aim of minimizing the heterogeneity of the resulting objects(Saha, 2008). The Multi-resolution segmentation algorithm consecutively merges pixels or existing image objects. Essentially, the procedure identifies single image objects of one pixel in size and merges them with their neighbors, based on relative homogeneity criteria. It is an optimization procedure for image segmentation, which maximizes the average homogeneity of the objects and minimizes heterogeneity. The assimilation of segments depends on the average spectral homogeneity of the segment formed, and weighted by its shape and compactness measures. Thus, the outcome of this segmentation algorithm is determined by three main factors :(i) the scale parameter that determines the average size of objects (ii) the weight of image layer for the segmentation process, (iii) the weight of composition of homogeneity criterion (shape, compactness and smoothness)(Definiens, 2007).

3.5.4.1. Criterion for homogeneity composition

The image object homogeneity determined by the scale parameter refers is defined in the composition of homogeneity criterion field. Internally three criteria are computed: Color, smoothness, and compactness. The color criterion is the most important for creating meaningful objects. However, a certain degree of shape homogeneity criteria often improves the quality of image object extraction. Hence, the shape criteria are especially helpful in avoiding highly fractured image object results in strongly textured data (Definiens, 2007). Figure: 9 shows the flows diagram of multi resolution segmentation.

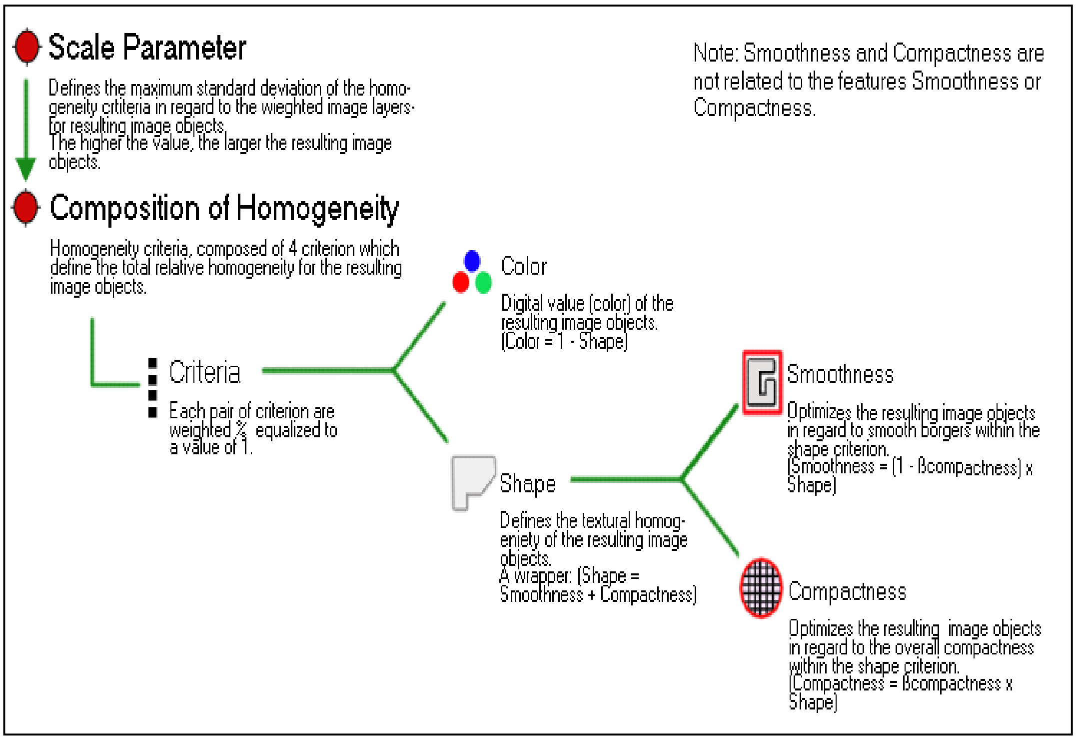


Figure 9. Multi resolution concept flow diagram (Definiens, 2007)

3.5.5. Spectral difference segmentation

Spectral difference segmentation algorithm is a powerful tool for object based segmentation applications that is particularly useful for applications that require distinction between similarly colored objects or regions. The spectral difference segmentation algorithms merge neighboring objects according to mean layer intensity values. The outcome of this segmentation algorithm is restricted by maximum spectral difference. It is designed to refine existing segmentation results, by merging spectrally similar image objects produced by multi-resolution segmentation. For the purpose of this research a spectral difference value of 6 was used for image segmentation(Ryherd & Woodcock, 1996).

3.5.6. Separation of bare lands, buildings, swamp and shadows areas

There are a number of land cover types in study area, which include bare lands, buildings, swamp, shadows and vegetation. The most appropriate way to separate vegetation from other land covers is by using vegetation indices. Vegetation indices measure the general quantity and vigor of green vegetation(Sims & Gamon, 2002). The simple ratio value was used for this research. A simple ratio is a division of the near infrared band and the red band reflectance which are very sensitive to vegetation. The simple ratio (infrared/ red) ranges from 0 to 30 with vegetation having higher values above 2.8. Objects with values greater than 2.8 were classified as vegetation and those with below were classified as bare lands, buildings, swamp, shadows area(L. Brown, et al 2000). The formula for this simple ratio of vegetation index is illustrated in equation 4.

$$\text{Simple Ratio} = \frac{\text{Near Infrared Band}}{\text{Red Band}}$$

----------------- Equation 1

3.5.7. Watershed transformation

After segmentation and classification of the image object, watershed transformation algorithm was carried out for shade trees. A watershed transformation algorithm which is a mathematics morphological method for image segmentation based on region processing(Roerdink & Meijster,2000; Goshal & Acharjya, 2012). A watershed transformation is calculated based on the inverted distance map for each pixel to the image object boarder and this makes the maximum value in original image to become minimum value in the inverted distance map(Definiens, 2009a.). This algorithm helps to split the overlapping shade tree crowns into individual tree crowns based on the splitting threshold. The overlapping tree crowns were separated by assigning length factor parameters. The length factor specified on the basis of average value of crown diameter measured in the field work. For watershed transformation algorithm, a length factor value of 16 pixels was used which is equivalent to the average tree crown diameter of 8 meters measured in the field of shade trees.

3.5.8. Morphology

Morphology operation was carried out to smooth the boarder of image objects segments for shade trees. ECognition software gives two basic operations in morphology *i.e.* close image objects and open image objects. Open image object removes the pixel which is isolated from an image object while close image objects will add surrounding isolated pixel to an image object. For this research, close image object operation was done so that the smaller holes due to shadow and difference in spectral properties were filled(Guide, n.d.). A morphology algorithm also provides an option to define the shape and size of the mask shade trees; hence, a circular mask option with a width value 10 was used to refine the shape of tree crowns. To obtained a desired shape to the shade tree crown segments. Objects with roundness values of more than 1.1 were removed.

3.5.9. Removal of undesired objects

After completed the image segmentation of shade trees, objects area with less than 16 pixels which is equivalent to the average tree crown diameter of 8 meters measured in the field were removed. Because, crown diameters of less than 8 meters whose reflectance would be hard to distinguish in a cocoa plantation. In the same way elongated objects in the image segmentation was removed.

The overall steps and rule sets for cocoa trees and shade trees segmentation using Worldview-2 image in eCognition software are shown in Appendix; 1 and Appendix: 2 respectively.

3.5.10. Manual delineation of shade trees

After the field work manual delineation of the identified shade trees was done for validation image segmentation accuracy. Manual delineation was done on 3*3 Pan-sharpened filtered images. Delineation of the individual shade trees was done only of the shade trees that actually recognized in the image and field. A total of 52 shade trees were delineated in the Worldvew-2 image.

3.5.11. Aboveground Biomass and Carbon Stocks Calculation

The aboveground biomass of living trees was estimated using allometric equations for both cocoa and shade trees(Chave *et al.,* 2005). (Chave *et al.,*2005) developed allometric equations based on trees harvested from moist and dry tropical forest sites around the world based on DBH, height and wood specific gravity (W) for an individual tree. The allometric equations are selected based on the total annual mean rainfall ranges of Goaso forest district.

$$\mathbf{AGB_i = \exp(-2.977 + \ln(W_i * DBH_i^2 * H_i))} \text{ ----------------- } \textbf{Equation 2}$$

$$\mathbf{= 0.0509 * (W_i * DBH_i^2 * H_i)}$$

Where, AGB_i= Aboveground biomass of an individual tree in kilogram (kg)

H_i = Individual tree height in meter (m)

DBH_i= Diameter of a tree at breast height level (1.3 m) in (cm)

W_i= Wood specific gravity of tree in (g cm^{-3})

- Specific wood gravity for cocoa tree is 0.42 g cm^{-3}(Chave *et al.,* 2005)
- Species specific wood gravity for shade trees was chosen from the world agroforestry wood density database. Wood specific gravity for shade tree is 0.53 g cm^{-3} (Asase A *et al.,* 2008).

The total above ground biomass obtained from these equations was converted to carbon stock using a conversion factor (IPCC 2011).

C=B * CF ----------------- Equation 3

Where, C= carbon stock (KgC)
AGB= Above Ground Biomass
CF= Carbon fraction of biomass (=0.47.5)

Carbon content is often estimated to be 50% of aboveground tree biomass; however, recent studies have shown that this assumption for carbon estimate is not accurate, with significant difference in carbon content among tree species and ecosystem types(Thomas & Martin, 2012). Kotto-same et al.,1997 used a 45 % conversion factor in Cameroonese agroforests. Therefore, the value of 47.5% conversion factor for aboveground carbon stock estimate of a single tree (Saj *et al.,* 2013) were used, these value corresponds to the mean of conventionally used of carbon conversion factor (Hairiah *et al.,* 2011).

3.5.12. Average image filtering using window size 45*45 for cocoa trees

Image smoothing refers to image to image transformation projected to smoothen an image by reducing the pixel to pixel variation in grey levels(R. C. Gonzalez & Woods, 2002). Image smoothing operated by applying an average mask that computes a weighted sum of the pixel grey level in a neighborhood and replaces the centre of the pixel with that grey level(Rakshit, Ghosh, & Uma Shankar, 2007). The average filter is one of the most basic image smoothing filtering method. Average filtering is often refers as a convolution process as the mask is sequentially moved across the image until each pixels has been covered (R. C. Gonzalez & Woods, 2002).

For the purpose of this research, a 45*45 average window size filter were applied on the segmented cocoa trees, this equivalent to the plot size (500m²) which was used for data collection in the field. Average filter is windowed filter of linear class, that smoothes the image. The average filter had done as low pass one. The main idea behind this filtering is the images take an average window size of 45*45 across its neighborhood pixels. The average reflectance with each window was expected to correlate with the cocoa carbon.

3.5.13. Validation of CPA Segmentation

The validation of image segmentation is influence by the quality of data (spectral and spatial resolution, noise) and the optimal parameter settings (Benz, *et al.,* 2004; Möller *et al.,* 2007). Validation of the CPA segmentation was done by matching the manually delineated segments with automatic segments obtained from eCognition software and comparison was done in terms of area overlapped reference polygons(Möller *et al.,* 2007).

The reference polygons of the individual tree crown segmented was considered as match when there was an overlap of at least 50% and above between the reference polygons of manually delineated individual tree crown and automatic segments obtained by eCognition software(Zhan, *et al.,* 2005). If the reference polygon is completely matched by automatically segments, best results are obtained (Benz *et al.,* 2004). One to one matching takes shape, position and size of an object into consideration and also takes completeness and correctness of the object(Zhan *et al.,* 2005). Figure: 10 shows that the various matching conditions of the two matched objects.

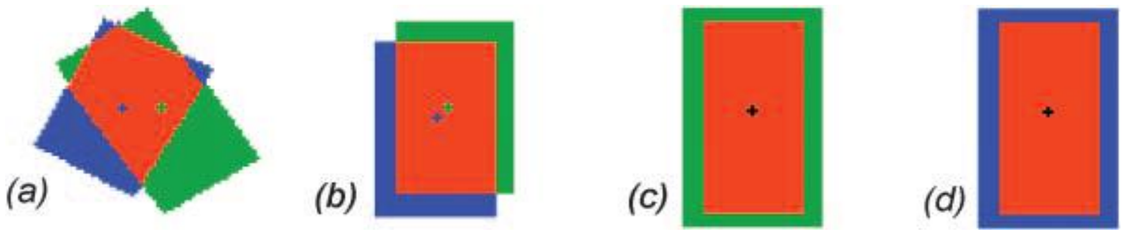


Figure 10. Illustrates four different matching conditions of the two matched objects(Zhan *et al.,* 2005)

Figure 10. Shows that the different matching conditions of reference object with automatic segmented objects (orange is shown the matched region; green indicates region that is not explained by the reference object; blue shows that region in the reference object is not extracted): (a) shows more than 50% match between reference and automatically segments objects; (b) shows an extracted reference object match with the same shape and size but different in position. (c) and (d) the reference object matches with the same position but differ in spatial extent.

3.5.14. Measures segmentation goodness

The goodness of fit for object based image segmentation was computed using "D" value. The "D" value is calculated by using the square root of over segmentation^2 and under segmentation^2(Nicholas *et al.,* 2008). The range of over segmentation and under segmentation is (0, 1). The result "D" value of over segmentation =0 and under segmentation =0 define as a perfect segmentation, where the manual segments match perfectly with the automatic segments(Nicholas *et al.,* 2008).

3.6. Lidar data Processing

Creating a raster dataset from the Lidar data is a precondition procedure for creation of DEM and DSM(Meng, Currit, & Zhao, 2010). The CHM, which is required for tree height estimates, was obtained after the DEM and DSM were generated. This process can help to for further analysis such as extracting the tree height from CHM.

3.6.1. DEM and DSM generation

The CHM, The DEM was created by subtracting the last return Lidar point clouds into ground points using the lasground2 function in Lastools software. The filtered ground points were interpolated by triangulated irregular network (TIN) method using the blast2dem with a cell size of 0.5m. In the same way, the DSM was created by gridding the first return non ground Lidar points using the lasgrid2 function with a cell size of 0.5m. The grid size of 0.5 meter was chosen for DEM and DSM to match the spatial resolution of the pan-sharpened worldview-2 image.

3.6.2. CHM derivation from Lidar data

The Canopy Height Model (CHM) was obtained by subtraction of the height value of the DEM at each pixel from the height value of the DSM. CHM represent the absolute height of the trees. Figure: 13.Shows that the DSM and DEM obtained from Lidar data.

3.7. Statistical Analysis and model validation

Linear Regression analysis was done for determining the relationship between independent and dependent variable and to know the cause and effect relationship of the variables. The change in independent variable results in change in dependent variable (Husch, et al.,2003). Linear relationship between plot reflectance value (blue, green and red) of cocoa trees and carbon stock per plot were computed.

Validation of the regression model was carried out by comparing the amount of carbon predicted by the model and amount carbon calculated from the field measured data. Root mean square error (RMSE) was calculated to check the amount of error occurred in the carbon stock map using the following questions.

$$\textbf{RMSE} = \sqrt{\sum \frac{(\textbf{Cp}-\textbf{Co})^2}{\textbf{N}}} \quad \text{-----------------} \ \textbf{Equation 4}$$

Where, RMSE = Root Mean Square Error

Cp- Predicted carbon by the regression model

Co- Calculated carbon

N-Number of observations

3.8.Cococa Carbon Mapping

The overall flowchart of the methods for cocoa carbon mapping based on Pan-sharpened Worldview-2 images, Lidar data and Field measured data(DBH and Height) (seee Figure: 11)

<u>**N.B:**</u>

- Calculated Carbon obtained from allommetric Equestion using field measured DBH and height.
- Predicted carbon obtanied from model based on regression equestion using measured DBH in the field, and Lidar dervid heighh
- Carbon estimated for cocoa trees at plot level(500m²) equvalent to 45*45 window size on 0.5pansharpend Worldview-2 image
- Carbon estimated for shade trees at indvigual level based on CPA, DBH and height from field

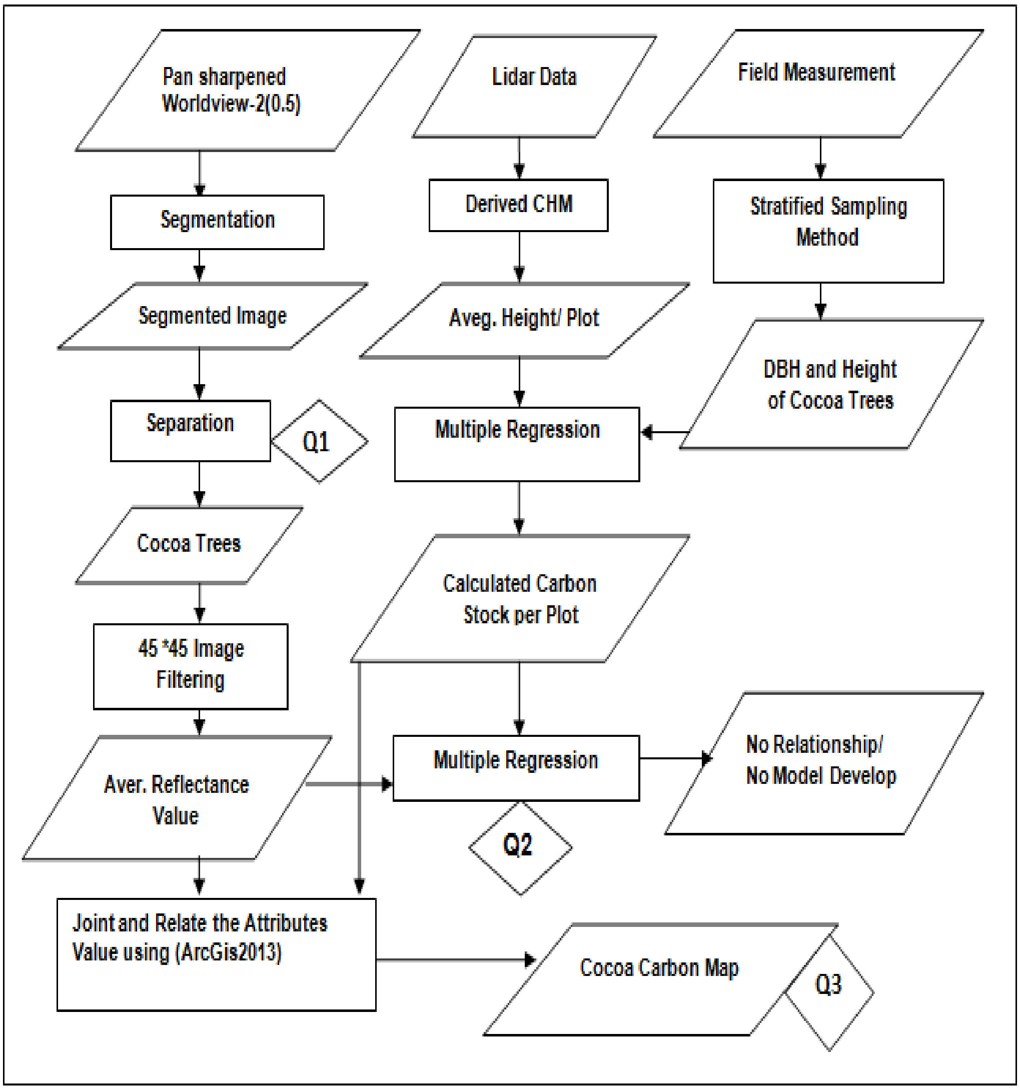


Figure 11. Overall flowchart for cocoa mapping

4. Results and Discussion

4.1. Descriptive statistics for cocoa trees

A total of 3597 cocoa trees were measured in the field from 57 plots. The average tree DBH and height of plots was computed. The mean value of DBH, field measured height, and Lidar heights are 12.8, 5.9 and 6.2 respectively. The summary statistics of cocoa trees described in Table: 4.

Table: 4. Summary statistics of cocoa trees parameters

	Cococa Trees			
	Average	Min	Max	Std. Dev
Aver. DBH(cm)	12.8	7.3	18.3	2.13
Aver. Field height(m)	5.9	2.8	7.9	10.5
Aver. Lidar height(m)	6.2	4.3	9.3	7.6
Canopy density (%)	75	50	85	6.8
No of Trees/ Plot	63.1	32	110	18.66

Average value of field measured DBH and heights were analyzed using box plot (see Figure: 12).

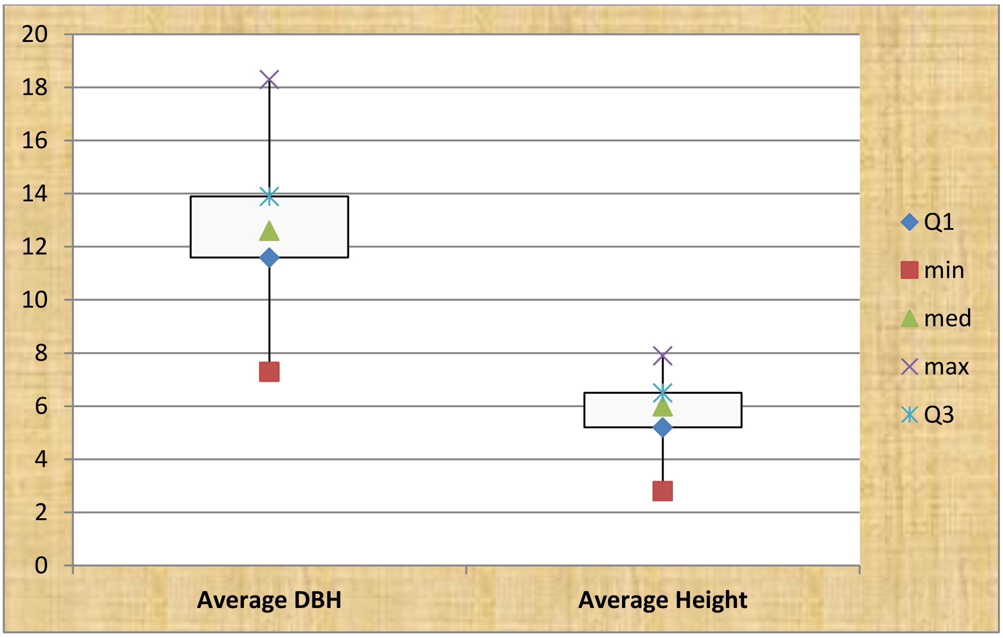


Figure: 12. Box plots of the DBH and height for cocoa trees

4.2. Descriptive statistics for shade trees

A total of 52 shade trees were recognized and the summary statistics computed (see table: 5).The mean value of DBH, field height, Lidar heights and crown diameter are computed as follow 68.4, 25.5, 28, and 8 respectively.

Table: 5. Summary statistics of shade trees parameters

	Shade Trees			
	Average	Min	Max	Std. Dev
DBH(cm)	68.4	11.5	140	36.75
Field height(m)	25.5	15.5	38	6.6
Lidar height(m)	28	18	35	4.5
Crown diameter	8	6	10	1.85

Similarly, DBH and tree heights measured in the field were analyzed using box plot for shade trees. Box pots of DBH at breast height and height are shown below in figure: 13.

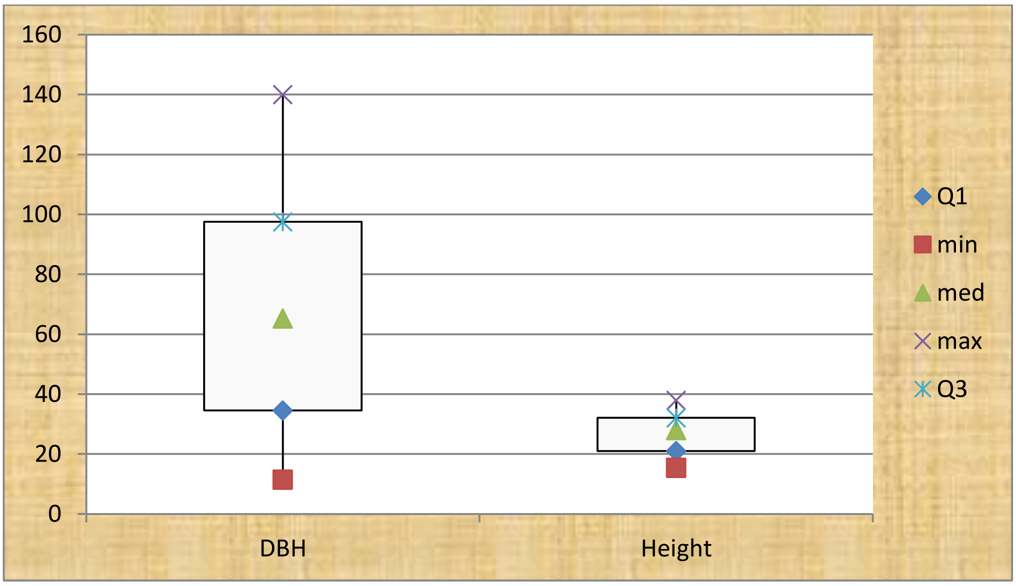
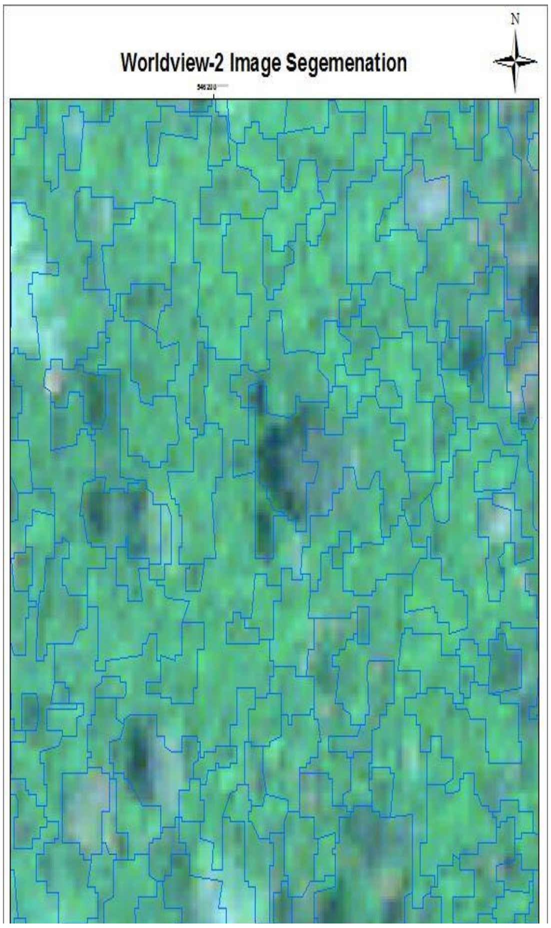


Figure: 13. Box plots of the DBH and height of shade trees

4.3. Image segmentation using Worldview-2 image

Image segmentation was done on panchromatic images of Worldview-2. Multi-resolution segmentation and spectral difference were carried out to group the pixels into homogenous area to form an object. Shadow, bare lands, buildings, and swamp area was masked out from the image for segmentation process so as to increase the segmentation accuracy. Figure: 14 and Figure: 15 Shows the final output of image segmentation.

Multi-resolution segmentation and spectral difference segmentation was used to segments the Worldview-2 image based on the scale parameters value of 26 and 6 respectively. The value of scale parameter was determined by ESP tools.



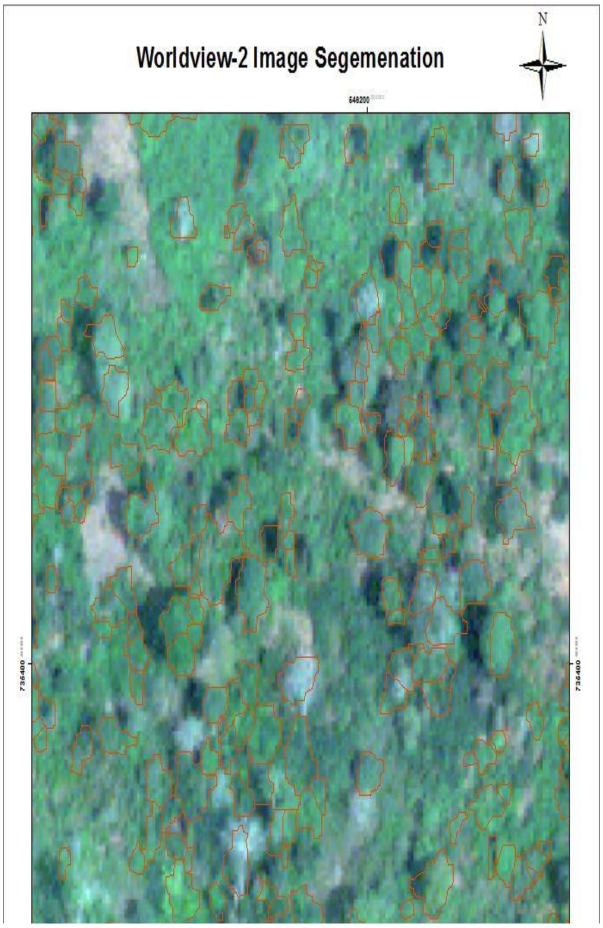


Figure. 14 Cocoa plantation obtained from segmentation

Figure. 15 Indivigual shade tree CPA obtained from segmentation

4.4. Accuracy assessment for shade tree of CPA segmentation

The segmentation accuracy for the individual tree crown was commuted using "D" value. A total of 150 shade trees were manually delineated. Manually delineated against the automatic segments of shade tree CPA, obtained from eCognition software was used for accuracy assessment. The subset of overlapping manually delineated (Blue color) against automatically segments (Orange color) polygons are shown in Figure: 16. The accuracy of segmentation were computed using D value and one to one matching between manually delineated CPA and automatic segmented CPA.

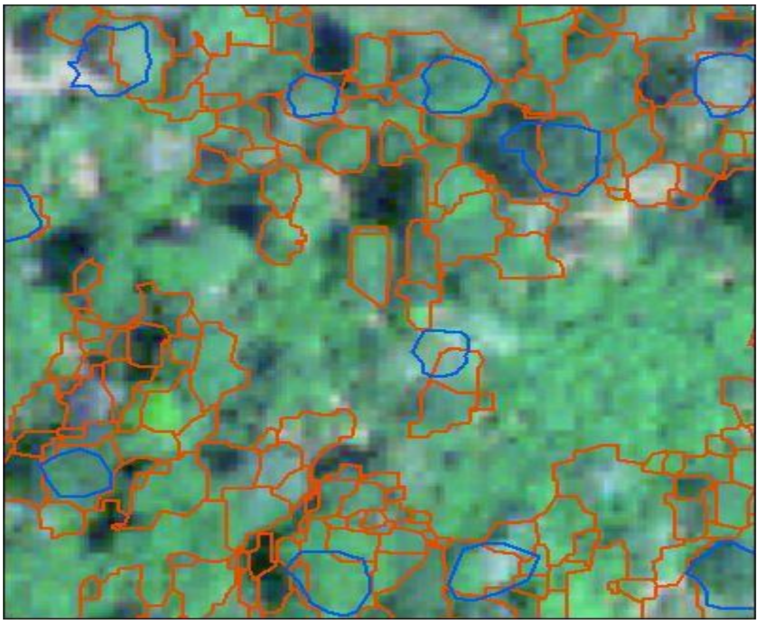


Figure : 16. Shows manually delineated CPA (blue color) against automatically segments CPA (orange color).

Table: 6. shows the accuarcy assesement result of CPA segements using "D" value

Table 6. Accuarcy assesement result for CPA segmentes

Over segmentation	0.42
Under segmentation	0.28
D value	0.35
Total Segmentation Accuracy	65%

The result of over segmentation and under segmentation is 0.42 and 0.39 respectively with "D" value of 0.35, which means an error of 35% in the segmentation of CPA and therefore, the accuracy of segmentation is 65%.

Segmentation accuracy was observed by 1:1 matching manual delenated against automatic segmented polygons. Out of 150 manually delinated crown trees, 96 automatic segmented ploygons are explain a 1:1 relationship.

Segmentation accuracy assessment for individual shade trees crown delineation was obtained by "D" value calculation and 1:1 matching of manually delineated polygons against automatic segments polygons. The segmentation resulted in 65% accuracy in "D" value and 62% in one to one matching. Therefore, accuracy assessment based on D'" value offered better result than one to one matching. The results of CPA segmentation accuracy achieved in this research is similar to (Ke, *et al;* 2010) obtained segmentation accuracy of 63.3% based on region growing algorithmin diverse forest of broad leaf. The study area was conducted in cocoa plantation, thus the segmentation accuracy was relatively low than (Wang, *et al;* 2004) was obtained 75.6% accuracy of segmentation while separating tree CPA from non crown segments. The low accuracy of CPA derivation was because of some shade trees are small and confusion between cocoa trees and shade trees. But the segmentation result at least 50% matching between the manual segmented and automatic segmented then the segmentation was considered as correctly segmented as carried out by (Zhan *et al.,* 2005).

4.5. Model development for cocoa trees per plot

4.5.1. Relationship between DBH, Lidar height and carbon stock of cocoa trees per plot

Multiple linear regression analysis was carried out to test the relationship between DBH; height derived from Lidar data and calculated carbon stocks per plot (obtained from DBH and height measured in the field). Multiple linear regression analysis was carried out using 21 observations for predicted carbon model development. The coefficient of determination obtained in the regression model was (R^2=0.75), which means that 75% of the total variation in predicted carbon can be explained by field measured DBH and height derived from Lidar data (see Table:7).

Table 7. Regression model of cocoa trees

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1312.52	451.02	-2.910	0.009	-2260.084	-364.965
DBH	78.44	33.76	2.323	0.032	7.506	149.376
Lidar Height	150.51	40.29	3.736	0.002	65.868	235.151

Therefore, the model developed for predicted carbon for cocoa trees/ plot is given in equation 5

Predicted carbon stocks = - 1312.52 + 78.44(DBH) +150.51(Lidar Height) ----Equation: 5

4.6. Carbon model validation for cocoa trees per plot

The predicted carbon stocks were plotted against calculated carbon stocks. The model was validated using 30 field sample points (see Figure:17), which resulted in a coefficient of determination(R^2) for model validation of 0.79, which means that 79% of the calculated carbon measured in the field was explained by the predicted carbon based on the multiple linear regression model. The test of goodness of fit was carried out and RMSE is 30.4%.

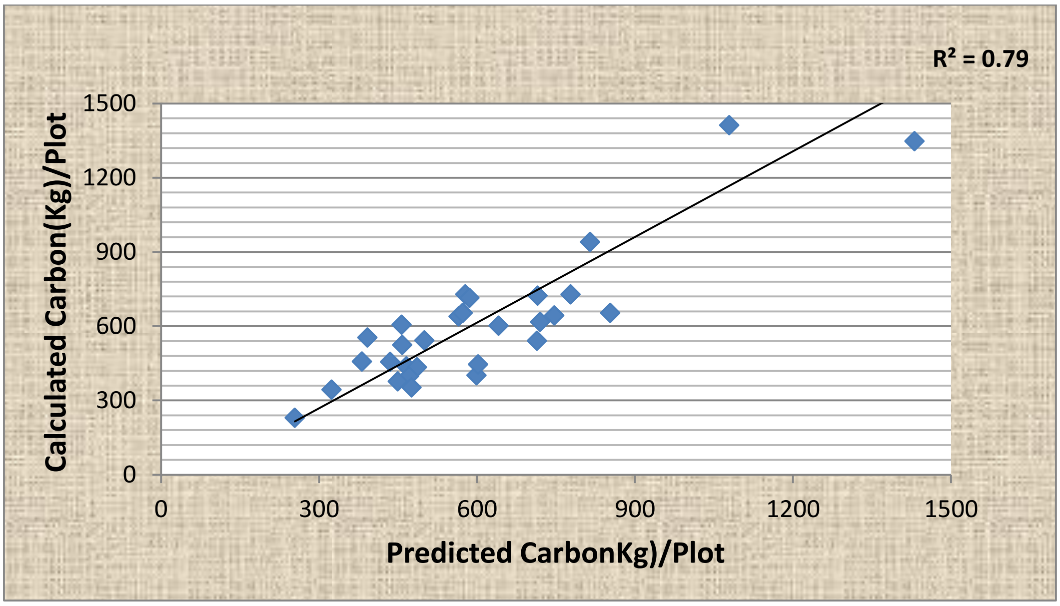


Figure 17. Scatter plot of carbon model validation of cocoa tree

4.7. Relationship between reflectance value and predicted carbon stock/ plot of cocoa trees

Linear regression analysis was done to test if there is a relationship between reflectance value (blue, green and red) of 45*45 filtered Worldview-2 image and predicted carbon stocks obtained from field measured DBH and Lidar height(see Equation:6). Linear regression was carried out using 32 observations for model development. The coefficient of determination (R^2) of the reflectance value of blue, green, and red are R2=0.002, R^2 =0.016, and R^2 = 0.005 respectively. (Figure: 18). Therefore, the coefficient of determination (R^2) obtained from the regression model showed that there is no relationship between the plot reflectance value of (blue, green and red) and the predicted carbon stocks. Which means that the predicted carbon stock is not be explained by the reflectance value of (blue, red, and green). Therefore, it is not possible to develop a model based on a window size of 45*45 pan_sharpend Worldview-2 image and predicted carbon obtained from field measured DBH and Lidar height.

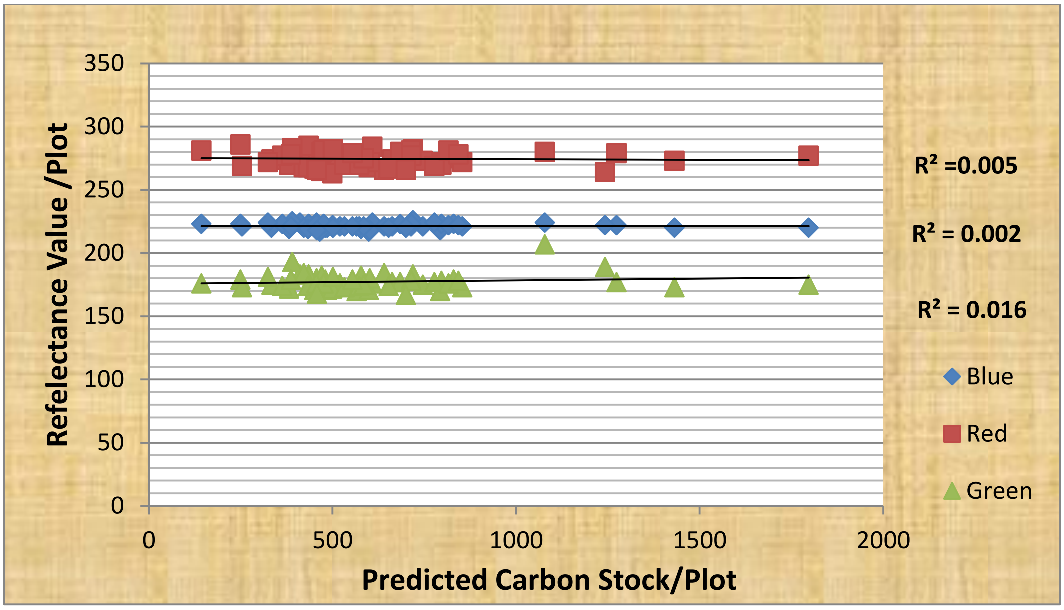


Figure: 18. Scatter plot of reflectance value of plot and predicted carbon stock

The pan-sharpened Worldview-2 image of window size 45*45 filtering and carbon stock per plot was examined for cocoa model development. The coefficient determination obtained from the regression model showed that there is no relationship between the reflectance value (blue, green and red) and carbon stock of cocoa per level. There is no difference in reflectance value (blue, red and green) for old (high carbon) and young (low carbon) trees. In this study the leafs of young and old trees reflect the same. So, plots with high carbon stocks may score low reflectance value (blue, red and green) and vice versa. The reason is cocoa canopy in a plantation closes already at quite early stage so there is hardly any difference in canopy closure between young and old trees. This due to the planting strategy of the farmers who aim for many trees in their field. And also farmers managed their own farm by applying different cocoa management activities like fertilizer application, pesticide application, thinning and cutting of cocoa trees.

4.8. Model development for shade trees using worldview-2 image and Lidar data

4. 8.1. Relationship between CPA and Carbon stocks

Non linear regression was carried out to test the relationship between CPA and calculated carbon. Regression analysis was done using 32 observations for model development(see Table.8). The coefficient of determination obtained in the regression model is R^2=0.74 (see Figure 19), which means that 74 % of the total variation in predicted carbon can be explained by the non-linear relationship between CPA, CPA^2 (as described by the regression equation: 6). The other 26% of the total variation in calculated carbon is unexplained.

The regression equation is:

Predicted carbon stocks/ trees = -2209.07+ (35.47*CPA)-(0.044*CPA^2) ----- Equation: 6

Table 8. Non-linear regression analysis of shade trees

	Coefficients	Standard Error	t Stat	P-value
Intercept	-2209.07	1307.618271	-1.69	0.097
CPA	35.47	13.80293983	2.57	0.013
CPA^2	-0.044	0.033856787	-1.31	0.197

One way ANOVA was employed to test the significance of coefficient of determination (R^2). Table: 9. shows the relationship between CPA and carbon was found to be significant at 95% confidence level.

Table 9. One way ANOVA analysis of shade trees

ANOVA					
	df	SS	MS	F	Significance F
Regression	2	57286867	28643434	47.165	7.66E-10
Residual	29	17611763	607302.2		
Total	31	74898630			

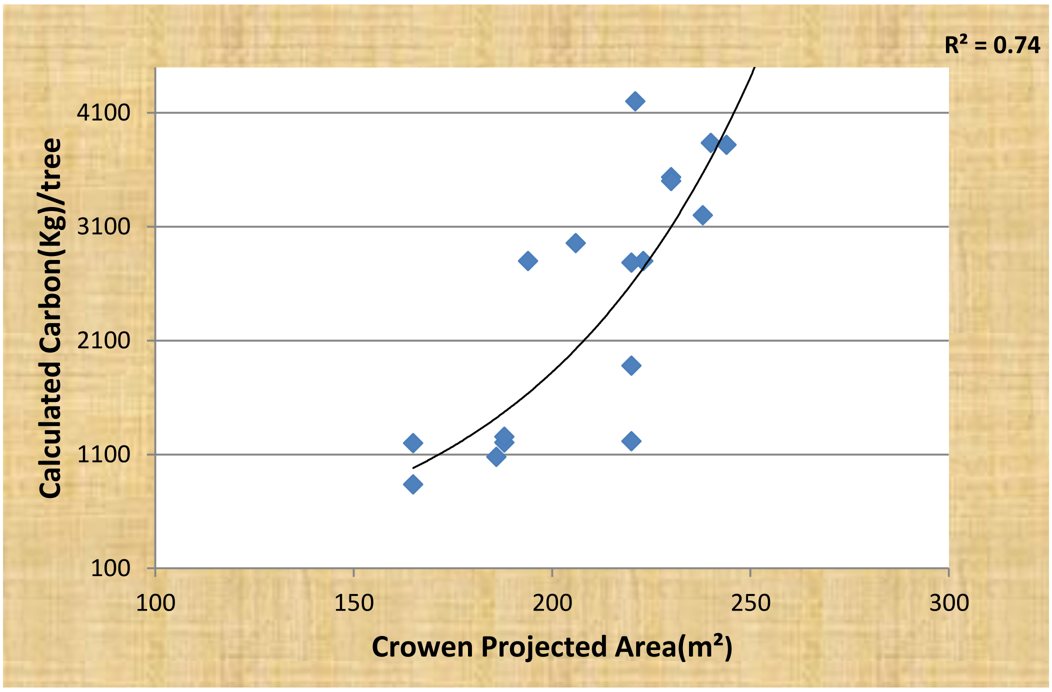


Figure: 19. Scatter plot shows the non-linear relationship between CPA and carbon

4.8. Carbon model validation for shade trees

The calculated carbon stocks, based on field data, were plotted against predicted carbon stocks, based on the model. The model was validated using 20 field sample points(see Figure:20),which resulted in a coefficient of determination(R^2) for model validation of 0.84, which means that 84% of the calculated carbon measured in the field was explained by the predicted carbon based on the non-linear regression model. The test of goodness of fit was carried out and RMSE is 34%.

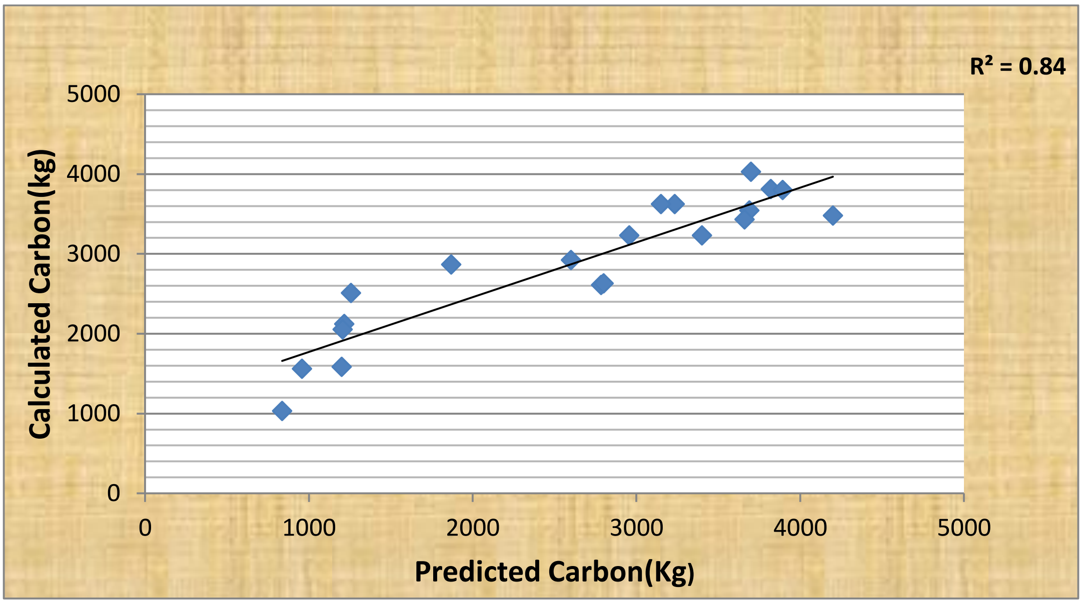


Figure: 20. Scatter plot of carbon model validation of shade trees

Non-linear regression mode was carried out for shade tree carbon estimation because non- linear relationship does not give a negative value of carbon content when using CPA. In natural environment non- linear regression model was preferred to linear regression model, because in dominant forest, tree growth does not follow a linear relationship between DBH and crown area (Köhl, et al., 2006). Similarly in the natural forest where high competition between tree species occur the relationship between DBH and CPA is non-linear(Shimano, 1997) as the tree grows, the rate of increase in CPA will slow down when tree size is affected by competition between adjacent trees. The coefficient of determination of the models developed for shade tree was (R^2=0.74), which is comparable with the result of 80% of coefficient of determination obtained by(Shimano, 1997).

4.9. Relationship between Lidar derived height and height from field measured for shade trees

Shade tree height was measured from field using a Haga altimeter and height derived from Lidar data was evaluated using Pearson's correlation coefficient and one way ANOVA statistic analysis. 30 points were used for the correlation of height measured from field and height derived from lidar. The average mean value of tree height is 25.5m and 28m of field measured and Lidar derived respectively. On average the mean Lidar derived tree height is 2.5m greater than field measured tree height. Goodness of fit between field measured and Lidar extracted tree height was analyzed using linear regression statistics. The coefficient of determination (R^2) showed that Lidar derived tree height was best predicted at 78%, which means that the 78% of the Lidar derived height was explained by field measured height. Figure: 21 show the relationship between field measured and Lidar derived heights.

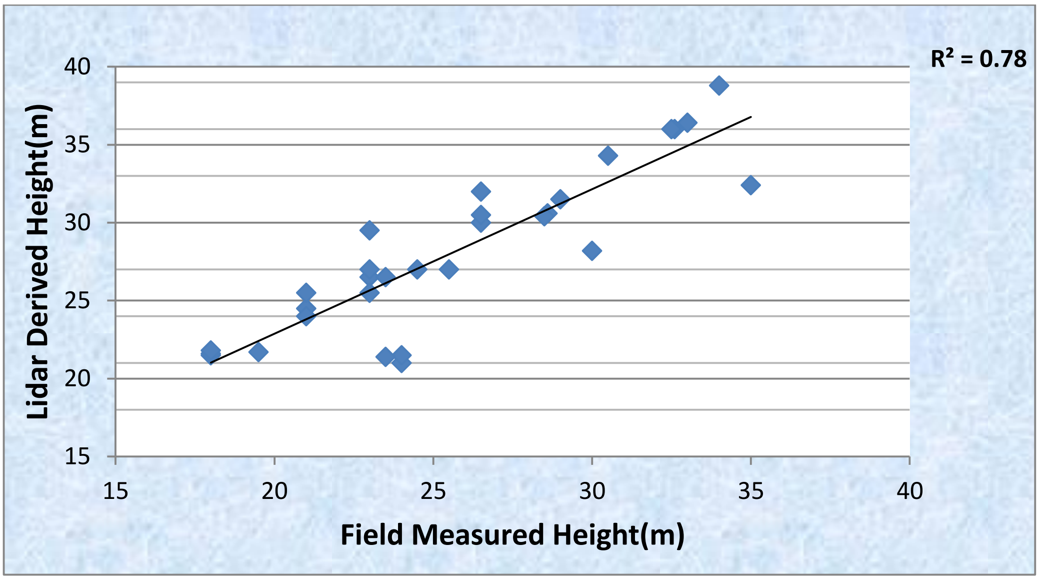


Figure: 21. Scatter plot of shade tree height analysis

One way ANOVA and T-test statistics was calculated to test the significant difference between fields measured tree height and tree height derived from Lidar derived. Hence the result shows that there is a significant difference between tree height measured from field and height derived from Lidar data at 95 %(0.05) significance level. The RMSE percent of the regression model was to be 4.8.

Table: 10. One way ANOVA analysis of shade trees height

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	602.609	602.609	99.641	1.00145E-10
Residual	28	169.339	6.048		
Total	29	771.948			

4.10. Carbon stock mapping using Worldview-2 and Lidar data in cocoa Plantation

A combination of plot pixel value of 45*45 filtered pan-sharpened Worldview-2 image, and predicted carbon stocks/plot obtained from the regression model (Equation: 6) was used for mapping cocoa trees (Figure 22). A total of 10210464 kg of carbon was estimated in the study area, which covered an area of 792ha, thus the amount of carbon stored in cocoa trees is 12892 $KgCha^{-1}$. The carbon stocks in cocoa plantation was estimated approximately 2892 Kg Cha−1 which is higher than the result of (Norgrove & Hauser, 2013) who obtained by the carbon stock 1362 Kg Cha−1. He established an allometric relationship using DBH and height measured in the field. In this study the carbon stock Kg Cha−1 is higher than the other study; this is due to large number of trees counted in the plot, and the tree height variables difference. For this study DBH from field and Lidar height was used for carbon estimation . And also the amount of carbon stored in shade tree is 2896 Kg/ tree.

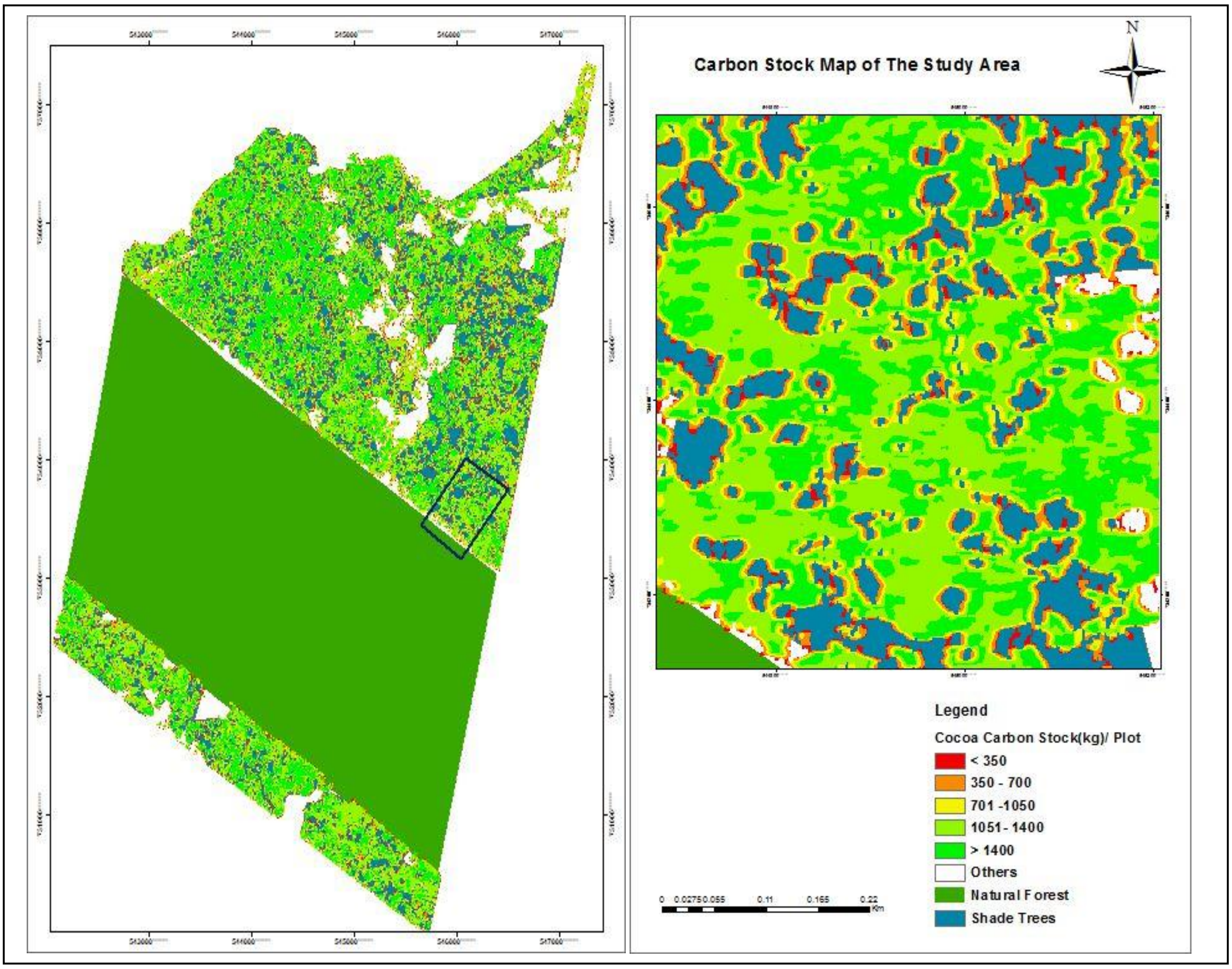


Figure: 22. Carbon stocks map of the study area

5. Conclusions and Recommendations

5.1. Conclusions

The main objective of this research was to develop a method for accurately estimating and mapping aboveground carbon stocks in cocoa plantations using worldview-2 satellite imagery and Lidar data, Therefore, the use of Worlsdview-2 and Lidar data are found to be advantages in estimating and mapping carbon stocks in cocoa plantation. But, for cocoa carbon model development using a window size of 45*45 image filters on the pan_sharpend wordview-2 image is not offered good relationship between the average reflectance value (blue, green and red) and predicted carbon stocks plot level (see figure 19).

Research question 1. How can cocoa trees be separated from shade trees using remote sensing data?

Cocoa trees can be separated from shade trees by combined application of Worldview-2 image and Lidar data. Multispectral resolution and spectral difference segmentation algorithm offered better result. And also small shade trees remove manual.

Research question 2. What is the relationship between DBH, Lidar derived tree height and carbon stock in cocoa trees?

The coefficient of determination (R^2) of 75% for cocoa trees indicated that there is a strong relationship between DBH; Lidar derived tree height and carbon stocks.

Research questions 3. What is the relationship between the reflectance value of Worldview-2 image and predicted carbon?

There is no relationship between the reflectance value of 45*45 filtered pan-sharpened Worldview-2 image and predicted carbon stocks.

Research question 4. What is the relationship between crown projection area and carbon stocks of shade trees

Non-linear relationship between CPA derived from Worldview-2 image and carbon stock obtained from DBH and height measured in the field. The coefficient of determination of 0.74 for shade trees shows that there is a strong relationship between CPA and calculated carbon stock. The coefficient of determination (R^2) of the carbon model validation results is 0.84, which means that 84% of the predicted carbon can be explained by calculated carbon?

Research question 5. How much aboveground carbon is stored by cocoa plantation in the study area?

The total amount of carbon stocks in the cocoa tree was 10210464 kg which was approximately 12892 $KgCha^{-1}$.

5.2. Recommendations

In this research, segmentation of cocoa trees from shade trees was a bit complex due to the vertical arrangements of shade trees. Hence a combination of image segmentation algorithm (multi-resolution and spectrally difference segmentation) with manual removal of small shade tree is offered the better results. Therefore, this study contributed for further studies on carbon stock estimation and mapping in cocoa plantation.

The amount of carbon stored in cocoa plantation highly influenced by occurrence of pests and diseases and the management practices of the farmers like fertilizer application, pesticide application, coppicing, and thinning of cocoa trees. Therefore, this thing should be considered before using this method for estimating and mapping carbon stocks in cocoa plantation. Because, the management practices for cocoa trees, influence on the reflectance value of the cocoa trees.

7. References

Asase A., Wade S.A., Ofori-Frimpong K., Hadley P., N. K. (2008). Carbon storage and the heath of cocoa agroforestry ecosystems in south-eastern Ghana, (November), 25–27.

Adhikari, M. (2005). A Non-destructive Approach for Quantitative Assessment of Tree Resources Outside the A Non-destructive Approach for Quantitative Assessment of Tree Resources Outside the Forest.

Aduse-Poku, K., Nyinaku, F., Atiase, V., Awuah, R., Mensah, E.O., Nyantakyi, D., Owusu, H.K., Agyenim-Boateng, B. (2003). *Improving rural livelihoods within the context of sustainable development*.

Asare and Kwakye. (2013). A Guide to Implementing REDD + in Ghana : Criteria and modalities for developing a REDD + project, (December).

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, *58*, 239–258. doi:10.1016/j.isprsjprs.2003.10.002

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65*(1), 2–16. doi:10.1016/j.isprsjprs.2009.06.004

Blaschke, T., & Hay, G. J. (2001). Object-oriented image analysis and scale-space: theory and methods for modeling and evaluating multiscale landscape structure. *International Archives of Photogrammetry and Remote Sensing*, *34*(August), 22–29. Retrieved from http://crs.itb.ac.id/media/Jurnal/Refs/Draft/RemoteSensing/Object-Based/blaschke_hay_short_paper.pdf\nhttp://crs.itb.ac.id/media/jurnal/Refs/Draft/RemoteSensing/Object-Based/blaschke_hay_short_paper.pdf

Brown, L., Chen, J. M., Leblanc, S. G., & Cihlar, J. (2000). A shortwave infrared modification to the simple ratio for LAI retrieval in boreal forests: An image and model analysis. *Remote Sensing of Environment*, *71*(99), 16–25. doi:10.1016/S0034-4257(99)00035-8

Brown, S. (2002). Measuring carbon in forests: current status and future challenges. *Environmental Pollution (Barking, Essex : 1987)*, *116*(3), 363–72. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11822714

Cao, L., Coops, N., Innes, J., Dai, J., & She, G. (2014). Mapping Above- and Below-Ground Biomass Components in Subtropical Forests Using Small-Footprint LiDAR. *Forests*, *5*(6), 1356–1373. doi:10.3390/f5061356

Chave, J., Andalo, C., Brown, S., Cairns, M. a, Chambers, J. Q., Eamus, D., … Yamakura, T. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, *145*(1), 87–99. doi:10.1007/s00442-005-0100-x

Chavez, P. S., Sides, S. C., & Anderson, J. A. (1991). Comparison of Three Different Methods to Merge Multiresolution and Multispectral Data:Landsat TM and SPOT Panchromatic.

Chen, Q., Baldocchi, D., Gong, P., & Kelly, M. (2006). Isolating Individual Trees in a Savanna Woodland Using Small Footprint Lidar Data. *Photogrammetric Engineering & Remote Sensing*, *72*(8), 923–932. doi:10.14358/PERS.72.8.923

Darwish, a., Leukert, K., & Reinhardt, W. (2003). Image segmentation for the purpose of object-based classification. *IGARSS 2003. 2003 IEEE International Geoscience and Remote Sensing Symposium. Proceedings (IEEE Cat. No.03CH37477)*, *3*. doi:10.1109/IGARSS.2003.1294332

Definiens. (2007). Definiens Developer 7 Reference Book, 192. Retrieved from www.definiens.com

Definiens. (n.d.). Definiens eCognition Developer 8 Reference Book. *GIS-Business*, 34–37.

Drăguţ, L., Tiede, D., & Levick, S. R. (2010). ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. *International Journal of Geographical Information Science*, *24*(6), 859–871. doi:10.1080/13658810903174803

FAO. (n.d.). Accuracy assessment of satellite derived land-cover data: a review. Photogrammetric Engineering & Remote Sensing, 60, 419-426. Retrieved June 03, 2014, from file:///C:/Users/Maleda/Downloads/177508-2.pdf

Geosystems, L. (2011). ERDAS Field Guide.

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), 045023. doi:10.1088/1748-9326/2/4/045023

Gockowski, J., & Sonwa, D. (2011). Cocoa intensification scenarios and their predicted impact on CO2 emissions, biodiversity conservation, and rural livelihoods in the rain forest of West Africa. *Environmental Management*, *48*(2), 307–21. doi:10.1007/s00267-010-9602-3

Gonzalez, P., Asner, G. P., Battles, J. 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. doi:10.1016/j.rse.2010.02.011

Gonzalez, R. C., & Woods, R. E. (2002). Digital Image Processing, 2nd ed.

Goshal, D., & Acharjya, P. P. (2012). MRI Image Segmentation Using Watershed Transform, *2*(1), 2–5.

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. doi:10.1016/j.rse.2005.02.015

Gschwantner, T., Schadauer, K., Vidal, C., Lanz, A., Tomppo, E., Cosmo, L., … Lawrence, M. (2009). Common Tree Definitions for National Forest Inventories in Europe, *43*(July 2008).

Guide, U. (n.d.). Developer XD 2.0.4.

Hairiah K, Dewi S, Agus F, Velarde S, Ekadinata A, Rahayu S, van N. M.-. (n.d.). *Measuring carbon stocks , across land use systems* (p. 2011).

Hernández-Stefanoni, J., Dupuy, J., Johnson, K., Birdsey, R., Tun-Dzul, F., Peduzzi, A., … López-Merlín, D. (2014). Improving species diversity and biomass estimates of tropical dry forests using airborne Lidar. *Remote Sensing*, *6*(6), 4741–4763. doi:10.3390/rs6064741

Hirata, Y., Tsubota, Y., & Sakai, 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. doi:10.1080/01431160903022977

http://www.arbonaut.com/. (n.d.). Arborlidar: MONITORING CHANGE IN CARBON STOCKS AND ACHIEVING REDD + TARGETS. *http://www.arbonaut.com/files/Arbonaut_REDD_en.pdf*, 8. Retrieved from http://www.arbonaut.com/files/Arbonaut_REDD_en.pdf

Hudak, A. T., Lefsky, M. a, Cohen, W. B., & Berterretche, M. (2002). Integration of lidar and Landsat ETM+ data for estimating and mapping forest canopy height. *Remote Sensing of Environment*, *82*(2-3), 397–416. doi:10.1016/S0034-4257(02)00056-1

Husch, B.; T.W. Beers, and J.A. Kershaw, J. (2003). 2003, 4th Ed. Forest Mensuration. John Wiley and Sons, Inc., New York. 443 p.

IPCC. (2006). Draft 2006 IPCC guidelines for national greenhouse gas inventories.

Jennings, S. B., Brown, N. D., & Sheil, D. (1999). Assessing forest canopies and understorey illumination : canopy closure , canopy cover and other measures, *72*(1).

Ke, Y., Quackenbush, L. J., & Im, J. (2010). Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification. *Remote Sensing of Environment*, *114*(6), 1141–1154. doi:10.1016/j.rse.2010.01.002

Köhl, M., Magnussen, S., & Marchetti, M. (2006). Sampling methods, remote sensing and GIS multiresource forest inventory.

Kotto-same, J., Woomer, P. L., Appolinaire, M., & Louis, Z. (1997). Carbon dynamics in slash-and-bum agriculture and land use alternatives of the humid forest zone in Cameroon, *809*(97).

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. doi:10.1016/0378-1127(91)90043-U

Leckie, D., Gougeon, F., Hill, D., Quinn, R., Armstrong, L., & Shreenan, R. (2003). Combined high-density lidar and multispectral imagery for individual tree crown analysis. *Canadian Journal of Remote Sensing*, *29*(5), 633–649. doi:10.5589/m03-024

Lee, A. C., & Lucas, R. M. (2007). A LiDAR-derived canopy density model for tree stem and crown mapping in Australian forests. *Remote Sensing of Environment*, *111*(4), 493–518. doi:10.1016/j.rse.2007.04.018

Lefsky, M. a., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies. *BioScience*, *52*(1), 19. doi:10.1641/0006-3568(2002)052[0019:LRSFES]2.0.CO;2

Lillesand, T. M., & Kiefer, R. W. (1979). Remote sensing and image interpretation, 1–2.

Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography*, *27*(1), 88–106. doi:10.1191/0309133303pp360ra

Malhi, Y., & Grace, J. (2000). Tropical forests and atmospheric carbon dioxide, *5347*(00), 332–337.

Meng, X., Currit, N., & Zhao, K. (2010). Ground filtering algorithms for airborne LiDAR data: A review of critical issues. *Remote Sensing*, *2*, 833–860. doi:10.3390/rs2030833

Möller, M., Lymburner, L., & Volk, M. (2007). The comparison index: A tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation*, *9*(3), 311–321. doi:10.1016/j.jag.2006.10.002

Motamayor, J. C., Lachenaud, P., da Silva E Mota, J. W., Loor, R., Kuhn, D. N., Brown, J. S., & Schnell, R. J. (2008). Geographic and genetic population differentiation of the Amazonian chocolate tree (Theobroma cacao L). *PloS One*, *3*(10), e3311. doi:10.1371/journal.pone.0003311

Moutinho, P., & Schwartzman, S. (2005). *Tropical Deforestation and Climate Change*.

Nicholas Clintona, *, Ashley Holta, Li Yanb, P. G. (2008). An accuracy assessment measure for object based image segementation, 1189–1194.

Norgrove, L., & Hauser, S. (2013). Carbon stocks in shaded Theobroma cacao farms and adjacent secondary forests of similar age in Cameroon. *Tropical Ecology*, *54*(1), 15–22.

Padwick, C., Scientist, P., Deskevich, M., Pacifici, F., & Smallwood, S. (2010). WorldView-2 Pan-Sharpening. Paper presented at the ASPRS 2010 Annual Conference. San Diego, California.

Paustian, K., Six, J., Elliott, E. T., & Hunt, H. W. (2000). Management options for reducing CO 2 emissions from agricultural soils, 147–163.

Pekkarinen, a. (2002). A method for the segmentation of very high spatial resolution images of forested landscapes. *International Journal of Remote Sensing*, *23*(January 2015), 2817–2836. doi:10.1080/01431160110076162

Pii Ashie Kotey, Johnny Francois, JGK Owusu, Raphael Yeboach, Kojo S Amanor, L. A. (1998). Falling into place. Ghana. International Institute for Environment and Development (IIED).

Popescu, S. C., & Wynne, R. H. (2004). Seeing the Trees in the Forest : Using Lidar and Multispectral Data Fusion with Local Filtering and Variable Window Size for Estimating Tree Height, *24061*(0324).

Rakshit, S., Ghosh, a., & Uma Shankar, B. (2007). Fast mean filtering technique (FMFT). *Pattern Recognition*, *40*, 890–897. doi:10.1016/j.patcog.2006.02.008

Rana, P., Korhonen, L., Gautam, B., & Tokola, T. (2014). Effect of field plot location on estimating tropical forest above-ground biomass in Nepal using airborne laser scanning data. *ISPRS Journal of Photogrammetry and Remote Sensing*, *94*, 55–62. doi:10.1016/j.isprsjprs.2014.04.012

Robert A. Rice and Russell Greenberg. (2000). cacao cultivation_conservation of biological diversity.

Ryherd, S., & Woodcock, C. (1996). Combining Spectral and Texture Data in the Segmentation of Remotely Sensed Images. *Photogrammetric Engineering Remote Sensing*, *62*(February), 181–194. Retrieved from http://www.asprs.org/publications/pers/96journal/february/1996_feb_181-194.pdf

Saha, R. R. S. K. (2008). Multi-resolution Segmentation for Object-based Classifi cation and Accuracy Assessment of Land Use / Land Cover Classifi cation using Remotely Sensed Data. *Journal of Indian Society of Remote Sensing*, (June), 189–201. doi:10.1007/s12524-008-0020-4

Saj, S., Jagoret, P., & Todem Ngogue, H. (2013). Carbon storage and density dynamics of associated trees in three contrasting Theobroma cacao agroforests of Central Cameroon. *Agroforestry Systems*, *87*(6), 1309–1320. doi:10.1007/s10457-013-9639-4

Sarup, J., & Singhai, A. (2011). Image fusion techniques for accurate classification of remote sensing data. *International Journal of Geomatics and Geosciences*, *2*(2), 602–612. Retrieved from http://www.ipublishing.co.in/jggsvol1no12010/voltwo/EIJGGS3052.pdf

Schroth, G., & Harvey, C. a. (2007). Biodiversity conservation in cocoa production landscapes: an overview. *Biodiversity and Conservation*, *16*(8), 2237–2244. doi:10.1007/s10531-007-9195-1

Shimano, K. (1997). Analysis of the relationship between DBH and crown projection area using a new model. *Journal of Forest Research*, *2*, 237–242. doi:10.1007/BF02348322

Sims, D. a, & Gamon, J. a. (2002). Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote Sensing of Environment*, *81*(2-3), 337–354. doi:10.1016/S0034-4257(02)00010-X

Thomas, S. C., & Martin, A. R. (2012). Carbon Content of Tree Tissues: A Synthesis. *Forests*, *3*(4), 332–352. doi:10.3390/f3020332

UNFCC. (1998). Kyoto protocol to the united nations framework convention on climate change.

Wang, L., Gong, P., & Biging, G. S. (2004). Individual Tree-Crown Delineation and Treetop Detection in High-Spatial-Resolution Aerial Imagery, *3114*(March), 351–358.

Zhan, Q., Molenaar, M., Tempfli, K., & Shi, W. (2005). Quality assessment for geo-spatial objects derived from remotely sensed data. *International Journal of Remote Sensing*, *26*(14), 2953–2974. doi:10.1080/01431160500057764

Zimble, D. a., Evans, D. L., Carlson, G. C., Parker, R. C., Grado, S. C., & Gerard, P. D. (2003). Characterizing vertical forest structure using small-footprint airborne LiDAR. *Remote Sensing of Environment*, *87*(2-3), 171–182. doi:10.1016/S0034-4257(03)00139-1

Appendix: 1. Tthe rule set of image segmentation for cocoa trees

- Landcover
  - Segementation
    - 26 [shape:0.8 compct.:0.5] creating 'New Level'
    - at New Level: spectral difference 6
  - Classification
    - with Brightness <= 285 at New Level: Shodwos
    - Shodwos at New Level: merge region
    - with Simple Ratio <= 2.8 at New Level: Others
    - Others at New Level: merge region
    - with Simple Ratio >= 3.7 and Brightness > 350 at New Level: Cocoa
    - Cocoa at New Level: merge region
    - with Mean Layer 1 <= 180 and Roundness <= 0.9 at New Level: Tree
  - Export cocoa trees
    - Cocoa at New Level: export object shapes to Cocoa Trees

Appendix: 2. The rule set of image segmentation for shade trees

- Landcover
  - Segementation
    - 26 [shape:0.8 compct.:0.5] creating 'New Level'
  - Classification
    - with Brightness <= 285 at New Level: Shodwos
    - Shodwos at New Level: merge region
    - with Simple Ratio <= 2.8 at New Level: Others
    - Others at New Level: merge region
    - with Simple Ratio >= 3.7 and Brightness > 350 at New Level: Cocoa
    - Cocoa at New Level: merge region
    - with Mean Layer 1 <= 180 and Roundness <= 0.9 at New Level: Tree
  - Separation of Culsters into indvigual tree
    - Tree at New Level: watershed transformation (16)
  - Smothing of indvigual tree
    - Tree at New Level: closing: Tree
  - Removal of undesired object
    - Tree with Roundness >= 1.1 at New Level: remove objects (merge by shape)
  - Export tree
    - 06.187 Tree at New Level: export object shapes to Shade trees