ASSESSMENT OF CARBON STOCKS FOR TREE RESOURCES ON FARMLANDS USING AN OBJECT BASED IMAGE ANALYSIS OF A VERY HIGH RESOLUTION SATELLITE IMAGE: A CASE STUDY IN EJISU-JUABEN DISTRICT, GHANA

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February, 2012

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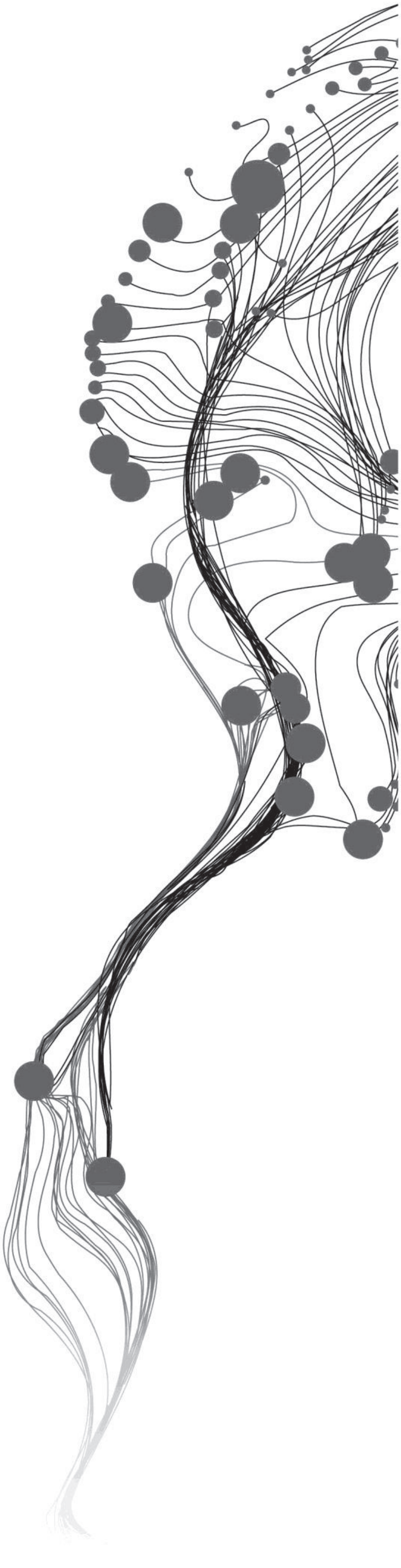

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ENOCK MUTANGA
Enschede, The Netherlands, February, 2012

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

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ABSTRACT

Conversion of once forested areas to other land uses such as agriculture has resulted in the loss of above ground biomass which stores a large amount of carbon. This has led recently to the recognition of trees on agricultural lands in addition to forests as major potential sinks of carbon. Trees on farmlands could absorb large quantities of carbon if they are retained and reintroduced to these systems and managed together with crops and or animals. As a response to the emerging carbon markets through the REDD+ programme such mechanisms are needed to sequester carbon through biological means. Efforts to estimate carbon stocks potential of agricultural lands have been conducted in African countries including Ghana and Kenya, but these efforts used practices which are costly and impractical at broader scales. Also despite there being many remote sensing approaches to carbon estimation, their application has been largely narrowed to forest environments with little emphasis on farmland tree resources. High resolution imagery could be a solution but the relative cost associated with their acquisition limits their application to local scales, thus creating the need for up-scaling approaches to better understand process at broader / regional scales.

The objective of the research was therefore to develop an approach to map carbon stocks for trees on farmlands using Object Based Image Analysis (OBIA) for high resolution data and up-scaling techniques to medium resolution. Multiresolution segmentation, a bottom-up approach designed to minimize heterogeneity in image objects, was used to generate image objects from the high resolution World View-2 satellite image. Crown Projection Area (CPA) derived through automatic masking of Oil palm using the whole image extent and manual masking of Oil palm using a only a subset of the image were used to develop models to predict carbon on farmlands. These image objects, representing tree CPA, were then used as training data for up-scaling carbon estimates from the high resolution satellite image to the medium resolution Aster image.

Despite confusion brought about in rule set development by Oil palm, which is widely grown in the area. Multiresolution proved to be a useful technique to delineate tree crowns on farmlands evidenced by the high tree identification rates 72% and 83% whole image and subset respectively. The developed model for carbon estimation for the subset had a higher coefficient of determination, R^2 of 0.66 compared to that of the whole image, R^2 of 0.61 and a total of 45.9 MgC/ha^{-1} was observed for the study area. The near infrared band was better able to predict carbon for tree crowns, R^2 of 0.50, compared to the red and green band which had R^2 of 0.23 and 0.09 respectively and therefore was used for the up-scaling process. The research showed the potential of OBIA for carbon estimation on farmlands and that use of vegetation indices alone cannot clearly separate Oil palm from trees. Other parameters like texture or manual delineation can be considered as an option.

Keywords: Object Based Image Analysis, Farmlands, Carbon Stocks, Up-scaling, High Resolution image

Dedicated to my Wife Regina and Son, Brandon Mutanga
for all the inspiration and support

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Enock Mutanga

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LIST OF ACRONYMS

AGB Above Ground Biomass

CPA Crown Projection Area

CO_2 Carbon Dioxide

DBH Diameter at Breast Height

ESP Estimation of Scale Parameter

FAO Food and Agricultural Organization of the United Nations

GIS Geographic Information System

GPS Global Positioning System

IPCC Inter-governmental Panel on Climate Change

NDVI Normalized Difference Vegetation Index

OBIA Object Based Image Analysis

REDD+ Reducing Emissions from Deforestation and Forest Degradation

SIC Satellite Imaging Corporation

UN United Nations

1. INTRODUCTION

1.1. Background

Forests present an important sink of carbon dioxide (CO_2) and are estimated to store more than one trillion tonnes of carbon worldwide (FAO, 2008). As a result, compliance markets for carbon have emerged through the Kyoto Protocol as well as voluntary mechanisms in order to mitigate global climate change (Dumanski, 2004). Signatories of the United Nations Framework Convention on Climate Change through the Bali Action Plan Conference of Parties (COP-13) opened the way for developing countries to play a part in the carbon market with the development of the programme for Reducing Emissions from Deforestation and Forest Degradation (REDD+). Through REDD+ developing countries can be compensated for developing afforestation and reforestation programmes, sustainable management of forests and enhancement of forest carbon stocks (UN-REDD, 2009).

Conversion of once forest area to other land uses such as agriculture has resulted in the loss of this important carbon sink globally. This is because forest above ground biomass store a large amount of carbon as living matter (Kale et al., 2009). Worldwide, forest resources are increasingly under threat. Rates of forests loss are largest in South America, Africa and South East Asia with an estimated rate of 12.9 million hectares per year between 2000 and 2005. This is mainly as a result of converting forests to agricultural land, but also due to expansion of settlements, infrastructure, and unsustainable logging practices (IPCC, 2007). This has led recently to the recognition of trees on agricultural lands, in addition to forests, as major potential carbon sink. Farmlands have the potential to absorb large quantities of carbon if trees are retained and reintroduced to these systems and managed together with crops and or animals. Thus, the importance of agroforestry as a land-use system is gaining recognition not only for agricultural sustainability but also in issues related to climate change(Albrecht andKandji, 2003).

Because of agriculture's important role in the economy of Ghana with cultivable area estimated to be 66.4% of the total area of the country (FAO, 2011), the varied agriculture systems practiced, such as perennial cropping and bush fallow have had considerable impact on the forest resources in Ghana. Forest cover had reduced to less than 18,000 km² by the late 1980s and as of 2007 to an estimate of about 16,000 km², representing an annual rate of forest loss of around 220 to 650 km² annually (Kusimi, 2008). The main causes of deforestation are poverty-driven agriculture, lack of rural wage employment other than farming, high household population levels, and conflict in traditional land practices (Appiah et al., 2009). This has resulted in only remnants of once forested areas being left as patches on farmlands. However, in spite of the important ecosystem services of these trees such as carbon sequestration, wind breaks, fruit provision, animal fodder, wildlife habitat and other economic farm uses, these trees are threatened by deforestation as little value is assigned to them by farmers. Also the unequal land and tree tenure system and share in the timber trade has resulted in loss of these tree resources to deforestation as the current policy is viewed as unfavourable by farmers (Hansen, 2011).

Tree resources on farmlands are distributed mainly along the boundaries of fields or inside and in homesteads depending on farmer preferences (Asamoah-Boateng, 2003). Information on these non-forest tree resources is often lacking and research on them is minimal as effort is mostly put on forest reserves in Ghana (Owubah et al., 2001). However, in order for Ghana to effectively participate in the REDD+ programme and to enhance benefits, assessment or accounting of carbon stocks of woody resources outside the forests and especially farmlands, which account for 66.4% of the total area of the country (FAO, 2011) needs to be conducted.

Various efforts to estimate carbon stocks potential of agricultural lands have been conducted in African countries including Ghana and Kenya, but these efforts were limited in scope to only below ground carbon (soil) and were using practices which are costly and impractical at broader scales (Gonzalez-Estrada et al., 2008). Also a study to assess the carbon storage potential of small holder farmlands in West Africa concluded that there is need for more research into sustainable farm management practices to enhance the carbon stocks of farmlands and improve the livelihoods of farmers (Gonzalez-Estrada, et al., 2008).

The use of remote sensing has enabled estimation of biomass, and hence carbon, on a wider scale from local , national and even to global scale (Gibbs et al., 2007; Kale, et al., 2009), but this comes with other requirements such as the need for allometric equations which are generally established using destructive techniques (Deans et al., 1996; Djomo et al., 2010). The most promising remote sensing approaches to biomass and hence carbon estimation are through using active sensors, Radar and Lidar. Radar operates in the microwave region and therefore is not affected by atmospheric conditions such as light precipitation and clouds (Patenaude et al., 2005). The most useful Radar sensor is the Synthetic Aperture Radar (SAR) which is found on satellites such as ERS-1, JERS-1 and Envisat (Gibbs, et al., 2007). However, the major limitation of Radar data is that it does not operate well with decreasing amount of biomass (Gibbs, et al., 2007). The Light Detection and Ranging sensor (LIDAR)which, though very accurate is more expensive, limited to more local levels and restricted range of environments (Rosenqvist et al., 2003). Flights are only conducted on requests, unlike optical sensors, which are in orbit and acquire data continuously or on demand. Optical sensors have produced inconsistent results when it comes to biomass estimation with weak models having been produced especially for the tropics (Gibbs, et al., 2007; Patenaude, et al., 2005).

Recent developments of very high resolution commercial satellites such as Geo-Eye, World View-2 and IKONOS, have made it possible to extract more accurate image information and enable the development of relations between image features and ground measurements (Blaschke, 2010) which can improve carbon estimation. Coupled with this is the development of object oriented image analysis approaches and image segmentation algorithms which incorporate the spectral, textural and geometry properties of the objects to be detected (Gamanya et al., 2007). Different segmentation techniques have been developed such as edge based, region growing and multiresolution segmentation (Ardila *et al.*, 2011) and selection of appropriate image segmentation algorithm and parameters is of crucial importance for successful image segmentation(Lamonaca et al., 2008). However, despite the availability of high resolution satellites in space, their high costs and limited geographic coverage have increased the need for up-scaling in order to understand ecosystem processes at regional scale (Hay *et al.*, 2001; Patenaude*, et al.*, 2005). In this process spatial statistics (Stein *et al.*, 1998) and relations of reflectance and objects (Gibbes *et al.*, 2010; Hansen. *et al.*, 2002) found in high resolution images can be applied in transforming scales at different levels.

1.2. Problem statement and Justification

Tree management on Ghanaian farmlands, off-reserves, is affected by a number of environmental problems. First, there is insecurity of land tenure induced by the increased value of land. This has led to conflicts between the traditional chiefs and ordinary farmers (Ubink andQuan, 2008) thereby increasing deforestation in off-reserves or farmlands (Owubah, et al., 2001) as farmers lack security of tenure and therefore find no incentives to maintain trees on farms than rather increase area under cultivation in order to achieve maximum benefits during the period under which they hold the land.

Second, the application of policy on the environment is not uniform especially in the high forest zones of southern Ghana where laws to protect the environment are only intensively applied in the commercially valuable timber reserves (Wiggins et al., 2004). A situation which has greatly increased vulnerability of tree resources on farmlands to illegal cutting especially from chain saw operators (Hansen, 2011). Coupled with this is the long and cumbersome processes involved for farmers to obtain permits to cut merchantable trees on their farmlands, a situation perceived by farmers as violating their moral values and thus worsening the situation (Hansen, 2011; Owubah*, et al.*, 2001) .

"The value of a resource is a function of what one knows about the resource" (Smith., 1990). The selective application of environment policies only to commercially high value reserve forests (Wiggins, et al., 2004) suggests that there is need for information generation to show the important value of tree resources on farmlands or off-reserves, especially with reference to the emerging carbon markets through the REDD+ programme. The programme may provide an option for landholders as an alternative source of income and act as an incentive for conservation of tree resources on farmlands. Carbon markets need mechanisms which sequester carbon through biological means (Flugge andAbadi, 2006), a service which tree resources on farmlands are capable of providing.

Therefore, the development of an approach to generate information on the carbon stocks of farmland tree resources is of major focus in the research. Although there are many remote sensing approaches to carbon estimation, their application has been largely narrowed to forest environments with little emphasis on farmland tree resources (Blaschke, 2010; Rasmussen *et al.*, 2011). Many studies that have used Object Based Image Analysis (OBIA) have applied it mostly on tropical or temperate forests environments. Results of carbon estimation using high resolution satellite images with OBIA have been very promising (Gibbs*, et al.*, 2007; Patenaude*, et al.*, 2005). Accurate individual tree crown identification is important on farmlands as trees are more isolated unlike in forest environments, therefore minimizing the problem of intermingling crowns. The hierarchical approach used in OBIA which classifies objects based on contextual attributes rather than spectral characteristics only is likely to improve the accurate identification and classification of tree crowns within farmland conditions. Also the availability of functions to calculate statistical information, such as band ratios like simple ratio and mean layer values at object level enables better discrimination of trees from surrounding environments such as grassland and built-up environments (Benz *et al.*, 2004). Despite this, the presence of both large and small Oil palm plantations (*Elaeis guineensis*) in the study area pose a serious problem in separating this crop from trees using broad bands within the visible-near infrared region. Therefore the availability of new narrow bands included in World View-2 imagery, coastal blue, 400-450 nanometer (nm) and red edge 700-745 nm (Digital Globe, 2008) is likely to enhance the separation between Oil palm and trees.

Also, despite the availability of very high resolution satellites at satellite platform level their acquisition is expensive and application for estimation of carbon stocks is only possible at local scales; therefore an up-scaling technique is needed. A technique, which utilizes and conserves information from high resolution satellite imagery (Hay*, et al.*, 2001; Stein*, et al.*, 1998) is likely to improve extrapolation of carbon estimation to broader scales. OBIA offers accurate identification of tree spatial distribution as it allows analysis of the object of interest (Gibbes*, et al.*, 2010), and therefore offers the potential for establishing relations between ground measured information and coarse resolution images. Integration of high and medium resolution data therefore offers an efficient and affordable basis on which landscape processes can thus be understood(Hansen.*, et al.*, 2002). Therefore, the research aims to develop an approach to assess carbon stocks using Object Based Image Analysis of a very high resolution satellite image, World View-2, and explore the potential of up-scaling carbon estimates for tree resources on Ghanaian farmlands.

1.3. Research Objectives

Overall Objective: Development of a method to accurately map carbon stocks for tree resources on Ghanaian farmlands using OBIA and up-scaling techniques

Specific Objectives

- To assess the relation between Crown Projection Area (CPA) on a high resolution image and field measured biomass, and hence carbon, for tree resources on farmlands
- To establish how Oil Palm affect individual tree delineation / identification on farmlands
- Assess whether carbon estimates on farmlands can be up-scaled from high (World View-2) to medium (Aster) resolution satellite image

Research Questions

- How may OBIA be used to map tree crowns and biomass /carbon of trees on farmlands?
- How does Oil palm affect individual tree delineation / identification on farmlands?
- Which regression model best describes the relation between carbon and CPA for tree resources on farmlands?
- Is there a relation between World View-2 objects and pixels reflection in a medium resolution Aster image?

Hypotheses

- OBIA can be used to identify and map carbon for farmlands trees with high accuracy level (overall tree identification accuracy >70%)
- Tree biomass in farmlands can be predicted from crown projection area at significant level of $p<0.05$
- There is a significant relation ($p<0.05$) between World View-2 objects or tree crowns and reflection from medium resolution Aster image

1.4. Study Assumptions

Farmlands are very dynamic ecosystems with micro and macro changes taking place within short time intervals as humans alter the landscape. These changes affect accurate estimation of carbon as trees are removed and therefore up-scaling strategies which rely on reflectance for medium and coarse resolution data. In this study, despite a time lag between image acquisition and field work, it is assumed that conditions remained stable and that field observations are the same as they would have been at the time of image acquisition.

2. CONCEPTS AND DEFINITIONS

2.1. Conceptual framework

Estimation of carbon stocks requires accurate and timely reliable data on available biomass in a particular ecosystem, which can be provided by satellite remote sensing (Kale, et al., 2009; Patenaude, et al., 2005). A major concern is the relative costs associated with this data acquisition technology (Patenaude, et al., 2005), but it becomes more favourable when compared to direct field measurements which are laborious, more costly and time consuming therefore making them non-applicable at large scales such as regional applications (Henry *et al.*, 2009; Patenaude*, et al.*, 2005). Despite the relatively low cost of satellite remote sensing, no sensor is able to measure carbon directly from space (Drake *et al.*, 2003; Rosenqvist*, et al.*, 2003) and therefore need to couple satellite data with ground based inventory data. This data can be combined and converted to carbon estimates using allometric relationships (Gibbs, et al., 2007).

Observable forest stand parameters deduced from remote sensing data such as leaf area index, canopy cover, crown projection area (Gibbs, et al., 2007) have made it possible for the estimation of terrestrial carbon stock. Through the use of statistical modelling techniques relationships are established for forest stand parameters such as tree height, Diameter at Breast Height (DBH) and crown diameter and remotely sensed observables such as Crown Projection Area (CPA) to model biomass and hence carbon. Hirata *et al*, (2009), found a relationship between DBH from field survey with DBH predicted based on CPA extracted from Quickbird imagery. Using DBH and CPA relations (Avsar andAyyildiz, 2005) and the emergent of OBIA (Trimble, 2010) statistical modelling of biomass and hence carbon has been made possible. Also relations between DBH and crown diameter were established recently by Mugo *et al*, (2011), with high coefficient of determination (R^2) between 0.65 to 0.87. However, despite the ability of very high resolution images to allow the direct interpretation of the object of interest (Hansen.*, et al.*, 2002), their costs remain high and therefore up-scaling by spatial aggregation is needed to understand processes at a broader scale. Figure 1 below is an illustration of the research conceptual framework.

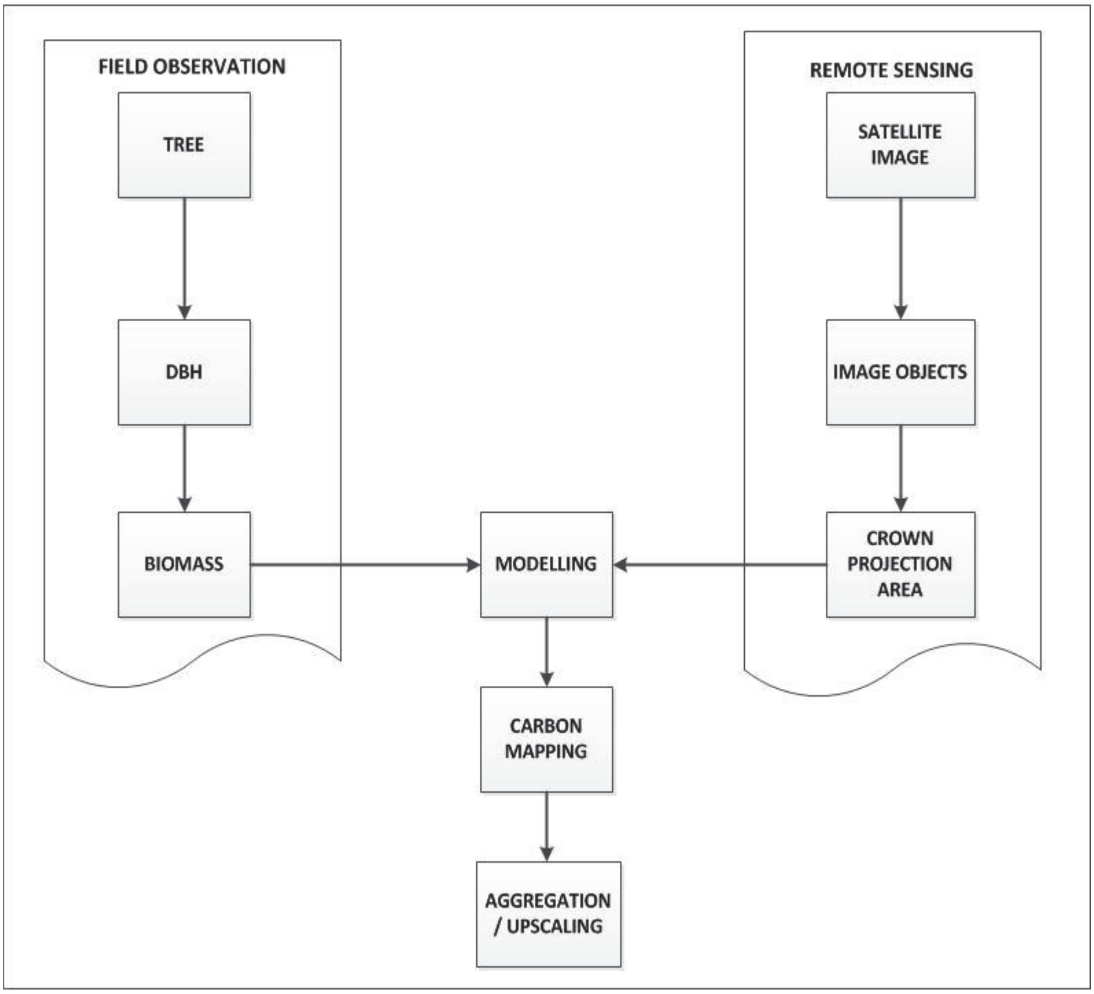


Figure 1: Research Conceptual Framework

2.2. Farmlands

Farmlands are managed lands designated and reserved for crop production and are categorized into three broad divisions; annual, perennial and fallow land (IPCC, 2006). These can be further categorized into croplands (annual and perennial), young fallow and old fallow (Gelens *et al.*, 2010). The latter classification was adopted for this research. Farmlands in Ghana comprise mostly of non-forest reserve areas and, according to the 1992 Constitution, ownership of these lands is vested in the appropriate traditional authority on behalf of and in trust for their people (Ubink andQuan, 2008).

Various vegetation or cover types characterize these farmland categories. Croplands are continually under cultivation. These are characterized by annual crops like cocoyam (*Xanthosoma sagittifolium*), rice and maize (*Zea mays*) and perennials such as cassava (*Manihot esculenta*), plantain (*Musa paradisiaca*). Tree retention in these systems is mostly minimal as crop production is given more emphasis, with few trees mainly found intercropped or at the margins of fields (Gelens*, et al.*, 2010).

Young fallow is land that has not been cultivated for a period of one to five years and is mostly characterized by dense shrubs as the main vegetation type. Old fallow is a secondary forest type landscape with potential for regeneration into a forest. The land has not been in cultivation for many years spanning between six to ten years. Tree density in this land use category is high as compared to other categories of croplands and young fallow (Gelens*, et al.*, 2010).

2.3. Biomass and Carbon

Biomass is the dry weight of trees and is divided into above and below ground biomass. Above ground (AGB) constitutes the leaves, stems and branches whilst below ground constitutes the roots. Carbon is stored in living plant material or biomass of trees, dead mass of litter, woody debris and soil organic matter (Fuchs *et al.*, 2009). AGB is directly impacted by anthropogenic activities such as deforestation and degradation. Carbon and biomass have a direct relationships with carbon constituting between 45% to 50% of above ground biomass and these ratios can be used for landscape wide studies of carbon (Kale, et al., 2009). Information about the status and distribution of above ground biomass is critical for monitoring changes of carbon stocks (Fuchs*, et al.*, 2009).

Biomass measurements can be classified into two broad approaches, direct field measurements which make use of biomass expansion factors (BEF) (Fuchs*, et al.*, 2009) and allometric models derived from *in situ* destructive sampling techniques (Deans, et al., 1996). The other classification is based on remote sensed data coupled with field data (Fuchs, et al., 2009) collection as remote sensing on its own cannot measure biomass directly (Gibbs, et al., 2007).

2.4. Crown Projection Area (CPA)

CPA refers to proportion of the ground covered by the vertical projection of the individual tree crown. It is an important stand parameter as it determines undergrowth, sunlight penetration and hence the type of vegetation (Jennings *et al.*, 1999). As remote sensing data collection is mostly from above, individual crowns are therefore important as they are the stand parameters that can be viewed by the sensor.

2.5. Allometric Equations

The use of remote sensing to estimate biomass and hence carbon (Gibbs, et al., 2007; Kale, et al., 2009) comes with requirements for allometric equations which are established using destructive techniques (Deans, et al., 1996; Djomo, et al., 2010) and regression models which relates image retrievals such as CPA to measured ground observables (Djomo, et al., 2010). Allometric equations are developed using tree samples where DBH, height and wood density are used to predict or explain dry weight of total above-ground biomass (Brown, 1997). Usually, species or site-specific allometric equations or models are developed and used to estimate carbon with the use of easy to measure plant variables such as DBH (Fuchs*, et al.*, 2009).

2.6. Object Based Image Analysis (OBIA)

Increased spatial resolution and the recent launch of very high resolution satellites (Blaschke, 2010) such as Quickbird, Ikonos, Geoeye and Worldview-2 with spatial resolution of less than a meter, has broadened the use of optical satellite systems into domains which were only possible using airborne sensors (Gibbs*, et al.*, 2007). Coupled with this has been the development of techniques to better extract image features as pixels are now smaller than the object of interest (Blaschke, 2010). This has led to OBIA to better extract image features such as CPA (Ardila*, et al.*, 2011; Gibbs*, et al.*, 2007) and the development of allometric relations (Gibbs, et al., 2007) and regression models (Djomo, et al., 2010) to better relate image features to ground based field measurements to estimate biomass, and hence carbon, with relatively low uncertainty.

OBIA uses the spectral, geometry and contextual characteristics of objects (Ardila, et al., 2011; Boggs, 2010) to come up with less or more homogeneous objects which yield more information than the single pixel (Trimble, 2010). These characteristics make it superior over pixel based classification as objects are now relatively large than pixels an issue which may result in error if pixel based classification is applied (Blaschke, 2010; Boggs, 2010). Different segmentation techniques are available such as chessboard, region growing and multiresolution segmentation (Ardila*, et al.*, 2011; Trimble, 2010). Chessboard is a top-down algorithm which cuts the image into smaller objects of a given size unlike bottom-up approaches like multiresolution and region grow which merge pixels or existing objects in the case of chessboard segmented data to create larger ones (Trimble, 2010). Selection of appropriate image segmentation algorithm and parameters is of crucial importance for successful image segmentation (Lamonaca, et al., 2008).

2.7. Up-scaling

"Scale is the ratio between a unit on the map and the unit in reality" (Stein, et al., 1998). Up-scaling involves the use of a very high resolution satellite data to generate a low or coarse resolution data which is assumed to preserve the spatial information content of the high resolution image (Atkinson, 2006; Hay, et al., 2001; Stein, et al., 1998). The choice of any up-scaling technique is dependent on the type of data for example for quantitative data spatial averaging or aggregation is applied and for qualitative a majority value is used (Stein, et al., 1998). The need to conserve information through scale has resulted in the use of high resolution segmented objects to transfer data from fine to coarse scales as the variable of interest is easily extracted from high resolution data (Hansen.*, et al.*, 2002; Hay*, et al.*, 2001).

3. METHODS AND MATERIALS

3.1. Study Area

3.1.1. Location and Justification

The research was conducted in the north-western part of Ejisu-Juaben district, which is one of the twenty seven administrative and political units in the Ashanti Region of Ghana. The district has a rich cultural heritage and tourist attractions notably the Kente weaving industry in Bonwire. The district covers an area of 637.2 km^2 and has Ejisu as its main capital. There are four dominant urban settlements in the district namely, Ejisu, Juaben, Besease and Bonwire (Ministry of Local Government and Rural Development, 2006).

The district is located 6^0 43' N and 1^0 28' W and shares boundaries with six other Districts in the Region. To the North East and North West of the district are Sekyere East and Kwabre Districts respectively, to the South are Bosomtwe-Atwirna-Kwanwoma and Asante -Akim South Districts, to the East is the Asante-Akim North district and to the West is the Kumasi Metropolitan (Anornu *et al.*, 2009; Ministry of Local Government and Rural Development, 2006).

The research was conducted in the north western part of Ejisu-Juaben district as the area is experiencing rapid land use / cover change as it falls within the peri-urban Kumasi zone, a rapidly growing urban metropolitan area, which is influencing land use change to nearby areas (Ubink andQuan, 2008). There is also growing pressure on tree resources due to agricultural expansion, especially the rapidly growing Oil Palm plantations, of note the Juaben Oil Palm Outgrowers Co-operative Society scheme (JOPOCOS). Forest resources in the district are also coming under pressure from the increasing population as Ashanti Region has one of the highest population (Government of Ghana, 2011). Figure 2 below is an illustration of the study area geographic location.

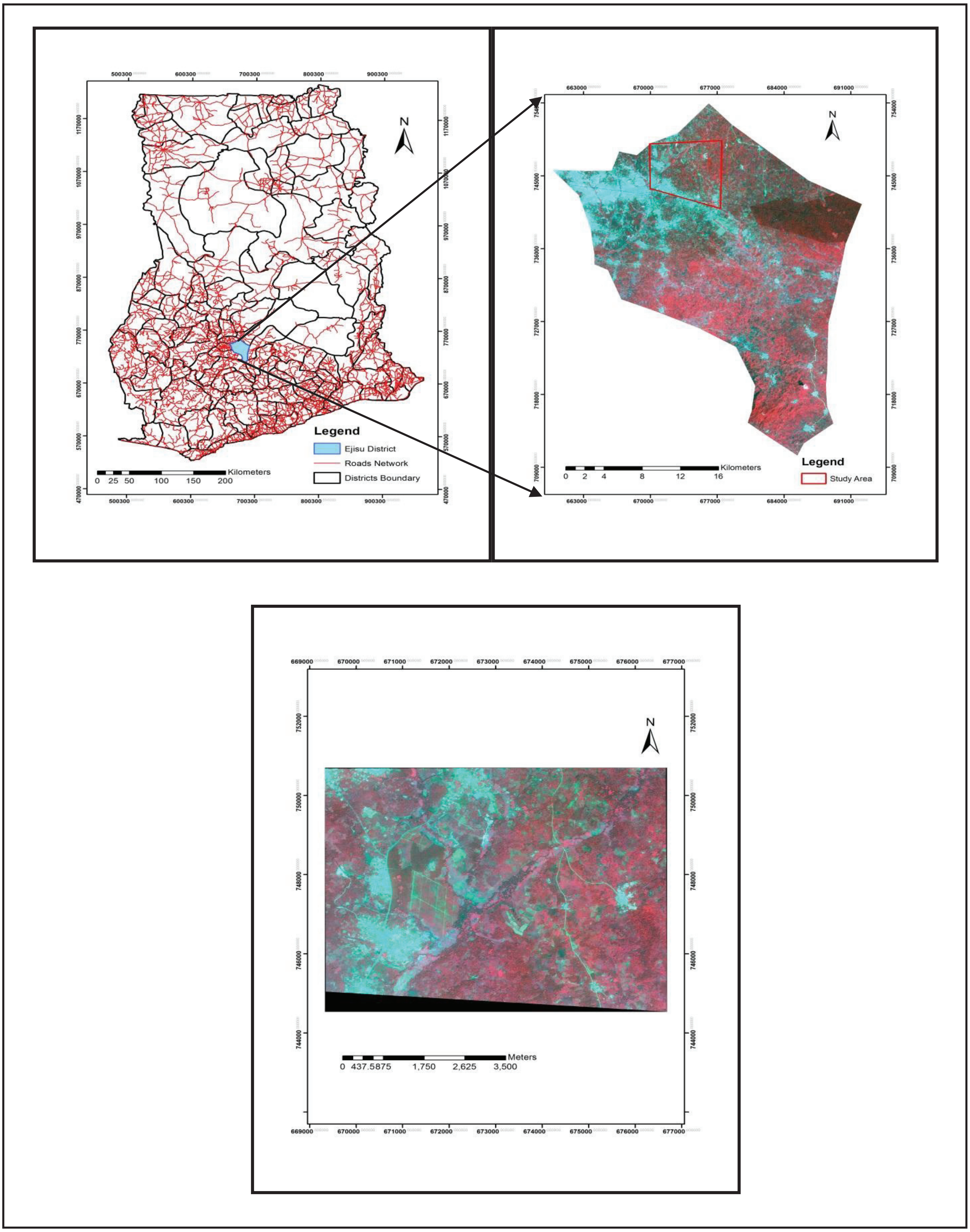


Figure 2: Study Area Location

3.1.2. Climate

The district experiences a bi-modal tropical rainfall pattern with annual rainfall ranging between 1092mm and 2344 mm and a mean annual value of about 1874 mm. Rainfall is experienced from March to July and again from September and normally ends in the latter part of November. Temperatures are high with a mean maximum monthly temperature of about 32°C occurring in February / March and a mean minimum monthly temperature of about 20°C in December / January. Average monthly temperature in the district is approximately 26°C. Relative humidity averages at 85% during the rainy season and 65% during the dry season (Anornu*, et al.*, 2009; Ministry of Local Government and Rural Development, 2006).

3.1.3. Vegetation

The district is situated in the semi-deciduous forest zone. Trees shed their leaves during the dry spells, but not all at the same time (Hall andSwaine, 1976). The district has two broad types of tree tenure management systems, mainly the Bobiri forest reserve and the off-reserve trees mostly found on farmlands. Off-reserve trees are mostly composed of remnants of forest patches and trees on farmlands where management is solely by farmers.

Outside forest reserve areas provide an important source of timber providing more than half of the nation's annual timber (Tropenbos International- Ghana 2009). However, unfavourable tree tenure systems and forest legislation have contributed to deforestation of this important timber source in Ghana, including the Ejusi-Juaben district (Hansen, 2011). Also the ecologically unfriendly farming practices and stone quarrying activities have resulted in the natural vegetation cover being degraded into secondary forest (Ministry of Local Government and Rural Development, 2006).

3.1.4. Soils

The district is dominated by crystalline rocks of Granite formation which give rise to very rich soil formation in the district offering opportunity for the cultivation of traditional and non-traditional cash crops and other staple food (Anornu*, et al.*, 2009; Ministry of Local Government and Rural Development, 2006).

3.1.5. Topography and drainage

The district is relatively flat and lies between 240 to 300 metres above sea level. A condition, which has favoured the growing of Oil palm, which is a major cash crop grown in the district. The district has a connection of a number of river systems, notable among them being the Oda, Anum, Bankro, Hwere and Baffoe rivers (Ministry of Local Government and Rural Development, 2006).

3.1.6. Economy / Agriculture

The major economic activity in the district is agriculture due to the favourable soils (Ministry of Local Government and Rural Development, 2006). Agricultural land area is estimated to be 180 931ha (annual crops : 76,265 Ha, under tree crops: 38,113 Ha ,under fallow: 60,393 Ha, under forest: 6,160 Ha) and average farm size estimated to be around 1.9 acres per family (Ministry of Food and Agriculture, 2011). As the backbone of the district economy agriculture constitutes 58.55% of the Gross Domestic Product (GDP). The main food crops grown are plantain, cassava, maize and cocoyam. Oil palm is a cash crop that is grown widely in the district (Ministry of Food and Agriculture, 2011; Ministry of Local Government and Rural Development, 2006). Appendix 1 and 2 are an illustration of the major crops grown and animal reared in the district.

3.1.7. Demographic Characteristics

Currently, the population of Ejisu-Juaben district stands at 144,272 (Ministry of Food and Agriculture, 2011). Majority of this population is employed in the agricultural sector (Anornu*, et al.*, 2009). The increase in population is mostly influenced by the four urban settlements in the district namely, Ejisu, Juaben, Besease and Bonwire (Ministry of Local Government and Rural Development, 2006).

3.2. Prefield work

3.2.1. Sampling Design

The study used a Stratified Random Sampling (STS) approach as trees on farmlands are found in various land use types or region of various tree density (Kleinn *et al.*, 2001). Also Stratification was chosen as it yields more precise estimates (Husch *et al.*, 2003).Six classes were derived using a preliminary unsupervised classification of the Aster 2010 image acquired on 6th February 2010. Unsupervised classification using the Isodata classifier in Erdas Imagine 2011 was performed after visual interpretation of the Aster image. Based on the spectral reflectance the initially classified six classes were merged into four based on visual assessment or interpretation of the unsupervised image and the original image. These strata or classes were later identified as Cropland, Young fallow, Old fallow and Forest relict prior to field work. This initial classification was only made to facilitate field work planning. Verification and true identification of each stratum was made in the field. The number of plots was calculated proportional to stratum size. A large number of sample plots (n>30) allow accurate estimation of carbon stocks, therefore the following formula was used:

$$n = \frac{t^2 \sum_{j=1}^{M} P_j s_j^2}{E^2}$$

Where n = minimum number of samples required

t= t value associated with specified probability

S_j^2 = Variance of X for jth stratum

E= allowable standard error in units of X (Husch *et al.*, 2003)

P_j= proportion of total forest area

Source: Husch *et al* (2003)

Although initially prior to field work a total of 102 plots, 38-Cropland (2108ha), 21-Young fallow (1178ha), 17-forest Relict (930ha) and 27-Old fallow (1550ha) had been planned based on unsupervised classification and the Aster image extent (5766ha). Due to time and accessibility aspects only 68 plots (22-Cropland, 13-Young fallow, 17-forest Relict and 16-Old fallow) were sampled. Also field sampling was restricted to the boundary of the World View-2 image (4200ha). The image only became available during field work.

3.2.2. Satellite Data

Two Satellite images were acquired namely World View-2 of 4 January 2011 and an Aster Image of 6th February 2010. The World View-2 image was used for tree segmentation in Definiens software whilst the Aster image was used for up-scaling. World view-2 Digital Globe's Satellite was launched on October 8, 2009 and is the first high resolution commercial satellite to offer 8 multispectral bands. Worldview-2 provides 0.46m panchromatic band (Black and White) resampled to 0.5m. It has additional 8 multispectral bands of 1.84m which are again resampled to 2m for the user (SIC, 2010) as illustrated in Appendix 3.

Aster is one of the five sensor systems on-board Terra a satellite launched in December 1999 and was built by a consortium of Japanese government, industry, and research groups and covers a spatial resolution of 15 to 90 meters. The image was obtained by ITC already geo-referenced to UTM Zone 30N coordinates with WGS 84 datum. The satellite bands descriptions are detailed in table 1 below.

Table 1: Aster Bands Description

Instrument	**Visible and Near**	**Shortwave bands**	**Thermal bands (TIR)**
Bands	1-3	4-9	10-14
Spatial Resolution	15m	30m	90m
Swath Width	60km	60km	60km

3.2.3. Ejisu Boundary Shape file

A shape file of boundaries for Ghana districts developed by the Ghana Land Commission in 1991 was acquired and used in the masking Aster image to the study area boundary.

3.3. Field Work

3.3.1. Field work Equipment

Varied equipment for field data collection and navigation were used. A GPS and IPAQ with Arcpad software were used for navigation and determining plot centers in the field. A diameter tape and tape measure were used to measure tree DBH and crown diameter. The list of all equipment and usage is provided in the table 2 below.

Table 2: Fieldwork Equipment

Equipment	Usage / Purpose
Garmin GPS and IPAQ	Navigation
Diameter tape (5m)	DBH measurement
Measuring tape (50m)	Measuring radius of plot
Haga Altimeter	Tree height measurement
Compass	Plot orientation
Suunto clinometer	Slope
Data sheet	Recording plot parameters

3.3.2. Sampling plots

In determining the appropriate plot size for the different strata a guiding principle was that the plots should be large enough to contain a sufficient number of trees and relatively small so as not to take too much time per plot (Husch*, et al.*, 2003). Therefore due to varying tree densities for the four strata, 12.62m radius circular plots were used for stratum Forest relict and old Fallow and 25.24m radius circular plots were used for stratum Cropland and Young Fallow. These plots were 500m² and 2000m² respectively (Gelens*, et al.*, 2010). Slope correction was performed on those plots whose slope equaled 15% or more using a slope correction table (FAO, 2004). Circular plots were chosen as these are easy to project on the ground unlike other plots designs. Plot orientation was recorded using a compass and each tree in the plot marked with a numeric number with reference to the true north.

3.3.3. Plot data

Field data collection was conducted in September 2011. DBH was measured for each observed tree at 1.3m above the ground. However, for circumstances were forked trees were encountered; the tree was counted as one if the fork begins above 1.3m above the ground. In cases where the fork was observed below 1.3m each stem meeting the required DBH range was considered as a tree. Diameter was recorded for those trees with DBH ≥10cm only as those with smaller DBH are assumed to have a minimal contribution to the total biomass per plot (Brown, 1997). GPS and Ipaq were used to establish the center of the plots after which circular plots with radius 12.62m and 25.24m were established and measurements conducted. Figure 3 below is an illustration of how tree DBH was measured in the field.

Figure 3: Tree DBH Measurement Source (FAO, 2004)

Data on tree species was also collected for each plot in the native language which was later translated into the scientific name using a field guide of tree species found in Ghana (Hawthorne andGyakari, 2006). Out of the 524 trees measured only 10 trees were impossible to clearly identify the proper scientific name and these were classified as other species. Data on tree height and crown diameter was also collected for 62 and 52 trees respectively. Crown diameter was measured as the average of the longest and shortest width as illustrated in figure 4 below.

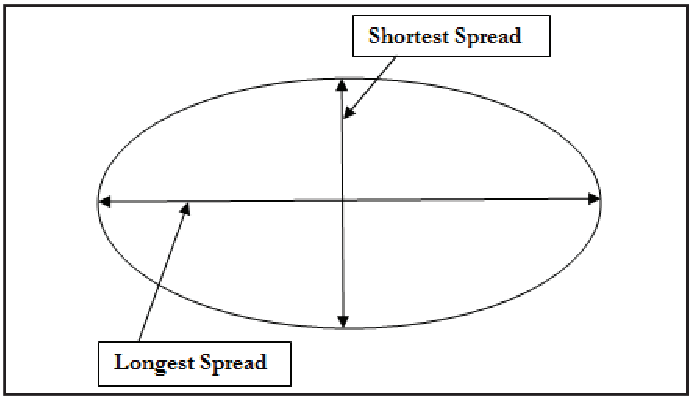


Figure 4: Crown Diameter Measurements

3.4. Post Field Work

3.4.1. Image preprocessing

Pan sharpening

Pan-sharpening is a technique that involves the combining of lower resolution colour pixels with the higher resolution panchromatic pixels to produce a high resolution multispectral image (Padwick *et al.*, 2010). The Hyperspherical Colour Sharpening algorithm which handles any number of input bands and especially applicable to World View-2 (Leica Geosystems, 2011a) was used to obtain a high resolution World View-2 image from the 8 multispectral bands. Figure 5 below is the methodology flow chart of the processes followed in the research.

Filtering and edge enhancement

Filtering is an image enhancement technique which involves the altering of spatial or spectral features of an image (Leica Geosystems, 2011a). Filtering was conducted in order to enhance the edges of pixels or features (trees) in the scene before the segmentation process. A 3 x3 low pass convolution filter was used which averages small sets of pixels within this window size to come up with an image whose features have more enhanced edges.

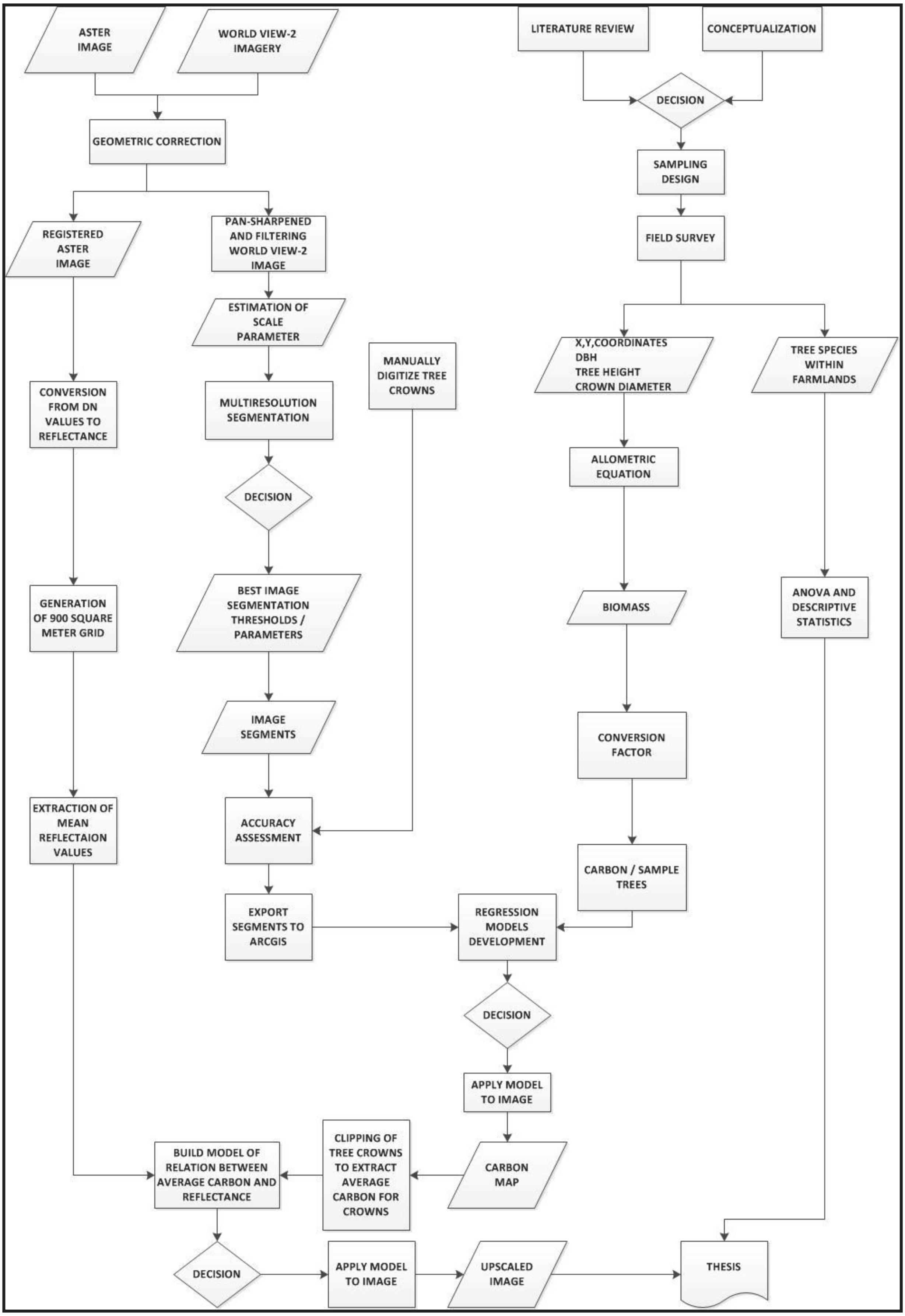


Figure 5: Methods Flowchart

Geo-referencing

The World View-2 and Aster satellite images were geometrically co-registered on the basis of six ground control points collected in the field from road junctions and root mean square errors obtained for each of the images. Although the two images were acquired already geo-referenced, this process was undertaken to increase accuracy of the images geographic coordinate system. Root Mean Square Error (RMSE) of 0.210m and 0.18m per pixel size was obtained for the World View-2 and Aster image respectively. Image mosaic using the MosaicPro algorithm in Erdas was also conducted for the Aster image as it was obtained in two separate data sets which covered the study area.

Atmospheric correction

Atmospheric correction is the process of eliminating the effect of the atmosphere in an optical image in order to obtain ground reflection for each band. The atmosphere affects information recorded at the sensor mainly by scattering and absorption and it adds an additional signal independent of the earth's surface (Leica Geosystems, 2011b). Therefore in the process of converting from digital numbers to reflectance values, effect of the atmosphere was also removed on the Aster image in order to effectively model the relation of segmented objects from the high resolution World View-2 image and reflectance from the medium resolution Aster. This conversion from Digital Numbers values to reflectance was performed using the ATCOR 2 module in Erdas imagine which computes a ground reflectance image for each band. The image was then re-sampled to a 15 x 15 m^2 pixel size using the nearest neighbour technique. Information needed to conduct the correction were found in the metafiles of the Aster bands and this included date of acquisition, solar elevation angle and the number of inputs bands. The terrain in the study area is flat so the ATCOR 2 module was preferred as it is designed for flat terrain.

3.4.2. Descriptive statistics

Descriptive statistics such as mean biomass and tree density per strata and normality tests were calculated for field data using SPSS and R-Software's. Histograms and box plots were plotted to visualize DBH, biomass and tree density distribution. Also one way Analysis Of Variance (ANOVA) was conducted on per hectare up-scaled plot data on tree density and biomass for the four strata (Cropland, Young fallow, Old fallow and Forest relict). ANOVA is used to determine whether there are any significant differences between the means of three or more independent groups(Husch*, et al.*, 2003).

3.4.3. Object Based Image Analysis (OBIA)

With increasing satellite spatial resolution has been the development of a technique to derive objects made up of several pixels termed OBIA. This technique utilizes spectral and contextual information for image processing (Blaschke, 2010). OBIA has proven effective for analysis of high resolution imagery as the pixel based approach cannot capture the spatial and spectral quality of these images. For example tree canopies, objects of interest in this research, may consist of a number of pixels with many different digital spectral values on high resolution image therefore making pixel based approach invalid (Lamonaca*, et al.*, 2008).

A way to build image objects in OBIA is image segmentation (Blaschke, 2010). 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 (Dragut *et al.*, 2010; Gibbes*, et al.*, 2010; Möller *et al.*, 2007; Trimble, 2010). In this study image segmentation was conducted in Definiens software 8.64 version.

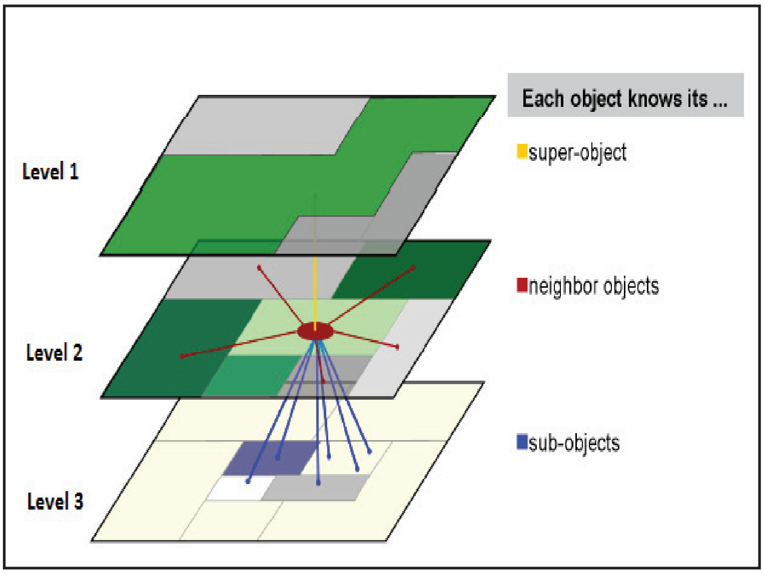


Figure 6: Objects Hierarchy Levels: Source Trimble (2010)

The segmentation process in OBIA results in image objects which are regions of homogeneity in terms of spectral and textural information (mean values per band, median values and variance) compared to single pixels making image analysis yield much more information (Blaschke, 2010). These objects are generated in a hierarchical network of image segments with increasingly homogeneous image segments as the hierarchical level decreases(Lamonaca*, et al.*, 2008). Each image object is connected to a superior object as illustrated in figure 6 above. This connectedness makes analysis possible at multi-scales (Lamonaca*, et al.*, 2008) as illustrated in figure 6 where the super object, level 1, is connected to small sub-objects at lower levels 2 and 3. Level 3 represent refined tree crowns in this research which are the final product of image segmentation.

Due to the complexity of the study area scenes which included a combination of built-up, bare surfaces, trees and Oil palm the segmentation process was divided into various stages. Built-up, bare surfaces and shadow were masked using the simple ratio index between the near infrared and red band of the World View-2 image. After masking out these surfaces and shadow segmentation was then conducted using two approaches. Approach one involved automatic masking of Oil palm and the whole extent of the image was used. In approach two as it was suspected that automatic separation of Oil palm from trees affect tree crowns, a subset with minimal Oil Palm was chosen and manual removal of the crop conducted. Steps followed in the segmentation process are discussed below.

Multiresolution segmentation

Multiresolution segmentation is one of the most powerful algorithms found in Definiens software which makes analysis of high resolution images more efficient (Lamonaca*, et al.*, 2008). The algorithm creates image objects in a bottom up approach as 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. The algorithm results are controlled by the user through scale parameters (Mallinis *et al.*, 2008). Scale parameters of 22 and 25 were chosen to segment the whole image and the subset respectively. Other parameters such as shape and compactness are also defined by the user in the multiresolution window. The more weight given to the shape window the more it will be considered in creating image objects and the more weight prescribed to the compactness value the higher it will be given consideration (Trimble, 2010). The shape criterion is important in creating image objects with distinct shape and thus, which are more homogenous in terms of their texture. Figure 7 below is an illustration of the main steps conducted in image segmentation.

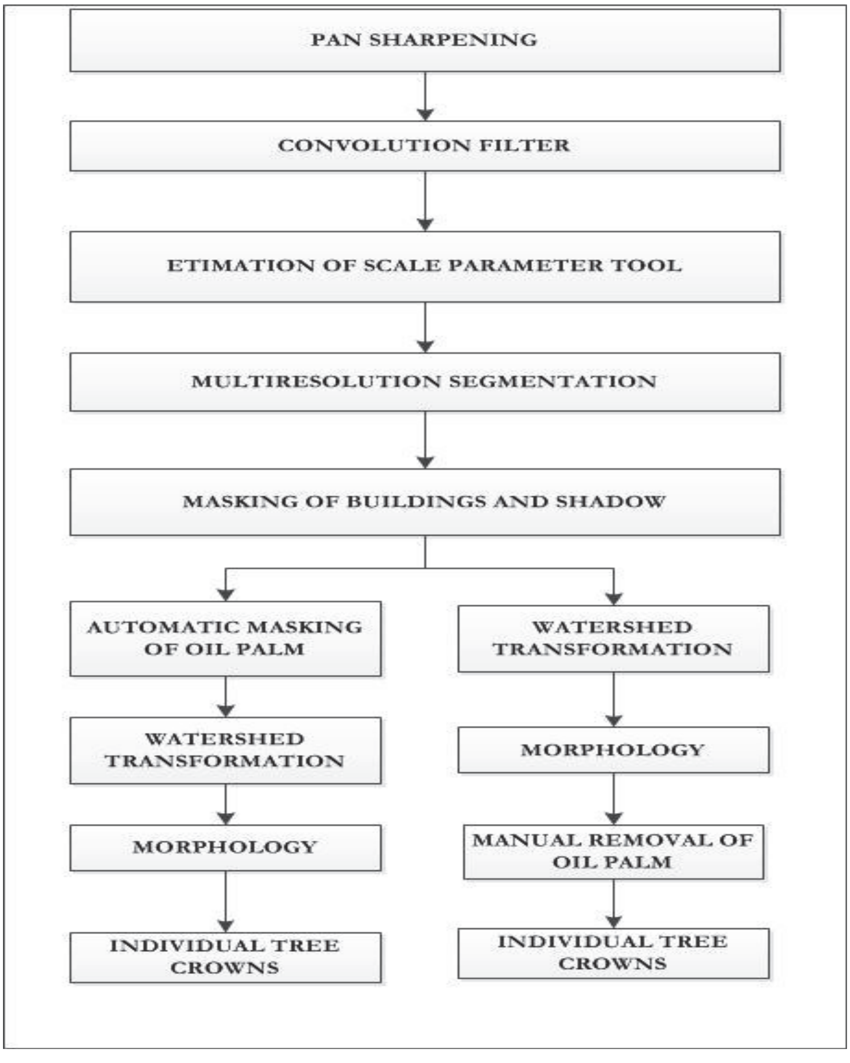


Figure 7: Steps followed in image segmentation

Estimation of scale parameter (ESP)

Prior to segmentation, scale was estimated using the Estimation of Scale Parameters (ESP) tool as this determines the size of segments so they best fit reality. As the Multiresolution approach was used in the study this tool proved useful as it works well with this image segmentation technique. The ESP tool builds on the idea of local variance (LV) for individual image objects / tree crowns within an image. Tree crowns have brighter tree tops and dark edges, with variance increasing with distance away from the centre of the crown to the edges. The local variance is 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 increase as opposed to local variance which is observed to increase as the scale increase (Dragut*, et al.*, 2010). Dragut, et al.(2010) established that the local variance alone cannot indicate the threshold at which to segment the image and thus proposed the rate of change of local variance (ROC-LV) whose peaks indicate the scale levels at which the image can be segmented in conjunction with the local variance curve. Figure 8 is an illustration of the ESP plot with the bold black being the local variance curve and the gray curve being the rates of change of local variance curve and the dotted lines (red circles) being the best thresholds at which the image can be segmented which coincide with the peak of the rate of change of local variance curve.

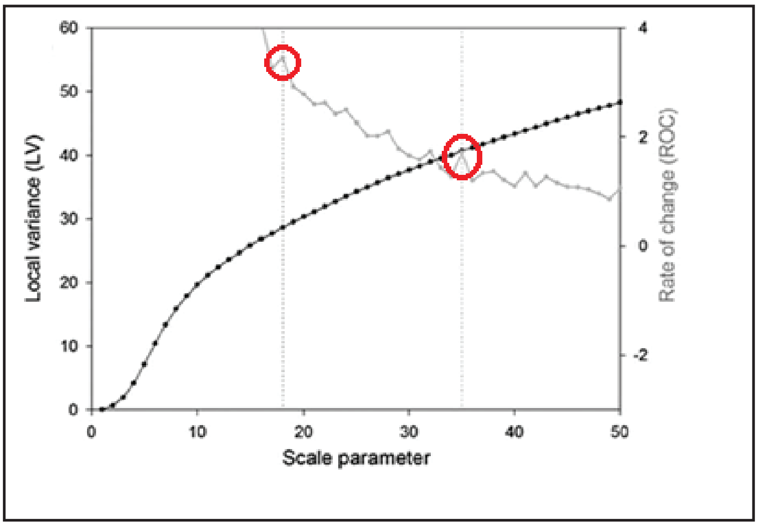


Figure 8: ESP tool plot, Source: Dragut *et al* (2010)

Masking of buildings and Shadow

A simple ratio is a division of the near infrared band and the red band reflectance which are very sensitive to vegetation and is one of the broadband greenness vegetation indices which measure the general quantity and vigour of green vegetation (Sims andGamon, 2002).In order to separate built-up and bare surfaces from vegetation the simple ratio was preferred as the contrast in reflectance within the near infrared and red band for built-up and vegetation surfaces is more distinct using these bands. The ratio ranges from 0 to 30 with vegetation having higher values above 2. In the study objects with values greater than 2.8 were classified as vegetation and those below were classifies as built-up or bare areas (Tucker, 1979).

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

Masking of Oil palm

As Oil Palm is a major cash tree crop grown widely in the study area and likely to confuse with trees, automatic detection and masking of the tree crop was conducted. Two vegetation indices Red Edge Comparison (Digital Globe, 2008) and the Modified Vegetation indices (Sims andGamon, 2002) were used to separate Oil Palm from trees.

World View-2 is the first satellite to offer the red edge band (705 -745 nm) at high resolution. According to Digital Globe, (2008), scientists have discovered that the red band (630 – 690 nm) to red-edge band comparison is more sensitive to vegetation type than the Normalized Difference Vegetation Index (NDVI). Use of the red and red edge bands has been shown to better seperate between species of weeds and conifer from broadleaf forest (Digital Globe, 2008). Also the red edge band has been shown not to be greatly affected by background (Sims andGamon, 2002), a condition which makes it useful for vegetation analysis. Oil palm have a needle like shape unlike deciduous trees which are found in the study area with broad leaves therefore due to this it was assumed that the red edge would aid in separation between Oil palm and trees considering variation in leaf structure. Cochrane, (2000), used the red edge to classify tree species in a study of tropical forests. Since tree canopies reflect high in the red edge and low in the red band as shown in figure 9, tree crowns have a higher value than Oil palms in this index. Values for the majority of Oil Palms were found to be less than 0.33 and that for trees were above 0.33. Thus based on this index the first separation between oil palm and tree crowns was achieved. The study used the red edge to red comparison by applying the formula below.

$$\text{Red Edge Comparison} = \frac{\text{Red Edge Band - Red Band}}{\text{Red Edge Band + Red Band}}$$

Further separation of remaining Oil Palm objects was achieved through using the Coastal blue band (400 - 450 nm) of the World View-2 image and the same Red Edge and Red bands in a modified vegetation index. The coastal blue band is new and better aid in vegetation analysis (Digital Globe, 2008). Oil Palms were found to reflect higher in the coastal blue band and red band than tree crowns, but lower in the red edge band as illustrated in figure 9 below. This is largely attributed to the different leaf structure and canopy architecture for Oil palm and trees. A threshold was established for tree crowns at values less than -0.25. Anything above was classified as Oil Palms. The formula for the index is illustrated below.

$$\text{Modified Vegetation Index} = \frac{\text{Red Edge Band} - \text{Coastal Blue Band}}{\text{Red Band} - \text{Coastal Blue Band}}$$

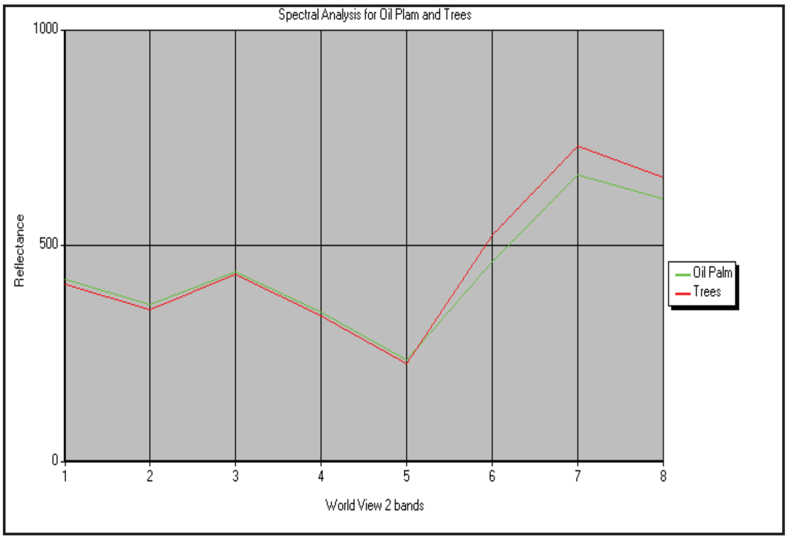


Figure 9: Trees and Oil Palm Reflectance

Apart from using vegetation indices manual masking of Oil palm was also conducted using a subset of the image where there was minimal proportion of the tree crop. This manual masking was conducted after identification and refinement of tree crowns as Oil palm has a distinct star shape and can easily be separated using visual interpretation.

Image differencing

Overlay functions in Erdas and ArcGiS software using image differencing and extraction by mask algorithms respectively for the classified Oil Palm layer after export from Definiens software was used to assign zero values to the Oil Palm regions. After masking Oil Palm further analysis was then conducted to automatically delineate tree crowns.

Watershed transformation

This algorithm was used to split clusters of tree crowns or image objects. The function operates in the form of a watershed in hydrology where there should be a distinct boarder between one watershed and the other. The maxima (or tree tops with high brightness value) is inverted to become the minima, valleys, which are flooded by increasing the level (Trimble, 2010; Wang. L *et al.*, 2004). Splitting is thus conducted where the watersheds meet, the edges of tree crowns creating individual crowns from clusters. The outputs are separated objects calculated through an inverted distance map.

Morphology

Morphology as a "discipline deals with the study of the shape and form of objects" (Shafri *et al.*, 2011). The size of the shape control window / mask in morphology is very important to achieve image objects which conform to reality. The mask is also important as it affects the changes induced in the objects for example the circular and square masks in Definiens software. In this study an open circular mask was chosen to depict tree crowns after which removal of non-circular objects was conducted for those objects with roundness values more than 1.2.

Segmentation Validation

Segmentation results need to be validated in order to assess their quality to ascertain whether they relate to true objects in reality (Clinton *et al.*, 2010; Möller*, et al.*, 2007). Two strategies were used to assess the accuracy of segmented image objects, visual interpretation known as 1:1 matching (Zhan *et al.*, 2005) and calculating the D value (Clinton*, et al.*, 2010). A total of 101 and 42 reference crowns were manually digitized for the whole image and subset image respectively.

Overlay operations and visual interpretation were utilized to assess the area of intersection between manually digitized reference polygons and image segments as based on the work of Zhan (2005). Polygons were considered one to one matching if the area of intersection is above 50% for the 101 and 42 manually digitized tree crowns for the whole image and subset respectively.

However visual interpretations are subjective and hence a further analysis was conducted using the D value as proposed by Clinton (2010) using the Intersector tool in Java environment. The tool overlays the reference polygons / digitized with the segmented and calculates over and under segmentation. The values are all subtracted from 1 and the closer the overall D value is to zero, the better the match between segmented and reference objects. Values close to 1 represent a large difference in extent between segmented and reference crowns (Ardila*, et al.*, 2011; Clinton*, et al.*, 2010). Over segmentation has occurred when the size of segmented objects is smaller than the size of reference objects and under segmentation is the vice versa (Clinton*, et al.*, 2010). Calculation of the D value was conducted using the formula below.

$$D_{ij} = \sqrt{\frac{OverSegmentation_{ij}^2 + UnderSegmentation_{ij}^2}{2}}.$$

Source: Clinton *et al* (2010)

3.4.4. Allometric Equations

Use of remote sensing to estimate biomass, and hence carbon, comes with requirements for allometric equations established through destructive sampling to come up with biomass estimates from easy to measure variables such as DBH and or height (Deans*, et al.*, 1996; Djomo*, et al.*, 2010). In this study a general allometric equation for tropical moist regions developed by Brown, (1997), was used as no specific equation for Ghana and specifically tree resources on farmlands exists. The equation was chosen as it is able to generate reliable biomass estimation for tropical moist regions and DBH alone explains well variability in biomass with coefficient of determination (R^2) of more than 0.84 (Brown, 1997). This equation is used with tree DBH ranges between 5-148 cm and should not be used for those outside this range. The derived biomass were then converted to carbon using equation 2 below as carbon and biomass have a direct relationships with carbon constituting between 45% to 50% of above ground biomass (Kale, *et al.*, 2009).

Biomass = 42.690 -12.800*(DBH) +1.242*(DBH²)…………1
Carbon = 0.47*biomass…………2

3.4.5. Regression analysis and carbon modeling

Regression modelling is used to establish a relation between predictor / independent variables and one response or dependant variable (Snee, 1977). This modelling approach was used in this study to come up with relations between biomass and CPA. However after a model has been established it needs to be validated therefore cross validation (Snee, 1977) approach was used as it was considered more useful. The data were split as 70% (estimation) and 30% (validation). The splitting of the data was conducted in a random way using the sample without replacement function in R software environment. Coefficients of determination (R^2), p-value, Root Mean Square Error (RMSE) and the Relative Root Mean Square Error ($RMSE_r$) were calculated to characterize the quality of the models. The RMSE and $RMSE_r$ reflect the proportion or amount of biomass, and hence carbon, that the model predicted biomass values differ from the field observed measurements. The coefficient of determination represents the extent of variation for the dependant variable explained by the explanatory / independent variable. These have been proved as useful checks for model quality (Muukkonen andHeiskanen, 2005; Snee, 1977). Candidate crowns for model development were those that were not greatly over and under segmented. Below is an illustration of the formulas for the calculation of the quality checks.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad \text{………………………….1}$$

$$\text{RMSE}_r = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\bar{y}} \times 100 \quad \text{………………….2}$$

Source: Muukkonen and Heiskanen (2005)

y_i= Observed value of dependant variable
$\bar{y}$= Mean of observed dependant variable
n= Number of samples in the validation data
$\hat{y}_i$ = Predicted value of dependant variable

3.5. Up-scaling

Up-scaling involves the transfer of information between scales (Stein*, et al.*, 1998) of high resolution to lower coarse resolution which cover broader landscape levels. There are many image up-scaling techniques found in commercial software and Hay et al, (2001), found out that these techniques such as nearest neighbour, bilinear interpolation and cubic convolution perform less efficiently as compared to object specific up-scaling especially when dealing with high resolution satellite imagery. In high resolution images pixels are smaller than the objects of interest, tree crowns, therefore aggregation of pixels to objects which relate to reflection in medium resolution images is needed to transfer between scales (Gibbes*, et al.*, 2010). Crown projection area derived from high resolution World View-2 image was used as training data to transfer information from high to medium resolution. The proportional areal coverage of tree crowns contribute much to reflection observed within a medium resolution pixel for a vegetated surface (Rasmussen*, et al.*, 2011) and has been used in many applications to transfer between scales (Gibbes*, et al.*, 2010; Hufkens *et al.*, 2008,).

An area based averaging technique for carbon based on the spatial coverage of image objects (tree crowns) within a 30 x 30 m^2 generated grid was used to upscale carbon from fine World View-2 (0.5 x 0.5 m^2) to coarse scale Aster (15 x 15 m^2). The generated grid covered four pixels in the Aster image in order to compensate for geo-referencing errors and these pixels were chosen at plot locations. Plots for strata cropland and young fallow (2000 m^2) covered the full extent of the four Aster pixels whilst for strata old fallow and forest relict the Aster pixels were relatively larger than the plot size of 500m^2. This was attributed to high tree density in forest relict and old fallow, thereby using smaller plots, as compared to cropland and young fallow. Average carbon was calculated for tree crowns within the 900m^2 window and this was multiplied by the proportion areal coverage of these crowns to come up with an area based average carbon within the generated 900m^2 Aster window (Hufkens*, et al.*, 2008). Table 3 is an illustration of the calculation. The formula for the analysis is given below:

$$\text{Area Based Carbon Average} = \frac{\text{Tree Crowns Total Area}}{\text{Grid Window Area (900 square metres)}} \text{ X } \text{Average Tree Crowns Carbon}$$

Up-scaling strategy modified from Hufkens *et al* (2008)

The obtained area based carbon average values were used to build a non-linear model to relate carbon and the extracted mean pixel reflection for the four pixels covered by the 900m^2 window for the visible-near infrared bands of the Aster image. These bands were chosen as they are found within the range in which vegetation is most sensitive as vegetation absorbs the red and green band and reflects strongly in the near infrared region(Sims andGamon, 2002; Tucker, 1979). Mean reflection for the four Aster pixels covered by the generated 30 x 30 m^2 window were extracted using a GIS zonal attributes function in Erdas software. This function facilitate the extraction of mean values from a raster using a reference vector layer, in this case the 30 x 30 m² grids (Leica Geosystems, 2011a).

Table 3: Calculation of Area Based Carbon Average

Plot Number	Aster Grid size (m²)	Area covered by Tree Crowns (m²)	Average Tree Crowns Carbon (kg)	Area based average carbon (kg)
22	900	54	475	28
62	900	189	407	85
65	900	182	2176	440
67	900	108	328	39
57	900	178	813	161
66	900	555	1140	703

4. RESULTS

4.1. Descriptive statistics

A total of 524 trees were measured their DBH in the study area and these were found to belong to 31 tree species (Appendix 4). Plot distribution was evenly distributed according to size of stratum with croplands having the highest plots as illustrated in table 4 below.

Table 4: Plot and tree distribution within strata

Stratum	No of Trees	No of plots	Average DBH (cm)
Cropland	104	22	37
Young fallow	54	13	30
Forest Relict	254	17	20
Old fallow	112	16	26

Trees with large DBH were found in croplands and young fallow strata and those with lower were distributed in forest relict and old fallow. Higher DBH classes were mostly found on cropland which had an average DBH of 37cm. This is mainly due to selective retention of some preferred tree species on croplands such as *Ceiba Petandra* and *Alstonia boonei* for shade and timber usage by farmers. DBH distribution in forest relict and old fallow followed an inverse J-shaped pattern (Appendix 5) and higher regenerative capacity as they were dominated mostly by lower DBH classes, a normal trend for healthy forests as compared to cropland and young fallow which had no distinct patterns as illustrated in figure 10 below.

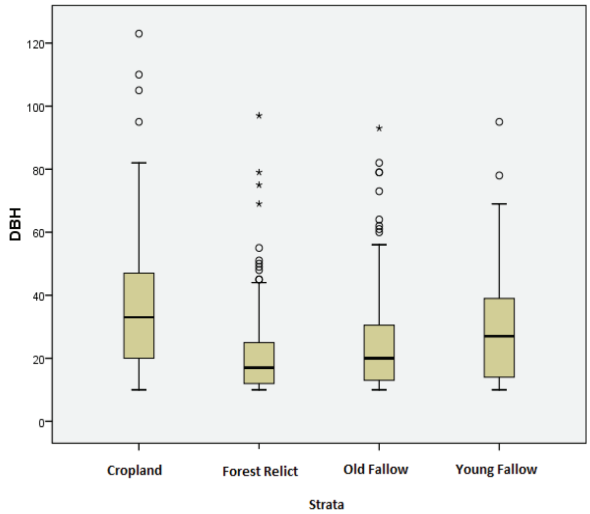
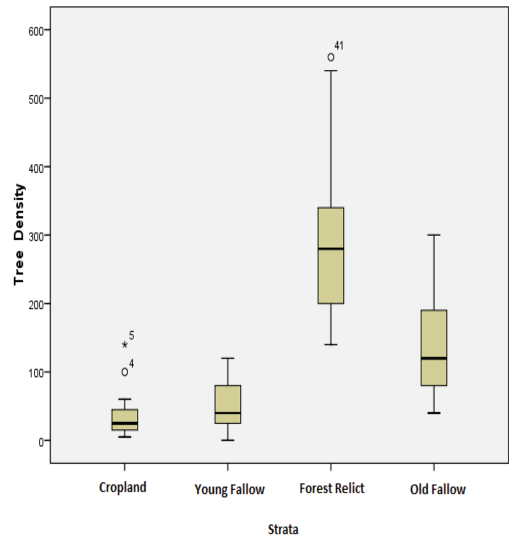


Figure 10: Tree DBH (cm) distribution within strata

Average biomass per tree was found to be high in cropland and young fallow 1925kg and 1251kg respectively and low in forest relict and old fallow 509kg and 975kg respectively. This is due to the large DBH ranges found within cropland and young fallow strata as compared to the relatively small DBH classes of the other two. Appendix 6 is a box plot of biomass distribution for trees within the four strata.

Despite having small amounts of biomass per individual tree in forest relict and old fallow, when extrapolated to per hectare / landscape level, the amount of biomass found in these strata is higher than in cropland and young fallow. Forest relict and old fallow had on average 152 and 136 tonnes of biomass per hectare whilst cropland and young fallow had on average 65 and 75 tonnes respectively. This is attributed to high average tree density for forest relict (301trees/ha) and old fallow (141trees/ha) as compared to young fallow (51trees/ha) and croplands (35trees/ha) where trees are felled to give way to agricultural production. Figure 11 below is an illustration of biomass distribution per hectare and tree density within the four strata.



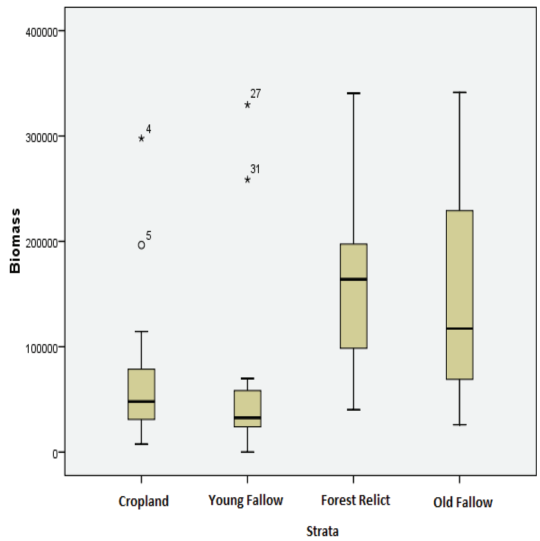


Figure 11: Biomass and tree density distribution per hectare

4.2. Testing Mean Difference

Further analysis was conducted on per hectare tree density and biomass data to really ascertain whether the variations in mean values between strata were really significant. This analysis was conducted using the Analysis Of Variance (ANOVA) statistic. Since one of the crucial assumptions of ANOVA is that the data should be normally distributed, biomass data on cropland and young fallow were observed to be not normally distributed and therefore the data set was log transformed in order to conduct the analysis. The same was also done for tree density. Results of normality tests are in Appendix 7. Subsequently the results revealed that there were significant differences in mean biomass and tree density between the strata at 95% confidence interval as illustrated in tables 5 and 6 below.

Table 5: Results for logarithmically transformed biomass data

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	36.90977	3	12.30325625	5.346337613	0.002384216	2.748190911
Within Groups	147.28	64	2.301249404			
Total	184.1897	67				

Table 6: Results for logarithmically transformed tree density data

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	69.76672572	3	23.25557524	33.01501905	5.12787E-13	2.748190911
Within Groups	45.0812042	64	0.704393816			
Total	114.8479299	67				

4.3. OBIA

Object based image analysis was conducted to extract tree crowns from the high resolution World View -2 image. This analysis followed a sequence of steps as discussed below. The study area presented a complex landscape ranging from settlements (built-up areas), Oil palm plantations and farmlands as illustrated in figure 12 below, which is part of the image.

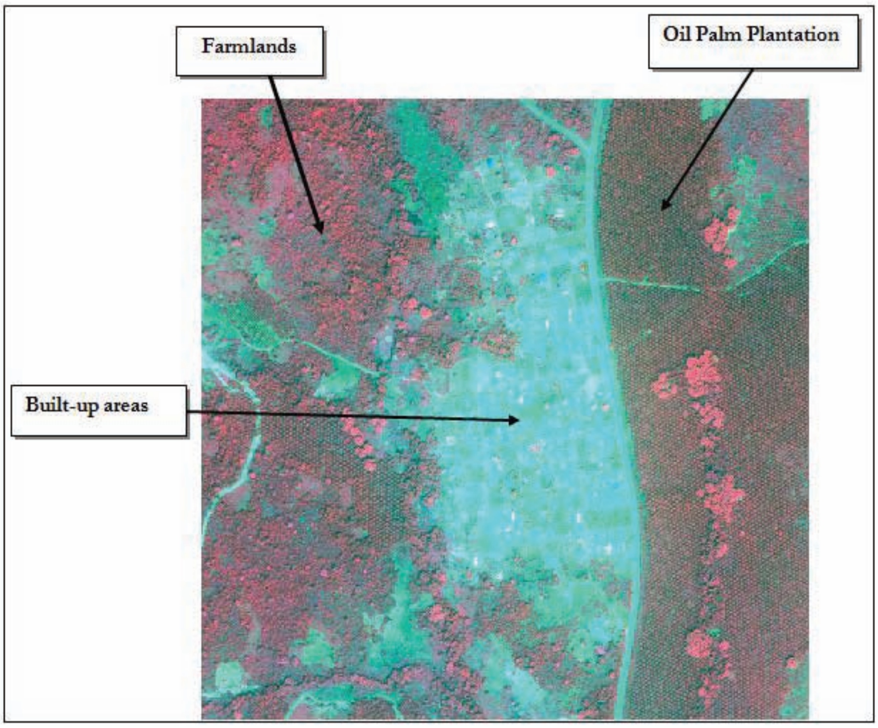


Figure 12: Illustration of complex scenes in the image (Farmlands, Built-up areas and Oil Palm Plantations

4.3.1. Scale parameter estimation

Estimation of scale parameter at which the World View-2 image could be best segmented revealed four main thresholds at 16, 18, 22 and 25. These thresholds were chosen as the best using the peaks in the rate of change of local variance plot as it was observed by Dragut, et al, (2010), that this curve explains best the best segmentation threshold. Scale parameters 22 and 25 were used to segment the whole image and subset respectively as they provided the best objects with meaningful shape size (1:1 matching) and low D value as shown in table 7. Figure 13 is the results obtained using the ESP tool.

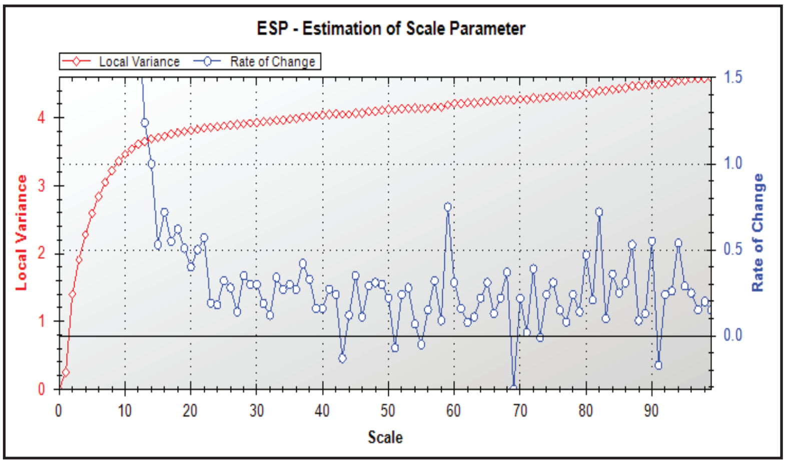


Figure 13: Results of ESP tool

4.3.2. Segmentation with automatic masking of Oil Palm

Image segmentation was first conducted with automatic identification and masking out of Oil palm using vegetation indices as explained in chapter three. Oil palm identification was conducted as an intermediate step before final identification and refinement of tree crowns. Figure 14 below is an illustration of part of the image showing segmented tree crowns and Oil palm with its unique star shape.

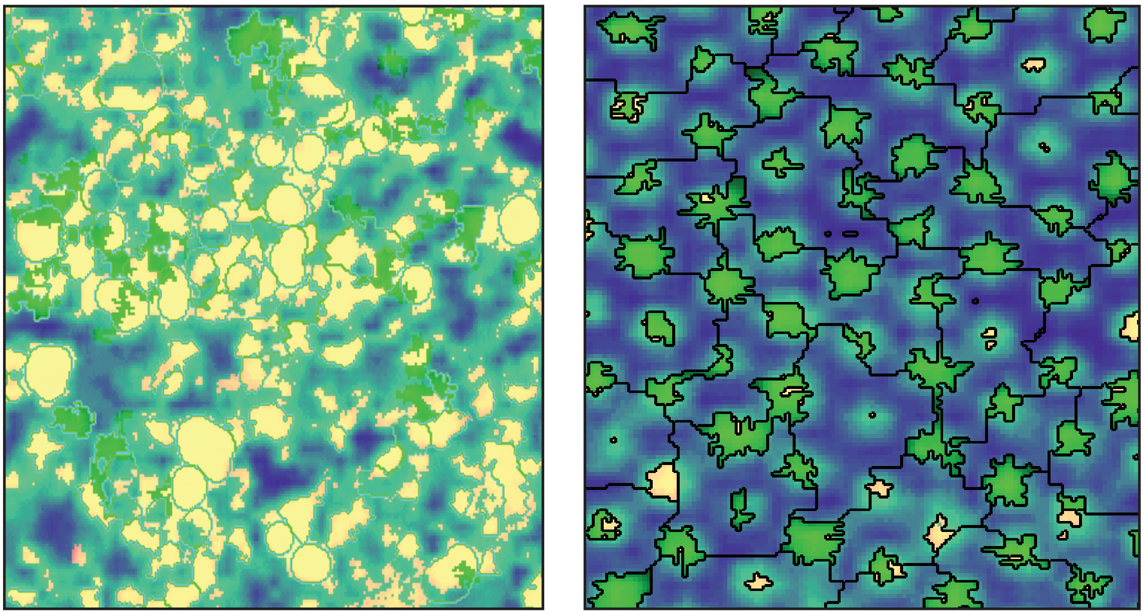


Figure 14: (a) Segmented Tree Crowns **(b) Segmented Oil Palm**

4.3.3. Segmentation accuracy assessment

Both visual and automated validation techniques were employed in the study to assess the correctness of produced segments by the Definiens software. CPA derived using automatic masking of Oil palm using the whole image extent had a 72% 1:1 matching using a scale parameter of 22. Figure 15 is an illustration of how 1:1 matching was conducted using overlay function.

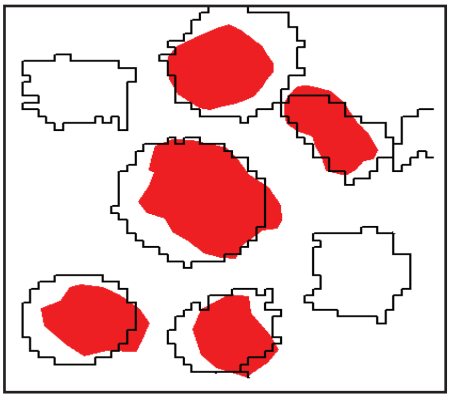


Figure 15: One to one matching validation procedure

However, better tree identification and a much higher 1:1 matching and lower error (D value) was obtained for CPA derived when manually masking Oil palm using a subset of the image as discussed latter in section 4.3.6 below. Table 7 is an illustration of segmentation validation results for the whole image and the subset.

Table 7: Segmentation Validation

Image	Reference Crowns	1:1 Matching	Percentage 1:1	D value
Whole Image	101	73	72%	0.32
Subset	42	35	83%	0.28

4.3.4. Carbon Modeling for Segmentation with Automatic masking of Oil Palm

Cross validation was applied to data and out of the 73 segmented crowns found to have 1:1 matching; those with perfect match and corresponding well with visual interpretation of crowns and data collected in the field were used to develop the model. A total of 55 crowns were used to establish a relation between biomass and crown projection area. Of these 39 were used for estimation and 16 for validation. Linear and non-linear models were evaluated and the latter was chosen as it had a higher coefficient of determination and low RMSE. The coefficient of determination (R^2) obtained was 0.61 and significant at 95% confidence interval, meaning that segmented CPA explained well the proportion of variability in biomass (response variable). The model also showed a high correlation (r) of 0.78 between the two variables. Table 8 below is a summary of the model developed.

Table 8: Summary of Regression model for model developed using automatic masking of Oil palm

Anova

	Sum of Squares	df	Mean Square	F	Sig.
Regression	9.960E7	2	4.980E7	27.978	.000
Residual	6.408E7	36	1779908.610		
Total	1.637E8	38			

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
CPA	1.892	42.345	.020	.045	.965
CPA ^ 2	.679	.397	.761	1.711	.096
(Constant)	656.383	936.517		.701	.488

*Biomass = 0.679*CPA^2+1.892*CPA+656.383*

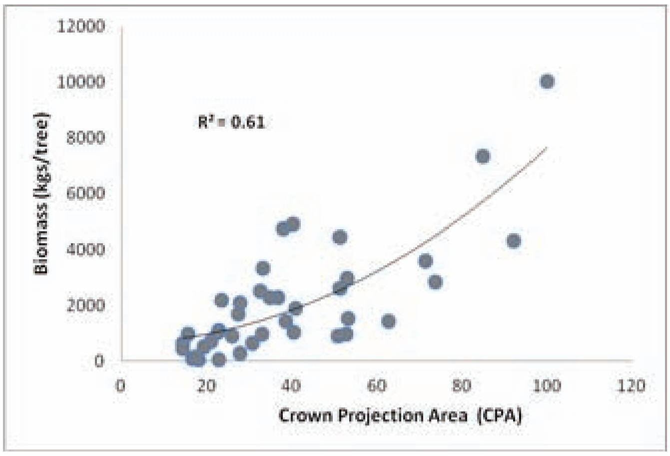


Figure 16: Non linear model for Biomass and CPA for model developed using automatic masking of Oil palm

Model validation was conducted using 16 test crowns and the relative root mean square error observed was 41.3% for validation and 60.7% for estimation data. A model was also developed between the predicted biomass and the observed and the coefficient of determination obtained was R^2=0.88 as illustrated below.

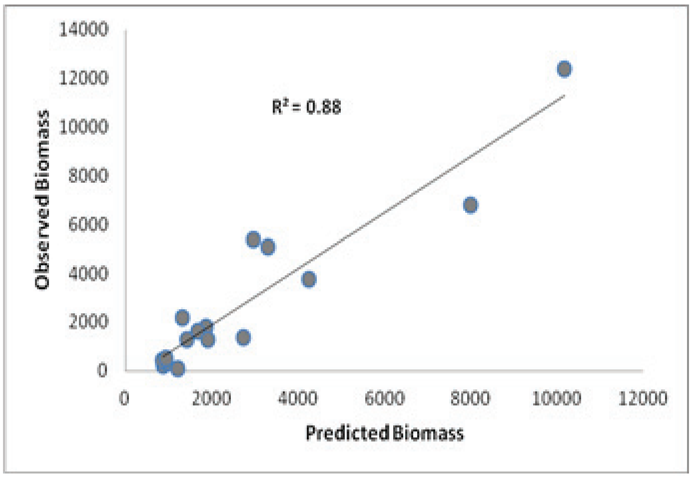


Figure 17: Linear model of predicted against observed Biomass for model developed using automatic masking of Oil palm

4.3.5. Oil Palm Problem

Results of image segmentation revealed that Oil palm affected accurate tree crown identification. Tree crown identification was affected in two ways. First, the automatic masking of Oil palm using outlined vegetation indices resulted in removal of parts of tree crowns. This is illustrated in figure 18 below where within the same area, tree crowns are represented differently. Figure 18 (a) shows part of tree crowns, classified green areas, having been lost due to Oil palm masking and figure 18(b), shows how well the crowns are reserved if Oil palm is removed manually and not through automatic detection an approach discussed and illustrated further in section 4.3.6 below. Second, tree identification was greatly affected as less tree crowns were identified when automatically masking out Oil palm than when manually removing the tree crop.

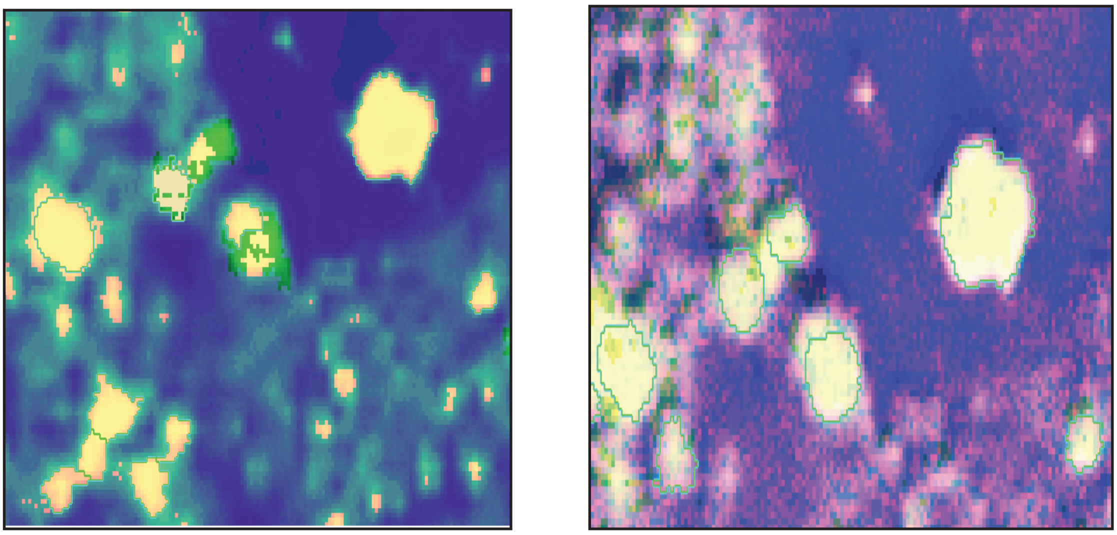


Figure 18: (a) With automatic masking of Oil Palm (b) Without automatic masking of Oil Palm

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4.3.6. Segmentation with manual masking of Oil Palm

As it was suspected that use of vegetation indices to automatically mask out Oil palm affected tree crowns delineation, it was decided to extract a subset of the image where minimal Oil palm was found and manually detect and delete it after the segmentation process. Oil palm has a distinct star shape clearly different from tree crowns and is more homogenous especially in large scale plantations. Only built up and bare areas were automatically masked out and the remaining layer was assumed tree crowns. Watershed transformation and morphology algorithms were then applied to image objects as explained in the method section to obtain individual tree crowns. Tree crowns obtained had better shape and high tree identification as compared to the approach where Oil Palm was automatically masked out. Figure 19 below is an illustration of results obtained using this approach.

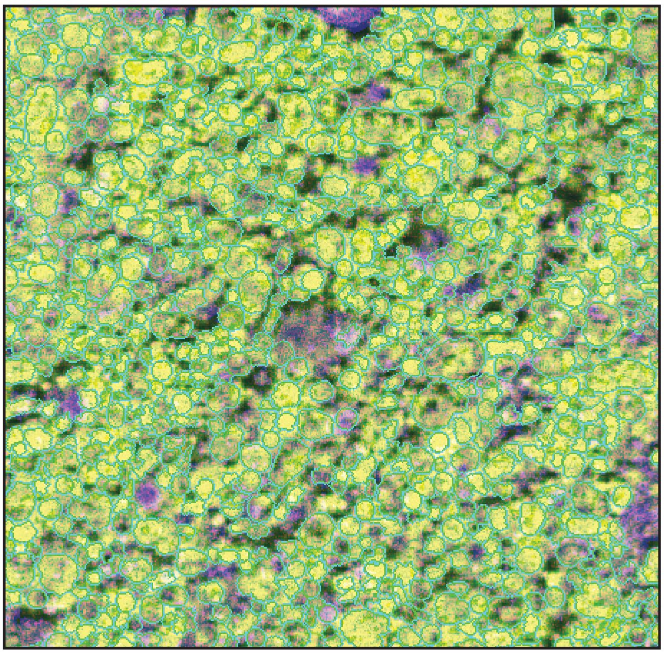

Figure 19: Tree crowns obtained after manually masking Oil Palm

4.3.7. Carbon Modeling for Segmentation with manual masking of Oil Palm

Cross validation method was applied and 23 segmented tree crowns were used for model development and 11 were used as test data. The coefficient of determination obtained using the estimation data was found to be higher R^2=0.66 using the non-linear model than that obtained when automatically masking out Oil Palm meaning that CPA explained better the variation in biomass. The model was significant at 95% confidence interval. Table 9 below is a summary of the model.

Table 9: Summary of Regression model developed using manual masking of Oil Palm

Anova

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.102E7	2	1.051E7	19.978	.000
Residual	1.052E7	20	526129.329		
Total	3.154E7	22			

Coefficients

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
CPA	38.930	51.379	.395	.758	.457
CPA ^ 2	.507	.619	.428	.820	.422
(Constant)	-402.902	984.230		-.409	.687

The model developed for Biomass and Crown projection area for approach 2 was:

*Biomass = 0.507*CPA^2+38.930*CPA-402.902*

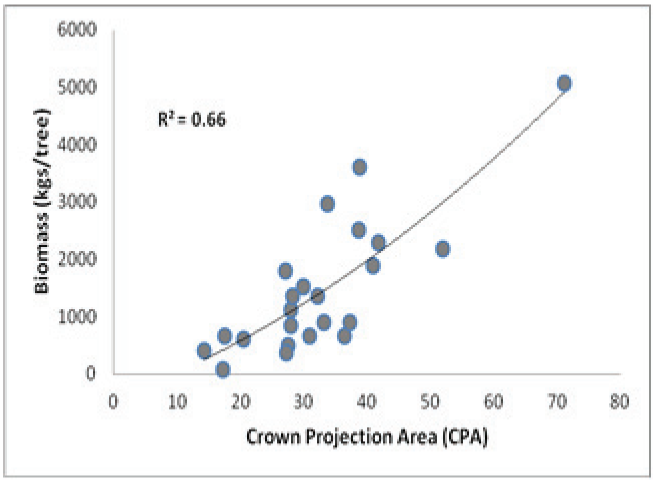

Figure 20: Non linear model for Biomass and CPA for model developed using manual masking of Oil Palm

Model validation was conducted using 11 test crowns and the relative root mean square error observed were 45.6% for estimation and 38.1% for validation data as compared to the model developed after automatically detecting and masking out Oil Palm. A model was also developed between the predicted biomass and that observed and the coefficient of determination obtained was (R^2) 0.81 as illustrated in figure 21 below.

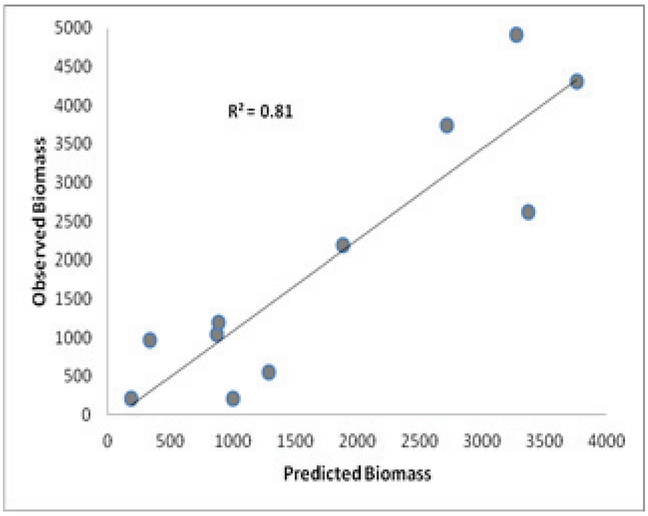

Figure 21: Linear model of predicted against observed Biomass for model developed using manual masking of Oil palm

4.3.8. Carbon Mapping

As the developed method (rule set) for manual masking of Oil palm resulted in better tree identification and model development, with less error, relative root mean square errors of 45.6% and 38.1% for estimation and validation data. This approach was used to generate image segments after which manual masking / removal of Oil palm was conducted for the whole image. The model for manually masking of Oil palm was adopted for coming up with the final carbon map for the study area. Carbon was derived from biomass using a conversion factor of 47%. The carbon map produced is illustrated in figure 22 below.

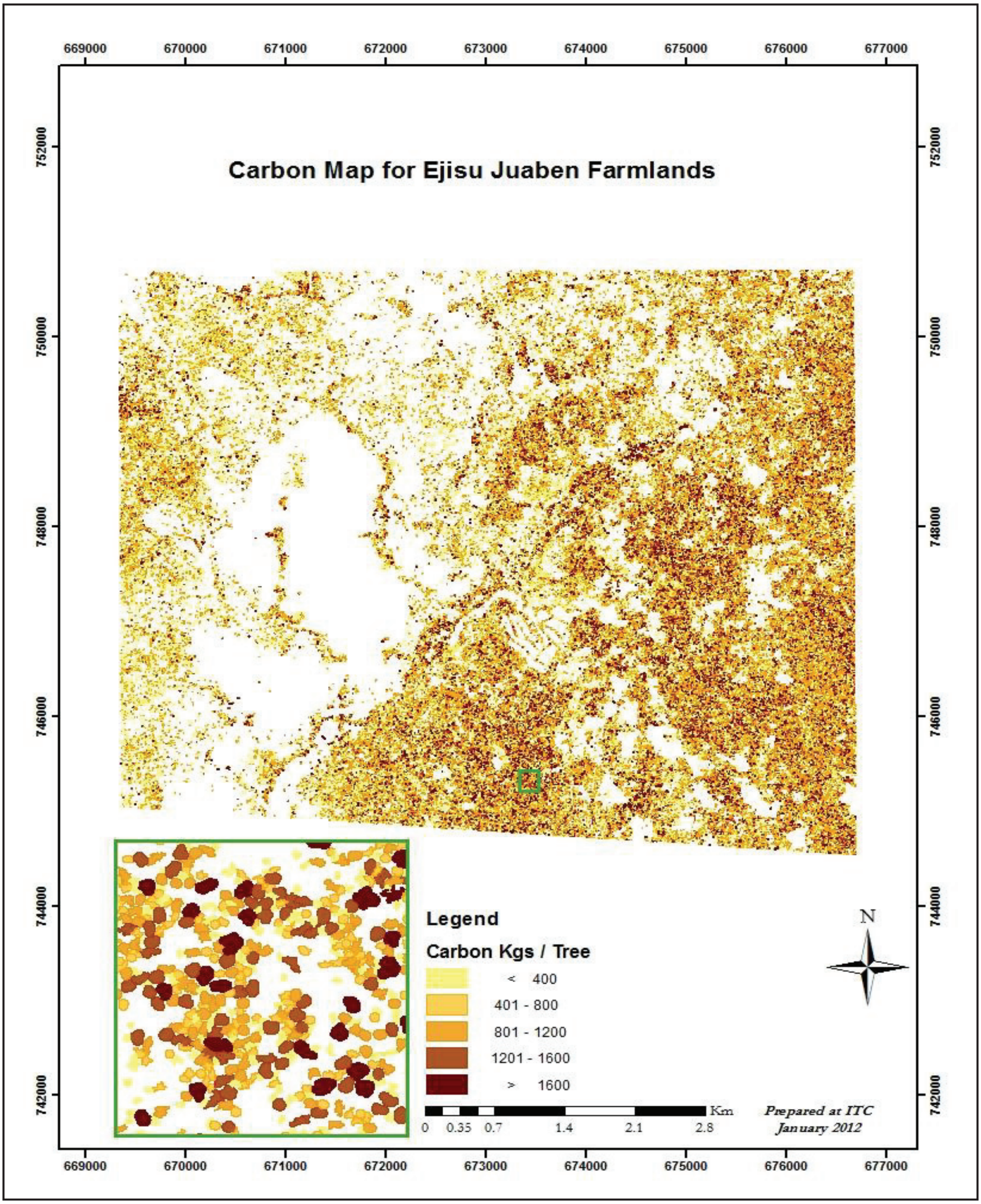

Figure 22: Carbon Map for Ejisu Juaben farmlands

4.4. Up-scaling

A Non linear relation was established between spectrally delineated CPA segmented from the higher resolution World View-2 and band 3 (near infrared) reflection values from the medium resolution Aster image. Samples of tree crowns falling within the 30 x 30 m² Aster generated window were obtained from 35 plots. As carbon for the tree crowns had already been obtained through regression modelling as explained above, average carbon per tree (based on segmented CPA) was calculated for each window and this was multiplied by the proportion area covered by tree crowns in the window as explained earlier in the methods section. Mean reflection values for the near infrared for the four pixels falling within the 30 x 30 m² Aster window showed a moderate correlation (r) with area based average carbon for image segments. Results of the correlation analysis are illustrated in table 10 below.

Table 10: Correlation analysis for average carbon and Aster bands

Bands (Aster Visible-Near Infrared)	r (Pearson Correlation Coefficient)
1 (Green band)	-0.18
2 (Red band)	-0.41
3 (near infrared)	0.66

The near infrared band predicted well carbon within the segmented tree crowns with a high coefficient of determination (R^2) of 0.50 as compared to other bands which had low R^2=0.23 and R^2=0.09 for red and green band respectively as illustrated in Appendix 8. The near infrared band followed a non-linear direct relation to carbon as compared to the red and green band which had an inverse non-linear relation, an observation made by Tucker, (1979), who investigated the relation between individual band radiance and biomass in vegetation. This relation is mostly due to the peak of reflection by vegetation in the near infrared region and peak absorption in the red band. The developed model was significant at 95% confidence interval as illustrated in table 11 below.

Table 11: Summary of Regression model for Up-scaling

Anova

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2531567.260	2	1265783.630	10.774	.001
Residual	2467153.001	21	117483.476		
Total	4998720.261	23			

Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Band 3	-9.730	10.529	-3.213	-.924	.366
Band 3^2	.003	.002	3.907	1.124	.274
(Constant)	9068.120	11792.814		.769	.450

The model developed for up scaling was:

*Average Carbon = 0.003*Band 3^2 – 9.730*Band 3 + 9068.120*

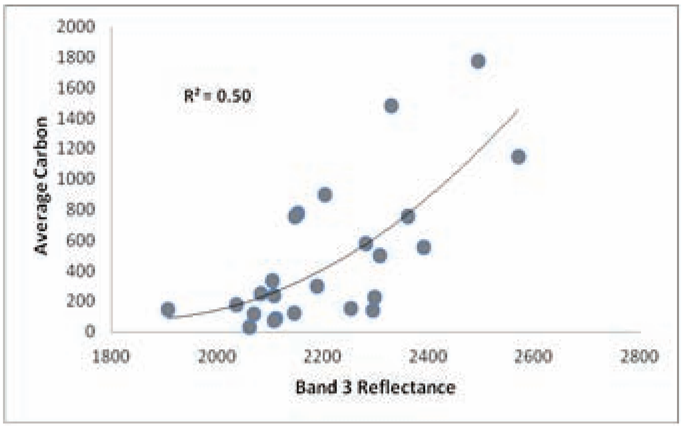

Figure 23: Up-scaling model

Validation resulted in a relative root mean square error of 40% for the validation data set. A model was also developed between the predicted area based average carbon and that observed and the coefficient of determination obtained was R^2=0.68 as illustrated in figure 24 below.

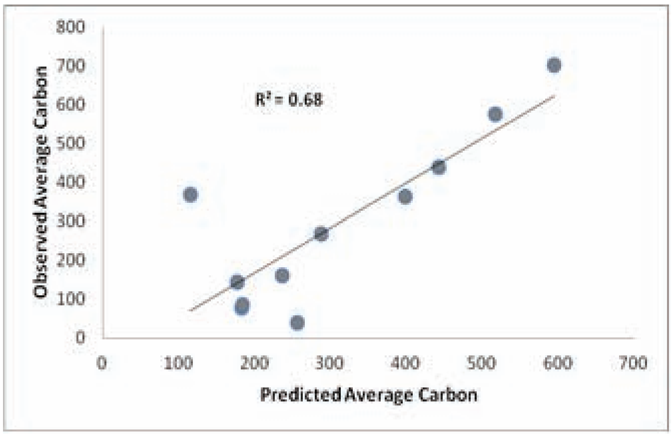

Figure 24: Up-scaling model Validation

Since the near infrared predicted better average carbon with higher coefficient of determination (R^2) 0.50 and relative root mean square error of 40 % it was used to come up with an up-scaled map of carbon from the Aster image for the study. Masking of the study area extent from the Aster image was conducted using the World View-2 image after which the model developed was applied to the near infrared band using the raster calculator in ArcGIS environment to come up with an up-scaled map of carbon. Figure 25 below is an illustration of the up-scaled carbon map for the study area.

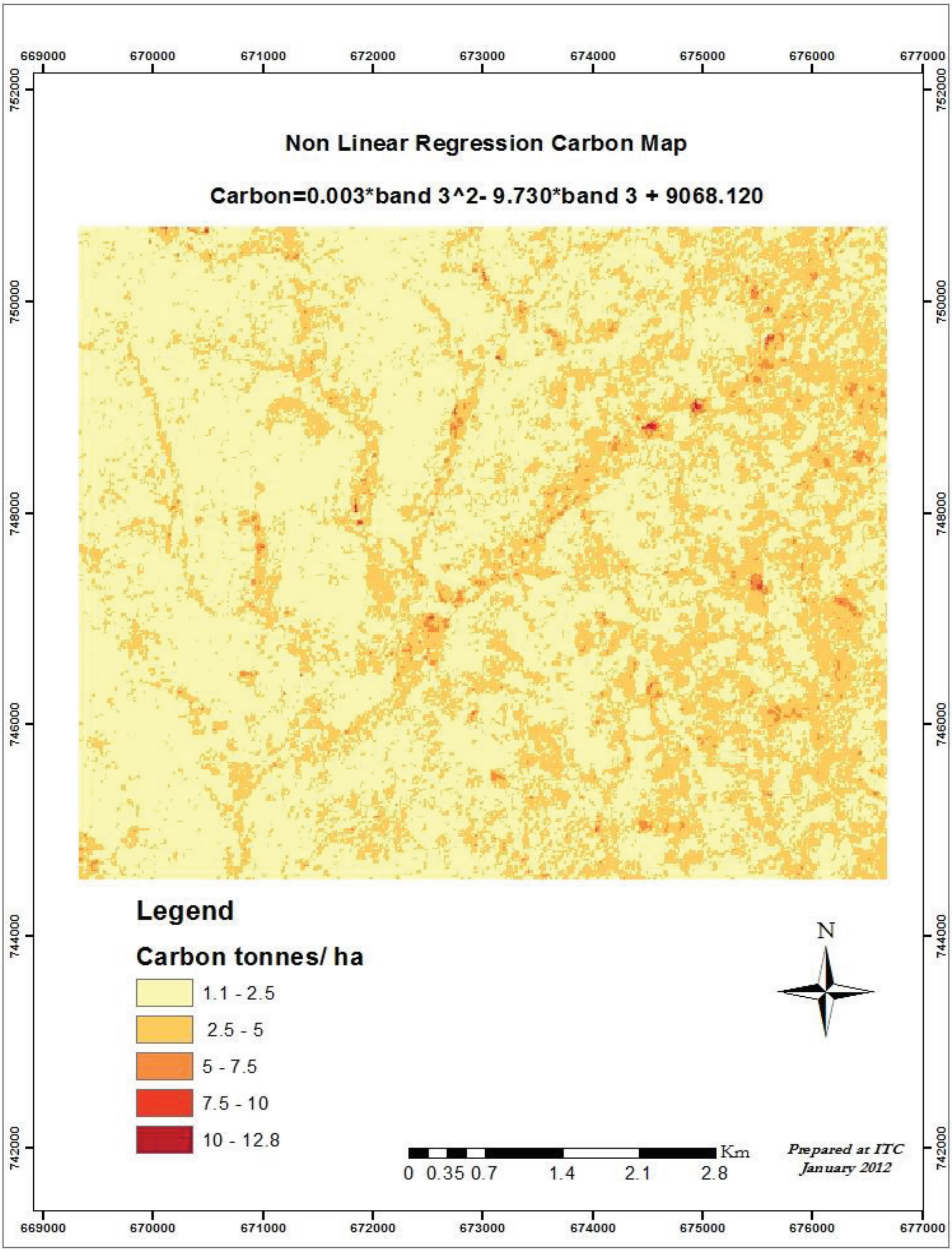

Figure 25: Up-scaled Carbon Map for Ejisu Juaben Farmlands

5. DISCUSSION

5.1. Image segmentation

Multiresolution segmentation, a bottom-up approach designed to minimize heterogeneity in image objects (Trimble, 2010), was chosen for the study as it has proven useful in the extraction of information in high resolution images in complex landscapes with many cover types (Benz*, et al.*, 2004). The approach has also been found to be a powerful technique in determining occurrence of canopy gaps and tree spatial distribution (Lamonaca*, et al.*, 2008), a situation found mostly with regards to trees on farmlands as trees are sparsely distributed as compared to forest environments. Although tree crops such as Oil palm affect segmentation results, the technique proved useful as evidenced by the relatively high tree identification rates 72% and 83% for the whole image (automatic Oil palm masking) and subset (manual masking of Oil palm) respectively indicating that it can be adopted as an approach for delineating tree crowns on farmlands were tree distribution is sparse unlike in forests environments.

Despite being a trial and error procedure, estimation of scale parameter is of prime importance in generation of meaningful image objects from high resolution satellite images. Scales of 22 and 25 were used based on the best representation and perfect match to reference manually digitized crowns (Clinton*, et al.*, 2010; Zhan*, et al.*, 2005). The chosen scales could be considered as fine scales based on the work of Benz *et al,(2004)*, who established that trees, buildings and roads are better discriminated from other land cover at a fine scale.

5.2. Palm Oil Masking

Due to the ability to compute object statistics based on single input layers or combinations within the image (Benz*, et al.*, 2004), use of vegetation indices was employed to automatically detect and mask out Oil palm. This proved useful as trees and Oil palms have different leaf structure and therefore reflectance characteristics. The distinct advantage offered by World View-2 satellite image of having new bands at high resolution, coastal blue and red edge bands, with improved potential for detailed vegetation analysis (Digital Globe, 2008) enabled the automatic detection of Oil palm from trees.

However, automated identification and masking of Oil palm trees using vegetation indices had an effect on the final tree CPA in two ways. First, part of tree crowns which had different spectral reflectance as the rest of the tree crown were lost in the masking as they fell within the set thresholds 0.33 and -0.25 for the red edge comparison and the modified vegetation index respectively for oil palm. This is so as the image was acquired during the dry season when leaves were dry and thus having low greenness since trees found in the study area are semi-deciduous (Hall andSwaine, 1976).

Therefore after object primitives are identified which represent a part of a tree or a tree (Benz*, et al.*, 2004), in the masking of Oil palm those which fell within the thresholds were lost together with Oil palm. This is best illustrated in figure 26 below which shows part of crowns, black regions separated from the reddish, which were lost as a result of use of vegetation indices to automatically detect and mask out Oil palm (figure 26(a)). Figure 26(b) is the false colour image of the plot and figure 26(c) is the same plot with segmentation results overlaid black tree crowns after segmentation is applied without automatically masking out Oil palm. The sizes of tree crowns in figure 26 (a) and 26 (c) are different especially with regards to tree crowns on the bottom left of the plot.

Figure 26: (a) With Oil Palm masking (b) False Colour Image (c) Without Oil Palm Masking

Second, apart from losing part of tree crowns as illustrated above some trees were completely lost in the process of automatic masking of Oil palm. Leaf dryness resulted in low reflectance as the image was acquired during the dry season. Figure 27 below is an illustration of a sample plot with figure 27(a) being a result of image segmentation without automatic detection and masking of Oil palm and figure 27 (b) being a result of segmentation after automatic detection and masking of Oil palm. Tree identification in figure 27(a) is high as opposed to figure 27 (b) on the right were some trees were lost as a result of automatic masking. This was further illustrated by the high tree identification in the subset 83% as opposed to the whole image extent 72%.

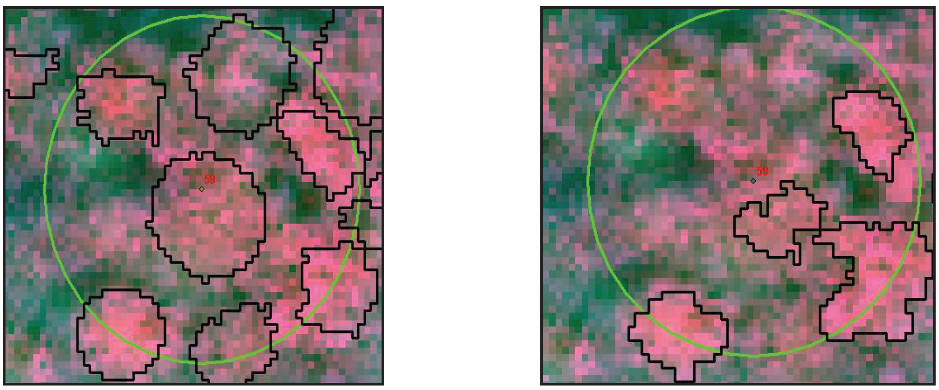

Figure 27: (a) Without automatic masking of Oil Palm (b) With automatic masking of Oil Palm

As a result of the above mentioned reasons the non linear model developed using automatic masking of Oil palm showed high relative root mean square error than that developed using manual masking. Non linear models were preferred as they had high coefficient of determination and less RMSE contrary to linear models. Tree growth exhibits a non-linear pattern even in open environments such as farmlands where trees are said to have "free growth" (Cabanettes *et al.*, 1998). Non-linear models have also been shown to predict well DBH from crown diameter as observed by Mugo et al,(2011), in a study of open grown trees in farmlands of Sondu-Nyando river catchment in Kenya. Also in a study of open widely grown trees similar to natural trees found on farmlands where there is human disturbance and damage caused by animals, Cabanettes *e*t al,(1998) found better results using non linear exponential function between DBH and height as dependent variables and the age of the tree as an explanatory variable.

5.3. Up-scaling

Area based carbon averaging rather than the average carbon of tree crowns gave satisfactory measure against which reflection from the Aster image could relate to the image objects / tree crowns from the World View-2 satellite image. This observation corresponds well to other studies conducted by Hufkens *et al*, (2008), and Gibbes (2010), who calculated proportion of crown coverage to upscale Leaf Area Index point measurements and tree crowns derived from IKONOS imagery to Landsat pixel resolution respectively. Using average carbon values of tree crowns alone without factoring in the proportional area covered by tree crowns yielded unsatisfactory results as reflection in the Aster image is due to the proportion of cover dominant in that pixel. Therefore area was utilized to come up with an area based carbon average value for up-scaling purpose. As plot size differed, the four pixel window covered the whole plot in the case of forest and old fallow strata and fell within the plot in the case of cropland and young fallow strata as illustrated in figure 28(a) and (b) below. Four pixels and averaging of reflection values was applied to cover for geo-referencing errors in locating plots(Fuchs*, et al.*, 2009).

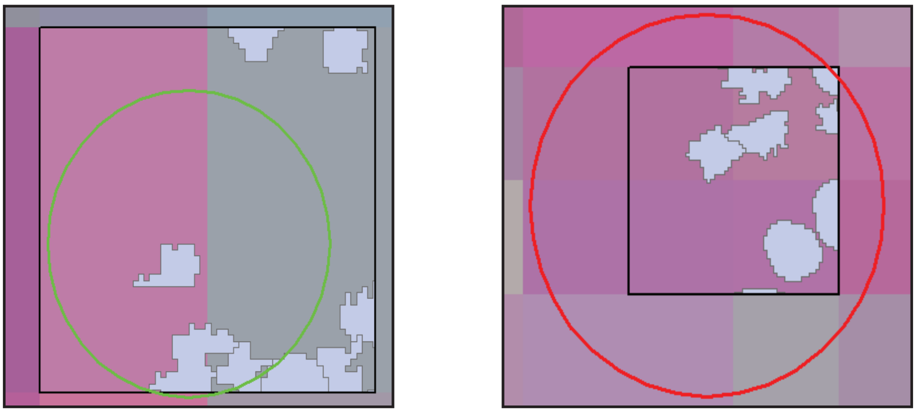

Figure 28: (a) Forest and Old Fallow strata (b) Young Fallow and Cropland strata (Black square represents the 30 x 30 m^2 window and the circles represent the plots for the strata)

Rasmussen *et al* (2011) established that tree crown area coverage is an essential remote sensing parameter as it affects greatly the amount of reflectance from a surface. Although unfavourable results were obtained, Rasmussen *et al* (2011), attempted to create a relation between NDVI from Aster 15m resolution and tree crowns derived from Quickbird imagery for study area in Sudan. Reasons for low correlation found being the low crown coverage in the study area (Rasmussen*, et al.*, 2011). However, spatial aggregation using crown area rather than relying on pixel information yield better results as evidenced by Hansen *et al,* (2002), who used crown cover from IKONOS as training data to aggregate to 30 meters Landsat ETM+ resolution using regression tree analysis and obtained relative root mean square error of 10%. The results revealed that high resolution satellite data allow direct interpretation of the variable of interest, crown projection area, while medium Aster resolution data enable the mapping of that variable over a wide region (Hansen.*, et al.*, 2002).

Band 3 (near infrared) of the Aster image showed great potential for the up-scaling approach as the model had a high coefficient of determination (R^2=0.50) when compared to other bands. This is due to the high sensitivity of the band to vegetation cover. Vegetation reflects more in the infrared than any other bands (Tucker, 1979). Results observed in the study correspond well to Tucker, (1979), who observed a direct non linear relation between the near infrared and biomass for plants which could also explain the positive correlation (r=0.66) as also observed in this study.

5.4. Biomass and Tree density

Assessment of differences in biomass and tree density per stratum showed that there are more trees and biomass per hectare in old fallow and forest strata than in young fallow and croplands. Mostly shrubs and bare land characterize croplands and young fallow as these are continually under cultivation and therefore low tree density and biomass per hectare (Gelens*, et al.*, 2010). Also on farmlands humans and animals damage trees by activities such as lopping which affect tree growth. This has an influence on allometric models, which relate different tree parameters to each other since trees are not allowed to grow undisturbed (Rasmussen*, et al.*, 2011). Despite this estimation of carbon in the study area revealed that the area had 45.9 Mg C/ha^{-1}. Tree retention on farmlands is estimated to have a potential of carbon storage of between 12 and 228 Mg C/ha^{-1}, with this large variability explained mainly by the diverse management system practised within farmlands (Albrecht andKandji, 2003).

5.5. Sources of uncertainty in carbon modelling

Error is inevitable in GIS and remote sensing applications and this error is brought about in number of ways which include data acquisition, processing, analysis and conversion. Errors increase in a multiplicative way up to the final product preparation (Lunetta *et al.*, 1991). In carbon estimation there are many ways through which error can be brought about in the estimation process either by the individual or through generalization in image processing techniques (Lunetta, *et al.*, 1991) and sampling error, measurement error and error associated with the type of regression model chosen (Brown, 2002). In this study error in the carbon modelling and up-scaling were mainly brought about by shadows, time of image acquisition, Oil palm and the choice of allometric equation as discussed below. Figure 29 is a schematic representation of the main steps for error propagation in a GIS and remote sensing analysis.

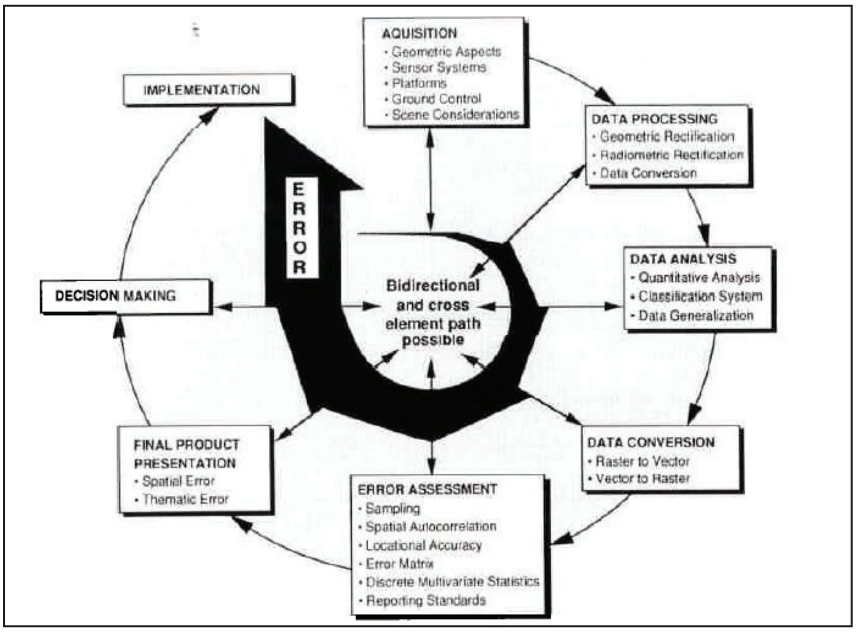

Figure 29: Error propagation within a GIS and Remote sensing system: Source Lunetta *et al* (1991)

5.5.1. Shadow

Satellite-images recorded at off-nadir geometry of the sensor show shadows, which complicates proper tree identification especially during image segmentation process in Definiens software (Rasmussen, *et al.*, 2011). The World View-2 satellite image used in the study was acquired at 13.1^0 off nadir which explains the present of shadow in some parts of the image as illustrated in figure 30 below where part of the tree crown in figure 30 (b) are obscured.

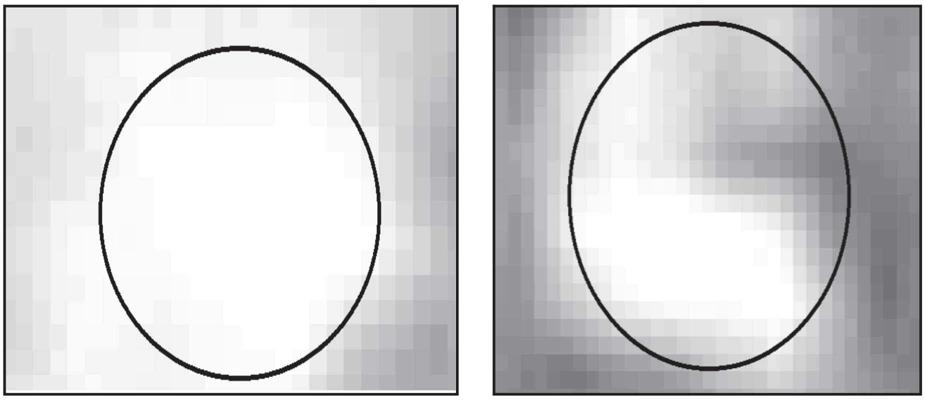

Figure 30: (a) Without shadow (b) With Shadow

5.5.2. Time of image acquisition

Since the World view-2 image was acquired during Ghana's dry season, the contrast between Oil palm and tree crowns could not be well established as some trees were probably dry making reflectance low and difficult to separate tree from Oil palm. Therefore an image acquired during peak greenness for trees might yield better results for separation between tree crowns and Oil palm.

5.5.3. Allometric Equations and biomass estimation

The use of the general equation for all species results in bias as some trees may be over predicted whilst other may have an under prediction in terms of their biomass values. Despite DBH explaining much of the variability of above ground biomass in the tropics with high coefficient of determination as observed by Brown, (1997), including other measurements such as height in the allometric equation significantly improves the estimates. For example in the study area there are tree such as *Ceiba petandra* with large DBH, but relatively small crowns and very tall in height, which raises the need of species specific equation for accurate biomass estimation. Therefore, use of recent technological developments such as the LIDAR to extract height information for trees will greatly improve carbon estimates on farmland. Chave *et al,* (2004), established that the most important source of error in biomass and carbon estimation is choice of the allometric model and recommended that efforts should be placed on improving the predictive power of allometric models for biomass. Trees on farmlands are also influenced by animals and people since they are not allowed to develop undisturbed (Rasmussen*, et al.*, 2011) a factor which may greatly affect their growth.

5.5.4. Up-scaling

The model developed for carbon estimation had $RMSE_r$ of 45.5% and 38.1% for the estimation and validation data set respectively with tree crown identification, 1:1 matching, of 83%. These relative errors from the subsequent process were taken into the up-scaling process as the tree crowns identified from the high resolution image were used as training data for the up-scaling process. Despite this however, visual assessment of the final carbon map produced in the up-scaling process showed a fair correspondence in relation to the proportion of crown cover in the study area as observed from the World view-2. Also the images used in the up-scaling process were of different dates and time span of a year between them, with the effect that a lot of land cover changes could have taken place in between the acquisition of the images, a situation very much likely especially when considering that the area is experiencing rapid population growth (Ministry of Food and Agriculture, 2011). Therefore, image acquisition should be exactly or almost close to each other with minimal time interval in between to reduce errors associated with these land cover changes.

The up-scaling approach for the research mainly focused on development of a method for transferring between scale from high to medium resolution image and not entirely coming up with a perfect carbon map. Also the validation of the up-scaled map was not conducted as only field data existed for the World View-2 image only and not other sites which covered the aster image extent. Therefore additional land cover data for those areas covering the Aster image need to be collected to perform a perfect validation for the up-scaled carbon map (Hansen*., et al.*, 2002).

6. CONCLUSION AND RECOMMENDATIONS

The study revealed the potential of biomass and hence carbon mapping for tree resources on farmlands using a combination of OBIA and an up-scaling strategy for Ejisu Juaben district in Ghana. The study was conducted to answer research questions which are outlined below:

Question: How may OBIA be used to map tree crowns and biomass / carbon of trees on farmlands?

Hypothesis: Object oriented segmentation can be used to identify and map carbon for farmlands trees with high accuracy level (overall accuracy tree identification >70%)

Multiresolution segmentation approach has been proved to offer an effective approach of image segmentation for tree resources on farmlands where a combination of built up, bare and vegetation cover exists. Using multiresolution approach a high tree identification / accuracy rate was observed, 72% and 83%, which indicate the potential of object based image segmentation for mapping of carbon for farmland trees. However, despite using algorithms, such as watershed transformation to reduce the occurrence of tree clusters the presence of clusters which represents multiple trees could not be avoided, an observation also made by Gibbes *et al* (2010).

Question: How does Oil palm affect individual tree delineation / identification on farmlands?

Two approaches to map biomass and hence carbon on farmland where tree crops having almost the same spectral characteristics as trees were presented. First, an approach were tree crops are automatically detected and masked out to estimate carbon and another were these are manually detected and deleted after segmentation were used. The study revealed that use of vegetation indices alone cannot clearly distinguish between Oil palm and trees without affecting the latter. This was observed through masking of parts of tree crowns or whole trees which might suggest use of other parameters like texture analysis to completely explore if Oil palm can successfully be distinguished from trees automatically. Also peak greenness (Hansen., *et al.*, 2002) images could also aid greatly in separation of Oil palm from trees as this proved difficult using the dry season image.

Question: Which regression model best describes the relation between biomass, and hence carbon, and CPA for tree resources on farmlands?

Hypothesis: Tree biomass can be predicted from CPA at significant level $p < 0.05$

The study showed the potential use of high resolution satellite imagery as noted by Gibbs *et al*,(2007), to map and estimate biomass, and hence carbon, as a respond to the need of the REDD+ programme. Biomass was modelled with a high significance level $p < 0.05$ for both the whole image and subset approaches using crown projection area as derived from image segments as the independent variable. The non linear model explained well biomass on farmlands as it had a higher coefficient of determination and showed well goodness of fit unlike the linear model.

Question: Is there a relation between World View-2 objects and pixels in a medium resolution Aster image?

Hypothesis: There is a significant relation ($p < 0.05$) between Worldview objects or object groups and medium resolution Aster pixels

Using average carbon values based on the proportion of tree crown coverage a significant relation at $p < 0.05$ was established between World Viev-2 image objects and reflection from the medium resolution Aster image. A non linear relation was established between near infrared band of the Aster image and objects from the high resolution image, showing the potential of the near infrared band for the up-scaling procedure. Results proved the potential use of combining high and medium resolution imagery to transfer between scales with the near infrared band of the Aster image showing great potential. The high resolution image being used for coming up with training data and studying the variable of interest (CPA) and the medium resolution being used to better understand processes at much broader scales. Data for validation of the up-scaled image need to be collected to properly assess the quality of up-scaled maps. In this research additional data was not collected as emphasis was mostly on method development. Further exploration of other image derived features such as texture and vegetation indices need to be explored together with the hierarchical function of Ecognition software in order to further refine up-scaling techniques.

Limitations of the study

- Satellite image used coincided with the dry season when leaves are dry therefore it might be most useful to use peak greenness images acquired during the wet season when vegetation growth is at its maximum
- The use of non-site specific allometric equation made for forests environments and not trees outside forests were tree growth is affected by human interactions
- Different acquisition dates for satellites used in the up-scaling bringing about a source of error as farmlands are very dynamic systems with changes experienced over a short timeframe

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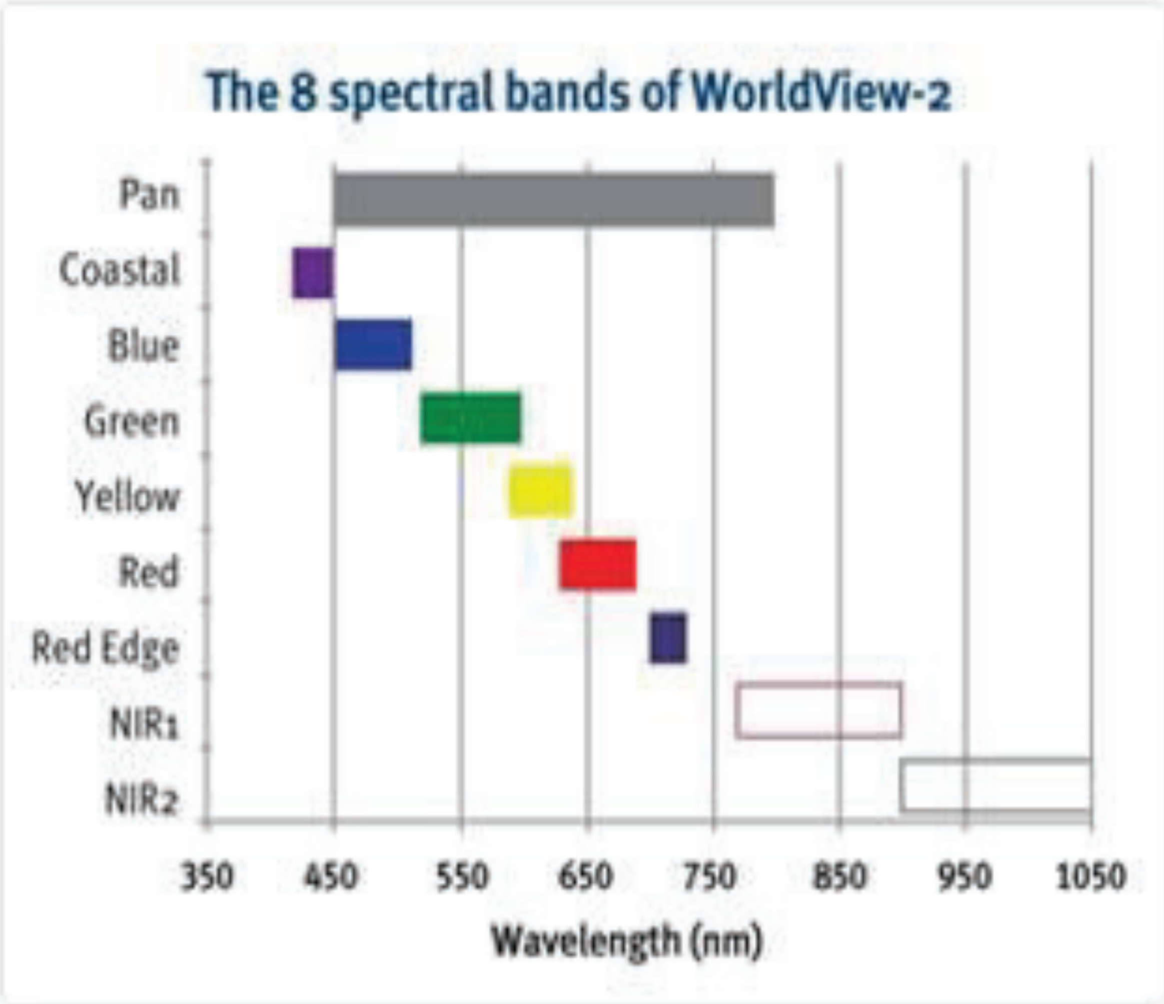
Appendix 1: Crops grown in Ejisu Juaben District

Type of Crop	**Output per season (Tonnes)**
Maize	5,400
Plantain	32,300
Cassava	81,200
Rice	1,632
Cocoyam	16,660
Yam	4,560
Cocoa	2,500
Oil palm	22,100.11
Citrus	16,970,54
Pepper	52.7

Appendix 2: Animals kept in Ejisu Juaben District

Type of Animal	**Total Stock**
Sheep	8,097
Goats	9,842
Pigs	11,100
Poultry local	118,198
Poultry exotic	501,000
Cattle	1,400
Duck	1784
Turkeys	92
Rabbit	56
Grasscutter	35
Guinea fowls	1273

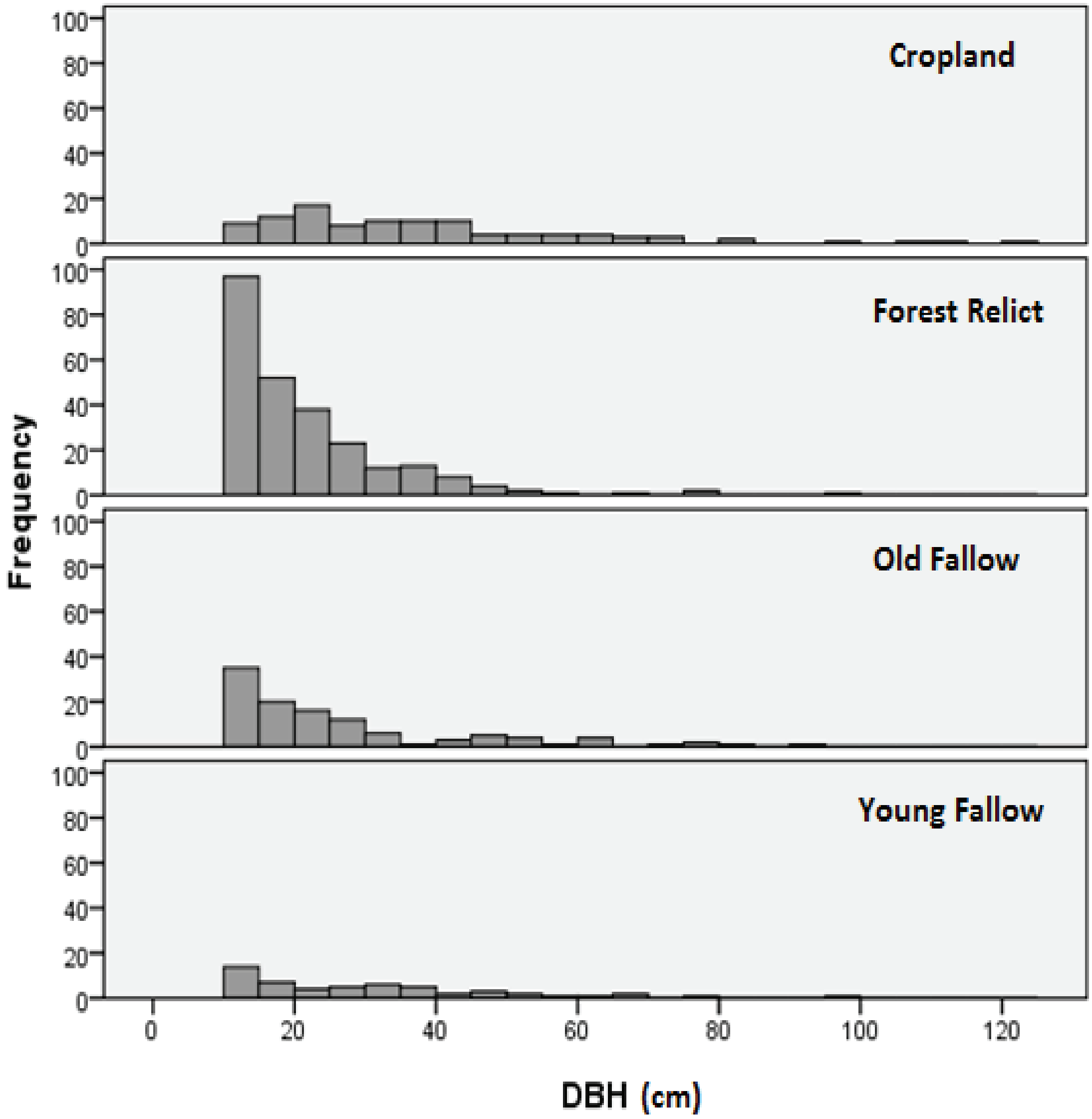
Appendix 3: World View-2 Spectral bands



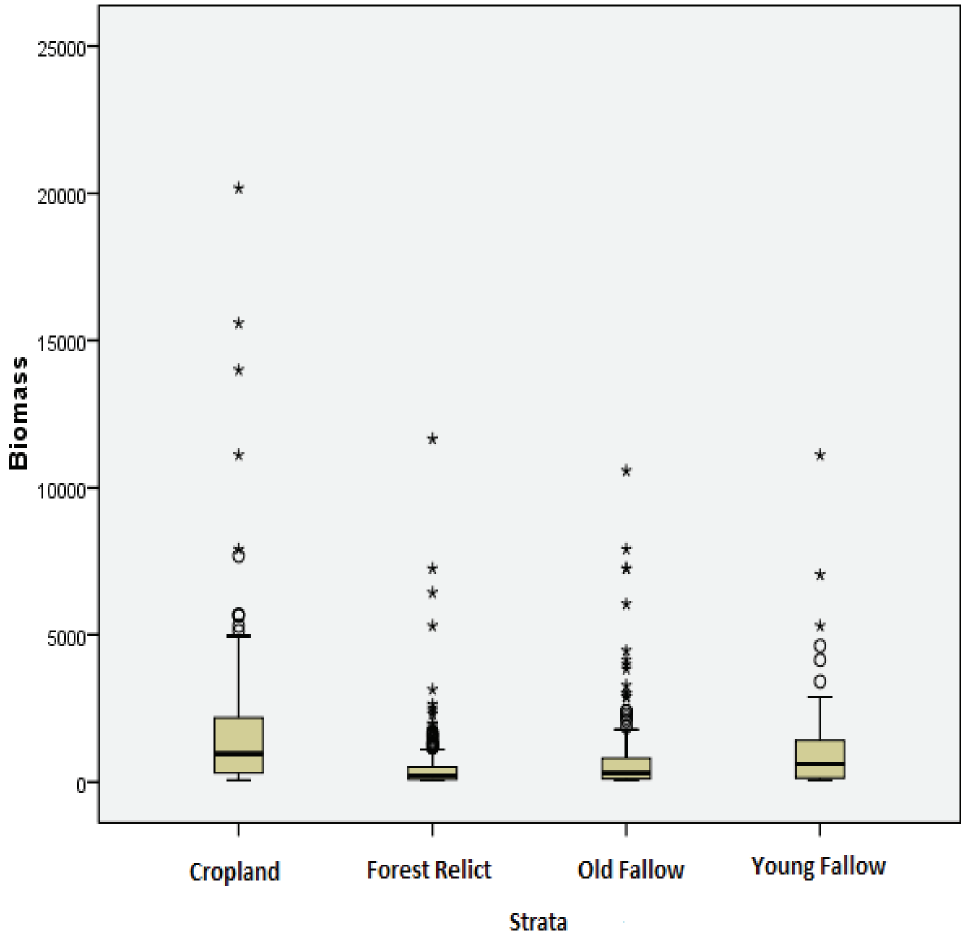
Appendix 4: Tree species found on Farmlands in Ghana

Number	Local Name	Scientific Name
1.	Odum	*Milicia excelsa*
2.	Pepia	*Margaritaria discoidea*
3.	Nyame dua	*Alstonia boonei*
4.	Pear	*Persea americana*
5.	Eno ni Ekyeni	*Cleistopholis patens*
6.	Otie	*Pycnanthus angolensis*
7.	Wawa	*Triplochiton scleroxylon*
8.	Kusia	*Nauclea diderrichii*
9.	Koto	*Bussea occidentalis*
10.	Okuo	*Zanthoxylum gilletii*
11.	Yaya	*Amphimas*
12.	Okoro fitaa	*Albizia zygia*
13.	Kyenkyen	*Antiaris toxicaria*
14.	Supua	*Vitex grandifolia*
15.	Foto'	*Glyphaea brevis*
16.	Nyankyeni	*Ficus exasperata*
17.	Onyina	*Ceiba pentandra*
18.	Opam	*Macaranga barteri*
19.	Onyina kobim	*Rhodognaphalon*
20.	Kwaku bisina	*Carapa procera*
21.	Emeri	*Terminalia ivorensis*
22.	Fotum	*Funtumia elastica*
23.	Dagoma	*Piptadeniastrum*
24.	Teak	*Tectona grandis*
25.	kuakunisuo	*Spathodea campanulata*
26.	Peperdiewuo	*Solanum erianthum*
27.	Woma	*Ricinodendron heudelotii*
28.	Otwisi	*Vitex ferruginea*
29.	Ofram	*Terminalia superba*
30.	Mango	*Mangifera indica*
31.	Sesei	*Trema orientalis*

Appendix 5: DBH distribution within Strata



Appendix 6: Individual Tree Biomass distribution within stratum



Appendix 7: Normality tests results for strata

Biomass

Stratum	Shapiro-Wilk normality test
LogCropland	W = 0.9847, p-value = 0.9727
LogYoung fallow	W = 0.9371, p-value = 0.4611
LogOld fallow	W = 0.9672, p-value = 0.7907
LogForest Relict	W = 0.9596, p-value = 0.6236

Tree Density

Stratum	Shapiro-Wilk normality test
LogCropland	W = 0.9796, p-value = 0.9089
LogYoung fallow	W = 0.9132, p-value = 0.2344
LogOld fallow	W = 0.9507, p-value = 0.5002
LogForest Relict	W = 0.968, p-value = 0.7826

Appendix 8: Up-scaling models for Aster band 2(Red) and 1(Green)