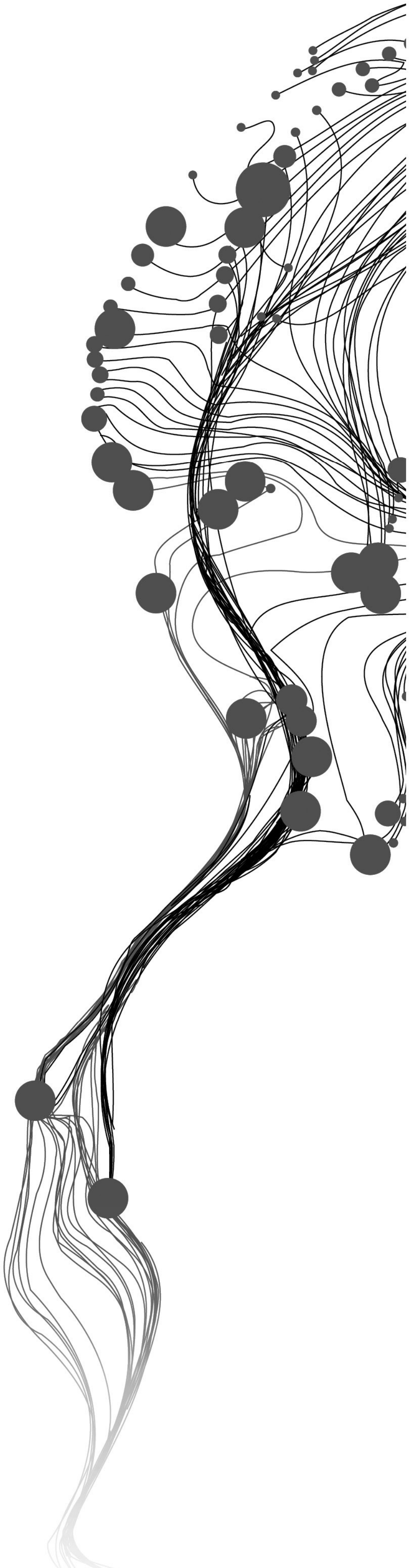
SPATIAL VARIATION OF TREES OUTSIDE FOREST AND THEIR CONTRIBUTION TO THE ABOVE GROUND BIOMASS (AHAUS, GERMANY-ENSCHEDE, THE NETHERLANDS)

MOSTARIN ARA
May, 2017

SUPERVISORS:
Ir. L.M. van Leeuwen
Dr. I.C. Van Duren



SPATIAL VARIATION OF TREES OUTSIDE FOREST AND THEIR CONTRIBUTION TO THE ABOVE GROUND BIOMASS (AHAUS, GERMANY- ENSCHEDE, THE NETHERLANDS)

MOSTARIN ARA
Enschede, The Netherlands, May, 2017

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: Environmental Modelling and Management

SUPERVISORS:
Ir. L.M. van Leeuwen
Dr. I.C. Van Duren

THESIS ASSESSMENT BOARD:
Chair: Prof. Dr. A.K. Skidmore
External Examiner: Dr. Tuomo kauranne (Lappeenranta University of Technology, Finland)

ABSTRACT

Non forest trees like discrete, linear or small groups of trees are considered as Trees Outside Forest (TOF). TOF provide important ecological, economic and social function. Biomass estimation of trees from areas outside forest is required to aid the holistic decision for climate change mitigation and adaptation. Because of the development of remote sensing technology over decades biomass can be estimated accurately using Very High Resolution (VHR) image as an alternative of ground based measurement which is costly and time consuming. However, high acquisition cost, large space to storage as well as long time for image processing limits the use of VHR image for large area biomass estimation. In this perspective, as a potential solution, this study attempted to develop an approach for biomass estimation over large area by using both very high and medium resolution satellite images. The study was conducted near Germany-Netherlands border where six different spatial arrangements of TOF were identified. Pleiades high resolution (0.5m) image was used in this study to discern individual tree crowns using Object Based Image Analysis (OBIA). Individual tree crowns were used to develop the model for Above Ground Biomass (AGB) estimation as a function of tree crown area. OBIA delineated tree crowns with 73% accuracy by calculating D index and the developed model of biomass estimation explained 78% variance of the biomass as a function of tree crown area. The derived biomass map for the whole area was used to upscale biomass to the Sentinel-2 image. The aggregation of biomass was done using area based averaging technique within a particular area (10X10m) and average NDVI was also calculated within the same area. This process was repeated many times for each spatial arrangement to obtain adequate sample for model development and validation. Finally, regression model was carried out for each spatial arrangement to develop the model of biomass estimation as a function of NDVI (Sentinel-2). The sequence of correlation coefficient in these six spatial arrangement of TOF ranked from high to low was as follows: Double line closed canopy (0.88), single line closed canopy (0.80), wind break (0.80), single line open canopy (0.76), double line open canopy (0.72) and patch (0.38). The research findings indicated that the Above Ground Biomass (AGB) can be estimated as a function of Crown Projection Area (CPA) of trees but further research is needed to improve the accuracy of the model. Moreover, the proposed approach for upscaling biomass can be used for areas with low density of TOF, on the other hand, further research is required to upscale biomass in the case where tree crowns are strongly interlocked and arranged in a compact way.

Key Words: TOF, Above Ground Biomass, Object based Image Analysis, TOF configuration.

ACKNOWLEDGEMENTS

This research would not have been possible to accomplish without the support of different organizations and individuals who directly and indirectly assisted throughout the work. This is the opportunity and I would like to show my thanks, gratitude and appreciation to all who contributed to the completion of this research. First and for most, I would like to show my gratitude to the almighty God who helped me and given me the strength to accomplish the work and helped me and made me patience in all ups and downs to reach at the end of the research.

My heartfelt gratitude goes to my first supervisor Ir. L.M. van Leeuwen for her innovative ideas, invaluable support and guidance, encouragement and help in every step throughout the entire research. It was really an opportunity and pleasure for me to work under her supervision. I would like to take this opportunity to thank my second supervisor Dr. I.C. Van Duren for her constructive suggestions, comments and consultation from the beginning to the end of my research. Prof. Dr. A.K. Skidmore also deserves special thanks and appreciation for his critical comments during the proposal writing phase. I would like to mention the support and cooperation of Dr. Y.A. Hussin during my research work and thesis writing.

I would like to appreciate Semhar Kiflay (MSc student of ITC) for her help during field data collection as well as for the discussion and cooperation during the field data analysis phase of the research. I would also like to mention the name of Sofia Tilon (MSc student, ITC) for her cooperation during my writing. I am also owed to the farmers of the area near to the border of Germany-Netherlands who cooperated to collect data from their field.

My special gratitude goes to EU Erasmus Mundus programme for supporting my study in two different universities (Lund University, Sweden, Twente University, Netherlands). I thank all the professors, lecturers, course coordinators and colleagues for the time we had together in these two universities.

Lastly, my deepest gratitude goes to all of my family members and some of my friends specially Md. Abdullah Al Bari Tusar, Serajis Salekin who were always with me in my ups and downs throughout the journey of my MSc programme.

Mostarin Ara
29th May, 2017
Enschede

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Introduction

Sustainable management of natural resources has received special attention in the past decades to combat the negative effect of exploitation and degradation (Kleinn et al., 2001). In this context, globally substantial efforts are given for the monitoring of forest resources because of multiple ecosystem services provided by forest. (FAO, 2010). However, tree resources that are grown outside forest are not taken into consideration for forest monitoring even though they play a relevant role as forest. These tree resources are summarized with the term Trees Outside Forest (TOF) which was coined by FAO (Pain-orcet & bellofontaine, 2004). TOF refers to those trees on land which are not defined as forest or other wooded land (FAO, 2000). TOF includes: trees on the land which fulfils the requirement of forest and other wooded land, scattered trees in the permanent meadows and pastures, permanent tree crops, orchards, industrial fruit trees, trees on agricultural system and trees in urban environments (Bellefontaine et al., 2002). A wide range of ecological, economic and social functions is offered by TOF (Auclair et al., 2000, Bellefontaine et al., 2002, Idol et al., 2011). For example, they function as a source of timber and fuel wood (Mezzalira, 1997a) as well as non- timber production (Mezzalira, 1997b). TOF can also store CO_2 out of the atmosphere (Schoeder, 1994) and as a consequence they have positive impact on climate change mitigation (Borin & Maccatrozzo, 2005). Additionally, they protect soil and water quality (Endreny, 2002) as well as conserve biodiversity (Bellefontaine et al., 2002). TOF play a different role in developing countries than developed countries. For developing countries, TOF are the source of wood product and energy for the rural people especially where the forest is scarce (Biasoli, 2002). On the other hand, in developed areas, TOF are more linked to the quality of natural environment and to the living standard of the population than to wood and non-wood production (Paletto, 2006). Classification of TOF is complex because many criteria exist for generating meaningful categories (Schnell, 2015). Examples of the meaningful categories are: Geometric pattern of trees, their origin and function as well as their location in which land class. TOF can be broadly classified as TOF on agricultural land, TOF on urban areas and TOF on non- urban and non- agricultural land (Bellefontaine et al., 2002). The spatial arrangement of TOF can be categorized as isolated and scattered trees, trees in block and planting along linear formation (Alexandre et al., 1999). Land owners, government organizations and stockholder need information of TOF at national level to support policy and legislation for their use and conservation. Information on TOF is needed at international level because different organizations who are working on environment and climate change need the information of all tree resources. Moreover to support management of TOF, information is needed at local level (Schnell, 2015). In most countries, TOF are not generally included in official national monitoring and ignored in the land use planning and policy development (FAO, 2010).

FAO attempts to monitor TOF and as a consequence of that many countries have widened their scope for TOF monitoring. Since attention has increased on carbon trading and climate change mitigation, it is needed to accounts for all possible carbon sources and sinks including Trees Outside Forest.

It is essential to estimate biomass for TOF at different scale to know the actual role of TOF for reducing atmospheric CO_2. There are different approaches for biomass estimation where field measurement is the most accurate one but there is a problem associated with time, money and application over large area which makes it inconvenient (Brown et al., 2002). In the last decades remote sensing was under a strong development because of its different spectral, spatial, and temporal resolution of satellite imagery. Recently, remote sensing has become an attractive source of data for biomass estimation and assessment at multiple scales with large spatial and temporal coverage (Kleinn et al., 2001, Main-korn et al., 2011). Although currently, no remote sensing technique can estimate biomass directly but the combination of limited field and remote sensing data can potentially improve the estimation of biomass for large areas (Du et al., 2014). Several studies have been conducted to demonstrate the effectiveness of the combination of remote sensing and field data to estimate Above Ground Biomass (AGB) (Hame et al., 1997, Drake et al., 2003, Baccini et al., 2004). Several methods have been used to develop biomass functions using remote sensing technology. The one most frequently used is the regression analysis using forest inventory biomass data and satellite generated data (Viana et al., 2012) such as spectral reflectance, crown diameter (Woodcock et al., 1997, Phua et al., 2003, Baccini. et al., 2004) and vegetation indices (Tomppo et al., 2002, Carriers et al., 2006, Lu, 2006). The high spatial resolution data are recently used to estimate and map Above Ground Biomass accurately (Gibbs et al., 2012). The method of above ground biomass estimation is changing because of high resolution of images and development of image analysis software. Crown Projection Area (CPA) of trees can be delineated from Very High Resolution (VHR) image using different software and Shimano (1997) narrated that the DBH and CPA are related. Although DBH is often used to estimate biomass, attempts to model biomass as a function of CPA from VHR image and limited sample field measurement are on progress. Delineation of CPA and spatial arrangement of TOF is more challenging than of forest because of the complex interaction of TOF with other surrounding features. Object Based Image Analysis (OBIA) is adequate to capture the geometry of TOF. Numerous studies have been done using OBIA for mapping woody plantation in agricultural land and rural landscape around the globe. For example, hedgerow of 2m width was identified accurately with areal imagery in Berkhire, UK by Tansey et al., (2009). Aksoy et al., (2010) carried out a study to identify linear wooded strip using OBIA in Germany, Czech Republic and Cyprus. Other related study includes the identification of shelterbelt for large area in Manitoba, Canada by Wiseman et al., (2009). OBIA also provided new opportunities to improve biomass estimation using CPA of individual trees. Many studies have been carried out to delineate individual tree crown using OBIA. For example, Erikson (2004) delineated individual tree crown using different algorithm which resulted in 73-95% correctly segmented tree depending on forest type and method. Ke (2011) also used different algorithm for tree crown delineation and found more accurate result for coniferous tree than deciduous. Accuracy of CPA delineation is a key factor for model development because CPA influences other variables of the model (Ke, 2008) and improvement of CPA delineation improves the model (Hirata et al., 2009).

1.2. Problem Statement

The importance and change of global carbon cycle led to increasing demand for knowledge of all possible carbon sinks and sources at different spatial and temporal scale (Grosse et al., 2008, Gibbs et al., 2012). In addition, due to the need of monitoring biomass and reporting for the Kyoto protocol, demand for biomass estimation over large area has increased. Moreover, biomass estimation over large area can raise our understanding of carbon cycle and dynamics with land use and climate change (Woodwell et al., 1978, Adams et al., 1990, Keeling et al., 1996). Because field data measurements are very expensive to apply over large areas, remote sensing technique can be used as optimistic tool. Very High Resolution (VHR) images can estimate biomass accurately (Gibbs et al., 2012) but long processing time for image analysis over large areas, large space needed for data storage, low spatial coverage as well as acquisition cost, limits the application of VHR images in large areas (Lu, 2006). However, because of the accuracy maintained by VHR to estimate biomass, it can be used as reference data. Therefore, extrapolation of the result obtained from VHR data to a medium resolution image can produce reliable result with affordable cost (Manitis & Mollicone, 2010). Many studies have been done to estimate biomass over large area in combination of very high and medium resolution imagery. Propastin (2013) estimated biomass over large area in a tropical forest of Indonesia using Landsat ETM and MODIS data where a geostatistical method was used to relate ground truth and Landsat ETM and to produce AGB 3D surface and then assign biomass with MODIS band to map biomass over the large areas covered by MODIS data. Tomppo et al., (2002) estimated biomass for large areas by simultaneously using Landsat-TM and IRS-1C WiFS data where a map of variable of interest was produced from VHR data and field measurement and subsequently aggregated to coarser resolution to use as a reference map. After that a pixel by pixel regression model was used to develop a relationship between the reference map and coarse resolution satellite image. Similar study was carried out by Koju et al., (2017) who upscaled biomass at district level in Nepal. Moreover, Zheng et al., (2007) used reflectance data of MODIS to estimate biomass over large area linking with an empirical model developed by Landsat ETM data in the Lake State, USA. Upscalling of biomass for Trees Outside Forest was done by Mutanga (2012) in a district of Ghana where biomass was estimated using VHR (World view-2) image and then correlate with band reflectance of medium resolution Aster image. This present study attempts to develop an approach to use of both very high and medium resolution image to estimate AGB of TOF over large area where biomass obtained as a function of CPA from VHR image will be aggregated with medium resolution image in an area based approach. TOF are classified into different configuration based on their spatial arrangement. Because of the variation of their arrangement and density, biomass could also differ in different configuration. Considering this issue, biomass will be scaled up separately for each configuration. The biomass for the proportion of area coverage will be linked to the NDVI of medium resolution data (Sentinel-2). Studies have explored that biomass of trees outside forest can be directly measured by NDVI and there is a positive relation between them. Yao et al., (2015) tried different vegetation indices for biomass estimation of urban green space in Xi'an, China and found that NDVI is strongly related to biomass than other vegetation indices. Moreover, Gunawardena et al., (2015) also found positive correlation between biomass and NDVI for biomass estimation of a national park in Sri Lanka. Similar finding was observed by Kanniah et al., (2014) where high positive correlation was found between biomass and NDVI in an urban forest, Malaysia.

Very few researches are carried out for biomass estimation of Trees Outside Forest over large area. Development of an approach to interlink very high and medium resolution images can be highly potential to estimate biomass for Trees Outside Forest at national or global scale.

1.3. Objectives of the research

The overall objective of this study is to develop an approach to estimate biomass using VHR and medium resolution (Sentinel-2) satellite images.

Specific objectives:

01. To model the relationship between Crown Projection Area (CPA) and Above Ground Biomass (AGB) of Tree Outside Forest (TOF).
02. To assess the accuracy of tree crown segmentation using VHR image of Pleiades satellite.
03. To upscale biomass and model the relationship between CPA based on VHR image and Vegetation Index (NDVI) of medium resolution (Sentinel-2) data for biomass estimation.

1.4. Research Questions

01. Is there a relation between CPA and AGB to model biomass estimation?
    Null Hypothesis: There is no relation between CPA and AGB.
    Alternative Hypothesis: There is a positive relation between CPA and AGB.
02. How accurate can biomass be estimated using a regression equation based on CPA?
03. How accurate can tree crowns be delineated using VHR image for Trees Outside Forest?
04. How can the estimated biomass from VHR image be scaled up to the Sentinel-2 satellite image?
05. Is there a relation between CPA based on VHR satellite image and NDVI of Sentinel-2 for biomass estimation?
    Null Hypothesis: There is no relation between CPA based on VHR satellite image and NDVI of Sentinel-2 for biomass estimation.
    Alternative Hypothesis: There is a positive relation between CPA based on VHR satellite image and NDVI of Sentinel-2 for biomass estimation.

2. MATERIALS AND METHOD

2.1. Description of the study area

The study was conducted in a farmland near the border of Germany and Netherlands covering an area of 36 km². The study area was closed to the city of Ahaus, Germany and partly to the East of the city Enschede, The Netherlands. The study area is geographically located between latitude $52^0 09`35``$ N- $52^0 12`13``$ N and longitude $6^0 51`17``$E- $6^0 59`23``$E (Figure 2-1) and 42m above from the mean sea level.

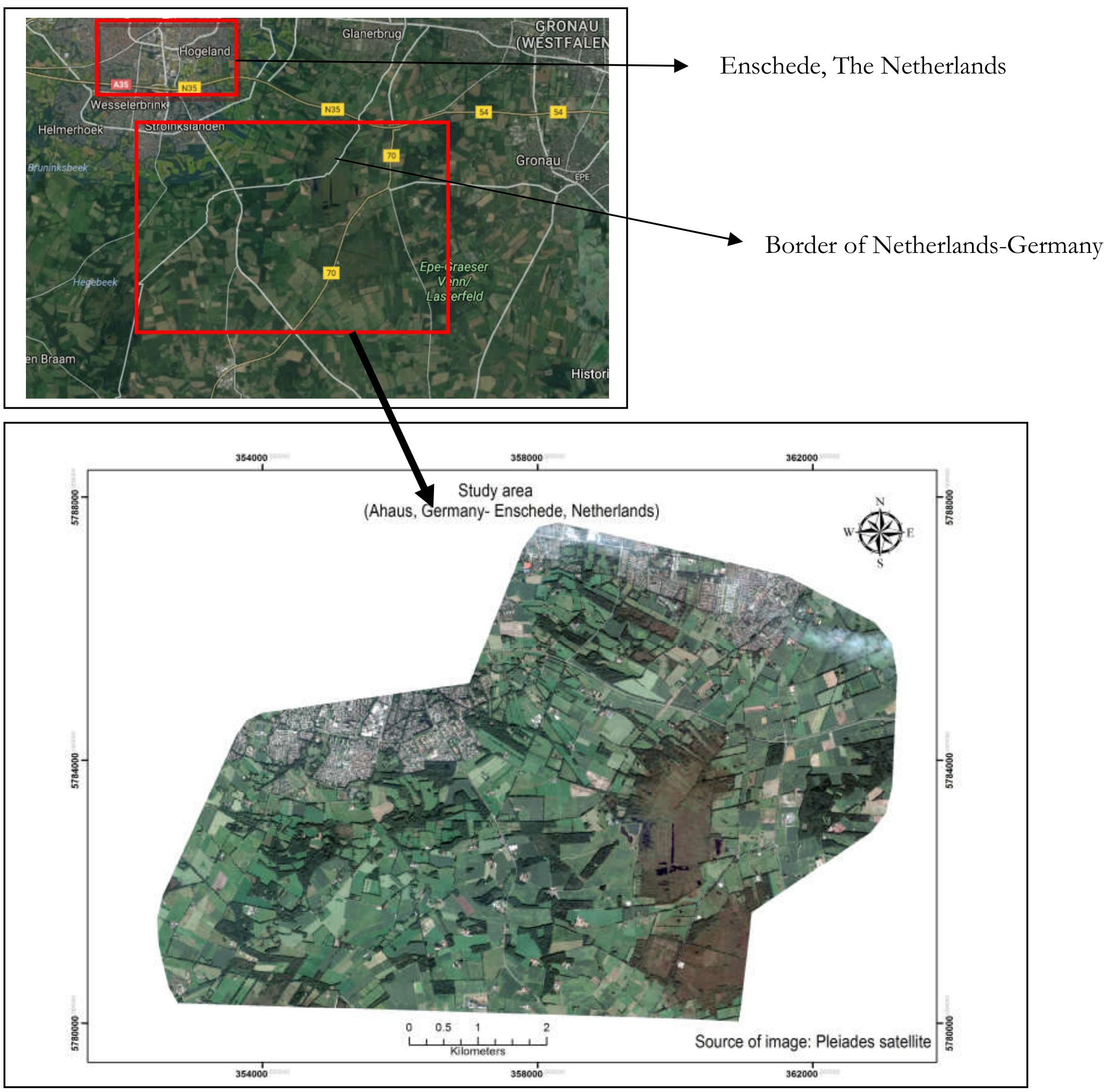


Figure 2-1: Location and map of the study area

The present study deals with the spatial variation and different configuration of TOF. The selected study area was with adequate feature of interest which was one of main reasons to select this area as study area. Moreover, VHR image was also available for the area. During area selection, the area was chosen in such a way that can cover as much features of interest as possible (spatial arrangement of tree) which made the study area a very irregular shape.

Most of the land in the study area is occupied by farmlands including agriculture, such as cropland and pastures. Linear tree formations are located along the roadsides. Trees are planted along the boundary of the land which acts as wind break between agricultural fields. There are also small patches within this study area including different softwoods and hardwoods. Scots Pine (*Pinus Sylvestris*), Oak (*Quercus robur*), Beech (Fagus *sylvatica*), Birch (*Betula pendula*) are the most common species in this area. Oak is the most common tree along the roadsides. Farmers generally planted trees along their fields and roadside trees are managed by administrative authority.

2.2. Dataset and Materials

Datasets

This research used a Pleiades (Very High Resolution) satellite and medium resolution Sentinel-2 optical satellite image. Additionally, Google Earth was used to locate sample points and to facilitate manual delineation of CPA from Pleiades image. Pleiades 1b satellite was successfully launched on December 2, 2012. It provides ortho-rectified colour image at 0.5m resolution and capable of acquiring VHR stereo imagery. It has five spectral bands including Blue, Green, Red and Near Infrared and Panchromatic. On the other hand, Sentinel-2 is an earth observation mission developed by ESA to perform services like forest monitoring, land cover change detection, natural disaster management. It provides multi spectral data with 13 spectral bands including visible bands, Near Infrared and Short wave infrared part of the spectrum with special resolution 10, 20 and 60m. Details of the dataset and their sources are described in Table 2-1.

Table 2-1: Dataset used in the research and its sources

Spatial data	Data description	Source
1. Pleiades	Date of Acquisition: 1st November, 2015, 10.46.55 am Spatial resolution: Panchromatic: 0.5m Multispectral: 2m Spectral range: Blue: 430-550 nm Green: 490-610 nm Red: 600-720 nm NIR: 750-950 nm Projection: WGS-1984-UTM-Zone-32N Datum: D-WGS-1984 Sun angle azimuthal: 172.2328354518122° Sun angle elevation: 23.28878868024778°	https://www.intelligence-airbusds.com
2. Sentinel-2	Date of Acquisition: 25th September, 2016 Spatial resolution: 10m Spectral range: Blue: 490 Green: 560 Red: 665 NIR: 842 Projection: WGS-1984-UTM-Zone-32N Datum: D-WGS-1984 Sun angle azimuthal: 168.25^{0}	https://earthexplorer.usgs.gov

Field equipment

Various equipment was used for conducting field work within the time period between 25th September to 25th October, 2016 for data collection and measurement. The equipment and their purpose are listed in the Table 2-2.

Table 2-2: List of field equipments and its purpose

Equipment	Purpose
GPS and iPAQ	Navigation
Diameter Tape	Measuring diameter of tree at breast height
Data sheet	Recording the measured data and other information from the field
Measuring Tape	Measuring the area of sample plots.

Software

Different software was used in this study for spatial data analysis as well as numeric calculation for biomass estimation. The software and its specific use are described in Table 2-3

Table 2-3: List of software used and its purpose

Software	Purpose
ArcGIS version 10.4	GIS analysis
ENVI 5.3	Image processing
eCognition Developer8	Object based image analysis
SPSS , R and Microsoft Excel	Statistical Analysis
Microsoft Word	Writing thesis
Draw.io	Diagrammatic representation
Microsoft Power Point	Presentation of the research

2.3. Method

The method of this research consisted two major parts.

1. Model development and biomass estimation for Trees Outside Forest using VHR image. This part consisted of field data collection and analysis as well as biomass estimation from field data, image analysis and relates image data to the field measured data. 2. Upscaling biomass from VHR (Pleiades) to Sentinel-2 image and analysing the relationship between biomass obtained from VHR image to the NDVI of Sentinel-2. Detail of each step for part one and two is explained in the methodology which is depicted in the Figure 2-2 and 2-3 respectively.

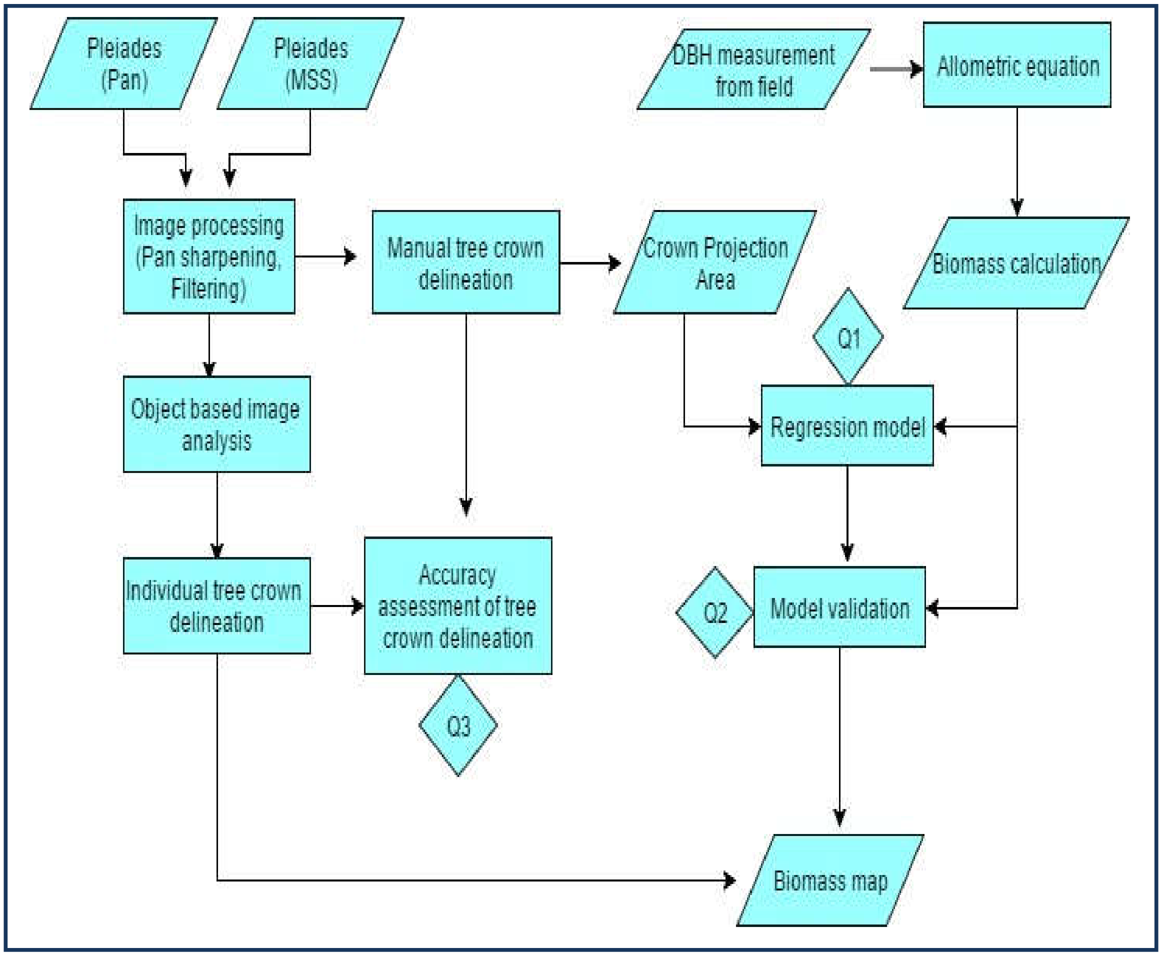


Figure 2-2: The methodological flow chart of above ground biomass estimation using VHR image and field data.

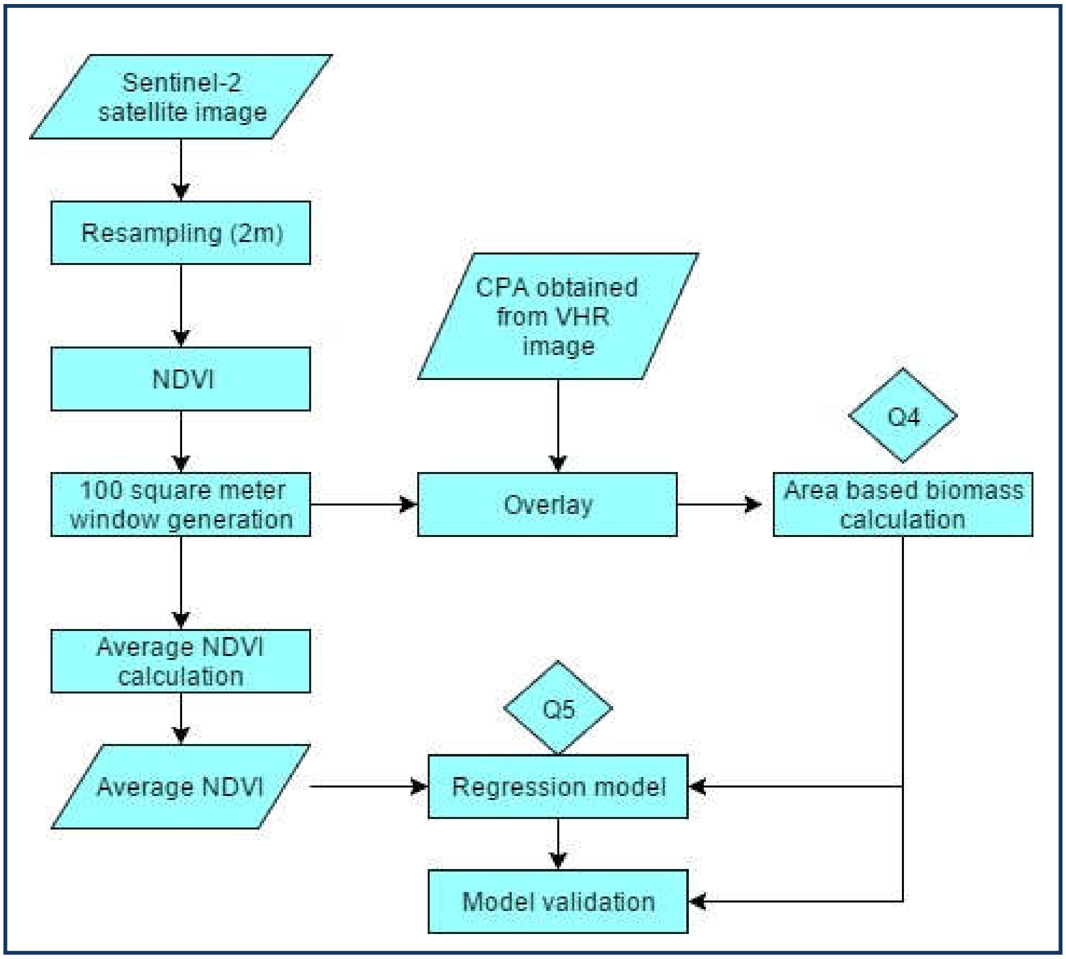


Figure 2-3: Methodological flow chart for upscaling biomass to the Sentinel-2 satellite image. The procedure is repeated for each configuration to develop model for each configuration

2.3.1. Sampling design for field data collection

In this research, biomass was quantified for number of representative locations and extrapolated them for the larger spatial extent, thus it was crucial that sample is a good representative for the whole area for the features of interest (Brown, 1997). In this study area, six different spatial arrangements of TOF were found included: patch, windbreak, double line open and double line closed canopy, single line open and closed canopy. The group of trees looks like small forest was considered as patch (Figure 2-4). Linear tree formation along the road was considered as line tree formation. If the trees were in one side of the road was called as single line and if the trees were in both sides of the road was called as double line configuration. If there was canopy gap in between two trees in a linear tree formation was called as open canopy (Figure 2-6) and if the canopies were so closed and overlapped with each other, was considered as closed canopy linear tree formation (Figure 2-5). Linear tree formation which was located along and in between two agricultural lands was considered as windbreak.

Considering these six spatial arrangements, the study area was stratified into six homogeneous areas. After stratification, sample plots were selected randomly in each stratum. The stratification insured the representation of all stratums and increases the precision (Husch et al., 2003). The number of samples in each stratum was in proportion to the area size of each stratum in the study area. In this context, sample plots were distributed in such a way that it is uniform and cover more or less the whole study area. Before field work, sample plots were pointed out in the Google Earth for each configuration of TOF throughout the study area. Before selecting the sampling points of patches, area of patches were measured by measuring tool of Google Earth. If the area was lower than 0.5 ha, only then it was included as sample plot because according to FAO (1995) the forest area less than 0.5 ha is considered as patch.

Figure 2-4: Patch tree formation

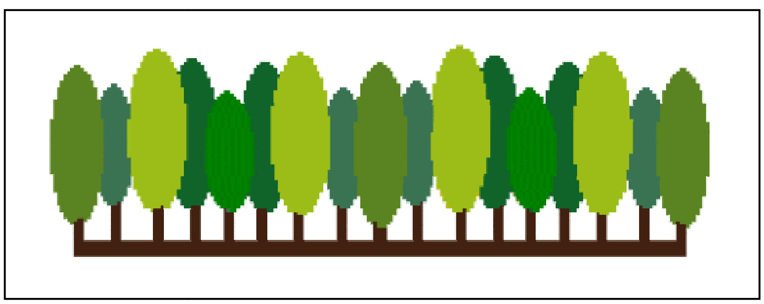


Figure 2-5: Linear tree formation with closed canopy

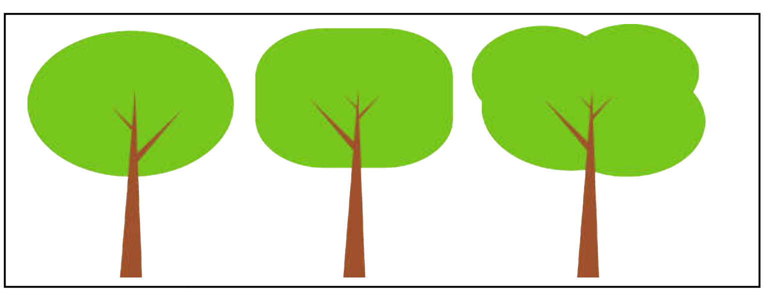


Figure 2-6: Linear tree formation with open canopy

(Source of photos: Canstock photo, 2016)

The major constituting elements in plot design are plot size and shape. Different plot sizes are recommended for sampling technique considering the cost and feasibility of field work (Neigh et al., 2014). However, the problem arises when discussing plot design for TOF because of their spatial arrangement and density variation. Since variability in each stratum is expected, different plot size were designed to address the variability of tree density and arrangement of each stratum. As a sample plot size for patch, 32X32 m dimension was considered and 50 X Total width of the tree line was considered for linear tree formation (Singh & Chand, 2012). Due to comparatively high density of windbreak than other linear formation, the length of the sample plot was taken as 25 m instead of 50 m. The width of the tree line was taken 10 m for this study. The sample plot size with their numbers is listed in table 2-4.

Table 2-4: List of different configurations and their sample plot size and numbers

Configuration of TOF	Sample size (m^2)	Number of plots
Patch	32X32	13
Wind break	25X10	12
Double line open canopy	50X10	9
Double line closed canopy	50X10	7
Single line open canopy	50X10	9
Single line closed canopy	50X10	9

2.3.2. Field data collection and analysis

The measurements were carried out from September to October 2016. DBH is the most common biophysical parameter that is used to estimate biomass and it can explain 95% variation of biomass alone. Considering this issue and uncertainty related to the height estimation, allometric equation based on DBH was used in this study. During the field work, DBH of the tree was measured for all trees of the sample plots to develop and validate model for biomass estimation using CPA. A total of 59 sampling plots with 420 individual trees were measured for the whole area from different TOF configurations. Diameter of all trees was measured in the sample plots except of trees with diameter less than 10 cm. Trees smaller than 10 cm DBH were excluded because of their minimal contribution to the biomass (Brown, 2002). DBH was measured at a tree stem height of 1.3 m above the ground. For DBH measurement, forking was considered. If a fork stem shape is above 1.3 m, the tree is considered as tree with one stem while fork below 1.3 m was considered as two stems. Four different species of trees including Oak (*Quercus robur*), Birch (*Betula pendula*), Beech (*Fagus sylvatica*) and Scots Pine (*Pinus sylvestris*) were identified within the sample plots of our study area. Picture index including identification feature of trees was prepared during pre-fieldwork time to identify them in the field level. Name of the species and their DBH were recorded in the data entry sheet.

After field work, species with their DBH were organized in the Microsoft excel and descriptive statistics of data were carried out using SPSS.

2.3.3. Image Processing

As pre-processing pansharpening and low pass filtering was done to the image to enhance the visual interpretation and facilitate object based image analysis. The detail of this processing is described in the following paragraph.

Image fusion is the process of combining information which can be obtained by various sensors or by same sensor in different measuring context (Simone et al., 2002). Pan- sharpening is pixel level fusion of image which is generally used to improve spatial resolution as well as structural and textural details and retail spectral properties of the original data (Zhang et al., 2010). The high spectral and high spatial information of multispectral image was maintained for easy interpretation. In this study, a stacked multispectral image (2m resolution) was fused with a panchromatic image (0.5m) of Pleiades to obtain a spatial pan sharpened multispectral image of 0.5 m spatial resolution. The fusion was carried out using Gram Schmidt pan sharpening algorithm in ENVI 5.3. This method maximizes image sharpness and minimizes colour distortion. Next, spatial filtering was applied to the pan sharpened image to enhance the image information and interpretability.

2.3.4. Manual tree crown delineation

Tree crowns in the sample plots were manually delineated from the pansharpend Pleiades image using ArcGIS 10.4. This was done for two main purposes, one was for regression modelling between crown projection area and field measured data and the other one was to use manually delineated CPA as reference data for accuracy assessment of automatic delineation. During tree crown delineation, in some cases, Google Earth was used for visualization of tree crown to facilitate crown delineation

2.3.5. Allometric equation and biomass estimation

Allometric equations were used for this study to calculate above ground biomass using field data. The application of the appropriate allometric equation is crucial for reducing error in biomass estimation (Chave et al., 2005). In our study area, three broadleaf and one coniferous species were found and species specific allomtric equations were used for three species and a general equation was used for one species. Species specific equations were developed for different forest around Europe (Jean et al., 2003). Due to the availability of the species specific equation for Oak, a general allometric equation was used for Oak which was developed for broadleaf species in a temperate forest of US (IPCC, 2003).

Species specific equations are:

1. Birch: $AGB= 0.3*(DBH)^{2.22}$(kg/tree) Equation 1
2. Beech: $AGB= 0.1293*(DBH)^{2.44}$ (kg/tree) Equation 2
3. Scots pine: $AGB= 0.0943*(DBH)^{2} -0.95$ (kg/tree) Equation 3

General equation of broadleaf is:

1. AGB = 0.5*[25000*(DBH)$^{2.5}$)/ ((DBH)$^{2.5}$ +246872)] (kg/tree) Equation 4

2.3.6. Relationship between biophysical parameters

Prior to the model development of AGB estimation, it is necessary to find the relationship between variables which is required for scientific approach. To determine the relationship, field measured DBH was plotted against manually delineated CPA from image and the co-efficient of determination was calculated. Based on relationship, a regression model was developed.

2.3.7. Model development and validation

Due to the shadow problem and image quality, it was difficult to delineate adequate number of tree crowns for each configuration to develop individual model for each configuration. Considering this issue, one model was developed for all configuration using samples from each configuration classes. Ninety (90) tree crowns from different configurations were manually delineated to develop a model for AGB estimation as a function of CPA. Only clearly visible crowns were manually delineated from the image. The field data was divided into training (n=90) for model development and test (n= 67) for model validation. Different methods are used to validate model. The two most widely used method for validation is co efficient of determination (R^2) and Root Mean Square Error (RMSE) (Lu, 2006). In our study, both R^2 and RMSE were used to validate the model. R^2 was used to know the fitness of the model to apply outside the range of sample data and RMSE was calculated to know how much our prediction deviated on average from the actual values of the dataset. R^2 was determined by plotting estimated and measured biomass against each other and RMSE was calculated using following equation

$$\text{RMSE}= \sqrt{\frac{1}{n}\sum_{1}^{n}(Cp-Co)^2} \qquad \text{Equation 5}$$

Where,

C_p = Predicted Biomass

C_o = Observed Biomass

n= Number of observation

2.3.8. Tree Crown delineation in eCognition

Individual tree crowns were delineated to obtain the biomass of each tree in the whole study area which was used as training data for upscaling biomass to the Sentinel-2 image. Individual tree crown delineation was done by image segmentation in eCognition. Segmentation is a spatial clustering technique which subdivided image into non-overlapping units or segments (Möller et al., 2007) It is a building block of object based image analysis in identifying homogenous areas and groups them into specific objects. There are two basic segmentation principles.

1. Cutting something big into smaller part which is called Top down approach and
2. Merging small pieces to get something bigger based on homogenous criteria called Bottom up approach.

Trees Outside Forest is not continuous land class and scattered. Because of this, it is better to start from a small piece and merge them to get bigger based on homogenous criteria. Considering the issue related to TOF, bottom up approach was used in this study.

2.3.9. Algorithm for segmentation

Crown delineation can be done using different processes. It can be done manually with a high spatial resolution image however this is very laboured intensive and impracticable for large area (Ferreira et al., 2014). Different automated segmentation algorithms have been developed and most of them are applicable for coniferous and temperate deciduous forest (Latif et al., 2016). According to the requirement, specific segmentation algorithm can be used to extract feature of interest. Multiresolution region growing approach was used for our study to separate TOF from other land class as well as to delineate individual tree crown. Multiresolution segmentation algorithm locally minimizes the average heterogeneity of image object and maximizes their respective homogeneity (Definiens, 2009b). The homogeneity of objects on which the scale parameter refers to is called composition of homogeneity which depends upon colour, smoothness and compactness. The value of shape field modifies the relationship between shape and colour criteria and the compactness is used when different image objects are rather compact and separated from non compact objects only by relatively weak spectral contrast. The process starts with one pixel of an object and merges similar neighbouring objects together in subsequent steps up to a heterogeneity threshold (Benz et al., 2004). Beyond pure spectral information, image objects contain different shape and texture information which is considered in this algorithm. This is more logical for distinction between different land classes which is important to separate TOF from other classes.

2.3.10. Scale Parameter

Scale parameter is an important parameter for multiresolution segmentation. The scale parameter is a term that is used to determine the maximum allowed heterogeneity for the resulting image object. By changing the value of the scale parameter, the size of object can be determined. The primary goal for this segmentation was to maintain the image objects which are purely tree crown. To obtain acceptable tree crowns, different scale parameters were applied on the subset of image in a trial and error process and finally below mentioned scale parameter was used for the whole area. This combination showed best representation of tree crown among all other parameter combination.

Scale parameter: 20

Shape: 0.9

Compactness: 0.8

2.3.11. Individual tree crown extraction

After general segmentation using definite scale parameter, shape and compactness, the main aim was to separate TOF areas from non-TOF areas. In this study, the process relied primarily on the following attributes to separate a TOF from non-TOF image object: Mean value of NIR spectral band and Red band, standard deviation of NIR band. A threshold was developed using above mentioned feature to separate different non-TOF areas from TOF areas. Different spectral bands and their information to develop a threshold were tested but the above mentioned attributes gave the optimal result to distinguish TOF from non-TOF. Selection of the threshold was done using observed feature information of Non-TOF objects compared to that of the tree objects. Separation of TOF from non-TOF was done with subsequent steps.

In the first level, bare, build land and shadow was separated using the mean value of red spectral band. After separating building and bare land, standard deviation of NIR was used to separate grass lands. However, some grassland was unclassified which was further classified using mean value of NIR. Finally, the non-TOF areas were merged. An additional rule was used such as relation to the neighbour objects to distinguish non-TOF which was not classified after first level of classification as well as to add some misclassified TOF into non-TOF class. The extracted trees were not in the shape of real trees and some trees were in cluster form. To obtain individual tree crown and smooth shape of tree crown, watershed transformation and morphology operation was done. Watershed transformation was carried out to separate large tree crowns into individual trees. Watershed transformation works by calculating inverted distance map. At first watershed transformation calculates inverted distance map which is based on the inverted distance for each pixel to the image object border. This makes the maximum value in the original image to become minimum value to the inverted distance map (Definiens, 2009b). Further, morphology operation was applied to smooth the boundary of the segmented object of TOF. Refinement of tree crown shape was applied using open image object (Figure 2-7: Rule set for total segmentation and classification process)

The classification result was exported as vector data from eCognition to ArcGIS 10.4 for further analysis. Non-TOF areas were not completely separated by the separation process in eCognition, some non-TOF were classified as TOF. This misclassified TOF were manually merged to the non-TOF areas. Some unwanted features were also merged to the non-TOF areas using ArcGIS 10.4. Finally non-TOF areas were masked off and TOF tree crowns were exported as a vector layer. Biomass for each tree was calculated by applying the model equation developed in the modelling phase. The result was used as a reference data for upscaling biomass to the Sentinel-2 image.

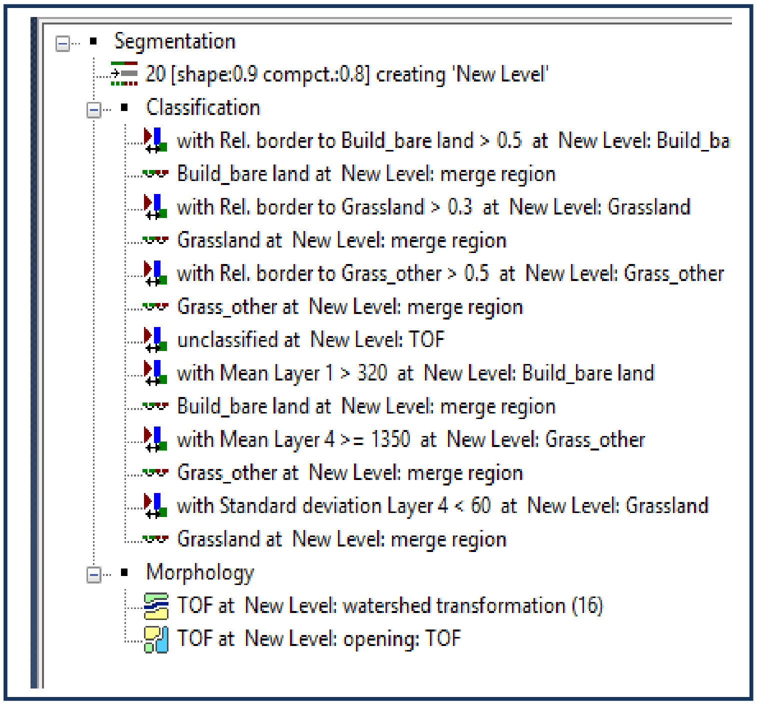


Figure 2-7 Process of tree crown segmentation and elimination of other land class in eCognition Developer

2.3.12. Accuracy assessment of tree crown delineation

Accuracy assessment of tree crown delineation was carried out because the accuracy of the final biomass calculation is dependent on the accuracy of CPA delineation (Hirata et al., 2009). In this study, accuracy of tree crown delineation was assessed by calculating the D index. The index can be explained as the closeness of an ideal segmentation result in comparison to the manual segmented tree crowns (Clinton et al., 2010). The value of D ranges from 0-1. The closer the value near 0, better the segmentation. The method takes into account the area and the positional difference between obtained segmentation and reference segmentation which is called over and under segmentation. Manually delineated tree crowns from field sample plots were used as a reference data and automatic segmentation tree crowns from eCognition were used as obtained tree crowns. Over and under segmentation was calculated from the following equations:

Over segmentation$= 1 - \frac{area(x \cap y)}{area(x)}$ Equation 6

Under segmentation $= 1 - \frac{area(x \cap y)}{area(y)}$ Equation 7

Where, x and y are reference and automatic segmentation respectively.

Over and Under segmentation ranges between 0 to 1, where 0 indicates a perfect segmentation with reference and segmented object. Combining the over and under segmentation, the index D (goodness of fit) was interpreted by the following equation which was developed by Clinton et al., (2010).

$$D = \sqrt{\frac{(Over\ segmentation)^2+(Under\ segmentation)^2}{2}} \qquad \text{Equation 8}$$

2.4. Information transfer from VHR image to Medium resolution Sentinel-2 image

2.4.1. Up scaling

Upscaling is the processing of scaling up spatial data from a finer spatial resolution image to a coarser resolution image (Stein et al., 1998). The basic idea of upscaling biomass is to map biomass with a moderate resolution image in the landscape using a VHR image as training data. In the high resolution image, pixels are smaller than the object of interest. Therefore aggregation of pixels to objects which relates the reflection in medium resolution images is needed to transfer between scales (Gibbs et al., 2012). In this study, crown projection area obtained from VHR image was used as training data to transfer information from a VHR image to a medium resolution image of Sentinel-2 satellite image.
A comparative analysis of the relationship between spectral responses and forest biophysical parameter like biomass is needed to upscale above ground biomass derived from the small area to the large area. Vegetation indices such as NDVI is commonly used for biomass estimation and it is the most used vegetation indices (Lu et al.,2004). The NDVI was calculated based on Sentinel 2 image in ArcGIS 10.4 using the following equation:

$$NDVI= \frac{(NIR-RED)}{(NIR+RED)} \qquad \text{Equation 9}$$

2.4.2. Approach for Upscaling

An area based averaging technique for biomass estimation was used for upscaling biomass from VHR image (Pleiades) to medium resolution Sentinel-2 image. An area based averaging technique provides satisfactory result for upscaling in comparison to the typical average technique (Hufkens et al., 2008, Mutanga, 2012). CPA derived from VHR image was overlaid on the Sentinel-2 NDVI (Figure 2-8). 10 m X10 m windows were generated to calculate biomass within the area. To optimize the area covered by trees and minimize the area of another land class in the window, Sentinel-2 data was resampled into 2 m cell size. After, biomass based on the CPA obtained from VHR image and average NDVI of Sentinel-2 was calculated for the window. This process was repeated for several windows until an adequate number of samples were obtained to develop the regression model. This was done separately for each tree configuration. The number of sample size differs from each configuration to the other because of their proportion in the study area (Table 2-5). Small window size was used to get more plots for model development and validation.

Average biomass was calculated from some representative samples which are fully covered by crowns within the specified area. This fixed average biomass was used to calculate area based weighted average biomass for every configuration by multiplying the proportion of area covered by the tree crowns within the specified area in each configuration. The methodology was adopted from Hufkens et al., (2008) who modified upscaling method from the traditional one to upscale LAI in a semi -arid woodland

$$\text{Area weighted average biomass} = \frac{Tree\ crown\ total\ area}{Window\ area} \times Average\ \ biomass \qquad \text{Equation 10}$$

Figure 2-8: Overlay of tree crown from VHR image (Pleiades) with NDVI of Sentinel-2 data

Table 2-5: Window size and number of plots for model development at each configuration of TOF

Configuration of TOF	Window size (m^2)	Number of plots
Patch	10X10	14
Wind break	10X10	16
Double line open canopy	10X10	17
Double line closed canopy	10X10	15
Single line open canopy	10X10	14
Single line closed canopy	10X10	14

Finally linear and non-linear regression model was developed for each configuration to predict biomass using NDVI of Sentinel-2 image. The number of plots varied from configuration to configuration because of their proportion in the study area.

The developed model for each configuration was validated using the datasets that were not used in model development. However, because of low the R^2 value obtained from the patch, no validation was carried out for patch. For model validation, the two most common methods (i.e., R^2 and RMSE) were used.

3. RESULTS

3.1. Descriptive analysis of field measured data

In the study area, a total 420 individual trees from 59 sample plots were recorded with their DBH. Moreover, four different species were identified in the study area. Among them Oak (*Quercus robur*) is the most dominant tree species in this area especially along the road side. Patches are dominated by Birch (*Betula pendula*) and Beech(*Fagus sylvatica*) followed by Scots Pine (*Pinus sylvestris*). Diameter of trees in the area ranges between 10.5-90 cm but majority of the tree's DBH are within the range 20-35 cm (Figure 3-1). The distribution of DBH means that data is not completely distributed as bell shape which is supposed to be for normal distribution of data. It can be seen that data is skewed in one side because DBH was measured for trees diameter greater than or equal to 10 cm. If the DBH less than 10 cm would be plotted the distribution should be normal.

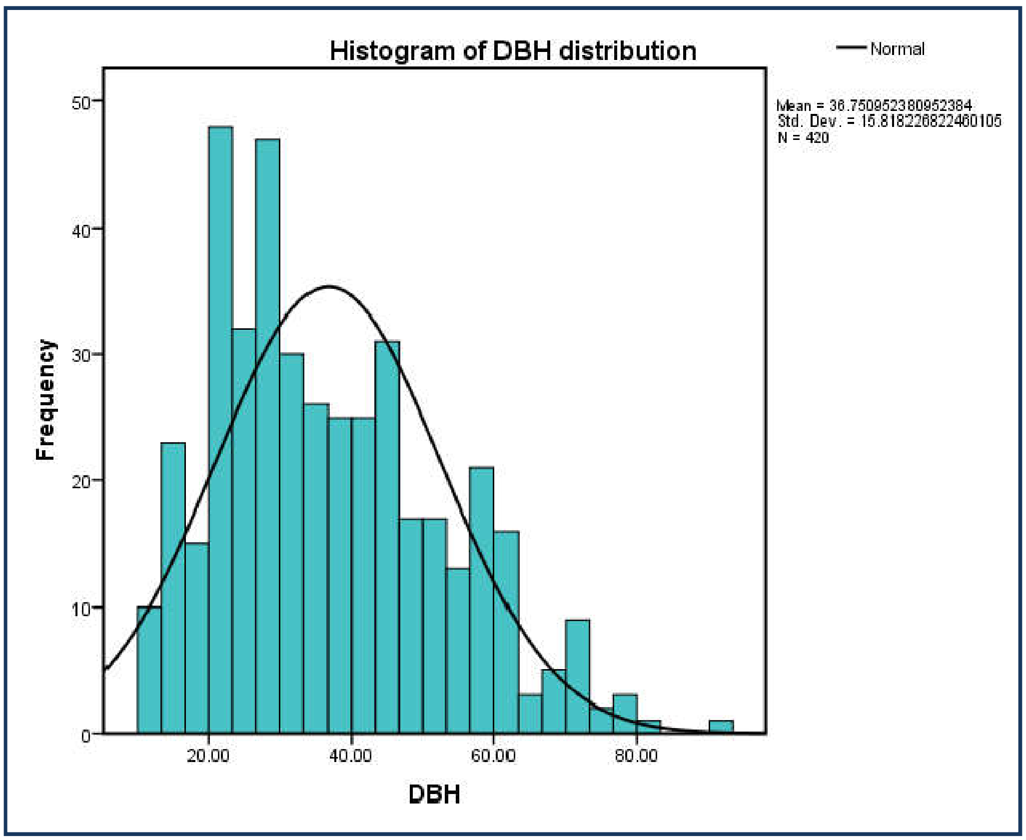


Figure 3-1: Histogram of the data (DBH) distribution for Trees Outside Forest

From the Kolmogorov-Smirnov and Shapiro Wilk normality test it can be seen that p value is less than 0.05 (Table 3-1). The stated null hypothesis was that data is not normally distributed. The p value less than 0.05 means that null hypothesis is rejected and data is normally distributed. Shapiro Wilk test was considered because it is more powerful for normality test than Kolmogorov test (Yap, 2011). Considering Shapiro Wilk test, it can also be concluded that data is normally distributed.

Table 3-1: Normality test for data (DBH) distribution for Trees Outside Forest

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
DBH	.101	420	.000	.961	420	.000

a. Lilliefors Significance Correction

Observations during the field campaign showed a difference in DBH among different configuration classes. Statistical information (mean DBH) represented the difference among different classes. It appeared that trees from double line with open canopy had lowest mean DBH (mean from the all samples taken from field) in comparison to other five configurations (Figure 3-2). Moreover, error bar from all configuration overlap with each other except double line open canopy. This indicated that the mean DBH of double line open canopy is significantly different than other configurations.

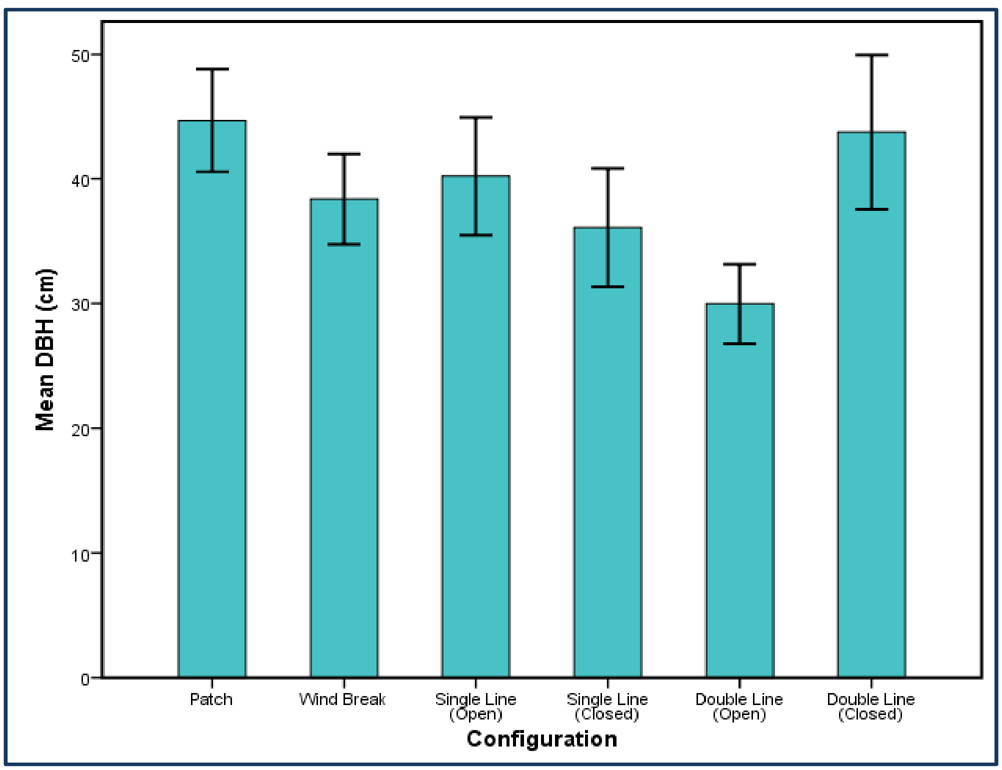


Figure 3-2: Comparison of DBH from different configurations of Trees Outside Forest

With an ANOVA test, the overall significance of the difference of mean DBH among different configurations was tested and the statistical result showed that the calculated F value is greater than the critical F value with a degree of freedom is 414 (Table 3-2-A) This implies that there is significant difference among the mean DBH of all different configurations. Moreover, Homogenous Subset analysis (produced by Post Hoc test) was carried out to know is any individual configuration has significant different mean DBH or not. The output revealed that, mean DBH from double line open canopy is significantly different than others because it appeared individually in a different subset than other. The appearance of mean DBH of other configuration in one subset indicated that there is no significance difference within them (Table 3-2-B). This indicated that the significant difference of DBH from double line open canopy influenced on the overall significance of the difference of mean DBH among configurations.

Table 3-2: ANOVA test for different configuration of Trees Outside Forest

A) Analysis of Variance

Sources of variation	Sum of Square	Df	Mean Square	F	F_{crit}
Regression	15778.27	5	3155.65	14.66	2.23
Residual	89062.35	414	215.12		
Total	104840.63	419			

B) Homogenous subset for DBH

Configuration	Subset 1	Subset 2
	Mean DBH (cm)	Mean DBH (cm)
Double line open canopy	25.49	
Wind break		36.37
Single line open canopy		39.10
Single line closed canopy		39.37
Double line closed canopy		40.29
Patch		44.68
Significance	1.00	.09

3.2. Relationship between field measured DBH and satellite image based CPA

In order to understand the relationship between field measured DBH and delineated CPA from image, a linear regression model was developed which resulted into a coefficient of determination value of 0.78 at 95 % confidence level (Table and Figure 3-3). This linear relationship reveals that larger delineated tree crowns are related to the larger DBH. An ANOVA test was done to test the significance of the model.

The null hypothesis stated that there is no relation between CPA and DBH for model development. The statistical F value indicated the significance of the model which means null hypothesis is rejected and there is a relation between DBH and CPA for all configurations in together (Table 3-3).

Table: 3-3 Linear regression statistics of DBH estimation model

(A) Regression Analysis	DBH vs CPA	
R^2	0.786	
Adjusted R^2	0.783	
Standard Error	5.75	
RMSE (%)	32%	
(B) Analysis of Variance	DBH vs CPA	
	Regression	Residual
DF	1	88
Sum of squares	10698	2909.842
F	323.53	
Significance	.000	

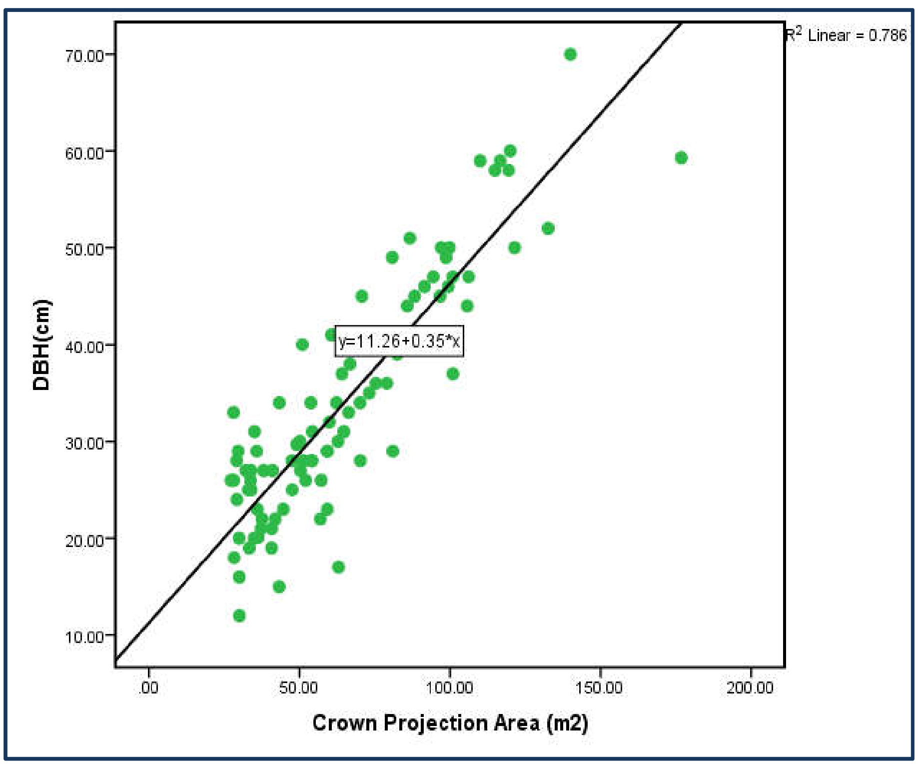


Figure 3-3: Regression relation between DBH vs CPA (including samples from all configurations) for Trees Outside Forest

3.3. Above Ground Biomass modeling as a function of CPA

In this section results are being described for the method that was followed to address the answer of the research question 1: Is there a relation between CPA and AGB to model biomass? and 2: How accurate can biomass be estimated using a regression equation based on CPA?

The statistical properties of the linear model for AGB estimation as a function of CPA is shown in Table (3-4). The regression analysis resulted with coefficient of determination of 0.78 with a positive slope which indicates the increase of biomass with increasing CPA. The regression line didn't pass through the origin (Figure 3-4) which indicates that the data distribution was not near the zero. That is possible for biomass because DBH was measure above 10cm and biomass is also an estimation which values are also not near zero. The R^2 value indicates that the predictor explains 78% variance of dependent variable. The parameter prediction for predicting biomass is given by the following equation

AGB=-495.07+20.07 X CPA Equation 11

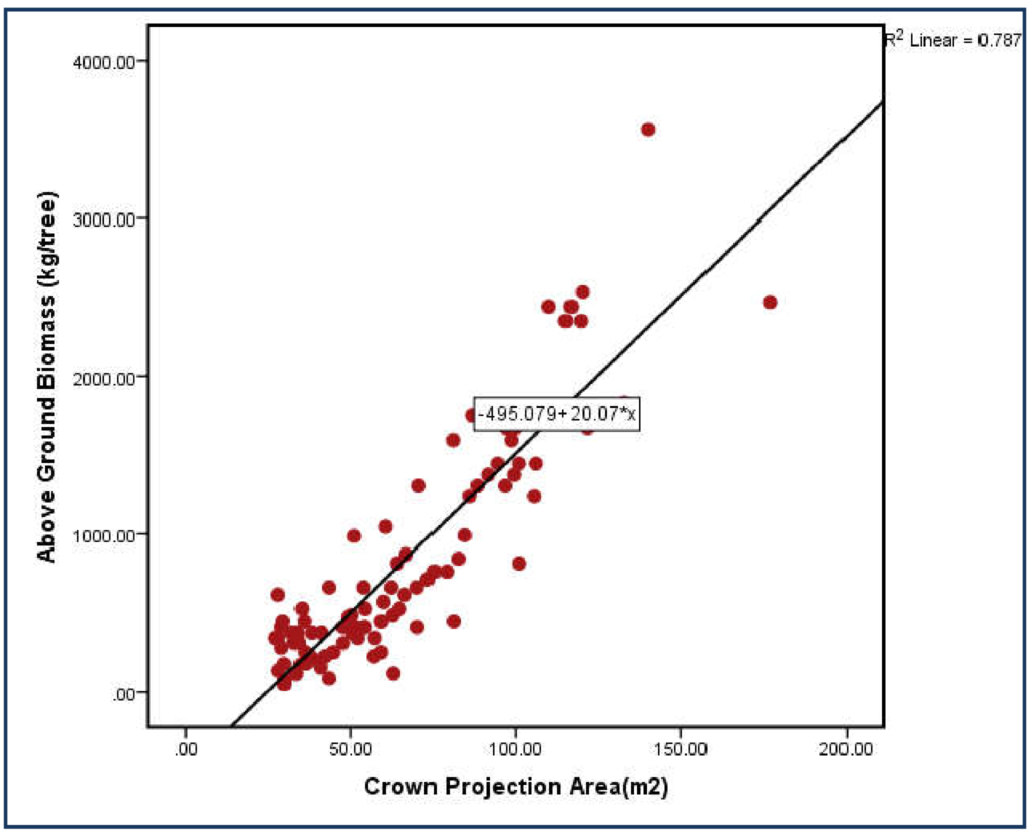


Figure 3-4: Regression relation between AGB (estimation based on allometric equations) and CPA for Trees Outside Forest

The predetermined null hypothesis was that there is no relationship between AGB and CPA. Through ANOVA test the significance of the model was tested and the result showed that the model was significant at 95% confidence level. The result of the F test demonstrated that the null hypothesis is rejected and there is a relationship between AGB and CPA (Table 3-4).

Table 3-4: Regression statistics for AGB estimation using CPA

(A) Regression statistics	CPA vs AGB	
R^2	0.787	
Adjusted R^2	0.785	
(B) Analysis of variance	CPA vs AGB	
	Regression	Residual
DF	1	88
Sum of Square	35069549.43	9397001.62
F value	328.41	
Significance value	.000	
(C) Variation in the equation	CPA vs AGB	
	CPA	Constant
Beta	20.07	-495.079
SE of B	1.01	79.560
T value	18.12	-6.223
Significance	.000	.000

In order to validate the fitted equation, calculated biomass from a new dataset was compared with the predicted biomass. The calculated biomass was closed to the estimated biomass with 30% RMSE. Calculated biomass was plotted against predicted biomass and coefficient of determination value was found to be 0.75 (Figure 3-5) with slope 0.72 which indicates that the two dataset are correlated positively.

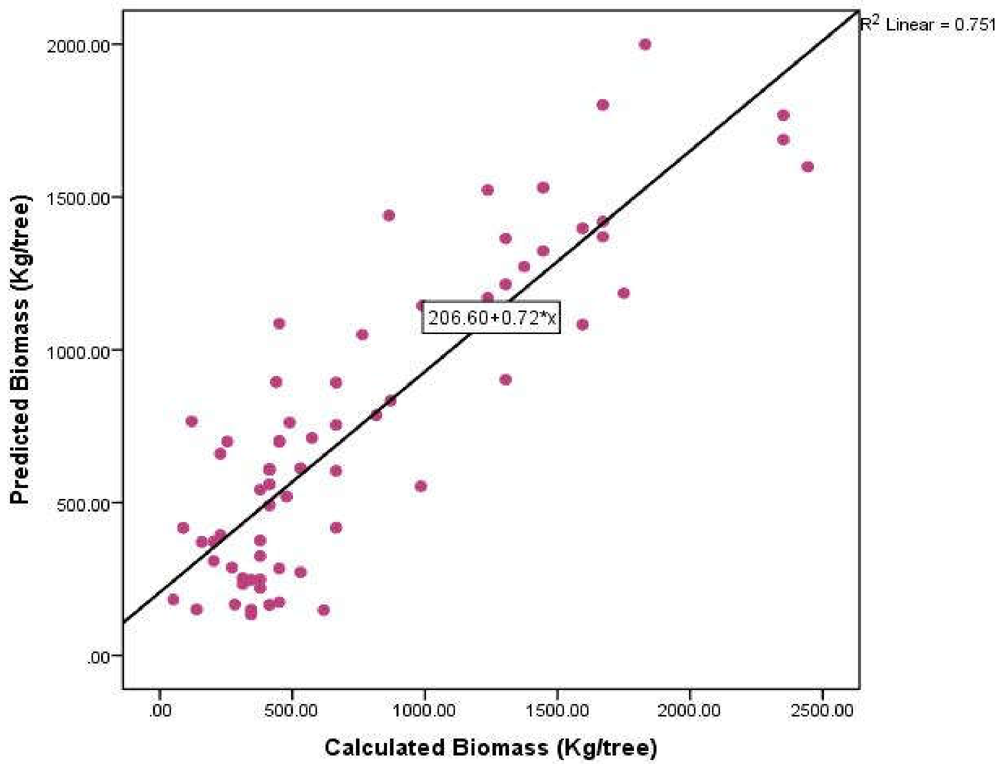


Figure 3-5: Comparison between predicted and calculated biomass for Trees Outside Forest

Six different spatial arrangement of trees were found within the study area and they were classified as patch, wind break, double line open and closed canopy, single line open and closed canopy. Statistical analysis showed that there is an overall variation of DBH in different configurations of TOF and mean DBH of double line open canopy is significantly different from other classes. The variation of DBH indicates the variation of CPA. In order to know how biomass is related to the CPA for each of the configuration classes, a trend line was drawn for each configuration and the sample points from each class was presented by each different colour (Figure 3-6). The trend line shows that each line is very close to other even overlapped by other (Trend line for patch was overlapped by other which can not seen in the figure). Moreover, it can be observed that all the trees from double line open canopy have very small CPA in comparison to other classes and these trees holding small amount of biomass. On the other hand, there was a wide variation of CPA of trees for the other classes.

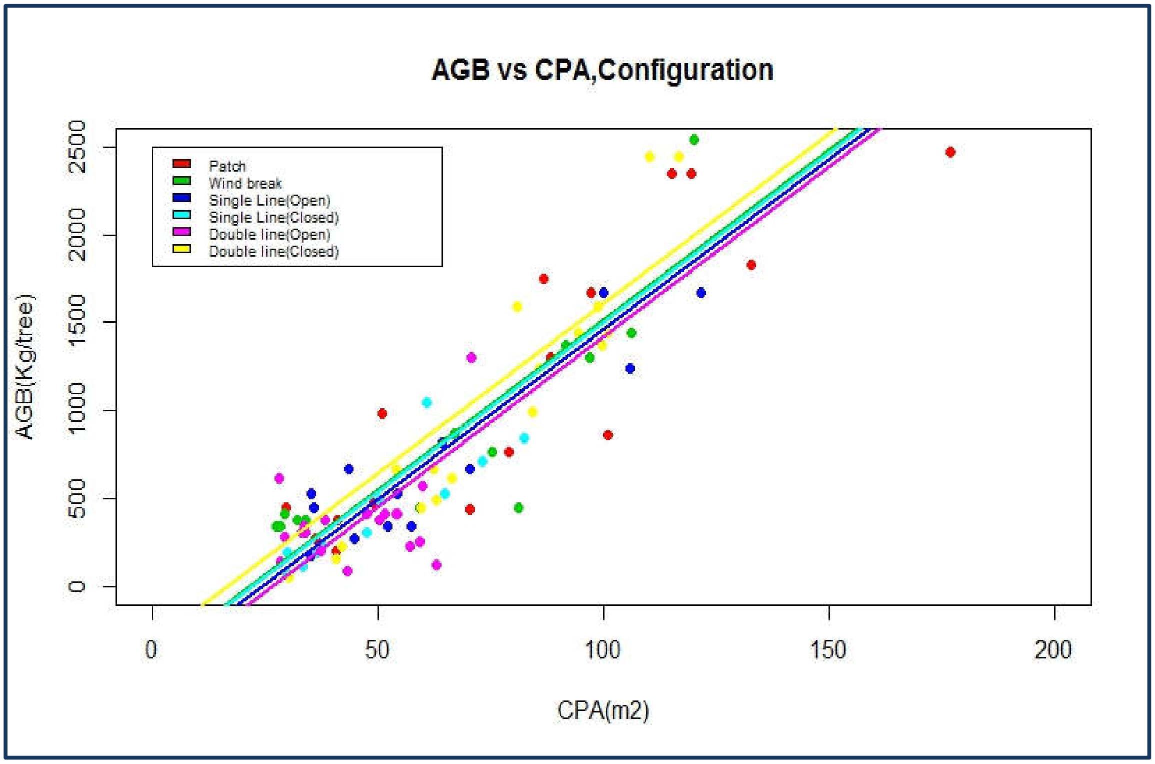


Figure 3-6: The relationship between AGB and CPA of individual tree in different configuration of Trees Outside Forest

3.4. Delineation of the crown of TOF

In this section result is being described for the method that was followed to address the answer of the research question 3: How accurate can tree crowns be delineated using VHR image for Trees Outside Forest?

Object Based Image Analysis (OBIA) of high resolution image (Pleiades) resulted in an accuracy of 73% in delineating tree crowns. The obtained D value was 0.27 which was an indication of the strength of the approach for TOF tree crown delineation. The subset of segmented tree crowns can be seen in Figure (3-7). The red polygons represent manually segmented tree crown (delineated from field sampled trees) overlaid on the automatically segmented tree crowns. A total of 100 manually segmented tree crowns were used for accuracy assessment. The accuracy assessment result and error statistics for tree crown delineation is listed in Table 3-5.

Table 3-5: Accuracy assessment of TOF crown delineation using multiresolution segmentation algorithm

Total reference crowns	Over segmentation	Under segmentation	D value	Accuracy
100	0.25	0.28	0.27	73%

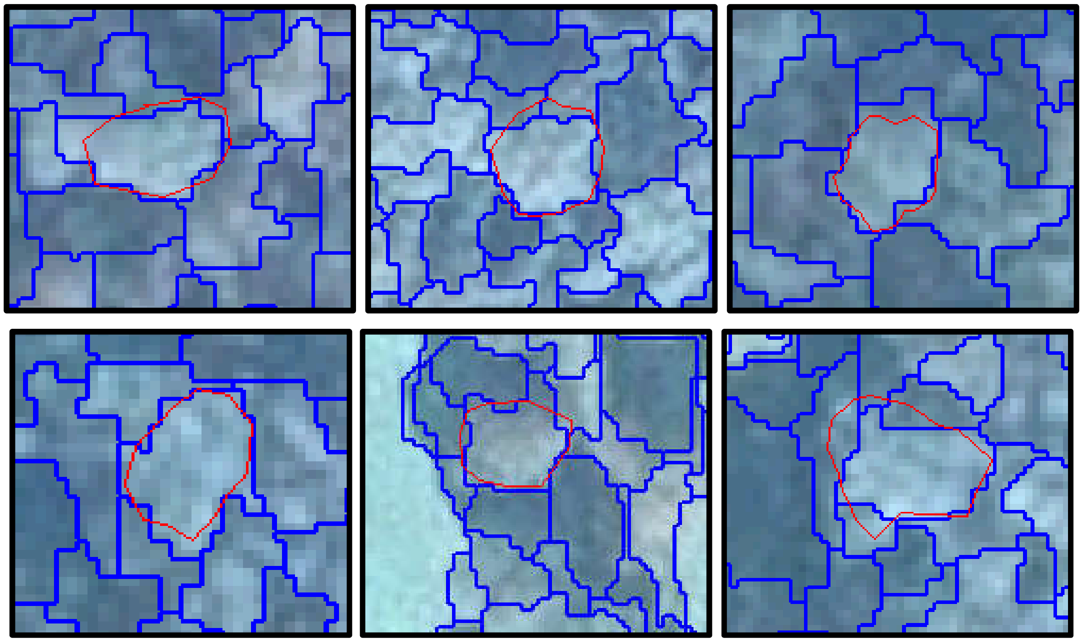


Figure 3-7: Subset of individual tree crown segmentation using multiresolution segmentation algorithm. The red polygons are describing the manually segmented tree crown overlaid on automatic segmented tree crown.

3.5. Delineation of TOF configuration

Object based image analysis detected the TOF configuration satisfactorily in expected geometrics except some omission and commission of trees. Patch configuration have been delineated consistently except some omission and commission of tree and over and under segmentation also can be seen. The shadow problem was mainly seen in the edge of the patch (Figure 3-8-A). Linear tree formation with single line also delineated in a reasonable geometry (Figure 3-8-B). Double line open canopy also delineated properly (Figure 3-8-D). In the case of double line closed canopy configuration, quite a number of trees are omitted in one side due to the shadow effect (Figure 3-8-C). Shadow from trees on one side was fallen on the top of the trees in other side which was classified as a shadow instead of a tree.

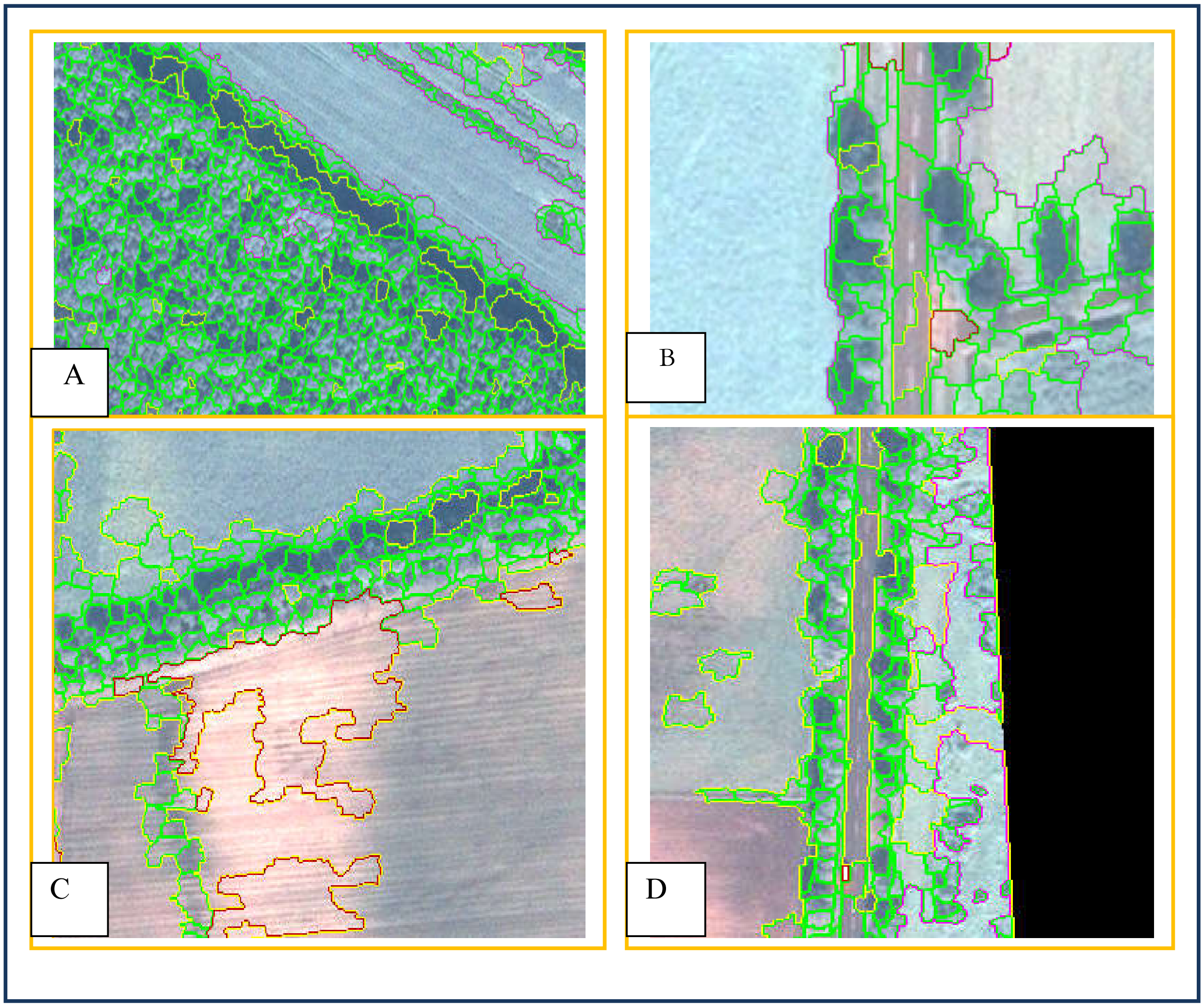


Figure 3-8: Picture A, B, C, D is showing the delineation of the configuration of patch, single line tree formation, double line closed canopy with shadow effect (comparatively darker colour is showing the shadow) and double line open canopy respectively

Subset of the tree crowns delineation after masking other land cover classes is depicted in Figure (3-9) where the green colour indicates the TOF crown. After classification and extraction of TOF, it can be observed that the OBIA method detected more individual trees which do not exists. Trees with red circle are the commission of trees (Figure 3-9). Commission of some linear feature can also be observed which is marked by red rectangular that also did not exist (Figure 3-9).

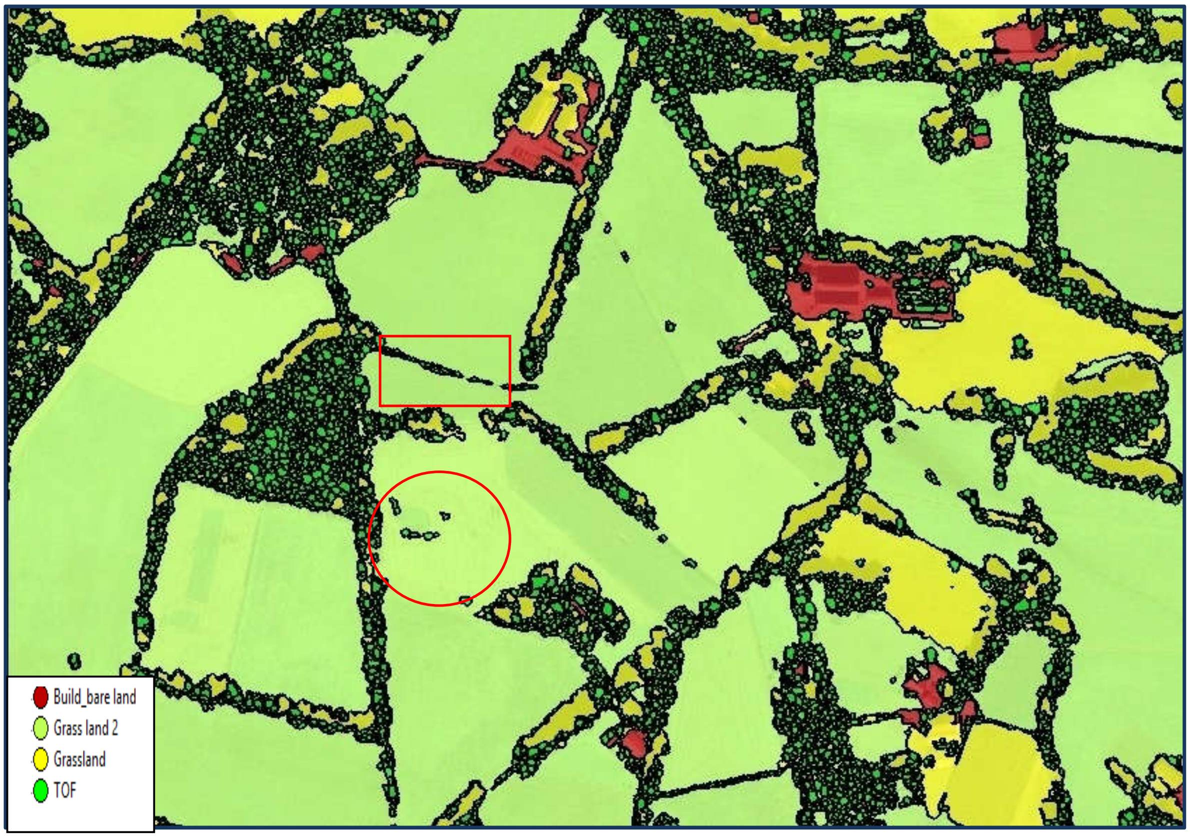


Figure 3-9: The delineation of TOF crowns for the subset of the study area

3.6. Above Ground Biomass mapping for individual tree

Based on the model established from CPA and individual tree crown obtained from the segmentation process, AGB of each tree was calculated for the whole study area. The obtained biomass was used as reference data for upscaling biomass to the Sentinel-2 data. A subset of the TOF with their biomass of the study area is shown in the Figure 3-10.

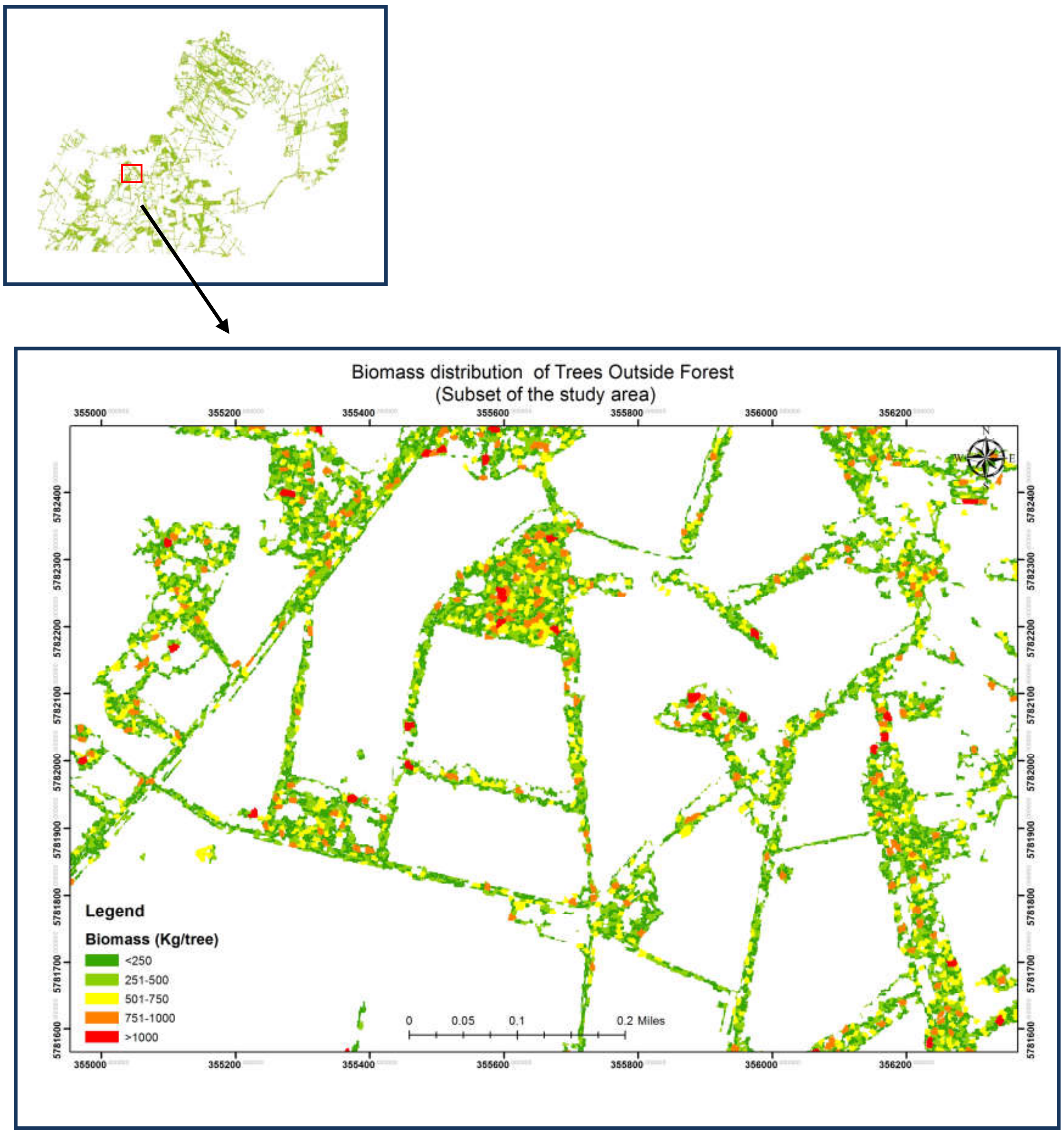


Figure 3-10: Subset of the study area with tree crowns and their corresponding biomass

3.7. Relationship analysis between biomass obtained from VHR image and Vegetation Indices (NDVI) of Sentinel-2

In this section results are being described for the method that was followed to address the answer of the research question 4: How can the estimated biomass from VHR image be scaled up to the Sentinel-2 satellite image? and 5: Is there a relation between CPA based on VHR satellite image and NDVI of Sentinel-2 for biomass estimation?

Crown projection Area (CPA) obtained from VHR image was aggregated within a particular area (10X10 m) of Sentinel-2 image and biomass was calculated within the area using area based average biomass approach. GIS based approach was used to aggregate CPA within the area of Sentinel-2 image.

The regression analysis was performed between area based biomass obtained from VHR image and vegetation indices (NDVI) from Sentinel-2 to understand their relationship. The linear and nonlinear (Quadratic) statistical models were developed for six different configurations of TOF. Results of the model showed that nonlinear models fit better than linear model for all configurations. The biomass from VHR image was highly correlated with Sentinel-2 NDVI for single line closed, double line closed and windbreak configuration. The correlation coefficient for these three configurations was 0.80, 0.88 and 0.80 respectively. In contrast, low correlation (R^2=0.38) was found for patches. Above ground biomass from the VHR image was moderately related with NDVI of Sentinel-2 for double line open and single line open canopy configuration and their R^2 value were 0.72 and 0.76 respectively. The sequence of correlation coefficient in these six configurations ranked from high to low was as follows: Double line closed canopy, single line closed canopy, wind break, single line open canopy, double line open canopy and patch (Table 3-6). Figure 3-11is representing the regression relationship between biomass from VHR image vs NDVI of Sentinel-2 for different configurations of TOF. See Appendix two for graphical representation of each configuration.

Table 3-6: Statistical models of estimated biomass for different configuration of TOF using NDVI

Configuration of TOF	Model	R^2
Double line closed canopy	$AGB=5314.07-15392.72*(NDVI)+1343.306*(NDVI)^2$	0.88
Single line closed canopy	$AGB=1411.53-5364.86*(NDVI)+7224.36*(NDVI)^2$	0.80
Wind break	$AGB= 981.14-1565.67*(NDVI)+2871.64*(NDVI)^2$	0.80
Single line open canopy	$AGB= 1262.96-3194.73*(NDVI)+4247.50*(NDVI)^2$	0.76
Double line open canopy	$AGB= 1081.44-2529.078*(NDVI)+3740.58*(NDVI)^2$	0.72
Patch	$AGB=16189.32-42766.72*(NDVI)+30815.57*(NDVI)^2$	0.38

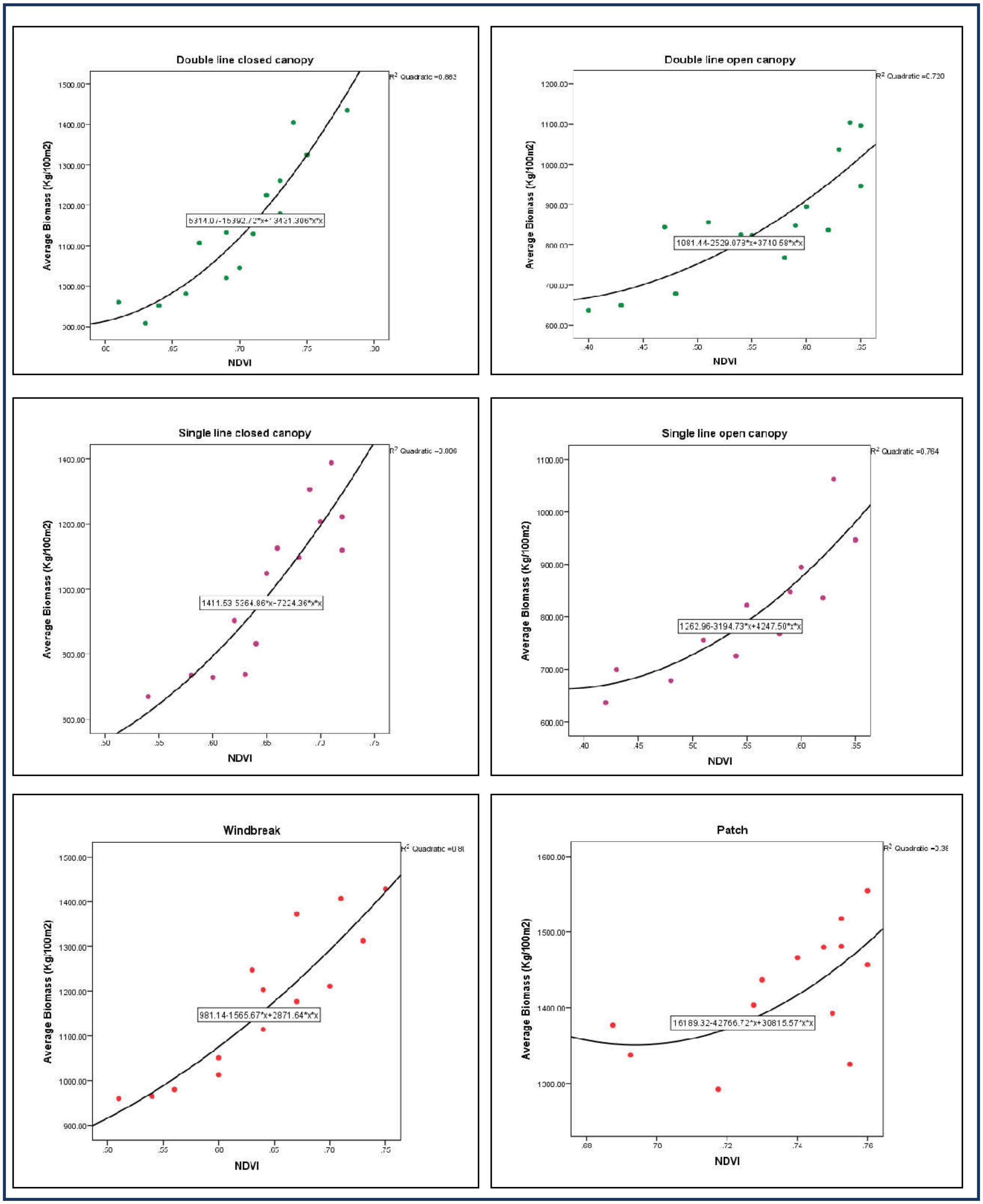


Figure 3-11: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 data for different configurations.

An ANOVA test was carried out for six configurations of TOF to test the significance of the model. Analysis result showed that for each configuration, the calculated F value was greater than the critical F value at 95% level of probability which indicated that the null hypothesis is rejected and there is a relationship between biomass and NDVI for each configuration. (Table 3-7)

Table 3-7: Regression summary of biomass estimation for different configuration of TOF

Analysis of Variance	Biomass vs NDVI					
	Regression		Residual			
Configuration	DF	Sum of Square	DF	Sum of Square	F	F_{crit}
Patch	1	18192540	26	1616865	292.54	4.22
Wind break	1	10941353	30	359738.3	912.44	4.17
Double line open canopy	1	5496379	32	376873	145.41	4.14
Double line closed canopy	1	9698889	28	386035	703.48	4.19
Single line open canopy	1	4597814	26	171550.6	696.83	4.22
Single line closed canopy	1	7110343	26	739473.6	250.00	4.22

3.8. Model validation

The biomass obtained from the model was compared against measured biomass to calibrate the model. Independent samples that were not used in the empirical model development were now used for model calibration. The validation was carried out for each configuration of TOF except patch, because of the poor fit of the model for patch. The sample size for validation varied from one configuration class to another based on their proportion on the ground (Table 3-8).

3.8.1. Windbreak

Regression line was fitted between measured and estimated biomass for windbreak resulted in a 0.84 coefficient of determination value (Figure 3-12) and a RMSE was found to be 15.11%. Descriptive analysis showed that measured biomass ranged from 1004.911 to 1368.49 $Kg/100m^2$ with a mean of 1176.68 which was very closed to the estimated biomass (Table 3-8)

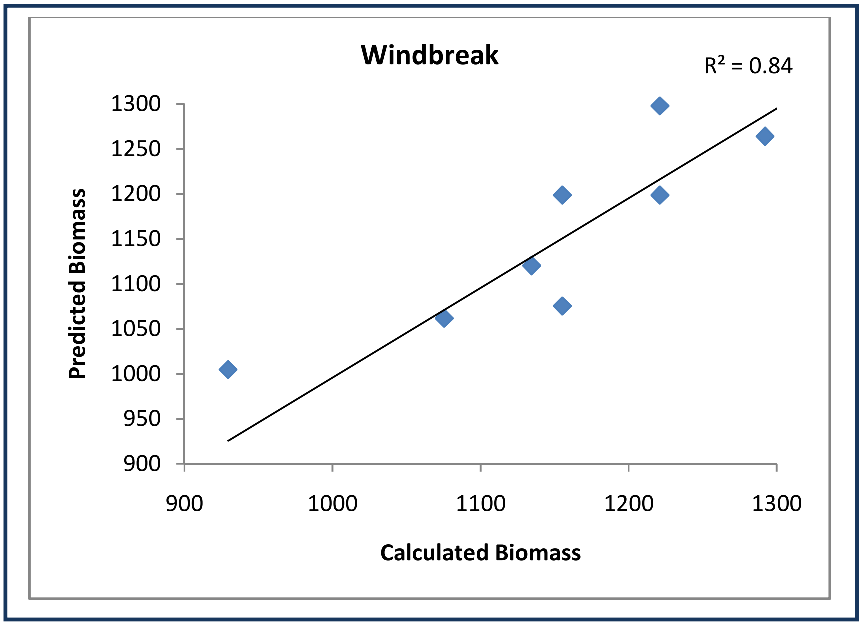


Figure 3-12: Comparison between measured and predicted biomass for windbreak

3.8.2. Single line closed canopy

Comparing estimated and measured biomass of trees for single line closed canopy showed that the two sets of data correlated with a coefficient of determination value of 0.80 (Figure 3-13) and RMSE was found to be 21.23%. Descriptive statistical analysis presented that the measured mean biomass was 2.35% lower than the estimated biomass (Table 3-8)

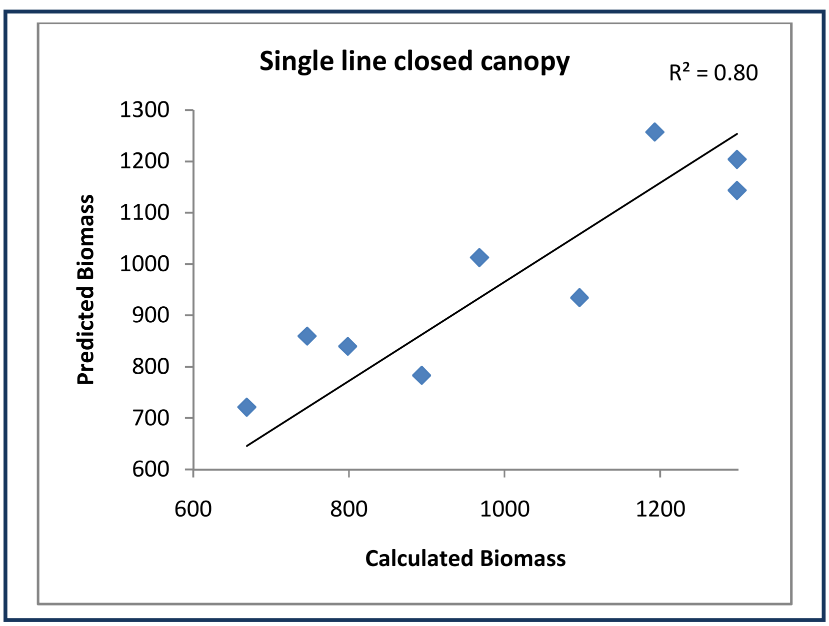


Figure 3-13: Comparison between measured and predicted biomass for single line closed canopy

3.8.3. Single line open canopy

For comparison of the measured and estimated biomass, one was plotted against other (Figure 3-14). The R^2 value was 0.77 and RMSE was found to be 20.24%. The mean biomass from the model was only 2.38% lower than the measured biomass (Table 3-8)

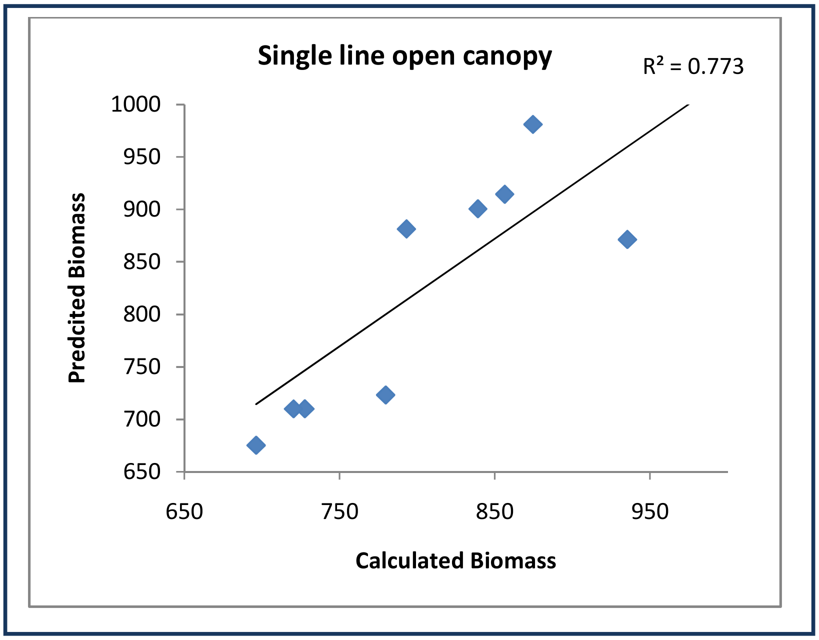


Figure 3-14: Comparison between measured and predicted biomass for single line open canopy

3.8.4. Double line closed canopy

The regression line fitted moderately between predicted and measured biomass of trees for double line closed canopy with a coefficient of determination 0.72 (Figure 3-15) and RMSE was found to be 19.49 %. The mean of the measured biomass was 1076.40 Kg/100m² and the estimated was 1065.47 Kg/100m² which means the measured and estimated biomass is closed (Table 3-8).

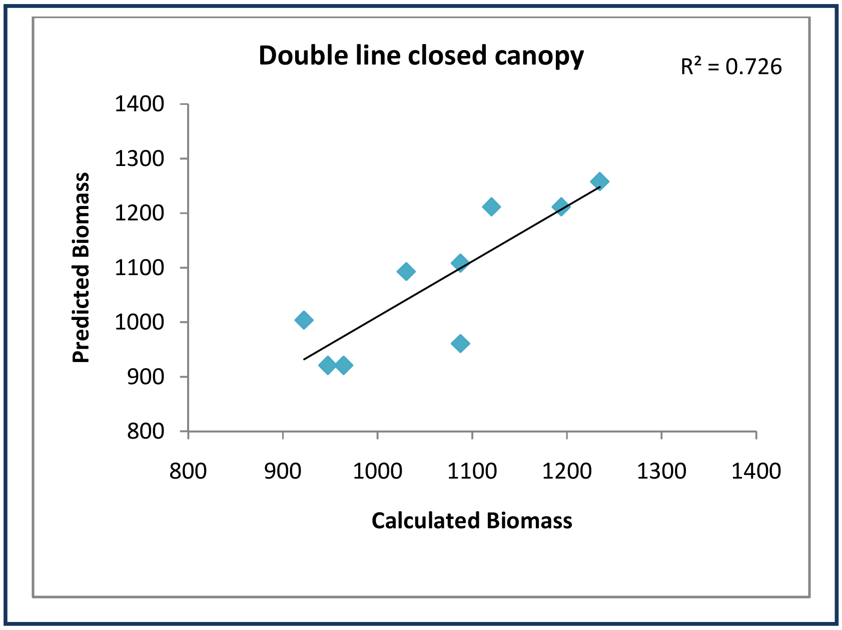


Figure 3-15: Comparison between measured and predicted biomass for double line closed canopy

3.8.5. Double line open canopy

Estimated biomass and measured biomass for trees at double line open canopy showed positive relation with coefficient of determination value 0.75 (Figure 3-16). The calculated RMSE was 20.15%. The mean value of estimated and measured biomass was 808.89 and 848.74 Kg/100m² respectively (Table 3-8)

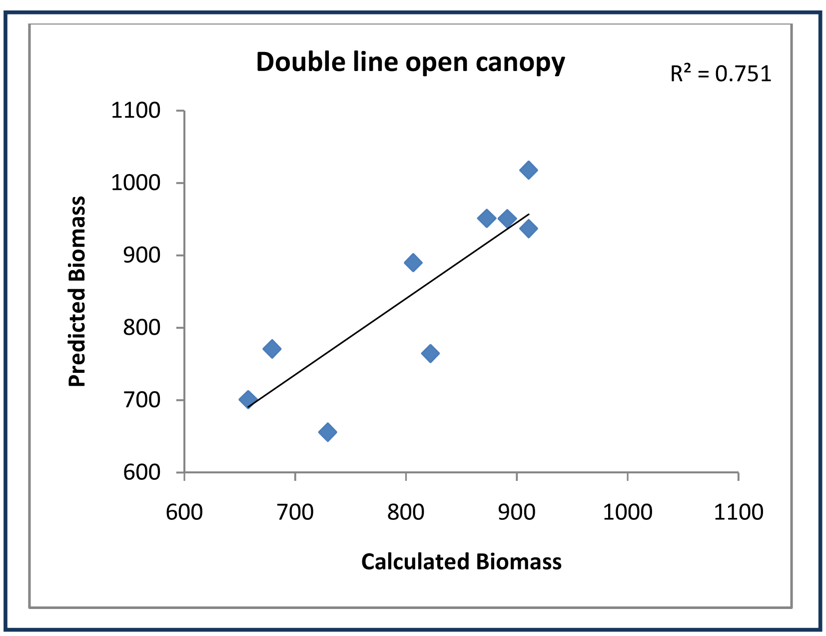


Figure 3-16: Comparison between measured and predicted biomass for double line open canopy

Table 3-8: Summary of biomass estimation using data for validation. The unit for Average biomass is Kg/100m²

Configuration	Average biomass	N	Minimum	Maximum	Mean	Std.Error	Std.dev
Windbreak	Estimated	9	929.56	1422.18	1178.57	45.87	137.63
	Measured	9	1004.91	1368.49	1176.68	40.16	120.50
Double line (closed)	Estimated	9	922.29	1234.92	1065.47	36.35	109.07
	Measured	9	920.80	1257.63	1076.40	43.74	131.23
Double line (open)	Estimated	9	655.75	1017.94	848.74	42.74	128.13
	Measured	9	657.76	910.60	808.89	32.87	98.61
Single line (closed)	Estimated	10	669.07	1298.56	995.70	79.17	237.53
	Measured	10	721.11	1257.13	972.8	64.12	192.36
Single line (open)	Estimated	10	696.31	980.93	820.81	29.81	94.28
	Measured	10	675.34	1033.10	840.00	39.93	126.29

4. DISCUSSIONS

4.1. Descriptive Statistics

The diameter distribution is well known and widely used for describing forest stand diameter structure (Duan et al., 2013). In this study, the distribution of tree diameter showed positive skewness. The possible reason for skewness could be that the measurements of DBH were taken from trees greater than 10 cm in diameter and if all the trees were measured it would not be skewed.

Besides, it can be seen that, there is a variation of DBH from one configuration to another and it was lowest for double line open canopy configuration. From the field campaign, it was observed that the trees from double line open canopy were newly planted. Low DBH for trees of this configuration could be explained by the tree age-DBH relationship because Lukaszkiewicz & Kosmala (2008) found that DBH increases with increasing age for road side trees.

4.2. Above Ground Biomass estimation using CPA

In this study, linear relationship between CPA and AGB indicates that biomass continues to increase linearly with increasing CPA. However, Shimano (1997) reported that the relationship between CPA and DBH fit best in a power sigmoid model. This relationship indicates that CPA increment decreases overtime but DBH continues to increase. At the younger stage, CPA starts to increase with increasing DBH because of less competition for resources. But later, due to the competition of nearby trees for light and other resources, CPA starts to stabilize when DBH reaches around 30 cm (Hemery et al., 2005) resulted to an exponential relation between CPA and DBH. However, many researchers found linear relationship between CPA and DBH. For example, Workie (2011) found linear relation between DBH and CPA for both broadleaf and coniferous forests of Netherlands. Moreover, Anderson et al., (2000) found linear relationship between CPA and DBH for different species. Hemery et al., (2005) also reported that within the diameter range 20-50 cm, a linear relation can be found between CPA and DBH. After this range, linear relation starts to distort and a slight reduction in the rate of CPA growth appears due to the effect of competition. This is practical in this study because most of the tree diameter was between 20-35 cm and mean diameter was less than 50 cm. This could lead to the linear relationship between DBH and CPA. Moreover, Mitchell & Popovich (1997) found a linear relation for a pine forest where tree cover was 60% and the relationship started to break down in denser crown area. Trees Outside Forest in our study site are well managed with some sylvicultural practices like thinning and pruning which keeps distance between trees and reduce competition. Moreover, TOF are not as dense as forest. Because of low density and management practice CPA can continue to increase. This could lead to a linear relation between CPA and DBH. The linear relationship indicates the effect of competition on the CPA of trees is insignificant in this study area.

This study revealed that 78% variability of biomass can be predicted by CPA and considerable amount of variance remains unexplained which needs further improvement. Improvement of the model can be possible by improving the accuracy of CPA delineation (Hirata et al., 2009). This is because accurate CPA delineation is the key factor for estimating other variables (Ke, 2008). Some possible sources of error could affect on the accuracy of CPA delineation as well as the biomass estimation. Due to the high shadow effect, slight over or under segmentation could affect the accuracy of CPA and its relationship with biomass. Moreover, the model for biomass estimation was developed by combining data from all configurations but our result showed that CPA varies from configuration to configuration. Development of models for different configurations could show the relation in different ways which could also has an effect on the relationship. In this study, manually delineated tree crowns were used for model development but shadow problems and image quality made it difficult to delineate adequate tree crowns in each configuration which made some limitation to develop a model for each configuration. An improved quality and shadow free image can privileges model development for each configuration. In addition, Workie (2011) and Anderson et al.,(2000) found that CPA-Biomass relationship also differs from species to species. This was not included in the developed model and could introduce error. Moreover, over and under segmentation due to the human error could also occur during the manual delineation of tree crowns which could also affect on the relationship between CPA and AGB.

4.3. Allometric equation and biomass estimation

Allometric equation is one of the crucial sources of uncertainty to calculate AGB from inventory data (Chave et al., 2004). There are several published equations for biomass estimation. A species specific equation is preferred for above ground biomass estimation because trees from different species differ in term of tree architecture and wood density. An advantage of species specific equation was proved by studying temperate and tropical regions (Basuki et al., 2009). Among four species in our study area, species specific equations were used for three species and a general equation for a temperate broadleaved species was used for Oak species. All the allometric equations were developed in different parts of Europe and US. Allometric equations are developed using certain number of individual trees from a limited region or broader combination of sites (Chambers et al., 2001). In our case, allometric equation was applied beyond the regions for which they were developed which can transfer an error, even when growth condition are very similar. Vieira et al., (2008) found 36% error for using an equation in a site different than the one which was developed for.

Incorporation of all appropriate structural variables like DBH, Height that affect AGB is an important requirement for developing accurate allometric equation (Rosa et al., 2014). However, the most typical tree parameter which is used to predict AGB model is DBH because it is easily measurable in a precise way that makes it a more reliable parameter (Valbuena et al., 2016, Ketterings et al., 2001, Fang et al., 2016). Thus, AGB allometric equations were widely developed based on DBH (Bartelink, 1996, Jenkins et al., 2003, Nelson et al., 1999, Zinnias & Seura 2005). However, the importance of including tree height in biomass estimation has been emphasized by several authors (Chave et al., 2014, Ketterings et al., 2001, Molto et al., 2014). Chave et al., (2005) mentioned to incorporate tree height for biomass estimation to obtain unbiased estimations. For example in Tapajos national forest in Brazilian state of para, it was observed that incorporation of height in biomass estimation provided 21% less biomass than the estimated biomass using DBH only. This finding was supported by Feldpausch et al., (2013) who found 13% lower biomass by incorporating tree height than the reference one based on DBH only. These results indicate that the allometric equation using DBH only overestimated biomass rather using DBH and height.

Even though an AGB model with height improves the model, it also depends on the accuracy of the tree height measurement. Different sources of uncertainty can contribute to the measurement of height accurately. Offset between measured distance and crown top position, tree top occlusion, ground slope, obstacles for distance measurement and clinometers operator (Hunter et al., 2013) are the main sources of error. Measuring height is also costly in field. Hunter et al., (2013) found 5-6% uncertainty of biomass estimation due to the imprecision of height measurement. Additionally, several authors also found negligible impact of height inclusion to predict biomass (Nelson et al., 1999, Kuyah et al., 2012, Shampaio et al., 2010). In this study, field height measurements were not precise. Moreover, lack of a suitable species specific allometric equation including both DBH and height made it difficult to use allometric equation in combination of DBH and height. The exclusion of height for biomass estimation could affect the accuracy of biomass estimation.

The allometric equations applied in this study for biomass estimation of trees outside forest were developed from data that was collected from forests. But the target population should resemble to the one used for model development for biomass estimation (Tanhuanpaa et al., 2017). The magnitude of the uncertainty for application of model developed for forest to the non-forest trees is unknown (Nowak, 1994). The transfer of model from forest to TOF pointed out over and underestimation by two reviewed studies (McHale et al., 2009, Kyung et al., 2013). In addition, Nowak (1994) found overestimation of biomass for urban environment using forest based equation. Generally, TOF varies in their spatial arrangement from single scattered trees over linear formation to dense forest like woodlots of small area extent. TOF are often exposed to the edge effects and increased course of radiation, wind speed, causing difference in specific gravity of wood and structure compared to forest trees may be observed for TOF (Zhou et al., 2006). Due to this variation, specific allometric model is needed for specific type of TOF. Unfortunately very few allometric equations are developed for TOF biomass estimation but most of them are for local site or local species. No two TOF types are similar in terms of planting arrangement, plant composition and stand density which makes it a challenge to determine biomass and extrapolate from one system to others. More studies are needed for the development of allometric equation for non forest trees. Species specific and site specific models could be an appropriate solution though it needs more resources. McHale et al., (2009) suggested applying averaged equations to reduce variability if a forest model is applied to the TOF. A multispecies model developed for forest or estimating of stem volume and converting to biomass by using wood density could be an alternative solution for TOF biomass estimation which was suggested by Nair (2011).

Besides allometric equation, omission and commission of TOF, because of misclassification could introduce error for biomass estimation in this study. Especially commission of scattered trees and linear tree formation in the grassland as well as the omission of some linear formations and trees from patches due to the shadow effect could also propagate uncertainty for biomass estimation. Moreover, the sources of error could also propagate during the data collection in the field. Field data collection (e.g.,DBH measurement) and sample tree location was mainly supported by GPS and printed image. The signal of GPS can be degraded by various factors and specially wind and cloudy weather during our field data collection. This noise could introduce error for DBH measurement which is source of error for biomass estimation. In addition error can be propagated in this study due to small number of sample plots for double line and single line linear tree formation. Small numbers of sample plots are not representative for the whole area. Moreover, in some points, trees with large basal area had some parasites and thick bark on it but it wasn't possible to remove parasites and bark which caused overestimated of the DBH.

Uncertainty analysis of biomass estimation from remote sensing based method has received attention to know the impact of various inputs on the variation of output. This provides guidelines to the modeller and analyst to identify the uncertainty caused by input as well as to reduce the uncertainty to improve the model. But due to the limitation of time, no uncertainty analysis was carried out for this study which limits the detailed information about model uncertainty and its improvement. This was one of the limitations of this research.

4.4. Tree crown delineation

The TOF crown detection and delineation is more difficult than forest because the landscape is extremely complex and it consists of several main elements including elimination of other land classes using threshold, seed detection of tree crown, region growth and refinement. Most delineation or segmentation algorithms have been developed for forest type. Comparison with existing studies of tree crown delineation of forest revealed that TOF show unique property because it is part of another land cover, hence it has a background. Considering these components and complexity, a reasonable tree crown delineation and accuracy was achieved with Object Based Image Analysis.

Region growing approach is widely used for different types of forests and their usefulness has been demonstrated. It is a robust method which can extract objects and smoothness boundaries (Cui & Guan, 2008). The accuracy of region growing algorithm varies from deciduous to coniferous forest and studies showed that the accuracy of tree delineation for coniferous species can reach upto 80% (Erikson & Olofsson, 2005) but the accuracy for a deciduous stand between 50-70% (Erikson & Olofsson, 2005, Wang et al., 2004). Locating tree top can be used as local maxima for growing the image object for tree crown which works greatly for coniferous stands. On the other hand, trees from deciduous stand don't have conical shapes like coniferous stands which make it difficult to find tree tops. The issue of overlapping tree layer and density of tropical forest makes it more difficult for good segmentation (Feret & Anser, 2013, Saliola, 2014). The spatial arrangement and distribution of trees of TOF makes the scenario different than forest. TOF are not generally dense like forest and gaps can be seen in the linear formation of tree without understory. Ngwayi (2012) and Mutanga (2012) also found a reasonable accuracy of tree crown segmentation for Trees Outside Forest using region growing multiresolution algorithm.

Over and under segmentation was observed for the multiresolution segmentation algorithm. This could be caused by the nearby vegetation surface such as grassland or agricultural land which is a hinder for identification and delineation of tree crown accurately (Bunting & Lucas, 2006, Ke & Quackenbush, 2008). Moreover, sensor viewing angle, sun elevation and topography have significant effect on the radiometric and geometric properties of tree crown in the satellite image (Yin et al., 2015). Moreover, shadow affects the quality of the image because it causes the loss of information from the feature (Haijian et al., 2008). The ideal situation for individual tree crown delineation is when the view area is within $\pm 15^0$ off nadir (Wang et al., 2004). The image of this study was acquired with a view area within approximately $\pm 23^0$ off nadir and not in the range of ideal off nadir, resulting in high shadows and inclination of trees in the image which can affect the over or under segmentation. Different studies attempted to minimize the shadow problem and each has some draw backs. Asner (2002) tried to avoid the shadow problem by manually tracing the trees but this is not possible for large areas. Ke et al., (2010) attempted to increase scale parameter for segmentation which decreased the shadow problem but in some points, objects became larger than forest stand. In addition, Li (2008) suggested decreasing the resolution of image which will reduce the shadow but will make it difficult to distinguish the boundary of the tree crown. In this research, trees from one side of double line linear trees were classified as shadow because of the shadow from one side tree fallen in the other side. To obtain the double line configuration, manual tracing of trees was done which is suggested by Asner (2002) but this was time consuming and it is not convenient to do for the whole area. Manual tracing could also affect over and under segmentation of tree crown resulting in an error on biomass estimation. Further study is needed for dealing with shadow problem.

TOF interacts in a very complex way with other landscape features. For this study, we needed to eliminate other features to extract TOF only. Different spectral threshold values were used to separate other features. During the separation, few misclassifications existed which can be observed visually by comparing the classified image and the original one. The differentiation of the boundary was difficult between two nearly identical spectral features which could introduce some misclassification especially where the tree cover and other vegetation exists nearly. Shadow over tree crowns also has its effect in the misclassification. Plantation is along the road side, so their branches spread over the road and in some places ground can be seen in between two trees. In this case, it is difficult to distinguish the boundary of features.

Future research needs to be conducted for robust tree crown delineation for Trees Outside Forest. Different algorithms can be applied over the same area or new algorithm needs to be developed for trees outside forest considering the spatial arrangement of TOF in relation to other land classes. Although each segmentation algorithm has its own limitation and advantages, combination of multiple algorithm can improve the delineation of tree crowns. Workie (2011) investigated three different types of segmentation algorithm for tree crown delineation of both broadleaf and coniferous species but no one was sufficient enough for CPA delineation. However, a combination of multiple algorithms improves the delineation of trees for both broadleaf and coniferous trees. Ke (2008) also indicated that development of a robust algorithm requires taking the advantages of the characteristic of multiple algorithms. Meneguzzo et al., (2013) used three different methods including OBIA for TOF extraction and faced problems in all cases which indicates the necessity to develop separate classification model for TOF landscape. Acquisition of image within the range of off- nadir and in perfect time could mitigate the problem related to shadow as well as can improve the CPA delineation resulting in an accurate model for biomass estimation. Moreover, Lidar is very helpful to distinguish building, roads, tree and low vegetation and shadow over objects using the height information which can reduce the misclassification. The combination of VHR image and Lidar data can be a possible option regarding TOF delineation.

4.5. Upscaling biomass

In this study, an approach was developed for upscaling biomass from VHR image of Pleiades satellite to the medium resolution Sentinel-2. The study developed a model for large area biomass estimation as a function of NDVI (Sentinel-2) through regression analysis. Area based biomass averaging techniques was used to aggregate biomass for upscaling which provided reasonable result in relation to NDVI of Sentinel-2 .This observation is supported by Hufkins et al., (2006) and Gibbs et al., (2010). Hufkins et al., (2006) calculated the proportion of crown coverage to upscale LAI point measurement and Gibss et al., (2010) identified tree crown from IKONOS imagery and scaled up to the Landsat pixel resolution. A similar conclusion was reported by Mutanga (2012) who upscaled biomass for Trees Outside Forest using area based averaging techniques. In this study, tree crown area was taken into account for biomass estimation because it is an essential parameter as it affects greatly the amount of reflectance from surface (Olander et al., 2011) and the aggregation of crown area rather than relying on pixel information yield better result (Hasnen et al., 2002).

The regression relation between biomass and NDVI of Sentinel-2 showed exponential relation for all configurations in the study area. The exponential relationship of the model is supported by many other studies (Asrar et al., 1984, Myeong et al., 2005, Goswami et al., 2015). This could be explained by the saturation problem of vegetation indices. As biomass increases, there is a trend in vegetation indices to be insensitive to the increase of biomass which was investigated by Tucker & Seller (1986). The curvilinear function between NDVI and biomass implied the limitation of vegetation indices. Moreover, Goswami et al., (2015) mentioned saturation problem of NDVI as the reason for the exponential relationship between biomass and NDVI. However, NDVI estimated poor yields where there is 100% vegetation cover and it saturates after a certain biomass density (Baret and Guyot, 1991, Jiang et al., 2008). This could be the reason for poor yield of biomass estimation in patch as a function of NDVI. A patch is small forest where the density of tree is high and its coverage approaches approximately 100%. In this situation, basal area continues to grow but the change in DBH does not directly affect information derived from remote sensing because optical remote sensing is sensitive to crown surface not to below canopy information. Therefore, the signal shows saturation effect (Franklin, 1986). On contrast, because of the low density of trees, the limitation of saturation was not significant in linear tree formation which resulted in a high R^2 value between biomass and NDVI. Myeong et al., 2005 and Yao et al. 2015 also mentioned low tree density as a reason for less saturation of biomass estimation using NDVI in urban green areas.

Saturation occurs when spectral values remain insensitive to increases of AGB beyond a certain value. Data saturation may occur by different factors such as remote sensing data themselves, vegetation and topography (Zhao et al., 2016). Patch is small forest where canopy gap have been closed by leaves and branches, trees and biomass increases but an optical sensor can't penetrate through the canopy which causes saturation. Due to this saturation problem, there is a need to improve the technique for biomass estimation in a dense vegetation area like in patches. In this context, SAR data could be an option because L- band (24cm) is capable to penetrate through the canopy and P band (70cm) is even more appropriate to penetrate and can capture the entire structure (Zhao et al., 2016). The integration of optical and SAR data can mitigate the problem associated with saturation problem for biomass estimation. Boyd (2012) showed the improvement of biomass estimation by reducing the saturation problem with integration of Landsat and SAR data. Attarchi & Gloaguen (2014) also reported that SAR data can improve the biomass estimation. Moreover, Lu's (2005) study showed that incorporation of texture information into spectral response improves biomass estimation. Other researches also supported incorporation of texture from optical and SAR data for improved biomass estimation (Sarker & Nichol, 2011, Timothy et al., 2015, Kelsey & Neff, 2014). Besides, narrow band vegetation indices can reduce the saturation problem related to NDVI. Mutanga & Skidmore (2004) used MNDVI, SR and TVI to reduce the saturation problem for biomass estimation.

The findings of the linear tree formation showed satisfactory result for biomass estimation using NDVI but considerable amount of variance was still unexplained in each linear tree configuration. The landscape of TOF is much more complex than general forest ecosystem because of the heterogeneous surface feature. Depending on the spatial resolution, the heterogeneity of TOF interacts with the sensor response function which gives mixed pixel effect (Myeong et al., 2006) and difficulty arises to extract target information due to this mixed pixel. Regression relation could over or underestimate the biomass storage due to the effect of mixed pixel. The main limitation of pixel based vegetation indices or reflectance value for biomass estimation is that they do not consider the mixed spectral information. This could be mitigated by pixel un-mixing analysis which is the most used method for deriving information from pixel (Lu et al., 2003) and extract vegetation information. Sun et al., (2015) experienced increased accuracy of biomass estimation in urban forest using spectral un-mixing analysis. This finding was supported by Basuki et al., (2012) where spectral unmixing analysis was used for biomass estimation in a tropical forest.

The error for upscaling biomass could also be introduced by the reference biomass map. All the error related to reference biomass map could propagate to the upscaled model. Issue related to the accurate biomass estimation using VHR image needs to be considered because accurate ground reference is essential for upscaling. Effort needs to be made to explore the AGB based on empirical regression methods and allometric equations. The suggested mitigation approach for reducing saturation for patch could also be used for linear tree formation for reducing saturation problem. Time series NDVI can result in more accurate biomass estimation and less saturation than using single NDVI (Zhu & Liu, 2014). This can also be considered for accurate biomass estimation for future research.

The regression analysis showed lower R^2 value for single and double line open canopy in comparison to other linear tree formations. The reason for lower coefficient of determination value could be explained by their spatial arrangement of trees. The linear formation (single and double line open) is located along the road side and due to the canopy gaps between trees (single line and double line) and road between two tree lines (double line), all these non-green and green are interwoven which could make it more difficult to extract information from the sensor than other linear tree formation. Leeuwen and Huete (1996) also mentioned that the gap between vegetation cover, site variations and bare soil reflectance can produce unpredictable bias in the quantification of the properties of vegetation. Moreover, soil background condition exerts considerable influence on partial canopy spectra and calculated vegetation indices (Huete, 1988) and NDVI is also sensitive for soil scattering which could occur for single line open and closed canopy because of their canopy gap between trees. All these could lead to lower R^2 value between NDVI and biomass for single and double line open canopy than for other linear configurations. In this context, EVI could be used to mitigate the soil scattering issues because it can eliminate background information. Moreover, SAVI can reduce to the inherence sensitivity of NDVI and MSAVI is designed to correct the weakness of SAVI in how vegetation responds as it moves away from soil line (Qi et al., 1994) which can be useful for sparse vegetation. Moreover, according to Yan et al., (2013) MSAVI and SAVI showed relatively higher correlation with aboveground biomass than NDVI in a sandy land of China.

Due to the variation of species composition, planting arrangement and stand density among different configurations, one approach may not fit for all configurations. Using only NDVI for all configurations could be mentioned as limitation of this study. Different vegetation indices could be useful in this context because different vegetation indices are sensitive to different range of biomass and fractional vegetated ground cover. Further research is essential for developing different approach in different configurations for upscaling. Moreover, species specific model development is essential for accurate biomass estimation for regional scale (Liangfu et al., 2005) which also needs to be addressed for future research. In addition, datasets for validation was only taken within the extent of VHR image but not the other site covered by Sentinel-2 image. Validation data from the other side of the VHR image could improve the accuracy of the model fitness for upscaling. Besides, the data for model development and validation was few in numbers. The increase of data for model development and validation could provide more accurate result. Moreover, according to the methodology of upscaling applied in this study, average biomass needs to be calculated from some samples within the window size which is fully covered by crowns. This fixed average biomass can be used to calculate area based average biomass for any window by multiplying the proportion of crown area within the window size. As there are six configurations in this study area, this fixed biomass needed to be calculated for each configuration. However, because of the limited time and it was not possible to obtain fully covered area in each configuration, the fixed biomass was calculated only from patches and double line closed canopy configuration and used for all configurations. This could also introduce error in biomass calculation in each configuration.

4.6. Consideration for wider application

The preliminary results based on the reference dataset showed that there is a strong relationship between CPA and DBH (R^2=0.78) and calibrated model for biomass estimation showed 0.75 R^2 value. This result suggested that the proposed method can be used to estimate biomass and related variables over relatively large areas. The tree crown mapping approach presented in the study was designed to account for tree crown size, spectral properties of different landscape features. The design included the use of geometric and spectral thresholds for separation of tree cover from the field. The spectral thresholds are sensor specific. The threshold value applied in this study would need to be adjusted to account for the difference in vegetation and atmospheric conditions. Identification of optimal spectral threshold values should be based on the prior knowledge about the structure and spectral properties of the local species and tree composition and field layer components. Biomass mapping and individual tree crown separation was limited to a small study area. Similar results in terms of detection and delineation accuracies are expected when the proposed method will be applied in the areas with similar tree cover structure but adjustment of threshold is needed.

VHR image is an effective way of tree crown delineation and biomass estimation but spatial coverage limits its use for large area biomass estimation. Integration of VHR and medium resolution image can be an alternative. The proposed approach for scaling up biomass can be used for TOF with low density but further improvement is essential for individual configuration. This approach could considerably reduce the requirements for field data for biomass estimation and could be used in extensive area where field data are limited. On the other hand, further research is required to upscale biomass in the case where tree crown are strongly interlocked and arranged in a compact way.

5. CONCLUSION

This study evaluated the use of very high resolution (Pleiades) satellite image for predicting TOF biomass and tried to upscale the estimated biomass over large area by incorporating VHR, Sentinel-2 (NDVI) and field measured data. The main objective of the research was to develop an approach to estimate biomass using VHR and medium resolution Sentinel-2 satellite image. The method was divided into two main parts (Above Ground Biomass estimation using VHR image and upscaling biomass to the Sentinel-2 image) to achieve the objective of the research.
In this study, regression model was developed between CPA and AGB. Object Based Image Analysis was employed to delineate TOF crown using VHR image of Pleiades satellite. This was followed by the accuracy assessment and biomass calculation for all trees in the study area. Finally, obtained biomass from VHR image was used to upscale biomass to Sentinel-2 image by applying an area based averaging technique and regression model developed between biomass and NDVI of Sentinel-2. Hence, research questions mentioned in the section 1.4 is answered properly.

1. Is there a relation between CPA and AGB to model biomass estimation?

Above Ground Biomass (AGB) can be predicted by the model developed as a function of Crown Projection Area (CPA) of trees. The model explained 78% variability of the biomass. The statistical analysis showed the significance of the model at 95% confidence level.

2. How accurate biomass can be estimated using a regression equation based on CPA?

The calibrated model showed 0.75 coefficient of determination value and found to be 30% RMSE value. The result indicated that the model can be extrapolated outside the boundary and a reasonable output will be obtained from the model.

3. How accurate can tree crowns be delineated using VHR image for Trees Outside Forest?

The Object Based Image Analysis delineated tree crowns with an accuracy of 73% by calculating D index. Considering the issues related to the TOF crown delineation such as other features surrounded by TOF, a reasonable accuracy was obtained.

4. How can the estimated biomass from VHR image be upscaled to the Sentinel-2 satellite image?

Crown projection Area (CPA) obtained from VHR image was aggregated within a particular area (10X10 m) of Sentinel-2 image and biomass was calculated within the area using area based average biomass approach.

5. Is there a relation between CPA based on VHR satellite image and NDVI of Sentinel-2 for biomass estimation?

The different coefficient of determination value was obtained for different configuration classes. The sequence of correlation coefficient in these six spatial arrangements of TOF ranked from high to low was as follows: Double line closed canopy (0.88), single line closed canopy (0.80), wind break (0.80), single line open canopy (0.76), double line open canopy (0.72) and patch (0.38). The results of upscaling biomass in different configurations showed that the proposed method performed better for linear formation of trees than group of trees (patches).

LIST OF REFERENCES

Adams, J.M., Faure, H., Taure-Denard, L., McGlade, J.M. and Woodward, H.I. (1990). Increase in terrestrial carbon storage from the last glacial maximum to the present. *Nature*, 348, 711 – 714.

Aksoy, S., Akcay, H.G., Cinbis, R.G., and Wassenaar, T. (2008). *Automatic mapping of linear woody vegetation features in agricultural landscapes*. Paper presented at IEEE International Geoscience and Remote Sensing Symposium, Boston, Massachusetts.

Alexandre, D. Y., Lescure, J. P., Bied-Charreton, M. and Fotsing, J. M. (1999*). Contribution à l'état des connaissances sur les arbres hors forêt (TOF).* Orléans, France, 185.

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

Asner, P. (2002). Estimating Canopy Structure in an Amazon Forest from Laser Range Finder and IKONOS Satellite Observations. *Biotropica*, 34(4), 483–492.

Asrar, G., Fuchs, M., Kanemasu, E. T., & Hatfield, J. L. (1984). Estimating absorbed photosynthetically active radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal*, 76, 300–306.

Attarchi, S., & Gloaguen, R. (2014). Improving the Estimation of Above Ground Biomass Using Dual Polarimetric PALSAR and ETM+ Data in the Hyrcanian Mountain Forest (Iran). *Remote Sensing*, 6, 3693–3715. http://doi.org/10.3390/rs6053693.

Auclair, D., Prinsley, R., and Davis, S. (2000). Trees on farms in industrialised countries: silvicultural, environmental and economics issues. *Proceedings of XXI IUFRO World Congress*, Kuala Lumpur, Malaysia.

Baccini, A., Friedl, M. A., Woodcock, C. E., & Warbington, R. (2004). Forest biomass estimation over regional scales using multisource data. *Geophysical Research Letters*, 31(10), 2–5. http://doi.org/10.1029/2004GL019782.

Baret, F., & Guyot, G. (1991). *Potentials and limits of vegetation indices of LAI and APAR assessment*. Paper presented at INRA Bioclimatologie, Montfavet, France. http://doi.org/10.1016/0034-4257(91)90009-U.

Basuki, T. M., Laake, P. E. Van, Skidmore, A. K., & Hussin, Y. A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management*, 257, 1684–1694. http://doi.org/10.1016/j.foreco.2009.01.027.

Basuki, T. M., Skidmore, A. K., Laake, P. E. Van, Van, I., Hussin, Y. A. (2012). The potential of spectral mixture analysis to improve the estimation accuracy of tropical forest biomass. *Geocarto International*, 27(4), 329-345. http://doi.org/10.1080/10106049.2011.634928.

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

Bellefontaine, R., Petit, S., Pain-orcet, M., Deleporte, P., Bertault, J.G. (2002). *Trees outside forests -Towards better awareness*. FAO Conservation Guide, 35, Rome.

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing,* 58(3-4), 239–258. http://doi.org/10.1016/j.isprsjprs.2003.10.002

Biasioli, M. (2002). Alberi fuori foresta - dialogo internazionale e due casi di studio: Francia e Inghilterra. *Dendronatura*, 2, 23-30.

Borin, M., & Maccatrozzo, G. (2005). Immobilizzazione della CO2 da parte delle siepi campestri. *Alberi e Territorio*, 7(8), 47-52.

Boyd, D. S. (2012). Estimating tropical forest biomass with a combination of SAR image texture and Landsat TM data: An assessment of prediction between regions. *ISPRS Journal of Photogrammetry and Remote Sensing,* 70, 66–77. http://doi.org/10.1016/j.isprsjprs.2012.03.011.

Brown, S. (1997). Estimating Biomass and Biomass Change of Tropical Forests: a Primer. *FAO Forestry Paper,* 134 , 1–4.

Brown, S. (2002). Measuring carbon in forest: Current status and future challenges. *Environment Pollution*, 116(3), 363-372.

Bunting, P., & Lucas, R. (2006). The delineation of tree crowns in Australian mixed species forests using hyperspectral Compact Airborne Spectrographic Imager (CASI) data. *Remote Sensing and Environment*, 101, 230-248.
http://doi.org/10.1016/j.rse.2005.12.015.

Carreiras, J.M., Pereira, J.M.C., Pereira, J.S. (2006). Estimation of tree canopy cover in evergreen oak woodlands using remote sensing. *Forest Ecology and Management*, 223, 45–53.

Chambers, J. Q., Ribeiro, R. J., & Higuchi, N. (2001). Tree damage , allometric relationships , and above-ground net primary production in central Amazon forest. *Forest Ecology and Management*, 152, 73–84.

Chave, J., Andalo, C., Brown, S., Cairns, M. A., Chambers, J. Q., Eamus, D., et al. (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*, 145(1), 87–99.

Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S., & Perez, R. (2004). Error propagation and scaling for tropical forest biomass estimates. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 359(1443), 409–420.

Chave, J., Rejou-Mechain, M., Burquez, A., Chidumayo, E., Colgan, M. S., Delitti, W. B., et al. (2014). Improved allometric models to estimate the aboveground biomass of tropical trees. *Global Change Biology,* 20(10), 3177–3190.

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2014). Accuracy Assessment Measures for Object- based Image Segmentation Goodness. *Photogrametric Engineering and Remote Sensing*, 76(3), 289-299.http://doi.org/10.14358/PERS.76.3.289

Cui, W., & Guan, Z. (2008). An Improved Region Growing Algorithm for Image Segmentation. *Proceeding of International Conference on Computer Science and Software Engineering*, Washington, USA.
http://doi.org/10.1109/CSSE.2008.891.

Definiens. (2009b). *Definiens eCognition Developer 8 User Guide.*

Drake, J. B., Knox, R. G., Dubayah, R. O., Clark, D. B., Condit, R., Blair, J. B., & Hofton, M. (2003). Above-ground biomass estimation in closed canopy Neotropical forests using lidar remote sensing: Factors affecting the generality of relationships. *Global Ecology and Biogeography*, 12(2), 147–159.
http://doi.org/10.1046/j.1466-822X.2003.00010.

Du, L., Zhou, T., Zou, Z., Zhao, X., Huang, K., & Wu, H. (2014). Mapping Forest Biomass Using Remote Sensing and National Forest Inventory in China. *Forest*, 5, 1267–1283.
http://doi.org/10.3390/f5061267.

Duan, A., Zhang, J., Zhang, X., & He, C. (2013). Stand Diameter Distribution Modelling and Prediction Based on Richards Function. *Plos One*, 8(4), 1–12. http://doi.org/10.1371/journal.pone.0062605.

Endreny, T.A. (2002). Forest buffer strips. Mapping the water quality benefits. *Journal of Forestry*, 1, 35-40.

Erikson, M. (2004). *Segmentation and Classification of Individual Tree Crowns*. MSc Thesis. Swedish University of Agricultural Sciences, Sweden.

Erikson, M., & Olofsson, K.(2005). Comparison of three individual tree crown detection methods. *Mach Vis Appli,* 16(4), 258-265.

Fang, R. (2016). Impacts of tree height-dbh allometry on lidar-based tree aboveground biomass modeling. *Forest Ecology and Management*, 146, 625–628. http://doi.org/10.5194/isprsarchives-XLI-B8-625-2016.

FAO (1995). *Forest products consumption in the Sudan. Final Report.* Rome.

FAO (2000). *Global Forest Resource Assessment. Main Report.* Rome

FAO (2010). *Global Forest Resource Assessment. Main Report.* Rome

Feldpausch, T. R., Lloyd, J., Lewis, S. L., Brienen, R. J. W., Gloor, M., & Mendoza, A. M. (2012). Tree height integrated into pantropical forest biomass estimates. *Biogeosciences*, 9, 3381–3403. http://doi.org/10.5194/bg-9-3381-2012.

Feret, J., & Asner, G. P. (2012). Semi-Supervised Methods to Identify Individual Crowns of Lowland Tropical Canopy Species Using Imaging Spectroscopy and LiDAR. *Remote Sens*, 4, 2457–2476. http://doi.org/10.3390/rs4082457.

Ferreira, M. P., Zanotta, D. C., Zortea, M., Korting, T. S., Fonseca, L. M. G., Shimabukuro, Y. E., & Souza Filho, C. R. (2014). *Automatic tree crown delineation in tropical forest using hyperspectral data.* Paper presented at the Geoscience and Remote Sensing Symposium.

Franklin, J. (1986). Thematic Mapper analysis of coniferous structure and composition. *International Journal of Remote Sensing*, 7, 1287– 1301.

Gibbs, C., Adhikari, S., Rostant, L., Southworth, J., & Qiu, Y. (2010). Application of Object Based Classification and High Resolution. *Remote Sensing*, 2, 2748–2772.

Gibbs, H. K., Brown, S., Niles, J. O., & Foley, J. A. (2012). Monitoring and estimating tropical forest carbon stocks : making REDD a reality. *Environment Research Letter*, 2, 13.

Goswami, S., Gamon, J. A., Vargas, S., Tweedie, C. E., Ridge, O. (2015*). Relationships of NDVI, Biomass, and Leaf Area Index (LAI) for six key plant species in Barrow, Alaska.* PrePrints

Grosse, M., Lorenz, W., & Tarigan, S. (2008). *Tropical Rainforests and Agroforests under Global Change.* International Symposium. Bali, Indoneshia.

Gunawardena, A. R., Nissanka, S. P., Dayawansa, N. D. K., & Fernando, T. T. (2015). Estimation of Above Ground Biomass in Horton Plains National Park , Sri Lanka Using Optical , Thermal and RADAR Remote Sensing Data. *Tropical Agricultural Research*, 26(4), 608–623.

Haijian, M., Qiming, Q. and Xinyi, S. (2008). Shadow segmentation and compensation in high resolution satellite images. *Proceedings of the IEEE International Geoscience and Remote Sensing Symposium*, Boston, Mass, USA.

Hame, T., Salli, A., Andersson, K., & Lohi, A. (1997). A new methodology for the estimation of biomass of conifer-dominated boreal forest using NOAA AVHRR data. *International Journal of Remote Sensing*, 18(15), 3211–3243. http://doi.org/Doi 10.1080/014311697217053.

Hansen, M. C., Defries, R. S., Townshend, J. R. G., Marufu, L., & Sohlberg, R. (2002). Development of a MODIS tree cover validation data set for Western Province, Zambia. *Remote Sensing of Environment*, 83, 320–335.

Hemery, G. E., Savill, P. S., & Pryor, S. N. (2005). Applications of the crown diameter – stem diameter relationship for different species of broadleaved trees. *Forest Ecology & Management*, 215, 285–294.http://doi.org/10.1016/j.foreco.2005.05.016.

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

Huete, A.R. (1988). A Soil-Adjusted Vegetation Index (SAVI). *Remote Sensing of Environment*, 25, 295-309.

Hufkens, K., Bogaert, J., Dong, Q. H., Lu, L., Huang, C. L., Ma, M. G., & Che, T. (2008). Impacts and uncertainties of upscaling of remote-sensing data validation for semi-arid woodland. *Journal of Arid Environment*, 72, 1490–1505. http://doi.org/10.1016/j.jaridenv.2008.02.012.

Hunter, M. O., Keller, M., Victoria, D., & Morton, D. C. (2013). Tree height and tropical forest biomass estimation. *Biogeosciences*,10, 8385–8399. http://doi.org/10.5194/bg-10-8385-2013.

Husch, B., Beers, T.W., & Kershaw, J.A. (2003). *Forest mensuration* (4th ed.). New York:John Wiley & Sons (443 pages)

Idol, T., Haggar, J., & Cox, L. (2011). Ecosystem services from smallholder forestry and agroforestry in the tropics. In W. B. Campbell & S. L. Ortiz (Eds.), *Integrating agriculture, conservation and ecotourism: examples from the field* (pp.209-270).Springer Netherlands.

IPCC (2003). *Good practice guidance for LULUCF*. IPCC National Greenhouse Gas Inventories Programme. Institute for Global Environment Strategies, Kanagawa.

Jean, L.,Michel, V., Bernard, P., Nadine, G.(2003). *Allometric relationship of selected European tree species*. EC joint research centre. Italy.

Jenkins, J. C., Chojnacky, D. C., Heath, L. S., & Birdsey, R. A. (2003). National-Scale Biomass Estimators for United States Tree Species. *Forest Science*, 49(1), 12-35.

Jiang, Z., Huete, A. R., Didan, K., & Miura, T. (2008). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Environment*, 112, 3833–3845.

Kanniah, K. D., Muhamad, N., Kang, C.S. (2014). *Remote sensing assessment of carbon storage by urban forest.* IOP Conf. Series: Earth and Environmental Science, Malaysia. http://doi.org/10.1088/1755-1315/18/1/012151.

Ke, Y. & Quackenbush, L. (2008). *Comparison of individual tree crowndetection and delineation methods.* In: ASPRS Annual conference"Bridging the Horizons: New Frontiers in GeospatialCollaboration", Portland, Oregon, US, ASPRS

Ke, Y., & Quackenbush, L. J. (2011). A comparison of three methods for automatic tree crown detection and delineation from high spatial resolution imagery. *International Journal of Remote Sensing*, 13(32), 3625-3647. http://doi.org/10.1080/01431161003762355.

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

Keeling, C.D., Chin, J.F.S. and Whorf, T.P. (1996). Increased activity of northern vegetation inferred from atmospheric CO2 measurements. *Nature*, 382, 146 – 149.

Kelsey, K. C., & Neff, J. C. (2014). Estimates of Aboveground Biomass from Texture Analysis of Landsat Imagery. *Remote Sensing*, 6, 6407–6422. http://doi.org/10.3390/rs6076407.

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

Kleinn, K., Morales, D., Ramirez, C. (2001, June 26-29). *Large area inventory of Tree Resources Outside the forest: what is the problem?* Paper presented at Proceedings of a IUFRO 4.11 Conference "Forest Biometry, Modeling and Information Science", University of Greenwich.

Koju, U., Zhang, J., & Gilani, H. (2011). *Exploring multi-scale forest above ground biomass estimation with optical remote sensing imageries*. IOP Conf. Series: Earth and Environmental Science. IOP Publishing.

Kuyah, S., Dietz, J., Muthuri, C., Jamnadass, R., Mwangi, P., Coe, R., & Neufeldt, H. (2012). Allometric equations for estimating biomass in agricultural landscapes: I. Aboveground biomass. *Agriculture, Ecosystems and Environment*, 158, 216–224. http://doi.org/10.1016/j.agee.2012.05.011.

Kyung, T., Park, C., Jeoung, S., Ko, S., Nam, K., Son, Y. (2013). Allometric equations for estimating the aboveground volume of five common urban street tree species in Daegu , Korea. *Urban Forestry and Urban Greening,* 12(3), 344–349. http://doi.org/10.1016/j.ufug.2013.03.006.

Latif, Z. A., Nordin, S., Omar, H. (2014, Oct 24-28). Crown segmentation of ramin melawis tree using hyperspectral imagery. *Proceeding in Asian Conference of Remote Sensing*. Manilla, Philippines.

Li, Z., Hayward, R., Zhang, J., & Liu, Y. (2008, Dec 1-3). *Individual Tree Crown Delineation Techniques for Vegetation Management in Power Line Corridor*. Paper presented at Digital Image Computing: Tecniques and Applications. Canberra, Australia. http://doi.org/10.1109/DICTA.2008.21.

Liangfu, C., Yanhua, G. A. O., Yu, C., Zheng, W. E. I., & Qing, X. (2005). Biomass estimation and uncertainty analysis based on CBERS-02 CCD camera data and field measurement. *Science in China Ser. E Engineering & Materials Science*, 48, 116–128. http://doi.org/10.1360/05ze1011.

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

Lu, D. (2006). The potential and challenge of remote sensing - based biomass estimation. *International Journal of Remote Sensing*, 27(7), 1297-1328. http://doi.org/10.1080/01431160500486732.

Lu, D., Moran, E., & Batistella, M. (2003). Linear mixture model applied to Amazonian vegetation classification. *Remote Sensing of Environment*, 87, 456–469.

Lukaszkiewicz, J., & Kosmala, M. (2008). Determining the Age of Streetside Trees with Diameter at Breast Height-based Multifactorial Model. *Arboriculture and Urban Forestry*, 34(3), 137–143.

Main-knorn, M., Moisen, G. G., Healey, S. P., Keeton, W. S., Freeman, E. A., & Hostert, P. (2011). Evaluating the Remote Sensing and Inventory-Based Estimation of Biomass in the Western Carpathians. *Remote Sensing*, 3(7), 1427–1446. http://doi.org/10.3390/rs3071427.

Maniatis, D., & Mollicone, D. (2010). Options for sampling and stratification for national forest inventories to implement REDD + under the UNFCCC. *Carbon Balance and Management*, 5(1), 9. http://doi.org/10.1186/1750-0680-5-9.

Mchale, M. R., Burke, I. C., Lefsky, M. A., Peper, P. J., & Mcpherson, E. G. (2009). Urban forest biomass estimates: is it important to use allometric relationships developed specifically for urban trees?.*Urban Forestry*, 12, 95–113. http://doi.org/10.1007/s11252-009-0081-3.

Meneguzzo, D. M., Liknes, G. C., & Nelson, M. D. (2013). Mapping trees outside forests using high-resolution aerial imagery: A comparison of pixel- and object-based classification approaches. *Environmental Monitoring and Assessment*, 185(8), 6261–6275. http://doi.org/10.1007/s10661-012-3022-1.

Mezzalira, G. (1997a). Siepi per la produzione di legna da ardere nella pianura veneta. *Sherwood*, 21, 13-18.

Mezzalira, G. (1997b). Valore apistico delle siepi campestri. *Sherwood*, 22, 11-14.

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

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

Molto, Q., Daullet, M., Rousteau, A., & Rossi, V. (2014). Predicting tree heights for biomass estimates in tropical forests – a test from French Guiana. *Biogeoscience*, 11, 3121–3130. http://doi.org/10.5194/bg-11-3121-2014.

Mutanga, E. (2012). *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.* MSc Thesis. ITC, Netherlands.

Mutanga, O., & Skidmore, A. K. (2004). Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing*, 25(9), 3999-4014. http://doi.org/10.1080/01431160310001654923.

Myeong, S., Nowak, D. J., & Duggin, M. J. (2006). A temporal analysis of urban forest carbon storage using remote sensing. *Remote Sensing of Environment*, 101, 277–282. http://doi.org/10.1016/j.rse.2005.12.001.

Nair, P. K. R. (2011). Carbon sequestration studies in agroforestry systems: a reality-check. *Agroforestry Syst*, 86, 243–253. http://doi.org/10.1007/s10457-011-9434-z.

Neigh, C. S. R., Bolton, D. K., Diabate, M., Williams, J. J., & Carvalhais, N. (2014). An Automated Approach to Map the History of Forest Disturbance from Insect Mortality and Harvest with Landsat Time-Series Data. *Remote Sensing*, 6 (4), 2782–2808. http://doi.org/10.3390/rs6042782.

Nelson, B. W., Mesquita, R., Pereira, J. L. G., De, S. G. A., Teixeira, G., & Bovino, L. (1999). Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. *Forest Ecology and Management*, 117, 149–167.

Ngwayi, C.I. (2012). *Mapping carbon stock in Trees Outside Forest: Comparing Very High Resolution optical satellite image (Geo Eye) and Airborne Lidar data in Chitwan, Nepal.* MSc Thesis, ITC, Netherlands.

Nowak, D. J. (1994). Atmospheric carbon dioxide reduction by Chicago's urban forest. In E. G. McPherson, D. J. Nowak, & R. A. Rowntree (Eds.), *Chicago's urban forest ecosystem: results of the Chicago urban forest climate project* (pp. 83– 94). Radnor: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station.

Olander, M., Göttsche, F., Diop, D., Mbow, C., Olesen, F., Fensholt, R., & Sandholt, I. (2011). Tree survey and allometric models for tiger bush in northern Senegal and comparison with tree parameters derived from high resolution satellite data. *International Journal of Applied Earth Observations and Geoinformation*, 13(4), 517–527. http://doi.org/10.1016/j.jag.2011.01.007.

Pain-Orcet, M. & Bellefontaine, R. (2004). Trees outside the forest: A new perspective on the management of forest resources in the tropics. In: Babin, D. (ed. *Beyond Tropical Deforestation.* Paris: UNESCO/CIRAD, 423-430.

Paletto, A., De Natale, F., Gasparini, P., Morelli, S., Tosi, V. (2006). L'Inventario degli Alberi Fuori Foresta (IAFF) come strumento di analisi del paesaggio e supporto alle scelte di pianificazione territoriale. *Forest*, 3 (2), 253-266.

Phua, M., Saito, H. (2003). Estimation of biomass of a mountainous tropical forest using Landsat TM data. *Canadian Journal of Remote Sensing*, 29, 429–440.

Propastin, P. (2013). Large-scale mapping of aboveground biomass of tropical rainforest in Sulawesi , Indonesia , using Landsat ETM + and MODIS data. *GIScience and Remote Sensing*, 50(6), 633–651. http://doi.org/10.1080/15481603.2013.850305.

Qi, J., Chehbouni, A., Huete, A. R., Kerr, Y. H., & Sorooshian, S. (1994). A Modified Soil Adjusted Vegetation Index. *Remote Sens. Environ*, 48, 119-126. http://doi.org/10.1016/0034-4257(94)90134-1.

Rosa, C.G., Oliver, L.P., & Timothy, R.B. (2014). The importance of crown dimensions to improve tropical tree biomass estimates. *Ecological Application*, 24(4), 680–698.

Saliola, A. (2014). *Object based image analysis for the delineation of canopy gaps and individual tree crowns using multi source data: A case study in Haliburton Forest, Ontario*. MSc Thesis. University of Toronto, Canada.

Sampaio, E., Gasson, P., Baracat, A., Cutler, D., Pareyn, F., & Costa, K. (2010). Tree biomass estimation in regenerating areas of tropical dry vegetation in northeast Brazil. *Forest Ecology and Management,* 259, 1135–1140. http://doi.org/10.1016/j.foreco.2009.12.028.

Sarker, L. R., & Nichol, J. E. (2011). Remote Sensing of Environment Improved forest biomass estimates using ALOS AVNIR-2 texture indices. *Remote Sensing of Environment*, 115(4), 968–977. http://doi.org/10.1016/j.rse.2010.11.010.

Schnell, S. (2015). *Integrating Trees Outside Forests into National Forest Inventories*. MSc Thesis. Swedish University of Agricultural Science, Sweden.

Schroeder, P. (1994). Carbon storage benefits of agroforestry systems. *Agroforestry Systems*, 27, 89-97.

Shimano, K. (1997). Analysis of the Relationship between DBH and Crown Projection Area Using a New Model. *J. For. Res*, 2, 237-242.

Singh, K., & Chand, P. (2012). Above-ground tree outside forest (TOF) phytomass and carbon estimation in the semi-arid region of southern Haryana: A synthesis approach of remote sensing and field data. *J. Earth Syst*, 121 (6), 1469–1482.

Stein, A. (1998). Integrating spatial statistics and remote sensing. *Int.J. Remote Sensing*, 19(9), 1793-1814. http://doi.org/10.1080/014311698215252.

Sun, H., Qie, G., Wang, G., Tan, Y., Li, J., Peng, Y., Luo, C. (2015). Increasing the Accuracy of Mapping Urban Forest Carbon Density by Combining Spatial Modeling and Spectral Unmixing Analysis. *Remote Sensing*, 7, 15114–15139. http://doi.org/10.3390/rs71115114.

Tanhuanpaa, T., Kankare, V., Setälä, H., & Yli-pelkonen, V. (2017). Assessing above-ground biomass of open-grown urban trees: A comparison between existing models and a volume-based approach. *Urban Forestry and Urban Greening*, 21, 239–246. http://doi.org/10.1016/j.ufug.2016.12.011.

Tansey, K., Chambers, I., Anstee, A., Denniss, A., & Lamb, A. (2009). Object-oriented classification of very high resolution airborne imagery for the extraction of hedgerows and field margin cover in agricultural areas. *Applied Geography*, 29(2), 145–157.

Timothy, D. (2015). Investigating the robustness of the new Landsat-8 Operational Land Imager derived texture metrics in estimating plantation plantation forest aboveground biomass in resource constrained areas. *ISPRS Journal of Photogrammetry and Remote Sensing*, 101, 36–46. http://doi.org/10.1016/j.isprsjprs.2014.11.001.

Tomppo, E., Nilsson, M., Rosengren, M., Aalto, P., & Kennedy, P. (2002). Simultaneous use of Landsat-TM and IRS-1C WiFS data in estimating large area tree stem volume and aboveground biomass. *Remote Sensing and Environment*, 82, 156–171.

Tonis, K. (2007). Remote sensing of urban areas: linear spectral unmixing of Landsat Thematic Mapper images acquired over Tartu (Estonia). *Proc. Estonian Acad. Sci. Biol. Ecol*, 56, 19–32.

Tucker, C. J., & Sellers, P. J. (1986). Satellite remote sensing of primary production. *International Journal of Remote Sensing*, 7(11), 1395– 1416.

Valbuena, R., Heiskanen, J., Aynekulu, E., & Pitkänen, S. (2016). Sensitivity of Above-Ground Biomass Estimates to Height-Diameter Modelling in Mixed-Species West African Woodlands. *Plos One*, 1–24. http://doi.org/10.1371/journal.pone.0158198.

Van Leeuwen, W.J.D. & Huete, A.R. (1996). Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices. *Remote Sensing Environment*, 55, 123–138.

Viana, H., Aranha, J., Lopes, D., & Cohen, W. B. (2012). Estimation of crown biomass of Pinus pinaster stands and shrubland above-ground biomass using forest inventory data, remotely sensed imagery and spatial prediction models. *Ecological Modelling*, 226, 22–35.

Vieira, S. A., Alves, L. F., Aidar, M., & Araújo, L. S. (2008). Estimation of biomass and carbon stocks : the case of the Atlantic Forest. *Biota neotrop*, 8(2), 21-29.

Wang, L., Gong, P., & Biging, G. S. (2004). Individual Tree-Crown Delineation and Treetop Detection in High-Spatial-Resolution Aerial Imagery. *Photogrametric Engineering and Remote Sensing*, 70(3), 351–358.

Wiseman, G., Kort, J., & Walker, D. (2009). Quantification of shelterbelt characteristics using high-resolution imagery. *Agriculture, Ecosystems and Environment*, 131, 111–117.

Woodcock, C.E., Collins, J.B., Jakabhazy, V.D., Li, X., Macomber, S., & Wu, Y. (1997). Inversion of the Li- Strahler canopy reflectance model for mapping forest structure. *IEEE Transactions on Geoscience and Remote Sensing*, 35, 405-440.

Woodwell, G.M., Whittaker , R.H., Reiners , W.A., Likens, G.E., Delwiche, C.C., Botkin, D.B. (1978). The biota and the world carbon budget. *Science*, 199, 141 – 146.

Workie, T.G. (2011). *Assessment of aboveground carbon stock in coniferous and broadleaf forests using high spatial resolution satellite images*. MSc Thesis, ITC, Netherlands.

Yan, F., Wu, B., & Wang, Y. (2013). Estimating aboveground biomass in Mu Us Sandy Land using Landsat spectral derived vegetation indices over the past 30 years. *J. Arid Land*, 5(4), 521–530. http://doi.org/10.1007/s40333-013-0180-0.

Yao, Z., Liu, J., Zhao, X., Long, D., & Wang, L. (2015). Spatial dynamics of aboveground carbon stock in urban green space : a case study of Xi ' an , China. *J. Arid Land*, 7(3), 350–360.

Yap, B. W., & Sim, C. H. (2011). Comparisons of various types of normality tests. Journal of Statistical Computation and Simulation, 81(12), 2141-2155. http://doi.org/10.1080/00949655.2010.520163.

Yin, W., Yang, J., Yamamoto, H., & Li, C. (2015). Object-based larch tree-crown delineation using high-resolution satellite imagery. *International Journal of Remote Sensing*, 36(3), 822–844. http://doi.org/10.1080/01431161.2014.999165.

Zhang, X., Feng, X., & Jiang, H. (2010). Object-oriented method for urban vegetation mapping using IKONOS imagery. *International Journal of Remote Sensing*, 31(1), 177–196. http://doi.org/10.1080/01431160902882603.

Zhao, P., Lu, D., Wang, G., Wu, C., & Huang, Y. (2016). Examining Spectral Reflectance Saturation in Landsat Imagery and Corresponding Solutions to Improve Forest Aboveground Biomass Estimation. *Remote Sensing*, 8(6), 469. http://doi.org/10.3390/rs8060469.

Zheng, D., Heath, L. S., & Ducey, M. J. (2007). Forest biomass estimated from MODIS and FIA data in the Lake States : MN, WI and MI, USA. *Forestry*, 8(3), 265-278. http://doi.org/10.1093/forestry/cpm015.

Zhou, X., Brandle, J. R., Schoeneberger, M. M., Awada, T., & Service, U. S. F. (2006). Developing above-ground woody biomass equations for open-grown, multiple-stemmed tree species: Shelterbelt-grown Russian-olive. *Ecological Modelling*, 2, 311–323.

Zhu, X., & Liu, D. (2015). Improving forest aboveground biomass estimation using seasonal Landsat NDVI time- series. *ISPRS Journal of Photogrammetry and Remote Sensing*, 102, 222–231. http://doi.org/10.1016/j.isprsjprs.2014.08.014.

Zianis, D., Muukkonen, P., & Mäkipää, R. (2005). Biomass and stem volume equations for tree species in Europe. *Silva Fennica Monographs*, 4, 1-63.

APPENDICES

Appendix 1: Field data collection sheet

<table>
<tr><td rowspan="4">S. no.</td><td colspan="10">Data Sheet for biomass/carbon estimation in Gronau Germany and Eastern Enschede</td><td>plot No:</td></tr>
<tr><td colspan="2">Date:</td><td>GPS</td><td>X</td><td></td><td></td><td colspan="2"></td><td></td><td></td><td>Observer Name/Group:</td></tr>
<tr><td colspan="2"></td><td></td><td>Y</td><td></td><td></td><td colspan="2"></td><td></td><td></td><td></td></tr>
<tr><td>Species (Scientific or/and common name)</td><td>DBH (cm)</td><td>Height (m)</td><td colspan="4">Configuration class</td><td colspan="4">Remarks</td></tr>
<tr><td></td><td></td><td></td><td></td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td></td><td></td><td></td><td></td><td colspan="4"></td><td colspan="4"></td></tr>
<tr><td></td><td></td><td></td><td></td><td colspan="4"></td><td colspan="4"></td></tr>
</table>

Appendix 2: Regression relationship between biomass obtained from VHR image and NDVI of Sentinel-2

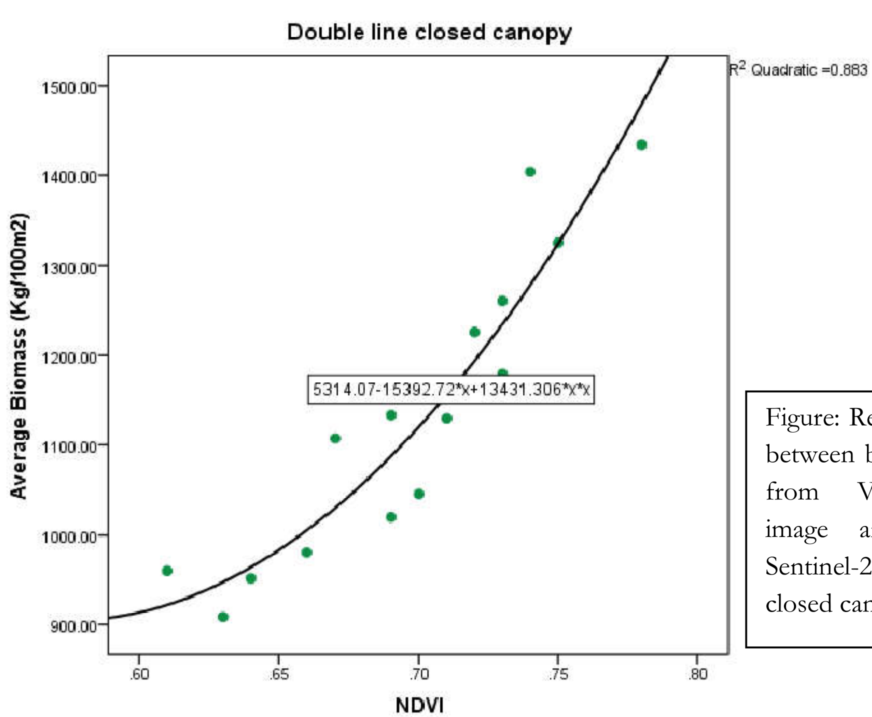


Figure: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 for double line closed canopy.

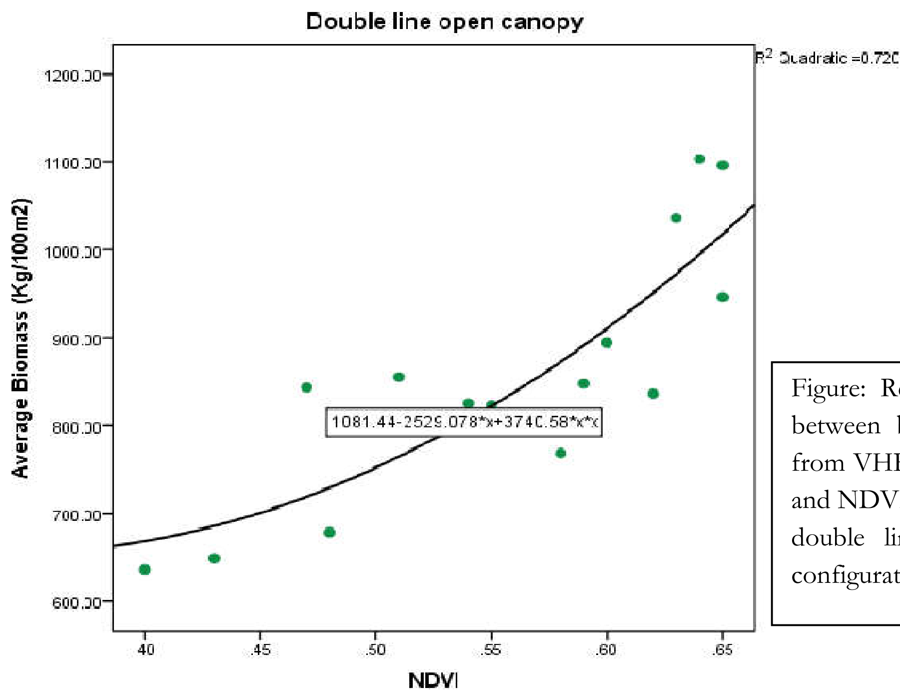


Figure: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 for double line open canopy configuration.

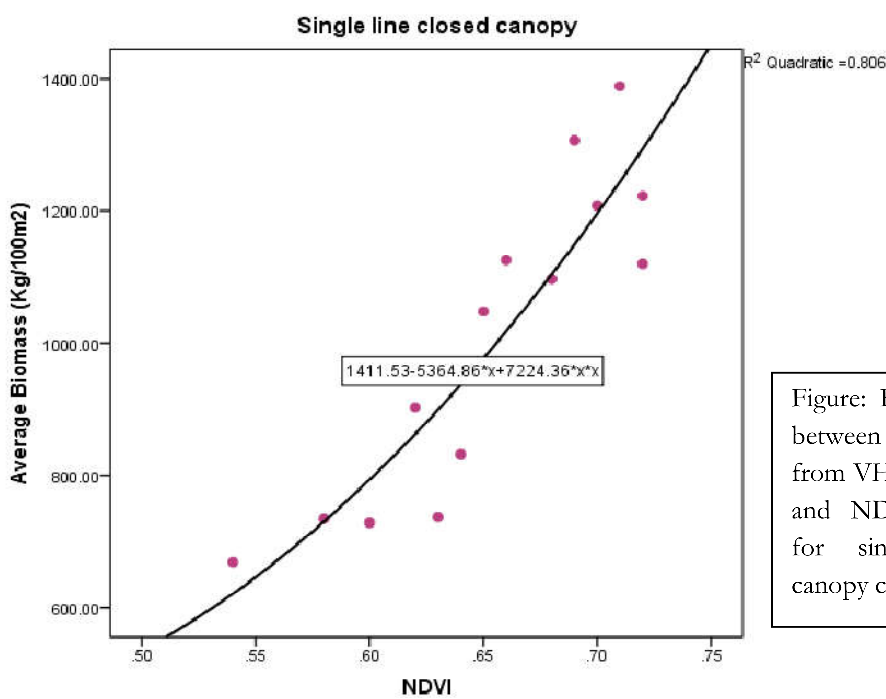


Figure: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 for single line closed canopy configuration.

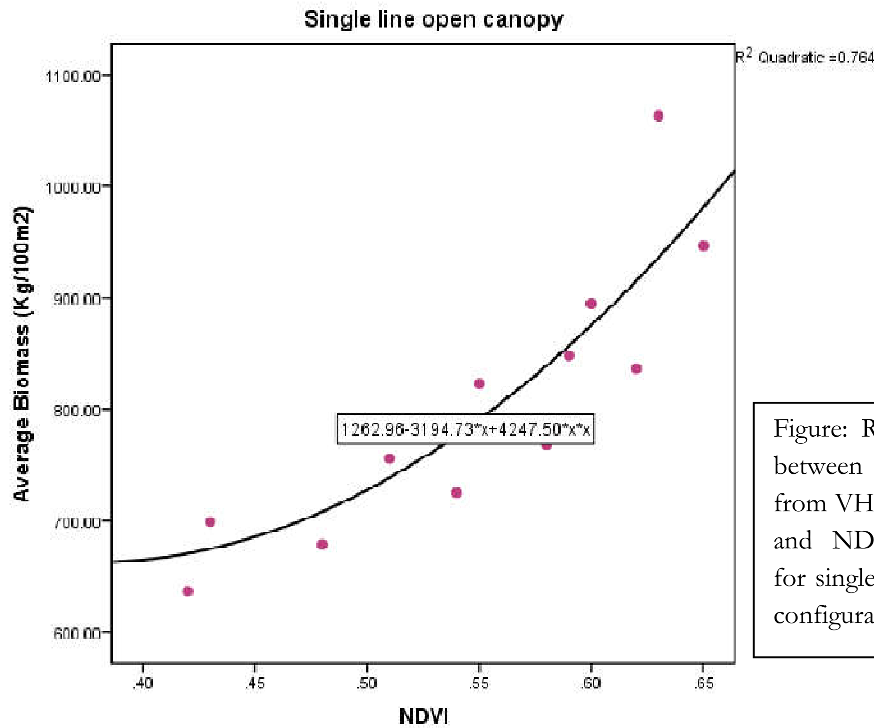


Figure: Regression relation between biomass obtained from VHR (Pleaides) image and NDVI of Sentinel-2 for single line open canopy configuration.

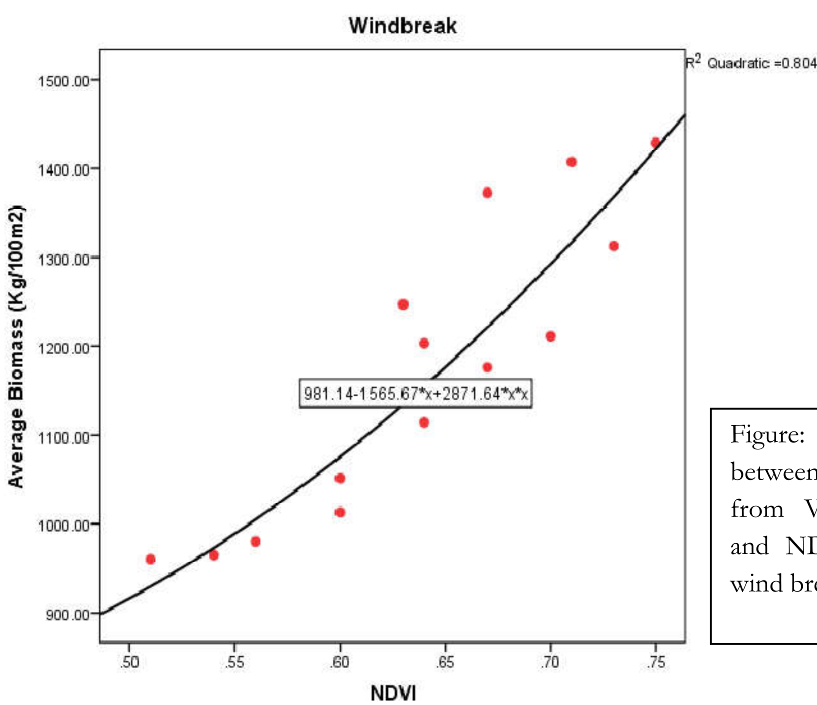


Figure: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 for wind break configuration.

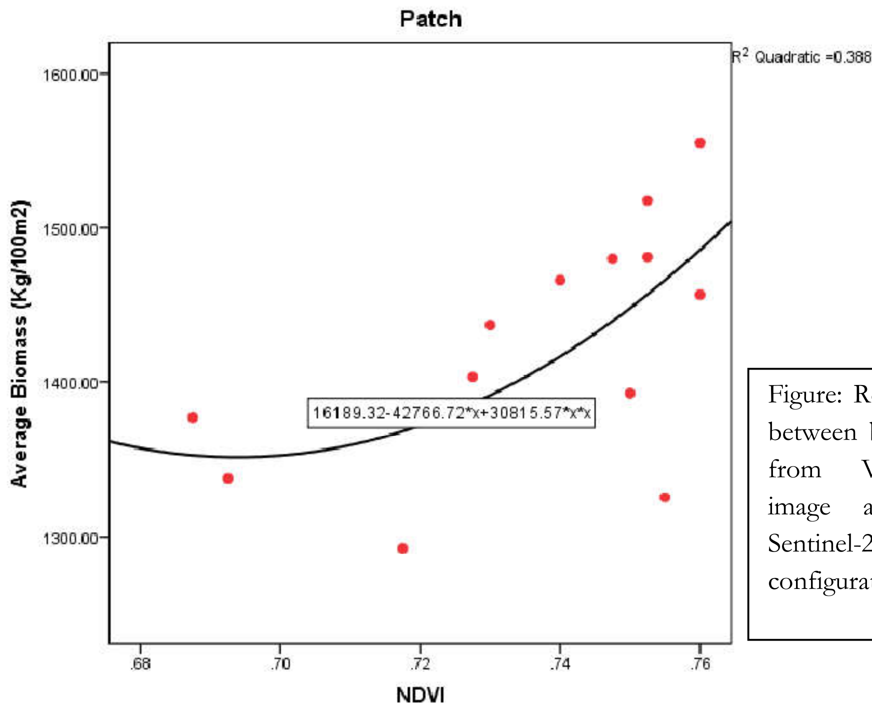


Figure: Regression relation between biomass obtained from VHR (Pleiades) image and NDVI of Sentinel-2 for patch configuration.