ASSESSMENT OF ABOVEGROUND CARBON STOCK IN CONIFEROUS AND BROADLEAF FORESTS, USING HIGH SPATIAL RESOLUTION SATELLITE IMAGES

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by

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Abstract

Information about above ground biomass (AGB) carbon is required at various spatial scales with high precision and accuracy for carbon trading, improvement of national carbon accounting and effective forests management. However, due to much uncertainty embedded on the conventional methods of spatial forest carbon estimation, robust and efficient methods which minimize estimation errors are sought. In this regard making use of high spatial resolution images believed to meet this demand.

The study employed Quick-bird images of both panchromatic and multispectral bands acquired in 2006 and sample field measurements of DBH in Haagse Bos and Snippert forest, the Netherlands. Tree crown delineation, aiming at deriving the CPA of trees, was performed on the panchromatic image using eCognition and ITC softwares. The CPAs obtained from a combination of algorithms which gave the best accuracy undergone to object oriented classification into coniferous and broadleaf trees. Hence, the carbon stocks as obtained from the sample DBH measurements, and CPAs of each forest tree types were modelled using regression equation. This was followed by a validation step to assess the developed model.

The best tree crown delineation was obtained by combining Valley following and marker free watershed transformation. These algorithms resulted in a reasonable accuracy, which is about 80 and 66% accuracy in terms of 'goodness of fit' and 76 and 58% 1:1 correspondence for coniferous and broadleaf trees, respectively. The developed model for coniferous and broadleaf trees explained about 60 and 55% of the variances in carbon stock, respectively. This indicated that CPA derived through semi automated tree crown delineation can be used to model AGB carbon. The model estimated the total forest carbon stock to be about of 26822 Mg C. This is equivalent to 80 Mg C / Ha. The AGB carbon estimation of the model for coniferous and broadleaf trees laid ± 0.17 and ± 0.38 Mg C/ tree with 95% confidence, respectively. This indicated the presence of some uncertainties in the model. These uncertainties mainly arise from random and systematic errors introduced through field DBH measurement, allometric equations and tree crown delineations. Despite this, the method showed its potential in estimating AGB carbon stock at individual tree level.

Generally, this research proved that AGB carbon estimation can be made from CPA of trees obtained from high spatial resolution images through object based analysis of images but further researches are required to improve the accuracy of estimation. This can be partly achieved by improving the accuracy of tree crown delineation.

Key words: AGB carbon, DBH, CPA, Valley following approach, Watershed transformation, Tree crown delineation

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List of Abbreviations

AGB	Above Ground Biomass
COP	Conference of Parties
CPA	Crown Projection Area
DBH	Diameter at Breast Height
FAO	Food and Agricultural Organisation
FNEA	Fractal Net Evolution Approach
GPS	Global Positioning System
IPCC	Intergovernmental Panel on Climate Change
ITC	Individual Tree Crown Delineation
LOG	Laplacian of the Gaussian operator
Mg C	Mega gram Carbon
REDD	Reduced Emission from Deforestation and Degradation
RMSE	Root Mean Square Error
UNFCC	United Nations Framework Convention on Climate Change

1. Introduction

1.1. Background of the study

Human induced greenhouse gas emissions and the consequent global warming is one of the biggest threats facing our globe today. After emissions from combustion of fossil fuels, the forest sector accounts the second largest sources of CO_2 emission. As the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC) indicates, one fifth of today's carbon emission is attributable to land use change (FAO 2009). Forests play an important role in global carbon balance as both sources and sinks. As a result they form an important component in combating global climate change (Watson 2010). Forests account for 80-90 % of the terrestrial plant carbon and about 30-40 % soil carbon (Sivrikaya et al 2006). They represent more than 50% of the global green house gas mitigation potential (Watson 2010). However, deforestation and forest degradation alone release 1.6 billion tons of carbon to the atmosphere each year (Denman et al. 2007).

Forest biomass is the organic materials both in above and below ground. In a forest there are five carbon storages. These include; above ground and below ground biomass, dead wood, litter and soil organic matter. The reduction of forest degradation and deforestation aims to maintain the carbon stock in the above ground biomass (IPCC: 2003). Despite this, conserving above ground biomass (AGB) favours higher below ground biomass and soil organic carbon. Trees often represent the greatest fraction of total biomass of a forested area. Others like the understory are estimated to be equivalent to 3%, dead wood 5-40% and fine litter only 5% of the AGB. Below ground biomass (BGB) is more variable ranging between 4-230 %. AGB of trees respond more rapidly and significantly as a result of land use change than other carbon pools. Hence, quantifying AGB carbon is of great interest to researchers (Watson 2010).

There are two policy related issues that necessitates forest carbon accounting; i) commitments under United Nations Framework Convention on Climate Change (UNFCCC) and ii) the potential implementation of carbon trading as established in the Kyoto protocol. Under the UNFCCC commitment, 150 countries are expected to update, publish and report their national inventories by sources and sinks of emissions of carbon to the conference of parties (COP) (Watson 2010). As a major part of the national inventories, the land use and the forestry sectors are the areas that the inventories must be done (Brown 2001). Countries ratifying the Kyoto protocol are also given an option to reduce the CO_2 emissions by 5% below the level that was apparent in 1990 through conservation and enhancement of the carbon stored in the forest ecosystem (Genevieve et al. 2005). Reduction of deforestation and forest degradation (REDD) is an important initiative set by the conference of parties (COP) as an emergent strategy for combating CO_2 emissions. If properly implemented, REDD will have multiple benefits for reducing climate change, conserving biodiversity and realizing sustainable development (Angelsen 2008).Hence global efforts are under way to reduce emissions through conserving forest resources. In the face of these efforts, information about global carbon budget and fluxes are required at various spatial and temporal scales (Gibbs et al. 2007). Moreover, each country needs to have a baseline against which carbon increase or decrease can be measured.

The Dutch government has pledge to UNFCCC commitments of reducing green house gas emissions. As part of its commitment the country needs to undertake inventories of the sources of carbon sinks and emissions. In order to quantify the emissions and removals caused by changes in forest biomass stocks due to forest management, harvesting, plantation establishment, abandonment of lands that re-grow to forests and forest conversion to non forest use , the carbon stock assessment is crucially important (Brown 2001). Biomass carbon accounting in the Netherlands follows a stand stock approach which is based on the total yearly increase of woody biomass corrected for yearly extraction of wood. This may not be entirely accurate, while a full ground survey would be too expensive. Hence, methods should be developed and may consist of a combination of forest inventory and remote sensed data (Nabuurs et al. 2000).

There are a range of techniques of AGB estimation and they can be generalised as 1) Field measurement based (Brown et al. 1989), 2) GIS based (Brown and Gaston 1995) and 3) Remote sensing based (Zheng et al. 2004, Lu 2005) approaches. The field measurement techniques are the most accurate ways of AGB estimation but they are often time consuming, labour intensive and difficult to implement especially in remote areas as they cannot provide spatial biomass distribution estimation of larger areas. GIS techniques are not widely applicable for AGB estimation due to the difficulty of obtaining good quality ancillary data, indirect relationships between AGB and ancillary data, and the comprehensive impacts of environmental conditions on AGB accumulation (Lu 2005).

Remote sensing has opened an effective way to estimate forest biomass and it is becoming the major source of AGB estimation. The repetitive data acquisition, synoptic view, availability of data in a digital format that allows fast processing of large quantities of data, and the high correlations between spectral bands and vegetation parameters, make it the primary source for large area AGB estimation (Lu 2005).

In combination with ground measurements, information acquired from Synthetic Aperture Radar (SAR), Light Detection and Ranging (lidar), Optical and Multi-sensor Synergy measurements are commonly used for carbon stock mapping (Goetz et al. 2009). In general, AGB can be directly or indirectly estimated using remotely sensed data. The direct approaches are based on multiple regression analysis, K nearest-neighbour, and neural network (Roy and Ravan 1996, Nelson et al. 2000, Steininger 2000, Foody et al. 2003, Zheng et al. 2004), and indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models (Wu and Strahler, 1994).

In conjunction with the advent of high spatial resolution images and developments in image analysis software, approaches of AGB estimation are changing. With this transformation, automation of individual tree crowns are made possible (Gougeon and Leckie 2006). Automated tree crowns represent the crown projection area (CPA) of trees. Studies indicated that CPA and tree diameter at breast height (DBH) forms strong relationship (Shimano 1997). DBH often used to estimate tree AGB with the help of allometric equations (Muukkonen 2007). Hence, attempts to model AGB from CPAs automated from high spatial resolution images and sample field measurements of tree DBH are on progress. This tree level analysis of AGB believed to improve the accuracy of estimation. Moreover, the estimation made from high spatial resolution images can be used for calibration and validation of biomass carbon models developed from medium and low resolution images (Lu, 2005). This study is envisaged with the aim of quantifying spatial AGB carbon from the relationships of CPA automated from high spatial resolution satellite images and AGB carbon from species specific allometric equations.

1.2. Problem Statement

Various methods of remote sensing based AGB carbon estimation have been developed. However, most of the existing methods have considerable uncertainties and thus reliable methods are required (Kohl et al. 2009). In this regard, utilizing high spatial resolution satellite images in spatial AGB carbon modelling believed to improve the accuracy of estimation (Zhenga et al. 2004). Moreover, greater uncertainties over the role of Dutch forests, forest soils, wood products and management and land use options on carbon sequestration are prevalent calling for the need of methods that combine remote sensing technique and field measurements (Naburus et al 2000). As compared to AGB carbon estimation which is exclusively based on field measurement data, developing such a method costs less time, less efforts and less finance. Thus, this research developed a relatively new and robust method to assess carbon stock using CPA derived from high spatial resolution satellite images through object based image analysis, and field DBH measurements.

1.3. Objectives of the study

The main objective of the study is to assess the carbon stocks in coniferous and broadleaf tree types. The specific objectives include,

1) To develop a method of estimating AGB carbon stock using CPA derived from high resolution satellite images
2) To assess the level of accuracy of tree crown segmentation in eCognition and ITC software.
3) To assess the accuracy of object oriented classification of CPAs of different tree types.
4) To estimate and validate AGB carbon stock using regression equation for the coniferous and broadleaf trees.
5) To map spatial AGB carbon stock of the study area.

1.4. Research questions

The research addresses the following research questions.

1) How accurately can tree crowns delineated by eCognition and ITC softwares? Which method yields the best accuracy for coniferous and broadleaf trees?
2) How accurately can the CPA of coniferous and broadleaf trees be classified?
3) How accurately can the AGB carbon of the study area be estimated using regression equation?
4) How forest biomass and carbon stock can be mapped using Quick-bird satellite image?

1.5. Conceptual framework

Forest biomass is the organic matter accumulated through the process of photosynthesis as primary production minus consumption through respiration and harvest (Watson 2010). Remote sensing has opened an effective way of spatial biomass estimation for larger area. Images acquired from both space and airborne sensors are often used for biomass estimation. The approach of estimation may vary depending on the spatial and spectral detail of the image, the extent of the area under consideration and the accuracy required. High spatial resolution images in combination with sample field measurements of tree biophysical characteristics such as tree diameter at breast height (DBH) and height, facilitates forest biomass estimation with higher accuracy (Brown 2001). Based on field measurements of DBH and height, the dry biomass of trees can be computed using species specific allometric equations (Brown 2003; Goetz et al.2009). The equation often reported to yield high correlation coefficient. For example, in pine and beech forests in the USA, the equation yielded very high correlation coefficient (r^2=0.98). Moreover, the carbon stock of the forest can be calculated directly from the above ground dry biomass as about 50% of the dry biomass is carbon (Solicha 2007). More recently, the advent of high spatial resolution commercial satellite images and developments in image segmentation software and algorithms have opened opportunities of tree crown delineation (Gougeon and Leckie 2006). Therefore, through image segmentation, the crown projected area (CPA) of trees can be extracted. Moreover, using object oriented classification; automated CPAs can be classified into different tree species. Hence, the relationship between CPAs and biomass carbon as obtained from the allometric biomass equation can be investigated through regression equation. Therefore based on the relationship established between sample CPAs and biomass carbon, the carbon stock of the whole study area can be estimated using regression modelling.

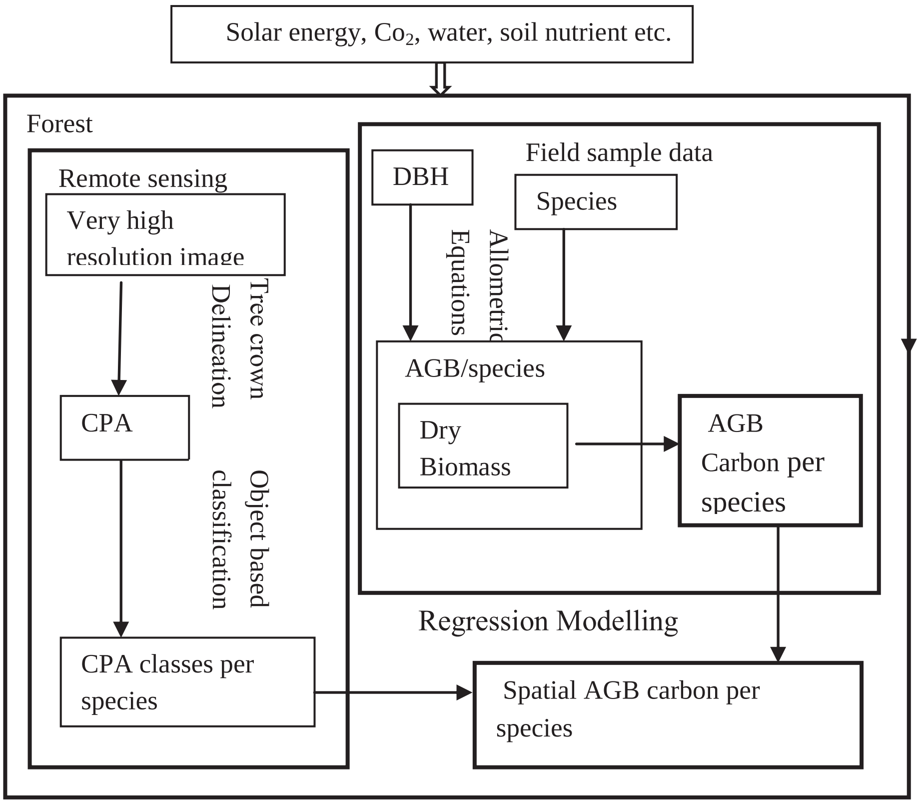


Figure 1 : Conceptual diagram

2. REMOTESENSING APPROACHES OF AGB ESTIMATION AND TREE CROWN DELINEATION ACCURACY ASSESSEMENT TECNIQUES

2.1. Space Born Optical Remote Sensing Approaches of AGB Estimation

Remote sensing has become a primary source of biomass estimation**.** Many factors, such as economic conditions, limitation of remotely sensed data in spectral, spatial, and radiometric resolutions, complex forest stand structure, quality and quantity of sample plots, selection of suitable variables, and the modeling algorithms, often interplay and affect the success of AGB estimation. Either optical sensor data or radar data are more suitable for forest sites with relatively simple forest stand structure than the sites with complex biophysical environments. However, a combination of spectral responses and image textures improves biomass estimation performance (Lu 2005).

In general, the AGB can be directly estimated using remotely sensed data with different approaches, such as multiple regression analysis, K nearest-neighbour, and neural network (Foody et al. 2003, Zheng et al. 2004), and indirectly estimated from canopy parameters, such as crown diameter, which are first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models(Wu and Strahler 1994) 1994).

Spatial AGB estimation can be made at various spatial scales. The algorithm, the satellite data required and the level of accuracy however varies with the variation of the spatial extent and the level of accuracy required. Generally speaking, the better the spatial detail, the lower the uncertainty will be (Gibbs et al. 2007).

2.1.1. High spatial resolution images

Satellite images with a spatial resolution of 10 m or less are usually classified as high spatial resolution. Since the past two decades, several countries have launched satellites that can acquire images with this resolution range. The availability of commercial satellites of high spatial resolution such as IKONOS, Quick Bird, OrbView-3 in the past few years enabled the acquisition of detailed forest information at individual tree scale level (Culvenor 2003). More recently, commercial satellite images such as GeoEye and World view 1 and 2 images are also emerged giving more detailed forest survey capabilities. This in turn has created a better opportunity for estimating forest parameters at tree species level such as AGB with much precision.

Using high resolution images tree quantification, tree crown delineation, species identification, crown density estimation, and forest stand polygon delineation is made possible (Gougeon and Leckie 2006). The advent of these high resolution images can facilitate efficient, consistent, and reliable tree scale inventories over larger areas (Culvenor 2003). A number of image segmentation algorithms are developed to derive these tree biophysical parameters such as tree crowns. The idea behind identification of the tree crowns is that the tree crowns on a remotely sensed image can be identified as discreet objects based on their colour, texture, shape and context. However, the successes of this processes depends on forest stand structures and environmental conditions. In broad leaf forest the trees often have overlapping tree crowns making delineation between them difficult unlike the coniferous trees (Gougeon and Leckie 2006).

2.1.2. Medium resolution images

The medium spatial-resolution ranges from 10 to 100 m. The most frequently used medium spatial-resolution data may be the time-series Land-sat data, which have become the primary source in many applications, including AGB estimation at local and regional scales (Foody et al. 2003, Zheng et al. 2004). Different success of AGB estimation was obtained using Land-sat images using neural networks, k- nearest neighbors, linear and multiple regression techniques. In some cases however saturation of canopy reflectance over time was found to be a problem of estimating AGB using land-sat images (Lu 2006).

Spectral signatures or vegetation indices are often used for AGB estimation. Many vegetation indices have been developed and applied to biophysical parameter studies. Vegetation indices have been recommended to remove variability caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties (Elvidge and Chen 1995). However, not all vegetation indices are significantly correlated with AGB. In general, vegetation indices can partially reduce the impacts of reflectance caused by environmental conditions and shadows, thereby improving the correlation between AGB and the specific vegetation indices, especially in those sites with complex vegetation stand structures. Image texture has also shown its importance in AGB estimation using medium resolution images. However, by itself, image texture or spectral information is not sufficient for AGB estimation and using both of this information together is reported to give a better estimation (Lu 2006).

2.1.3. Coarse resolution images

The coarse spatial resolution is often greater than 100 m. Common coarse spatial resolution data include NOAA Advanced Very High Resolution Radiometer (AVHRR), SPOT VEGETATION, and Moderate Resolution Imaging Spectro radiometer (MODIS). They are often used at national, continental, and global scales (Lu et al. 2006).

Table 1: Summary of coarse resolution data sets and techniques of AGB estimation (After Lu, 2006)

Datasets	Study area	Techniques	References
AVHRR NDVI	Canada, Finland, Norway, Russia, USA and Sweden	Regression models	Dong et al. (2003)
SPOT VEGETATION	Canada	Multiple regression and artificial neural network	Fraser and Li (2002)
Landsat TM and IRS-1C WiFS	Finland and Sweden	K nearest-neighbour method and nonlinear regression	Tomppo et al. (2002)
Landsat TM and AVHRR	Finland	Linear regression analysis	Hame et al. (1997)
MODIS, precipitation, temperature, and elevation	California, USA	Statistical models (generalized additive models, tree-based models,cross-validation analysis)	Baccini et al. (2004)

The AVHRR data have long been the primary source in large-area surveys because they offer a good trade-off between spatial resolution, image coverage, and frequency in data acquisition. It is likely that AVHRR data are the most extensively used datasets for studies of vegetation dynamics on a continental scale. The close relationship between middle infrared (MIR) reflectance and AGB implies that MIR reflectance may be more sensitive to change in forest properties than the reflectance in visible and near-infrared wavelengths (Boyd et al.1999).

Overall, the AGB estimation using coarse spatial-resolution data is still very limited because of the common occurrence of mixed pixels and the huge difference between the size of field-measurement data and pixel size in the image, resulting in difficulty in the integration of sample data and remote sensing-derived variables (Lu 2006).

2.1.4. Vegetation Canopy Models

Multiple regression analysis has been frequently used for AGB estimation in previous researchs. However, identifying suitable variables for developing a multiple regression model is often difficult and time consuming because many potential variables may be used. Also, AGB is a comprehensive parameter that is related to many factors such as canopy structure, tree density, and tree species composition. Change in AGB is not directly shown in change of reflectance. The optical sensors mainly capture canopy information, thus the optical sensor data may be more suitable for estimation of canopy parameters such as crown density than AGB (Lu, 2006).

At least 32 models of vegetation canopy reflectance were reviewed by Goel (1988). They can be grouped into four main categories: geometrical models, turbid medium models, hybrid models, and computer simulation models (Goel 1988). Qin and Goel (1995) found that almost all of these models were suitable for canopies with smaller leaves, high leaf area index (LAI), and high zenith angles. Because canopy parameters can be better estimated than AGB from remotely sensed data (Nelson et al. 2000), the AGB may be indirectly inferred from the relationships between canopy structure and biomass. Scientists have strived to model the vegetation canopies to predict the characteristics of specific types of structure within the canopy, such as tree height, density, and LAI through remotely sensed data. However, it remains a challenge to establish such models because of the complexity of canopy characteristics, atmospheric conditions, sun angle and viewing geometry, and terrain slope and aspect (Lu 2006).

2.1.5. Image segmentation and accuracy assessment techniques

Segmentation is the grouping of neighbouring pixels into regions (or segments) based on similarity criteria (digital number, texture). Image segmentation is becoming a common images analysis in the field of remote sensing particularly with increasing spatial resolution. There are a number of image segmentation software and algorithms having different characteristics. Meinel and Neubert (2002) have identified and make use of 7 software of image segmentation, these software include eCognition, data dissection tools, CASEAR, Info PACK, Image segmentation of Eardas imagine, Minimum Entropy Approach to Adaptive Image Polygonization and SPRING. According to their accuracy assessment best results were found from eCognition and info pack with the exception of info pack giving over segmentation of objects. In coniferous forests the Individual Tree crown Delineation (ITC) software suit also found to yield good segmentation of tree crowns (Gougeon and Leckie 2006).Wang (2007) also implemented tree crown delineation in Matlab. Each of the softwares constitutes various segmentation algorithms which can significantly affect the accuracy of segmentation. Some of the commonly used algorithms include watershed segmentation (Wang et al .2004; Ke 2008), region growing (Ke 2008), valley following approaches (Gougeon and Leckie 2006; Ke 2008) and Fractal Net Evolution Approach (FNEA) which is a multi-resolution segmentation algorithm (Yu et al. 2006). Most of the segmentation algorithms respond very quickly to minor variation in input parameters. Despite this, the user is confronted with a high degree of freedom, which should be minimised. For instance, when selecting parameters by the trial-and-error method the results are highly influenced by subjectivity. The integration of instruments for evaluation of segmentation quality appears desirable (Meinel and Neubert 2002).

The success of algorithms varies considerably depending on the specific local condition, the image used and the techniques of accuracy assessment (Ke 2008). Image segmentation requires accuracy assessment at various stages of the segmentation processes. Segmentation accuracy assessments are broadly made based on visual and geometrical techniques. The visual assessment which is subjective is based on visual judgement of the degree of fit of segmented objects with that of known objects while the geometrical assessment is made with a comparison of segmented objects with training / reference objects in terms of various indices.

Clinton et al., (2008) has developed a geometrical segmentation accuracy assessment of segmentation outputs with reference to clearly defined training sites. The quality of segmentation outputs are defined in terms of under and over segmentation as well as goodness of fit (D). The goodness of fit (D) is the function of the degree of under and over segmentation.

$$\textbf{Over segementioon} = \mathbf{1} - \left[\frac{\textbf{area}\ (\boldsymbol{Xi} \cap \boldsymbol{Yj})}{\boldsymbol{area}\ (\boldsymbol{Xi})}\right] \qquad \text{Equation 1}$$

$$\textbf{Under segementioon} = \mathbf{1} - \left[\frac{\textbf{area}\ (\boldsymbol{Xi} \cap \boldsymbol{Yj})}{\boldsymbol{area}\ (\boldsymbol{Yj})}\right] \qquad \text{Equation 2}$$

Where Xi = training objects, assumed polygons, relative to which the segmentation is to be judged and Yj = the set of all segments in the segmentation. Let Yj be a subset of Yi and, Y$\boldsymbol{i}$ = *{Yj: area (Xi ∩ Yj) ≠0}*. For each training object Xi, the following subsets of Yi exist,

$$
\left[
\begin{array}{l}
Ya = \{\text{all } Yj \text{ where the centroid of } Xi \text{ is in } Yj\} \\
Yb = \{\text{all } Yj \text{ where the centroid of } Yj \text{ is in } Xi\} \\
Yc = \{\text{all } Yj \text{ where area } (Xi \cap Yj) \text{ / area } (Yi) > 0.5\} \\
Yd = \{\text{all } Yj \text{ where area } (Xi \cap Yj) \text{ / area } (Xi) > 0.5\}
\end{array}
\right]
$$

Yi= Ya U Yb U Yc U Yd, therefore the over and under-segmentation formula above are defined for the segments in Yi. The over and under segmentation forms 'distance' index (D) which indicates the quality of segmentation. As the value of D increases, the deviation of segmented objects and their respective reference object increases showing high level of mismatch between objects (Equation 3).

$$\textbf{Goodness of fit (D)} = \sqrt{\frac{(\boldsymbol{Over\ segmentation^2}) + (\boldsymbol{Under\ segmentation^2})}{\mathbf{2}}} \qquad \text{Equation 3}$$

As the goodness of fit increases the degree of mismatch between the segmented and reference objects increases indicating minimum accuracy. Tree crown delineations are also assessed in terms of 1:1 correspondence between the segmented and reference objects. The higher the percentage of 1:1 correspondence indicates higher accuracy. Whereas over segmentation yields commission errors as one tree is segmented to more than one object for one reference tree exist. If no tree is identified for one reference tree exist, omission errors are made (Ke 2008). Meinel and Neubert (2002) also used area, perimeter, shape index (Shape index= (perimeter/ (4√area)), number of segments, and visual accuracy assessments. In this case, the best output will be the one with the minimum deviation from their respective training or reference object.

3. MATERIALS AND METHODS

3.1. Materials

3.1.1. Satellite Data

The major input satellite image data used in this study is the Quick-bird image acquired on September 2006. However, Google earth image and aerial photograph acquired in 2006 are also used to support the data collection and analysis.

3.1.2. Other Ancillary data

Forest management plan of the private forest owners was also used to support the identification of plant species types in different plantation sites.

3.1.3. Instruments

Various instruments were used during the data collection process (Table 2).

Table 2: Details of instruments used in collection of field data

No	Instruments	purpose
1	Ipaq GPS	Geospatial location of sample plots
2	Clinometer Haga	Measuring tree height
3	Calliper 100 cm	Measuring DBH
4	Clinometer Suunto	Aspect and slope measurement
5	Densiometer spherical	Measuring percent crown density
6	Compass Suunto	Measuring bearing/direction
7	Measuring tape 50 meter	Measuring radius of sample plots
8	Digital camera	Taking pictures of trees and other observations

3.1.4. Software

The following softwares are used for data base creation, processing and analysis.

- ArcGIS 10 for database creation and geospatial analysis.
- ENVI for image filtering and classification.
- eCognition 8.0 for image segmentation and accuracy assessment
- ITC for image segmentation
- JTS and Geo-tools for segmentation accuracy assessment (in Java environment)

- Microsoft Excel for field data analysis. Microsoft- Word 2007 and MS-Power Points for report preparation and presentations**.**
- JMP 9 statistical software.

3.2. Method

3.2.1. Research Approach

There are various methods of remote sensing technique of biomass carbon estimation and the accuracy of estimation quite varies depending on the approach used (Gibbs et al 2007). These approaches have been reviewed thoroughly and the CPA approach of biomass carbon estimation is chosen along with the availability of high spatial resolution satellite images. The research process can be divided into three phases the pre-field work, field work and post field work .The pre-fieldwork phase includes preparation of data required for the data collection campaign which includes image pre-processing, pixel based classification and locating of sample plots on a justifiable sampling technique. The field work is accompanied by biophysical characteristics inventory of trees with in sample plots. The post field work activities range from data entry and regression analysis of biophysical measurements of sample trees to image segmentation analysis and biomass carbon modelling. The method followed in this research is summarised in Figure 2

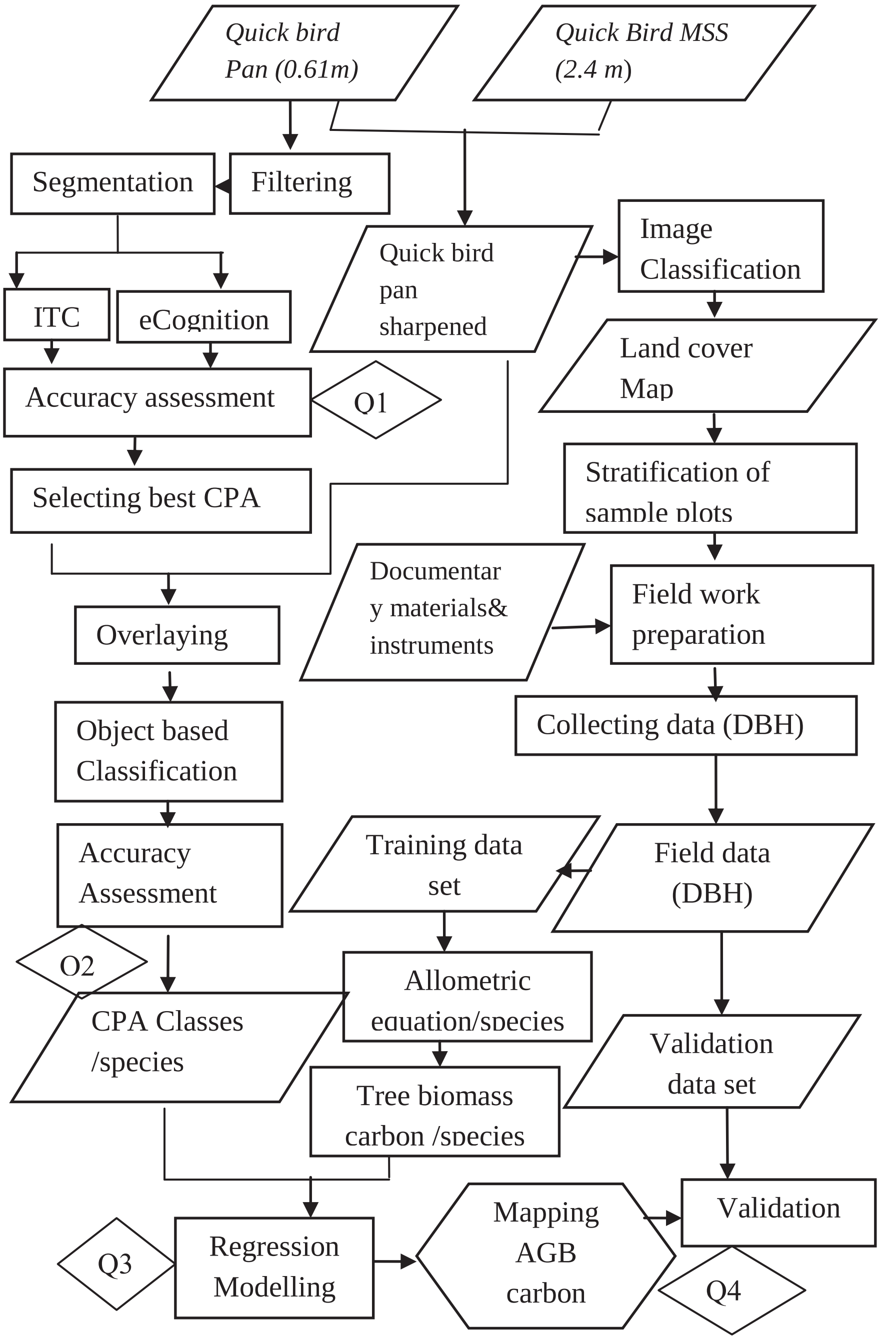


Figure 2 : Methodology flow chart

3.2.2. Pre-fieldwork

3.2.2.1. Image pre-processing

The Quick-bird image was geo-referenced and registered with UTM 32 N projection, WGS 84 spheroid and WGS 84 datum. The panchromatic image (spatial resolution 0.61m) was pan sharpened using the Quick-bird MSS image (2.4 m) to obtain a multispectral image with 0.61 meter spatial resolution.

3.2.2.2. Pixel based image classification

It is clear that, besides the number of sample sizes the variability of the population can affect the representativeness of the sample. Hence, to address this variability, the forest was classified as coniferous and broadleaf trees. The classification was done in a supervised technique using maximum likelihood classifier. The classified image was then smoothed by moving 7x7 low pass filter window. The boundary of the study area (Haagse Bos and Snipert) was also digitized and the image area of interest (AOI) was extracted out by clipping.

3.2.2.3. Sampling strategy

In forest inventory stratified sampling reported to yield a better precision than simple random sampling. This will be achieved if the established strata have greater homogeneity (Betram et al. 2003). Therefore subdivision of the forest types was done as mentioned above to obtain homogeneous strata. Taking the available time duration of the research, the size of the study area and the shortage of labour force into consideration, a total of 60 samples plot centres were distributed in a stratified random sample technique. However, due to various reasons sample measurements were done in 52 plots. From the sample plot centres 12.62 m radius buffer was created to establish the sample plots having an area of 500 m^2. The shape file of the sample plots was overlaid on the pan sharpen Quick-bird image and a print out of the image of the sample plots were prepared for the annotation and measurements of biophysical characteristics of the sample trees in the field. Moreover, the Quick-bird image (TIFF. format) was converted into Enhanced Compression Wavelet (ECW. format) and saved in the Ipaq GPS with the sample plot shape file for facilitating navigation to sample plots. Figure 3 shows forest types (pixel based classification) and sample plot centres.

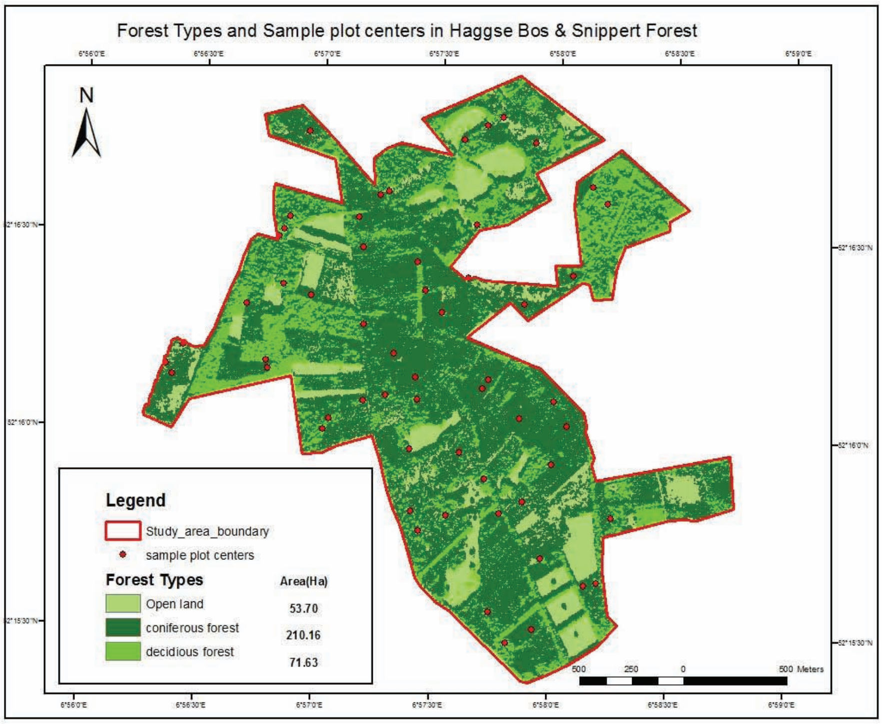


Figure 3 : Forest types (pixel based classification) and sample plot centres

3.2.3. Fieldwork

3.2.3.1. Navigation to sample plots

During the field work, navigation to sample plots was made with the help of the Ipac GPS and the printed image of the respective plots. However, the strength of GPS signals was highly variable depending on the density of the tree crown cover and the weather conditions. Thus, the error was also variable making the GPS location undependable in some cases. Hence, accurately locating the exact plot centres was challenging and time consuming task. In order to overcome these problems, the relative position of distinct tree species, open spaces, pedestrian roads has been used as a reference location to accurately identify trees with in sample plots. In addition to the GPS signal problem, the temporal variation of the image used in the study has increased the dimension of complexity in identifying the trees particularly in the private forest part as there were harvesting of trees since 2006 (after the image was acquired).

3.2.3.2. Biophysical characteristics measurement of sample trees

A circular plot with a radius of 12.62 m (500 m^2) was chosen as unit of sampling. All the trees within the plot having DBH ≥ 10 cm were measured for the biophysical characteristics such as DBH, crown diameter and crown density. The forest constitutes different tree species both coniferous and broadleaf types such as Norway spruce (*Picea abies)*, Scote pine (*Pinus sylvestris*), Douglas fir (*Pseudotsuga menziesii*), Larch (Western hemlock) (*Tsuga Canadensis)*, European Beech (*Fagus sylvatica*), Oak (*Quercus robur*), European white Birch *(Betula pendula)*, and Chestnut (*Castanea dentata)*. To identify the tree species in the field, a picture index of the species was prepared during the pre field work phase (See appendix 2). In addition to this, information about the location and species types of trees in the private forest part was obtained from the management plan of the private forest owners. The sampled trees were annotated by giving a number to each one of them on the printed image and their respective biophysical characteristics measurement are recorded on the data collection sheet (Appendix1).

3.2.4. Post Fieldwork

3.2.4.1. Organization of field data

The biophysical measurements of trees in the sample plots were organized in Microsoft excel and the crown of sample trees were digitized by overlying the sample plots shape file on the quick bird image in ArcGIS 10. This was done for a number of reasons: 1). An ease information exchange between the automated CPAs' and field measurement data during regression modelling can be made, 2). They are also serving as training data for image classification and accuracy assessment and 3). The accuracy of segmentation is evaluated with reference to these manually digitised CPAs.

3.2.4.2. Tree crown delineation in eCognition and ITC software

A). eCognition

In eCognition, tree crown delineation was done by image segmentation. Segmentation is any operation that creates new image objects or alters the morphology of existing image objects according to specific criteria. This means a segmentation can be a subdividing, a merging, or a reshaping operation. There are two basic segmentation principles; 1) Cutting something big into smaller pieces, which is a top-down strategy and includes Chessboard, Quadtree-based, Contrast Filter and Contrast Split segmentations and 2) Merging small pieces to get something bigger based on homogeneity criteria, which is a bottom-up strategy. An example of this is the Multiresolution Segmentation *(*Definiens 2009*)*. In this analysis both bottom up and top down algorithms were employed at different stage of image segmentation. The general process of segmentation in eCognition can be generally classified as the pre-processing and the tree crown delineation phase.

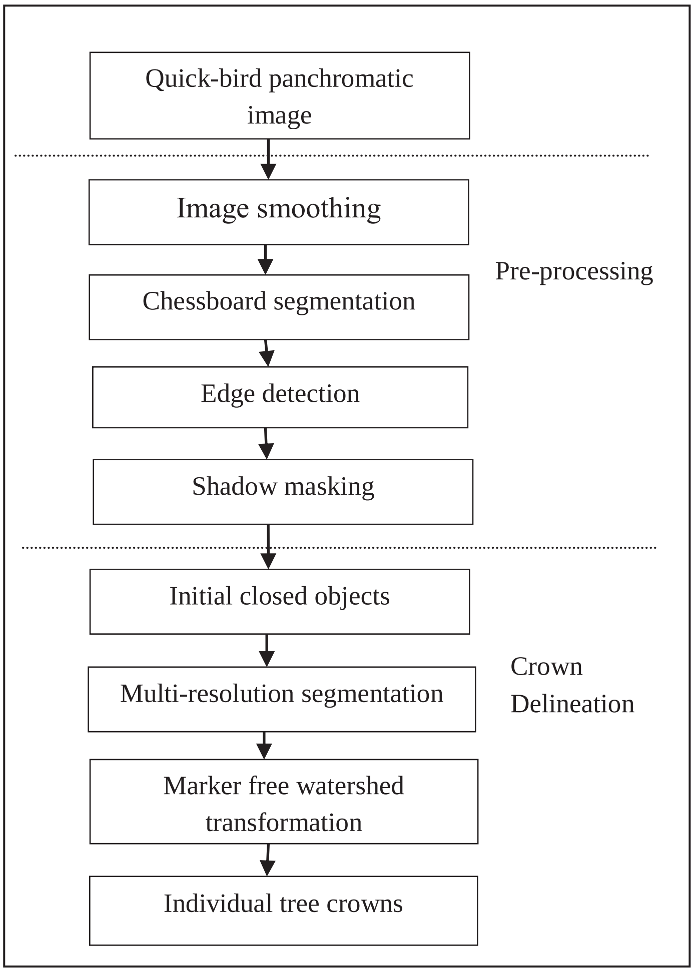


Figure 4: Tree crown delineation approach in eCognition

i). Smoothing filter

Filter operations are image enhancement technique used for noise reduction or sharpening image. It transforms the image and produces a new image whose pixel values are dependent on the former neighbours (Bakker et al., 2004). The panchromatic images undergone to low pass convolution and morphological filter mainly to smooth the image by removing the high frequency component of the image. This was made with the aim of reducing over segmentation of individual objects as well as having a better visualisation of the image. The image was filtered by moving different size kernel window and 5x5 window size was found to give a better enhancement of the image.

ii). Edge Detection and Shadow Masking

Understory, bare soils, shadow and open lands constitute considerable portion of the image. The separation of tree crowns from the background facilitates the tree crown delineation (Wang et al. 2004). An edge in an image corresponds to an intensity discontinuity of the underlying scene. This intensity discontinuity may arise from a depth discontinuity, a surface normal discontinuity, a reflectance discontinuity, or an illumination discontinuity (Marr and Hildreth 1980). The Laplacian of the Gaussian operator (LOG) detects rapid variation of intensity at the interface of image objects (Wang et al. 2004). As figure 5 indicates, in a continuous surface, sharp declines or rises of intensity are detected by the LOG operator. This allows masking out non-tree areas and retaining tree-crown objects for further segmentation and analysis. Hence, edge-detection method was used to derive the initial boundary of the tree crowns.

The LOG method can be divided into two steps. At the first step, a Gaussian smoothing (convolution) was applied to the image to remove noise as well as intensity variation due to the trees internal structure as stated in section i. A second step is to find the zero of the second derivative of the smoothed image (Wang et.al. 2004). To implement the second step the smallest areal unit should be defined. Hence the image was segmented using chessboard segmentation with a scale of 1 pixel so that each pixel was identified as an object. Then the Log operator was performed to identify the edge of the objects and created sharp gradients between image objects whenever there was discontinuity in intensity. After this operation, pixels which lays on the tree-crowns were given a value of zero where as shadows and none treed areas were assigned positive values as a result easy separation of tree crowns and none treed areas was possible. Figure 5 shows the 2-d Lapalcian of Gaussian (LoG) function.

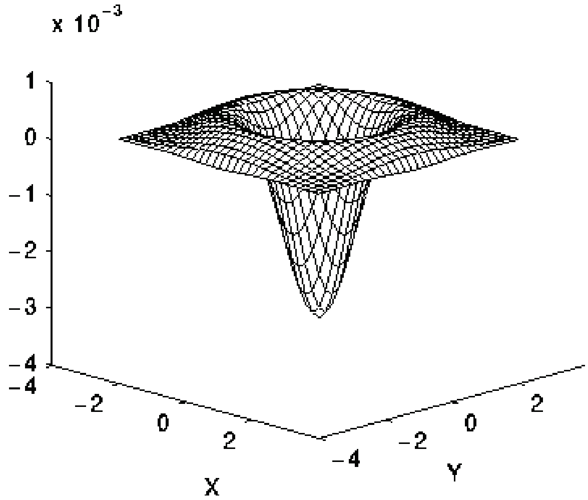


Figure 5: The 2-d Lapalcian of Gaussian (LoG) function. The x and y axes are marked in standard deviation HIPR2 (2000).

The LOG detector is written as (Marr, 1980).

$$Log(x, y) = -\frac{1}{\pi\delta^4}\left[1 - \frac{x2+y2}{2\delta}\right] \exp\left(\frac{x^2+y^2}{2\delta^2}\right) \qquad \text{Equation 4}$$

The smoothing scale δ in pixels determines the minimum width of the edge that can be captured. Although it may be useful to implement the LOG operator at a series of scales, it is very difficult to integrate the outputs from multiple scales (Lu and Jain 1989). Therefore a single smoothing scale of 4 pixel (δ=4), which represents the smallest tree crown diameter (2.4 m) in the image and lee sigma was used as the LOG operator (HIPR2 2000). However, the Laplacian of the Gaussian operator identify pseudo edges whenever there is a discontinuity in intensity with in dark objects themselves (see figure 6c). For example, the intensity of the shadow in between tree crowns my change from dark black to light dark as a result due to occurrences of discontinuity in intensity; an edge is detected within dark objects. Therefore, in addition to the LOG operator, a threshold in gray scale image (DN values ≤48) was set to be shadows.

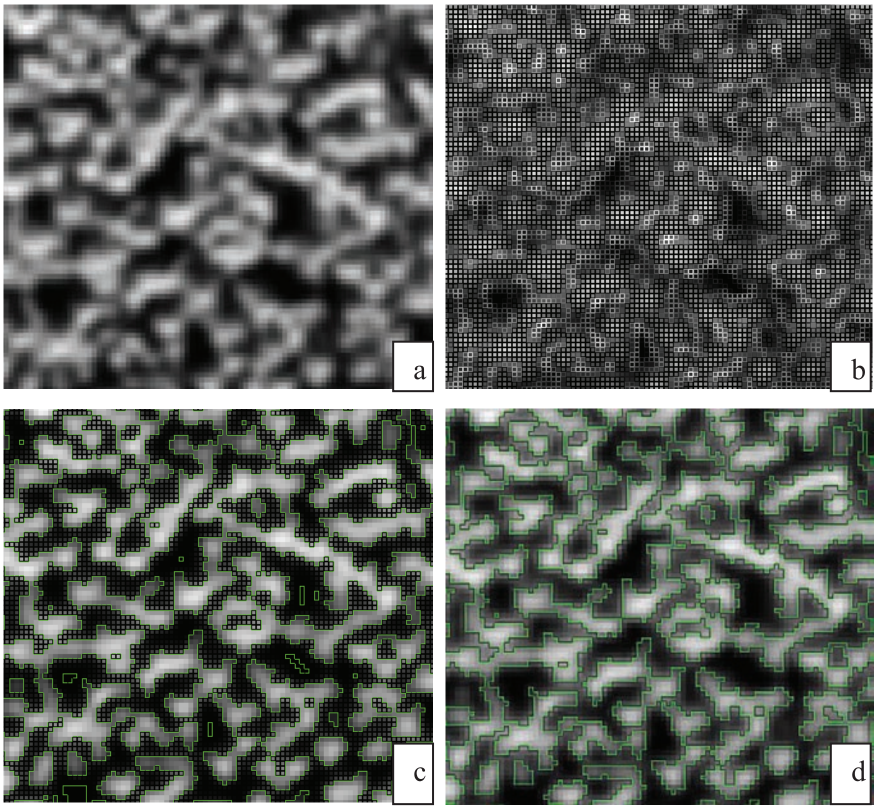


Figure 6: Panchromatic image (a), Edge detection (lee sigma, δ=4) (b), shadow masking (c) and Pseudo edge masking (d)

iii). Multi resolution segmentation

To date, image segmentations are performed using a number of software and algorithms. Procedures for image segmentation are main research focus in the area of image analysis for years. Many different approaches have been tested. However, few of them lead to qualitatively convincing results which are robust and under operational settings applicable (Baatz and Schape 2000). Factors such as the scale and the heterogeneity of the objects of interest, the spatial and spectral detail of the image and type of algorithms appears to be the key determinant factors affecting the success of segmentation.

Among the different segmentation algorithms that can be applied in eCognition environment, multi-resolution segmentation was used as a primary technique of tree crown delineation. This is mainly because of the difficulties of applying other tree crown delineation algorithms. Multi-resolution segmentation is the process of delineating individual objects in the scene based on homogeneity criteria such as colour, shape, texture etc. The success of the multi-resolution segmentation depends on selecting the appropriate parameter combinations. In order to select the best parameter combinations, the panchromatic image was segmented 63 times iteratively using different parameter combinations of scale, shape and compactness (Scale, 10, 15, 20, 25, 30, 35, and 40, Shape 0.3, 0.5, 0.7 and compactness 0.5, 0.7, and 0.9). Using the shape file of each segmentation output and the manually digitized reference tree crowns, the accuracy was assessed in the java environment using JTS and Geo-tools. A total of 70 and 33 coniferous and broadleaf trees respectively which were clearly seen were manually digitised as a reference for evaluating the segmentation crown outlines. The reference trees were distributed at different part of the forest and represented different species types. The measure of accuracy was made in terms of the degree of over segmentation, under segmentation and the goodness of fit (D) (Clinton et al. 2008) (Equations 1,2, and 3). Since the forest in the study area constitutes different tree species which considerably varies in terms of size and biophysical characteristics, the accuracy was assessed for coniferous and broadleaf trees separately.

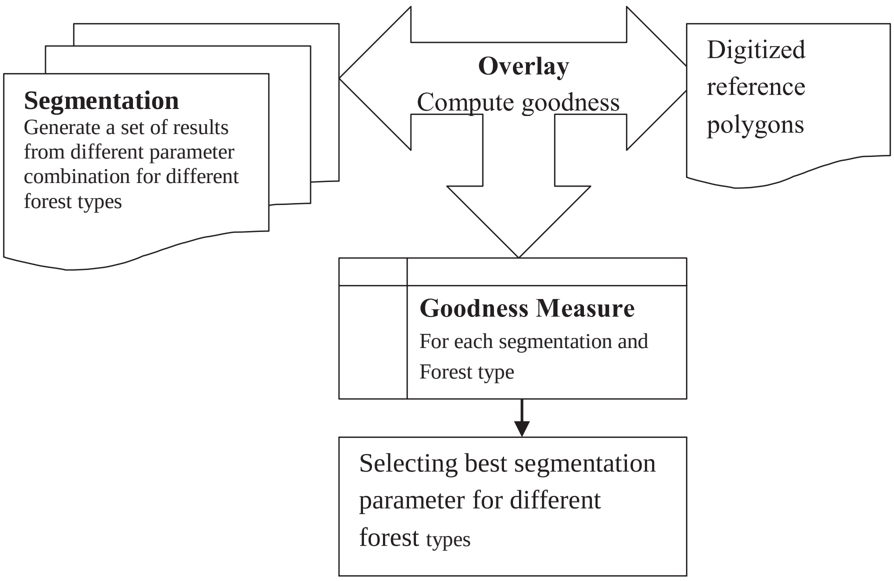


Figure 7 : Approaches of accuracy assessment

Therefore, parameter combinations which yield lower goodness of fit (D) were used to segment the panchromatic image. Moreover, since the best parameter combination for coniferous and broadleaf forests varies, a separate parameter combinations of multi-resolution segmentation were applied to plots which had dominantly distinct forest types (see Appendix 3). Despite the multi-resolution segmentation, the degree of under-segmentation was high indicating the requirement of further processing of the image objects. Hence, under-segmented trees were treated by transforming the objects into marker free watershed segmentation.

Iv). Marker free watershed segmentation

This tree crown delineation technique was used as a supplement of the Multi-resolution segmentation algorithm. This was made with the aim of solving the problem of under segmentation by the Multi-resolution segmentation described above. Watershed transformation considers the image to be processed as topographic surface. It includes three basic notions: local maxima, catchment basins and watershed lines (Chen et al. 2004). If a gray scale mage is inverted, the local maxima become the local minima and holes are punched at the local minima. In between the local maxima and minima are the catchment basins which correspond to the tree crowns. The watershed lines are the local maxima of an inverted image. Therefore, these watershed lines forms dams which prevent water entering from the adjacent basins in case of marker controlled watershed transformation (Ke 2008).Whereas dams are built at the local minima's of un-inverted image in case of the marker free watershed transformation. Hence, in the marker free watershed transformations holes are punched at the local minima unlike the marker controlled whose holes are punched at the prescribed marker (Zhao and Popescu 2007). Figure 8 shows the principles in watershed transformations.

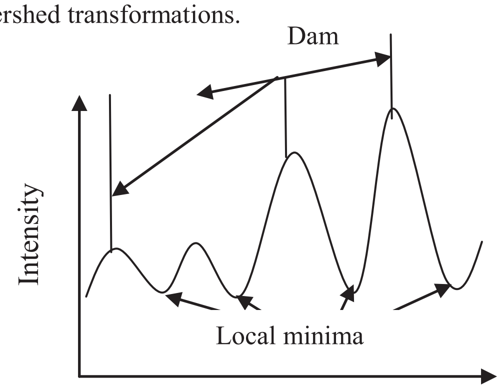


Figure 8: Illustration of the watershed segmentation principles

In this study the marker free watershed transformation version was implemented due to difficulties in identifying an appropriate marker of each tree. Hence, in the immersion paradigm from Vincent and Soille (1991), the topographic surface is flooded from its minima, thus generating different growing Catchment basins. Dams are built to avoid merging of water from two different Catchment basins. The segmentation result is defined by the locations of the dams (i.e., the watershed lines) when the whole image has been flooded (Derivaux et.al. 2010).

However, marker frees watershed segmentations results over segmentation of the image which creates more objects than the actual objects present in the image. However, image smoothing is often used to overcome this problem (Derivaux et.al. 2010). Hence, since the image was well smoothed, the image objects obtained after multi-resolution segmentation was transformed into a marker free watershed transformation. As a result the problem of under-segmentation of the Multi-resolution segmentation was overcome.

B). Individual tree crown delineation (ITC) software

For the purpose of comparing the accuracy of tree crown delineation obtained from eCognition, ITC software was also used for delineating the tree crowns. The tree crown delineation in ITC is made in two major steps as the valley following and rule based tree crown delineations. However, image smoothing and none vegetation masking was made as part of the image pre-processing.

i). None-vegetation masking

For tree crown delineation in ITC software, the same panchromatic image but filtered by moving a 3x3 smoothing window was used. The selection of the filter window size was made by visual comparison of the tree crown outlines obtained after crown delineations using a different smoothing window size. This was followed by non-vegetation masking. Simple thresholds or multispectral rules such as “detect pixels having a near infrared radiance smaller than its mean visible band radiance” can sometimes be used to create effective none vegetation masks (Gougeon and Leckie 2006). However, the vegetation masking options in the software do not give an effective none vegetated mask for the study area due to over masking of vegetated areas. Hence, the non-vegetated areas were manually digitised and masked out.

ii). Valley following and tree crown delineation

In the valley-following process, a threshold is first used to eliminate small areas of shade, areas typically devoid of significant trees in which following valleys of deeper shade would make little sense. Then, local minima are found in what are essentially the “pure” forested areas of the smoothed illumination image. They correspond with points of deepest shade, typically between four tree crowns. From these initial local minima, all possible valleys of shade in the image are followed pixel by pixel, resulting in a fairly good, yet often incomplete, separation of tree crowns. A valley pixel is defined as a pixel continuing the valley (8-connected) that has a radiance value lower than the pixels on its right and on its left when going in the valley direction (Gougeon and Leckie 2006).

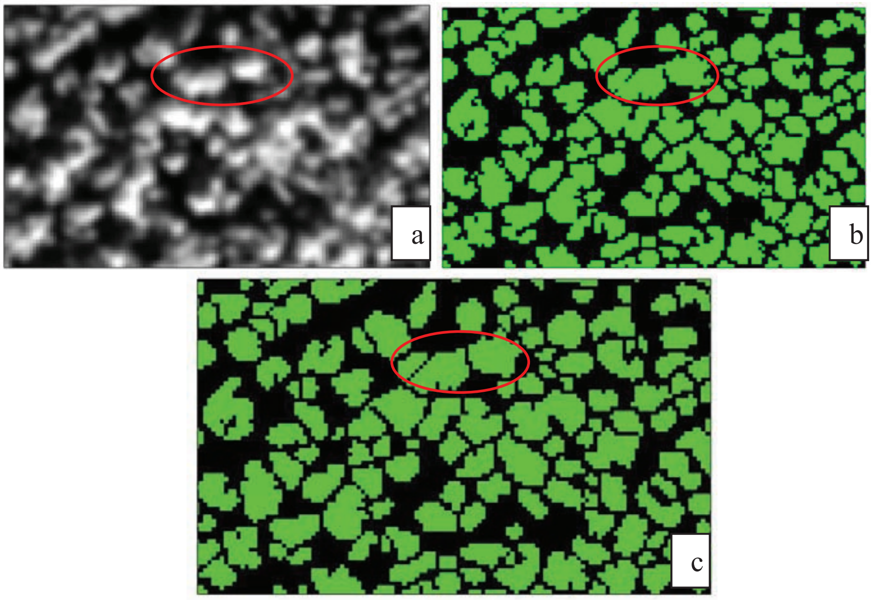


Figure 9: Processes of tree crown delineation in ITC software suit: panchromatic image (a), bit map of valley following approach (b) and rule based tree crown delineation (c)

The valley-following process was succeeded by a rule-based crown delineation process that attempts to finish the separation of tree crowns and produces tree crown outlines. It results in a bit map of objects that are referred to as Isols (isolations) and typically represent individual tree crowns or, under certain circumstances and/or poorer spatial resolution, can be tree clusters (Gougeon and Leckie 2006). Gougeon (1998) describe the rules employed for deriving the final tree crown outlines as follows.

'More specifically, after having read the bitmap of "shaded material" (SM) and "non-forested" areas produced by the "valley following" isolation process, the delineation process starts by scanning the image (right and down) for a first minimal block (2x2 pixels) of "vegetation material" (VM - defined here as the converse of the bitmap just read in). Starting on the left side of this block, it tries to follow the SM up, or up and right, moving by one pixel. It will continue to move one pixel of SM at a time, favoring a move in its on-going direction or preferably, one pixel to the right of its on-going direction (level 1 rule). Sometimes the only possible move will be to the front-left of its on-going direction, for example, if a tree branch is protruding from the crown. This move will be acceptable under level 2 rules, assuming that level 1 rule have been checked previously. On other occasions the only path available while following the SM is 90 degrees counterclockwise to the on-going direction (e.g., larger branch sticking out). Such a

move may be acceptable (level 3 rules), but only after having checked that a more favorable move cannot be executed by bridging a one-pixel-wide gap to some SM on the right or in front. Similarly, level 4 rules make possible turns that are 135 degrees counterclockwise, but only after substantial checking in the front-right direction for better moves that could be done by bridging gaps up to one meter wide. Finally, level 5 rules deal with possible moves implying a complete direction reversal from the on-going direction. Such situations typically represent a serious inlet into a crown (e.g., due to self-shading) or a serious indication that two or more crowns are present and should be separated. Again, a check is performed for SM up to a meter away from the end of the inlet to estimate whether a gap should be bridged. If it succeeds and the gap is bridged, it is possibly separating two distinct tree crowns. If this fails, the situation is considered as an irrelevant inlet within a single crown, and the inlet is actually erased before continuing the crown delineation'.

iii). Partial marker free watershed transformation (eCognition) of the tree crowns delineated through ITC software

The success of tree crown delineation in ITC software depends on the existence of shades in between tree crowns. Giving the spatial resolution of the image used and the existence of broadleaf trees of overlapping crowns, the Isol delineation gave rise to considerable amount of clustered tree crowns. Hence, these trees were further processed to separate them from the neighbouring tree crowns. As a result, clustered trees were selected based on a threshold of CPA (CPA> 100 pixels) and a marker free watershed transformation was applied to these clustered trees.

3.2.4.3. Accuracy assessment of tree crown delineation

The accuracy of the segmentation by the two software was assessed in terms of over segmentation, under segmentation and goodness of fit (D) using the technique described in section 2.1.5 on page 10-12. Hence, the output from the software which gave a better goodness of fit for the majority of the forest type was used for further analysis. Despite this, both of the softwares were involved to get the final tree crown outlines.

3.2.4.4. Object based Isol classifications and accuracy assessment

Object based classification is the categorization of objects created through image segmentation into similar categories based on spectral, textural, shape and contextual properties of image objects (Mathieu and Aryal 2005). The Isols obtained from image segmentation are overlaid on the pan-sharpened Quick-bird image and subjected to nearest neighbour classification. The field collected samples were split into two groups as training and classification accuracy assessment data. The training data were used to train the nearest neighbour classifier. After the training samples were selected, feature space optimization was done. This is to select variables related to spectral, textural and geometrical characteristics which can give better separation between classes. Hence, variables such as the mean NIR and red band, maximum, minimum, and standard deviation values of NIR band, area of the objects, etc were used to classify the Isols into coniferous and broadleaf trees.

The accuracy of classification was assessed using half of the field data as a ground truth. A confusion matrix was prepared by cross tabulating the ground truth and the classification data. Hence, the users, producers, overall accuracy and kappa coefficient of agreement were computed in ArcGis.

3.2.4.5. Allometric regression equations of tree species in the study area

Allometric equations are used to estimate AGB from volumetric and structural dimension of the trees. DBH and height of the trees are usually used to compute the biomass of the trees (IPCC 2003). However, when tree height data is scarce, only DBH can be used to compute biomass (Muukkonen 2007). Species specific allometric equation is available for some of the Dutch forest species. However, since the biomass carbon estimations are made at broader scale for coniferous and broadleaf trees, general allometric equations developed for the Canadian hardwood and softwood forests were used. In addition to the scarcity of generalised allometric equations applicable to the Dutch forests, most of the tree species in the private forest part are exotic and are commonly found in the Canadian forest. The allometric biomass equation takes the form of power function as follows (Lambert et al. 2005).

Softwood

Stem wood dry biomass (kg) = 0.0648 * (DBH^2.3923) +0.0107 Equation 5
Branch dry biomass (kg) = 0.0156 * (DBH^2.2916) + 0.0005 Equation 6

Foliage dry biomass (kg) = 0.0861 * (DBH^1.6261) + 0.0006 Equation 7
Bark dry biomass (kg) = 0.0162 * (DBH^2.1959) +0001 Equation 8

Hardwood

Stem wood dry biomass (kg) = 0.0871* (DBH^2.3702) + 0.0493 Equation 9

Branch dry biomass (kg) = 0.0167* (DBH^2.4803) + 0.0002 Equation 10

Foliage dry biomass (kg) = 0.0340* (DBH^1.622) + 0.0056 Equation 11

Bark dry biomass (kg) = 0.0241* (DBH^2.1969) + 0.0030 Equation 12

All the dry biomass of these tree components were then added together to give the AGB = [Stem wood biomass + branch biomass+ Foliage biomass + Bark biomass]

A). Biomass carbon regression modelling

The regression modelling is used to quantify the relationship between dependant and independent variables. Regression equations are common statistical techniques used in the process of AGB estimation (Lu 2005). The relationship between segmented CPA and carbon stock as obtained from the allometric biomass equations and carbon conversion factor are investigated through regression equations. To develop the model, the sample field data (168 coniferous and 90 broadleaf trees) were split systematically into two after putting the whole sample data, which are eligible for model development, in ascending order based on the sample plot number. Eligible samples CPAs are those which are neither over-segmented, nor under-segmented and not misclassified. Therefore, the first half was used as training data for developing the regression model.

B). Model Validation

Model validation purpose is to systematically establish a level of confidence of models (Buranathiti et al. 2006). The validity of the model developed was assessed using half of the sample data set. There are different techniques of model validation. However, in this study r^2 and root mean square errors (RMSE) are computed as an indicator of model validity.

3.2.4.6. Forest AGB carbon mapping

The spatial AGB carbon was mapped using the regression model developed for coniferous and broadleaf forests. Generally, 50% conversion factor of the dry biomass to carbon was used for both of the forest types (Solicha 2007).

4. DESCRIPTION OF THE STUDY AREA

4.1. Forest Management in the Netherlands

By the end of the 18^{th} century the natural forest of the country was almost completely exhausted due to expansion of towns and population increases. In the 19^{th} c some attempts of planting trees was apparent in response to wind erosions. The industrial revolution in the 20^{th} c had changed the very nature of society. As the pace of life increased, the demand for forestry products grew and these had to be marketed more quickly. Quick growing pine trees were planted for pit props and later for the paper industry. Poplars were planted for the manufacture of clogs and matches. Afforestation in the 1920s and 30s was primarily aimed at production and at curbing unemployment. After WW2 timber had to be produced more rationally and at lower cost. This had an impact on what the current woodlands of the country look like today. The entire forested areas have now been made part of the National Ecological Network. In 1990 about 3% of the country was woodland and the figure estimated to be more than 10% in 2000. The country has a total woodland area of 339 000 ha which means about 2000 m^3 woodland per person or twenty trees per head. Virtually all the woodland existing today has been planted by man, only 7% resulting from spontaneous regeneration (Stiching Prosbos 2000).

Forest management in the Netherlands is to a large extent (25%) concerned with developing the country side to make woodland more attractive for wildlife and for human beings. Timber production and recreational facilities are also important woodland activities. More than half of the countries' woodland consists of coniferous (57%), mostly Scot pine, Douglas fire larch and Norway spruce. The remaining woodland is deciduous with oak, beech, birch and popular the most common species. Dutch woodlands are rarely made up of only one species of tree. About a third of the total forested area in the Netherlands is mixed woodland (Stiching Prosbos 2000).

The ratio of coniferous and broad leaf trees are changing .The number of young conifers (diameter 5-20 cm) has decreased much more over the past 15 years than the number of young broadleaves. Scots pine, larch and spruce have declined more compared to the total number of trees; while the number of native deciduous trees is increasing .The amount of mixed woodland has grown from 81000 ha in 1985 to 91000 ha in the period 1993-1997. Most new mixed deciduous (+5000 ha) or mixed coniferous /deciduous (+7100 ha) (Stiching Prosbos 2000).

The country is pledged to UNFCC commitments and planted more than 10, 000 ha of forest since 1990 as emission reduction measure (Stiching Prosbos 2000). Though forests in the Netherlands are well monitored there is great uncertainty over the role of Dutch forests, forest soils, wood products and management and land use options on carbon sequestration. Biomass carbon accounting in the Netherlands follows a stand stock approach which is based on the total yearly increase of woody biomass corrected for yearly extraction of wood. Hence, methods should be developed and may consist of a combination of forest inventory and remote sensing data (Naburus et al. 2000). However, it is estimated that a growing tree absorbs about 0.7 tonnes of carbon per m^3 of wood. The faster a forest grows, and the longer it maintains this rate of growth, the more carbon it can extract from CO_2 in the air. In 1994 a total of some 234 million tonnes of carbon from CO_2 was absorbed by Dutch woodland. Because of the annual net increment, this quantity has now grown by about 0.6 million tonnes. Per ha, the net sink is 2.2 tonnes of CO_2 per year (Stiching Prosbos 2000).

4.2. Haagse Bos and Snippert Forest

The study area is found about 7 km away from Enschede in the North Easter direction in Haagse Bos. The forest lies between 5791566.81m N to 5794200 m N and 359268.03m E to 361909.61m E (Figure 10). It is partly private and partly natural monument. Previously it was coniferous forest managed for timber production. Now it is managed for nature conservation and recreation and has gradually been converted into mixed forest. It has a total area of 334 ha.

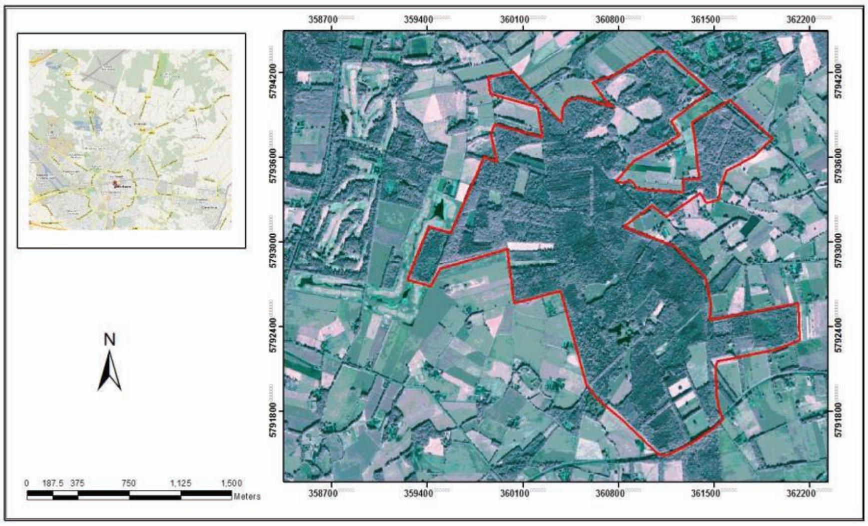


Figure 10: Location of the study area.

As the interview made with the private forest manager indicated, the privately owned forest in Haagse Bos was established in the 1890's as a production forest. It is an example of a process of land use /land cover change that took place in the 19th century when textile factory owners established forest and agricultural land on "waste" heath land areas. The second generation of the forest dates back in the 1950's and 60's. It constitutes both broadleaf and coniferous tress of both exotic and native species. The broad leaf trees are mainly planted in the pedestrian and road sides as aesthetic values. The forest in general selectively harvested once in six years. The harvesting is made in proportion to 50 -70% of the annual increment which indicates a sustainable forest harvest as the re-growth compensates the harvest. The forest is also serving as tourism and recreational areas as it is opened for public access. Due to this service the forest owners get little subsidies from the government. Despite this, government's support for reducing degradation and deforestation and other ecological services such as maintaining biodiversity are absent.

Haagse Bos forest is managed by a private company on behalf of the owner. The forest manager prepares a management plan in every 10 years. As part of the management activity, thinning is made once for trees greater than 10 cm in diameter. Regular thinning for all trees however is limited due to shortage of manpower and money. Despite this, thinning is naturally take place since the branches in the lower part of the stem die out due to shortage of sunlight and competitions from the nearby trees. However the nature monument part managed naturally without human intervention.

In General, the forest is a multipurpose forest for timber production, recreation, tourism, hunting and ecological conservation. It constituted mixed tree species such as, Scots pine (*Pinus sylvestris*), Norway spruce (*Picea abies*), Douglas fir (*Pseudotsuga menziesii)*, European larch, Eastern hemlock (*Tsuga Canadensis*), oak (*Quercus robur*.), European beech (*Fagus sylvatica*) etc.

5. RESULTS

5.1. Image segmentation in eCognition

5.1.1. Edge detection and shadow masking

The implementation of the Laplacian of the Gaussian operator on a convolution smoothed panchromatic image gave rise to the delineation of the initial closed objects. As indicated in Figures 11, the tree crowns are identified and separated from the shadows. Moreover, for some sparsely grown trees, the edge detection and shadow masking operation delineated their respective CPA. However, adjacent or close by grown trees and trees with overlapping crowns remains clustered. Generally, trees having CPA greater than 4 pixels (> 2.4 m^2) are identified.

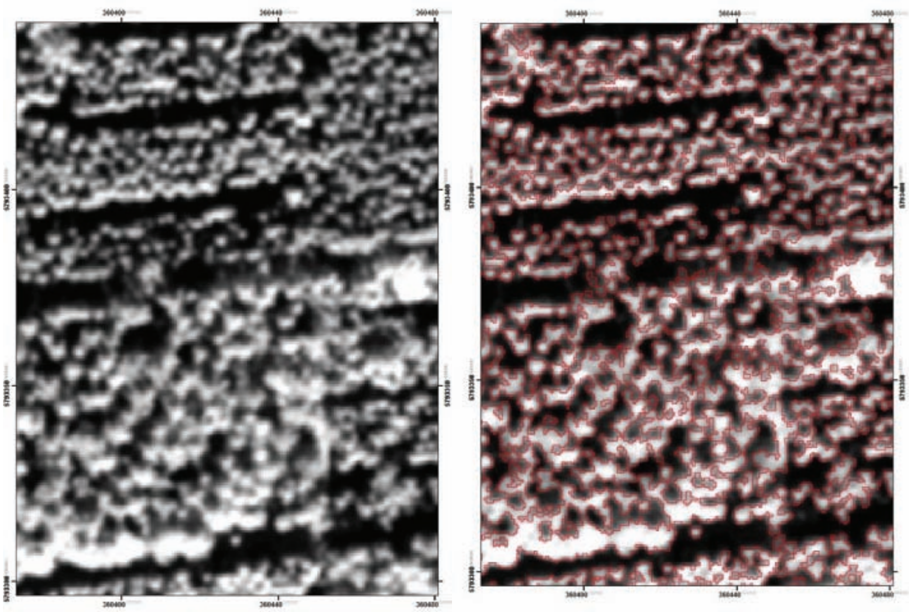


Figure 11: Quick-bird panchromatic image in north part of the private forest (left) and the resultant image after Edge detection (δ=4) and shadow masking (right).

Despite the edge detection and shadow masking, large portion of the tree crowns remains clustered. Since there are shadows in between most coniferous trees, better separations of objects are apparent after the edge detection and shadow masking operation unlike broadleaf trees which have overlapping tree crown.

5.1.2. Multi-resolution segmentation and marker free watershed transformation

The intermediate objects obtained after edge detection and shadow masking have undergone to multi-resolution segmentation. However, since there was considerable variation of tree crowns in terms of size for broadleaf and coniferous trees, a separate segmentation parameter combinations were applied. The best multi-resolution segmentation parameter combinations (scale, shape and compactness) for each forest type are obtained after an iterative segmentation of the image and subsequent accuracy assessments. The best segmentation scales for the coniferous and broadleaf forests were 15 and 30, respectively. Whereas the goodness of fit (D) remains poor for both forest types though a relatively better accuracy was found for broad leaf trees.

Table 3: Best multi-resolution segmentation parameter combinations

Tree types	Best scale	Best shape	Best Comp.	Over Seg.	Under Seg.	Goodness of fit(D)
Coniferous	15	0.5	0.9	0.25	0.52	0.41(59%)
Broadleaf	30	0.5	0.9	0.22	0.50	0.39 (61%)

Among all the segmentation parameters of scale, shape and compactness, a slight change in scale results a considerable change in the level of under segmentation and over segmentation. Generally, as the segmentation scale increases, the level of over segmentation increases resulting higher number of image objects than the actual number of objects and the vice versa. Figure 12 shows the variability of the goodness of fit (D) of the broadleaf and coniferous trees with change in scale, shape and compactness.

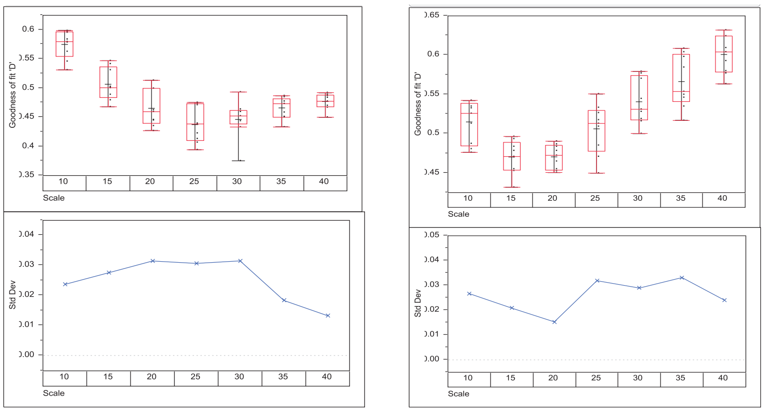


Figure 12: Variability of the goodness of fit (D) in broadleaf forests (left) and coniferous forest (right) with change in scale, shape and compactness.

To further improve the segmentation result, the tree crowns obtained from multi-resolution segmentation were transformed into marker free watershed segmentation. As a result, the overall goodness of fit improved from 0.41 and 0.39 to 0.27 and 0.33 for coniferous and broadleaf trees, respectively (Table 4). This improvement is resulted due to the improvement in the level of under segmentation. Nevertheless, over segmentation has increased for both coniferous and broadleaf trees.

Table 4: Accuracy of segmentation after watershed transformation of the multi-resolution segmentation

Tree types	Over segmentation	Under segmentation	Goodness of fit 'D'
Coniferous	0.31	0.25	0.27(73%)
Broad leaf	0.40	0.26	0.33(67%)

The watershed transformation has resulted dramatic change in over-segmentation for the broadleaf trees being the change from 0.22 to 0.40 whereas the over-segmentation of the coniferous trees has changed from 0.25 to 0.31. However, the watershed transformation performs well for the coniferous trees as the goodness of fit is considerably improved for this type of trees (Figure 13).

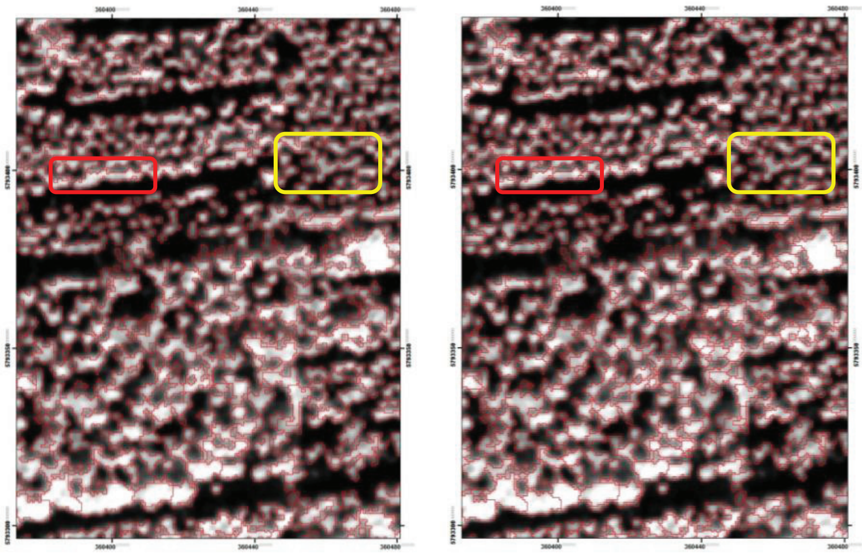


Figure 13: Multi-resolution segmentation image in north part of the private forest (left) and the same image after Watershed transformation of the multi-resolution segmentation (right).

Despite the slight improvement in the goodness of fit for the broadleaf trees, a dramatic improvement in the level of under-segmentation was compensated by an increase in the level of over-segmentation. For more information on the effects of marker free watershed transformation on broadleaf trees see Appendix 4.

5.2. Image segmentation in Individual Tree Delineation (ITC) software

5.2.1. Non-vegetation masking

For the succeeding operation to work out in ITC software, non-vegetated areas need to be masked out. There are different techniques of non vegetation masking. However, for this purpose, none-vegetation areas are digitised manually and masked out (Figure 14). As a result, the succeeding tree crown delineation was made only on the vegetated areas.

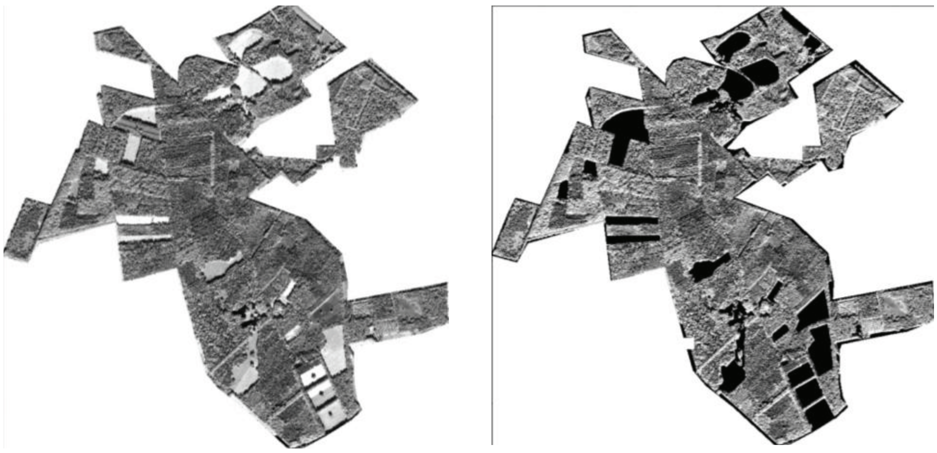


Figure 14: Panchromatic image (left) non-vegetation masking (right)

5.2.2. Valley following and Isol delineation

In the valley-following process, small areas of shade, areas devoid of significant vegetation and local minima's are followed pixel by pixel and gives valleys of shade. As a result good but often incomplete separations between tree crowns were obtained (Figure 15b). The valley-following process was succeeded by a rule-based crown delineation process that attempts to finish the separation of tree crowns and produces tree crown outlines (Gougeon and Leckie 2006). Figure 15c indicates a bit map of the rule based Isol delineation and the subsequent derivation of tree CPA of individual tree crowns. The resultant tree crown outlines (vector data format) as overlaid on the panchromatic image are presented in Appendix 5.

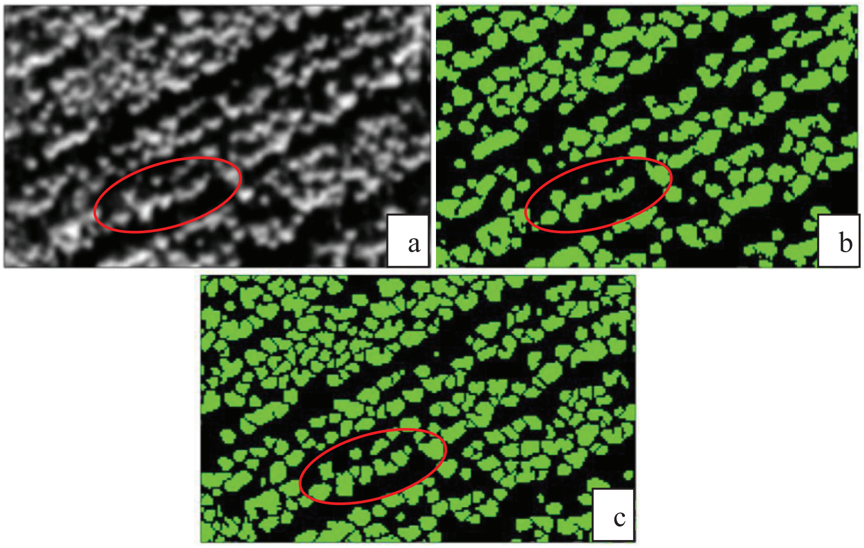


Figure 15: Panchromatic image (a) bit maps of Valley following (b) and rule based Isol delineation (c).

The accuracy from ITC software was slightly better than eCognition for the coniferous trees, the goodness of fit being 0.25. However, the level of under-segmentation was higher for both coniferous and broadleaf trees (Table5).

Table 5: Accuracy assessment of ITC software crown delineation

Tree types	Over segmentation	Under segmentation	Goodness of fit (D)
Coniferous	0. 17	0.33	0.25 (75%)
Broadleaf	0.26	0.42	0.35 (65%)

*the values in parenthesis are the percent tree crown delineation accuracy.

5.2.3. Partial marker free watershed transformation of Isols delineated by ITC in the eCognition environment

Clustered Isols obtained from ITC software crowns delineation were processed in the eCognition environment. As a result, under segmented tree crowns were further segmented in such a way that they represent the CPA of individual trees (Figure 16).

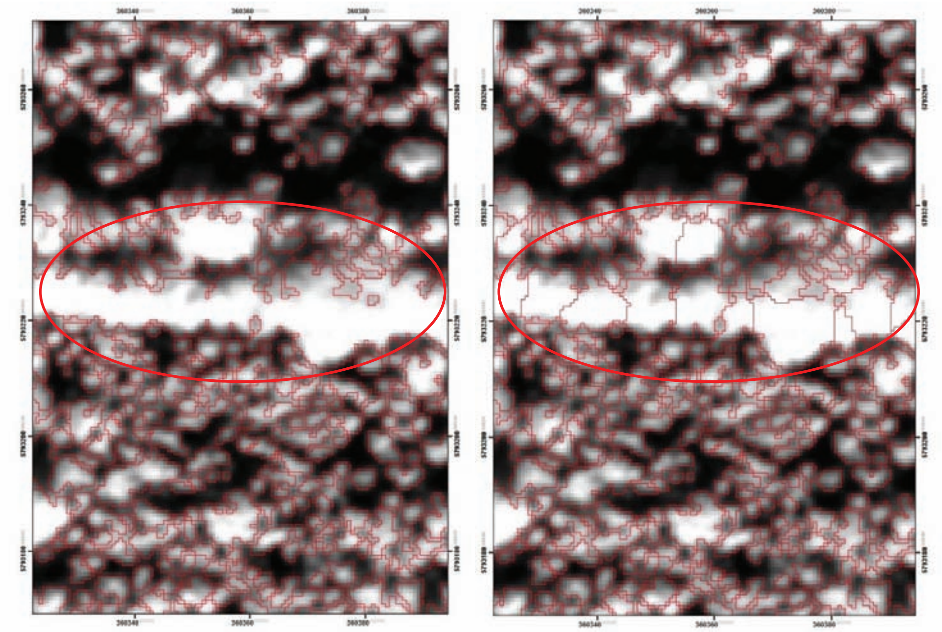


Figure 16: Clustered crowns from ITC software (left) and partial marker free watershed transformation in eCognition (right)

Under-segmented tree crowns were selected based on a threshold of CPAs. Hence, all CPAs > 100 m^2 were subjected to watershed transformation. As indicated in figure 21, the watershed transformation has given to a more realistic crown outlines of clamped trees by further segmenting them. Generally, the overall goodness of fit for coniferous and broadleaf trees improved to 0.20 and 0.34, respectively (Table 6).

Table 6: Accuracy assessment after partial marker free watershed transformation

Tree types	Over segmentation	Under segmentation	Goodness of fit (D)
coniferous	0.19	0.22	0.20(80%)
Broadleaf	0.40	0.27	0.34(66%)

*the values in parenthesis are the percent tree crown delineation accuracy

A total of 117589 and 119159 trees were identified from ITC and eCognition software, respectively (Table 7). This amount of tree is excluding very small trees that have CPA less than 2.4 m^2. In both softwares higher numbers of trees were identified in the private forest part.

Table 7: Total number of trees identified

Software	Total number of tree		Total number of trees
	Private forest	Nature Monument	
eCognition	70636	48903	119159
ITC	68973	48616	117589

5.3. Object based classification and accuracy assessment

Since the accuracy of the Isols obtained from ITC was better for the coniferous trees, which are the majority of the forest tree type in the study area, the CPAs obtained from this software were classified into two classes as coniferous and broadleaf tress.

Table 8: CPA classification results

Tree types	Total number of tree		Total number of trees
	Private forest	Nature Monument	
coniferous	54514	31428	85942
Broadleaf	14459	17188	31647
Total	68973	48616	117589

A total of 68973 and 48616 trees were identified in the private and nature monument part, among which 79.07% and 64.64 % are coniferous trees, respectively (Table 8).

Figure 17 : Forest types from object based classification

The overall classification accuracy was about 74%. Generally, the accuracy of coniferous trees classification was better than broadleaved trees.

Table 9: Classification accuracy assessment

References	Classification		
	coniferous	broadleaf	total
Coniferous	143	19	162
Broadleaf	59	75	134
total	202	94	296
	Accuracy measures		Percentage (%)
	Overall accuracy		74
	Users accuracy (coniferous)		88
	Users accuracy (broadleaf)		55
	producers accuracy (coniferous)		71
	producers accuracy (broadleaf)		80
	Overall kappa coefficient of agreement		45

5.4. Descriptive analysis of field measurement data

A total of 9 species are identified in the whole study area. Among which 5 are coniferous trees and Norway spruce was the dominant tree species. However, European beech was dominant tree species constituting about 46 % of the broadleaf trees.

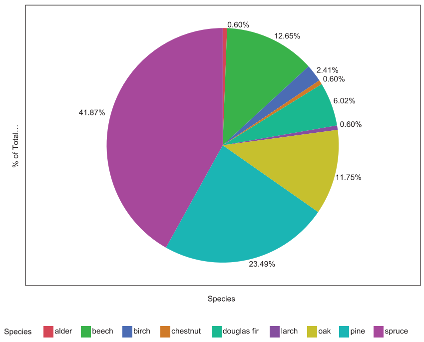


Figure 18: Tree species composition in the study area

Coniferous trees have mean DBH of 36.23 cm. However, the mean DBH of coniferous trees in the nature monument part is higher than the private forest. Generally, Scottish pine has higher mean DBH in both the nature monument and private forest part (Figure 19).

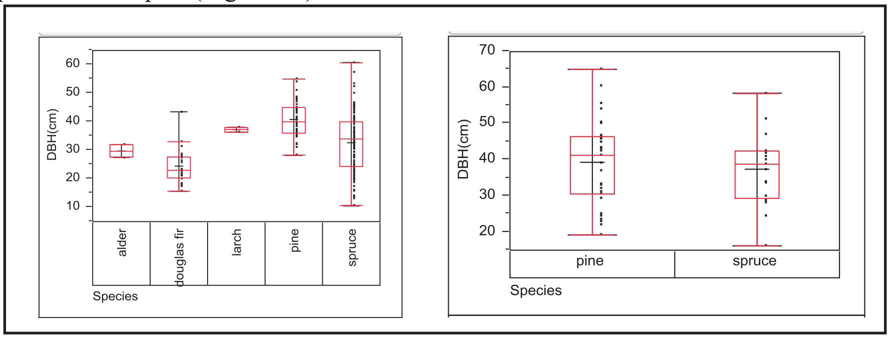


Figure 19 : DBH variability for the coniferous trees in the private forest (left) and the nature monument part of the forest (right).

The broadleaf trees have mean DBH value of about 41 cm. As compared with the coniferous trees, broadleaf trees have higher mean DBH values (Figure 20). Moreover, the mean DBH in Nature monument was higher than the private forest part. Among all broadleaf forests, European beech trees have highest mean DBH values in both parts of the forest.

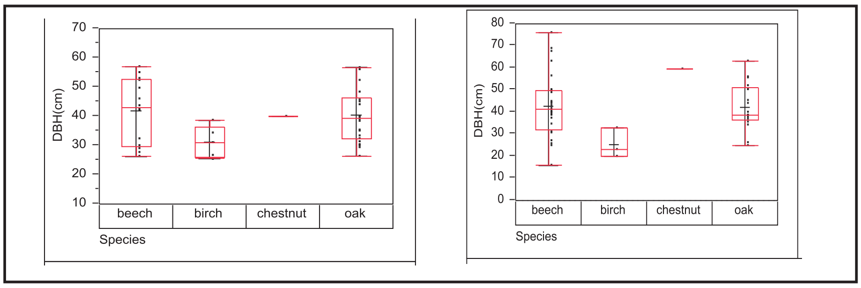


Figure 20: DBH variability for the broadleaf trees in the private forest (left) and the nature monument part of the forest (right).

The average crown diameters for coniferous and broadleaf trees were 6.09 and 8.76 m, respectively being higher mean crown diameter in the nature monument part. Generally, European beech and Norway spruce have higher mean crown diameters.

Table 10: crown diameter variability of the coniferous trees

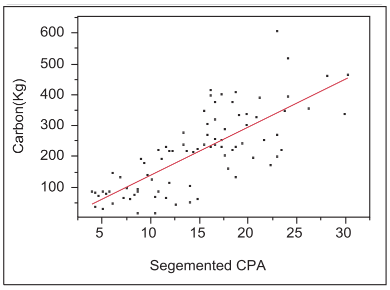
Forest Owner ship	Overall Mean	Overall Std Dev	Minimum.	Maximum.	Total Observations
Private forest	5.99	1.78	2.4	12.2	193
Nature Monument	6.54	1.47	4	11	48

Table 11: crown diameter variability of the broadleaf trees

Forest Owner ship	Overall Mean	Overall Std Dev	Minimum	Maximum	Total Observations
Private forest	8.69	3.4	3.4	14.8	42
Nature Monument	8. 83	4.62	5.2	19.3	49

5.5. Biomass carbon regression modelling

Linear regression model was developed from the CPAs obtained from the tree crown delineation and their respective carbon stocks obtained from the general allometric biomass equations. R^2 for coniferous and broadleaf forests was 0.58 and 0.54, respectively. This indicates that the predictor explains about 58 and 55% of the variance in the dependent variable. Moreover, the relationship between AGB carbon and CPA is significant at $\alpha = 0.01$ for both of the forest types.



Summary of Fit

RSquare	0.582298
RSquare Adj	0.577205
Root Mean Square Error	83.87066
Mean of Response	214.3327
Observations (or Sum Wgts)	84

Analysis of Variance

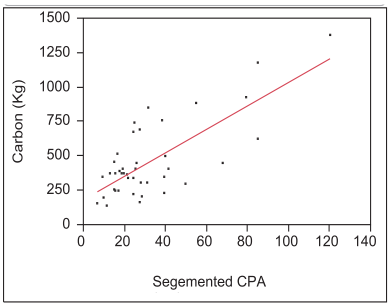
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	804106.3	804106	114.3124
Error	82	576811.5	7034	Prob > F
C. Total	83	1380917.8		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	-15.94549	23.40146	-0.68	0.4975	-62.49845	30.607474
Segemented CPA(m2)	15.547329	1.45415	10.69	<.0001 *	12.654562	18.440096

Figure 21 : Regression statistics of the coniferous trees

The model for the broadleaf and coniferous trees has RMSE of 187.06 and 83.87 kg of carbon per tree, respectively. Moreover, the confidence interval for the intercept and the slope of the model for coniferous trees is between -62.49 to 30.60 and 12.65 to 18.44 with 95 % confidence, respectively. Whereas for the broadleaf trees the confidence interval of the intercepts and slopes lays between 80.58 – 279.72 and 6.05 – 11.0, respectively.



Summary of Fit

RSquare	0.554242
RSquare Adj	0.542812
Root Mean Square Error	187.0651
Mean of Response	456.0624
Observations (or Sum Wgts)	41

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	1696874.9	1696875	48.4914
Error	39	1364740.6	34993	Prob > F
C. Total	40	3061615.5		<.0001 *

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	180.15726	49.22739	3.66	0.0007 *	80.585461	279.72905
Segemented CPA	8.5271455	1.224536	6.96	<.0001 *	6.0502879	11.004003

Figure 22 : Regression statistics of the broadleaf trees

5.6. Model validation

The validity of the model was assessed using half of the sample data. Hence, R^2 and RMSE error are computed as an indicator. The result indicates higher R^2 and lower RMSE error for the coniferous trees (Table 10).

Table 12: Model validation statistics

Tree types	R^2	MSE	RMSE	nRMSE (%)	Sample size
Coniferous	0.50	8984.93	94.84	42.28	84
Broadleaf	0.49	44910.16	211.92	45.13	41

5.7. AGB carbon mapping

The AGB carbon is modelled using the regression equation developed for coniferous and broadleaf trees.

Carbon stock for coniferous trees = -15.95 + 15.55 * segmented CPA Equation 13

Carbon stock for broadleaf trees = 180.16 + 8.53 * segmented CPA Equation 14

These regression models and the CPAs classified into coniferous and broadleaf trees through object oriented classification were used to map carbon stock for each broadleaf and coniferous tree types. The carbon stock estimate for broadleaf and coniferous trees in both private and nature monument part of the forest is presented in Table 13.

The forest in the whole study area has about 26822.29 Mg C stock. In both the nature monument and private forest part, higher mean carbon stock is found in broadleaf trees. The broadleaf trees generally have two times higher mean carbon stock than coniferous trees. The nature monument constitutes 43.29% of the total carbon stock. As compared with the broadleaf trees, the coniferous trees constituted the highest portion which is about 53% of the total carbon stock. In general the carbon density reaches about 80.31 Mg C/ha.

Table 13: Summary of carbon stock

Tree types	Carbon stock (Mg)		
	Private	Nature Monument	Total
Broad leaf	5810.11 (0.40)	6707.90 (0.39)	12518.02 (0.39)
Coniferous	9399.73 (0.17)	4904.55 (0.16)	14304.27 (0.17)
Total	15209.85 (0.22)	11612.44 (0.23)	26822.29 (0.23)

* Values in parenthesis are mean carbon stock (Mg C /tree)

Trees which have higher CPA have higher carbon stocks. In most cases broadleaf tree have the highest CPA as compared with their counterparts. However, higher CPA is rarely resulted due to errors in tree crown delineation particularly due to under-segmentation. Despite this some big coniferous trees also have higher carbon stock. The biggest CPA trees have carbon stock with a range of 2000- 2542 kg but most of the trees have carbon stocks between 17- 1200 kg. Figure 23 shows carbon stock in individual trees at different parts of the study area.

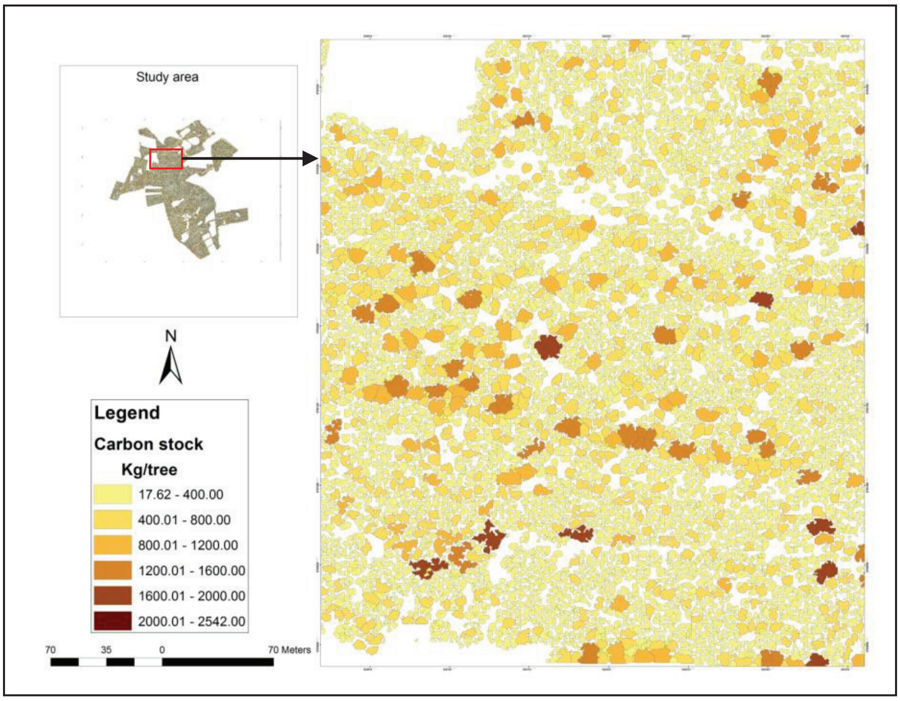


Figure 23 : Carbon stock in individual trees in part of the study area

6. DISCUSSION

6.1. Accuracy of tree crown delineation algorithms in eCognition and ITC software

eCognition provides various approaches of tree crown delineations including the most commonly used algorithms such as watershed, multi-resolution segmentation and region growing. Among the segmentation approaches, watershed transformation is the most popular and widely applicable technique of crown delineation (Ke 2008).Watershed segmentation can be carried out with marker free or marker controlled (Zhao and Popescu 2007). Both marker free and marker controlled watershed segmentations were tested for the study area however the application of marker controlled watershed transformation was constrained by difficulties in identifying the appropriate markers. Markers are points of the highest brightness values in the tree crowns and often found at the center of the tree crowns (Wang 2007). Points of high brightness values also serve as a seed in region growing tree crown delineation algorithms (Ke 2008; Li et al. 2008; Culvenor 2002).Unless appropriate markers are selected for each individual tree, accurately delineating tree crown are difficult (Ke 2007). Therefore region growing and marker controlled segmentation was not found to be appropriate for this study due to presence of multiple markers for broadleaf trees (see appendix 7). As a result, tree crown delineation in eCognition is carried out using a combination of multi-resolution segmentation and marker free watershed transformation.

As the accuracy assessment in Table 3 indicates, the multi-resolution segmentation performs better for the broadleaf trees. Despite this, higher under segmentation was observed for both coniferous and broadleaf trees. This partly indicates higher proportion of clumped trees. In multi-resolution segmentation the size of resultant image objects depends largely on the scale of segmentation (Baatz and Schape 2000). Thus controlling the size of the resultant objects can be possible by changing the scale of segmentation. However an attempt to improve the degree of under-segmentation by decreasing the scale of segmentation was not successful due to severe over-segmentation. Despite this, colour and shape of the segmentation also plays a role in the accuracy level of the Multi-resolution segmentation. In most cases the appropriate scale, shape and colour of trees varies depending on the type of tree species and the size of tree crowns as a result accurate tree crown delineation of a mixed tree species appears less successful using multi-resolution segmentation. However, to overcome the problem of under-segmentation of the multi-resolution segmentation, marker free watershed transformation was applied. In this algorithm watershed lines are created following the local minimas' but sometimes local minima's may arise within the catchment basin due to noises arising within trees crowns. As a result one tree crown might be segmented to more than one tree unless the image is well smoothed using an appropriate filter window size. Therefore, the 5x5 filter window size used in this process has greater contribution for controlling the degree of over segmentation. Hence, the tree crowns obtained from multi-resolution segmentation was transformed into marker free watershed segmentation. As a result clumped trees were segmented further to represent the individual tree crown outlines. Consequently, the overall accuracy of tree crown delineations was improved further.

The success of tree crown delineation in ITC software suite is largely dependent on the presence of shadows in between tree crowns (Gougeon and Leckie 2006). As indicated in Figure 16, ITC resulted considerable number of clumped trees whenever shadow was absent in between tree crowns. The initial accuracy assessment of the tree crown delineation indicates relatively better accuracy for coniferous than broadleaved trees (Table 5). The problem associated with delineating broadleaf tree crown is due to image noises and overlapping crowns which prevent the presence of shadows in-between crowns. A similar result was obtained from valley approach as applied to broadleaf and coniferous forests (Ke 2008). Since the CPAs were required with higher accuracy for the subsequent analysis, further refinement of the CPAs obtained from the valley following approach was essential. Hence, clumped tree crowns were selected and segmented by watershed transformation as a result more realistic tree crown outlines were derived.

6.2. Accuracies of combined tree crown delineation algorithms

Each image segmentation algorithms and software has its own limitations and advantages. For example marker controlled segmentation depends on the proper selection of markers, while region growing depends on the proper seed selection and criteria to limit the extent of region growing, and the valley following on the presence of sheds in between tree crowns (Ke 2008). The success of multi-resolution segmentation also largely depends on the selection of appropriate parameter combinations. As observed in this study area, the accuracy of the tree crown delineation from each one of the algorithm was not sufficient enough for the subsequent CPA based AGB carbon modelling. Not only in terms of the accuracy but unrealistic clumped tree crowns were apparent in large portion of the forest. Due to the variability of the success of each of the tree crown delineation algorithms as applied to different forest conditions, Ke (2008) indicated that developing a more robust algorithm with broad applicability would require taking advantage of the characteristics of multiple algorithms. Hence, in this study combining the algorithms was found to give improved tree crown delineation accuracies for both coniferous and broadleaf trees.

Combining algorithms was important in reducing the level of under segmentation. As compared to the broadleaf trees, the accuracy of coniferous trees was considerably improved as a result of combining algorithms together in eCognition (see Table 4). The broadleaf trees had slightly higher error due to high degree of over-segmentation which can be attributed to the over segmentation of the marker free watershed transformation. Delineating broadleaf tree crowns was problematic due to various reasons. Though 5x5 filter window was used, still there have been noises emerged at some part of the tree crowns. Hence object edges which facilitated the over segmentation of tree crowns was detected. Smoothing filter window often used to avoid noises in an image (Ke 2008, Gougeon and Leckie 2006). Filtering is important because on one hand, we had to use a very high resolution data of 61 cm a pixel so we can recognize every individual tree crown, but on the other the details in the image of each crown were too much in such a way that we had to use smoothing filter to reduce the variability in many pixels representing one crown. Therefore, it plays a key role in controlling the degree of over and under segmentation.. As the filter window size increases, the tree crown delineation tends to under segment the image objects (Li et al. 2008). Further increment in the filter window size however was not appropriate as it increased under segmentation of the image. Different size tree crowns requires different smoothing filter window (Wang 2007, Ke 2008, Li et al. 2008). However, applying an appropriate smoothing filter window size is a problem whenever there is mixed coniferous and broadleaf trees with variable crown sizes. Moreover, a separate parameter combination of scale, shape and compactness was applied to the plot where the majority of the tree types were coniferous and broadleaf. However, in reality the forest in the study area has no pure coniferous and broadleaf stands. Therefore, some broadleaf trees which were found in the coniferous forest stand were segmented with the parameter combination which was appropriate for coniferous trees leading to their over-segmentation.

The implementation of the valley following and watershed transformation together in the ITC and eCognition environment, respectively was also found to be effective than using a single algorithm. As the accuracy assessment after the watershed transformation of the clustered Isols obtained from the valley following approach, indicated in Table 6, the accuracy for both coniferous and broadleaf trees have improved considerably. This is because unlike the valley following approaches, the watershed transformation does not need the presence of shades between tree crowns to segment the clustered trees. The brightness values of tree crowns often decreases from the centre to the edge of the tree crown. So as long as there are local minima's which was often the case in clustered trees, boundaries which separate adjacent trees of the clustered trees was created. Therefore, watershed transformations overcome the limitation of the valley following approach associated with the absence of shades. Hence, the improvement in the accuracy of CPAs is due to the improvement in the level of under segmentation. Despite this, the partial watershed transformation was highly beneficial for improving the accuracy of coniferous trees relatively better than broadleaf trees. This happened due to the structural variation of the tree crowns of both forest types. The coniferous trees have compact crowns with less noise unlike the broadleaf trees (Ke 2008).

The accuracy of tree crown delineation can also be assessed in terms of correspondence between delineated and reference tree crowns (Ke 2008). Hence, the combination of multi-resolution and marker free watershed transformation, and, valley following approach and marker free watershed transformation were compared to each other in terms of degree of correspondence to reference objects. As indicated in Table 14 and 15, higher percentage of 1:1 correspondence (78%) was apparent in between automated CPAs obtained from a combination of valley following and marker free watershed transformation, and manually digitised reference CPAs for both forest types. In contrast, broadleaf trees have less percentage of 1:1 correspondence in both algorithm combinations and results obtained from a combination of multi-resolution segmentation and marker free watershed transformation gave high commission errors (Table 14) indicating the over segmentation of one or more objects. Since, previously done researches used a single algorithms (Gougeon and Leckie 2006; Ke 2008), comparing the result directly was not possible. Despite this, Ke (2008) compared the accuracy of three algorithms: valley following, region growing and watershed transformation. According to his accuracy assessment, which is based on degree of correspondence between delineated and reference trees, region growing was better followed by watershed transformation. Valley following was giving clustered trees particularly in the forest region where no thinning was performed. However, all the three algorithms performed well in delineating coniferous trees, whereas sever over-segmentation was a problem in delineating broadleaf trees. Gougeon and Leckie (2006) also got better tree crown delineation accuracy for coniferous trees than broadleaved using valley following approach of tree crown delineation.

Table 14: Correspondence of delineated and reference tree crowns in ITC and eCognition

Tree types	Reference CPA : Delineated CPA					
	1:0	1:1	1:2	1:3	1:4	>1:4	Total
Coniferous	2	53	11	3	0	0	70
	(2.86)	(75.71)	(15.71)	(4.29)			
Broadleaf	0	19	5	3	2	4	33
		(57.57)	(15.1)	(9.09)	(6.0)	(12.12)	

*the values in parenthesis are percentages

Table 15: Correspondence of delineated and reference tree crowns in eCognition

Tree type	Reference CPA : Delineated CPA					
	1:0	1:1	1:2	1:3	1:4	>1:4	Total
Coniferous	3 (4.27)	50 (71.41)	12 (17.14)	4 (5.71)	1 (1.42)	0	70
Broadleaf	0	18 (54.54)	5 (15.24)	3 (9.09)	2 (6.06)	5 (15.15)	33

*the values in parenthesis are percentages

Generally, in a forest where there are mixtures of different forest types, single algorithm might not give the required accuracy level and combing algorithms help to tap the advantages offered by each algorithm for a better accuracy and realistic tree crown delineation.

6.3. Object based classification and accuracy assessment

Object based classification is the processes of assigning homogeneous objects created through image segmentation into the same class based on spectral and textural characteristics of objects. The driver of this type of classification is to overcome the within object variation and it is extensively applied to image objects derived through segmentation from high spatial resolution images (Aplin and Smith 2008). Object based classification of the CPAs is intended to apply a separate regression model which suites the coniferous and broadleaf forest tree types.

The CPAs delineated through image segmentation are classified into coniferous and broadleaf forests by taking a signature from 9 species. As shown in Table 9, the user's accuracy of the coniferous trees was considerably higher than broadleaf trees. This reflects the coniferous trees are more reliably classified than broadleaved trees; hence the likelihood for the user to find the same coniferous tree on the ground is higher. Whereas, the producer's accuracy is slightly higher for broadleaf trees which indicates that the broadleaf trees on the map represent most of the broadleaf trees with minimal omission error. Most of the broadleaf trees in the study area are bigger in size and the influence of shades to affect the classification accuracy is minimal. Hence, easier classification of the broadleaf trees is partly due to the size of trees. Better producer accuracy was also found for broadleaf trees than the coniferous as applied to IKONOS image of a plantation forest (Gougeon and Leckie 2006). Both producer and user accuracies are expressed in the overall accuracies and hence 74% of the CPAs were correctly classified. The classification errors are generally arising due to the spectral similarity of species, shadows and the accuracy of tree crown delineations. As the visual assessment of the false colour composite image indicated, spectral similarity exists in different species particularly in between big Norway spruce and most broadleaf trees. Spectral differentiation in uneven aged trees composed of different species is often difficult (Gougeon and Leckie 2006). Big trees can affect the spectral characteristics of the nearby tree crowns by casting a shadow on it. Since the current forest under investigation is composed of different size trees in terms of height and tree crown size, their influence on the CPA classification was apparent. In addition to the spectral characteristics, the geometry of the tree crown such as the CPA was one of the most important variables involved in the feature space optimization to distinguish between broadleaf and coniferous trees. Hence, whenever big crown sizes are over-segmented, they tend to be similar in size with the coniferous trees facilitating misclassification. Despite this the kappa coefficient of agreement is less than 50%. This indicates the correctly assigned pixels might have been partly assigned by chance and not based on the classification decision rule (www.nrcan.gc.ca, 2011).

6.4. Estimation and mapping of AGBC

The AGB carbon estimation was made by using linear regression model as the best fit curve was linear. This indicates that the carbon stock continues to increase linearly with the increase of the CPA. However, Shimano (1997) found the best fit curve between DBH and CPA relationships to be power sigmoid. The power sigmoid curve assumes that the rate of CPA increment decreases overtime due to the competition of nearby trees for sunlight, nutrients and space. However, some studies found linear relationship between DBH and crown diameter. Particularly strong linear relationship exists for trees with a DBH range of 20- 50 cm and slight reduction in the rate of CPA growth appears due to the effect of senility for DBH exceeding 50 cm (Hemery et al. 2005). Moreover, the basal density appears to have its influence on the CPA-DBH relationship because in less dense forests the CPA can continue to grow without the effect of competition from the nearby trees. Therefore, the linear relationship obtained in this research can partly indicate that the effect of competition on the CPA of trees is insignificant. As described in section 4, this can be due to the fact that the forest is a plantation forest and thinning and selective harvesting are common management practices which make distances between trees and the relationship be linear. Generally, as the result in Figure 21 and 22 indicates, the residual variance from linear regression equation is lower for coniferous trees than broadleaved. However, still considerable amount of the variance remains unexplained by the model and as a result the model needs further improvement. This can be achieved by improving the accuracy of tree crown delineation (Hirta et al. 2009). Moreover, the allometric equation and the AGB carbon model do not fit to each other very well because the allometric equation used takes the form of power function (see Equations 5-12 on page 28) and the AGB carbon is linear model. Therefore, locally developed allometric biomass equations seem more appropriate.

The AGB carbon is mapped using the linear regression equation developed for the coniferous and broadleaf tress. The broadleaf trees in general have two times higher mean carbon stock than the coniferous trees. This is because the broadleaf trees in the study area are bigger in size than their counterpart. Among the total carbon stock in the forest, the highest proportion is found in the coniferous trees as the forest is dominated by coniferous trees. Moreover, the private forest part which constituted the highest number of trees (59%) constituted about 57% of the total carbon stock. Generally, the carbon stock density is about 80 Mg C/ ha. The biomass carbon estimation varies depending on the method of assessment employed, and comparing estimates made by different approaches might not give a good picture of the accuracy of estimation. Despite this as compared to the general estimates made for the Netherlands which is made based on standing stock approach (Annual increment –harvest) (Nabuurs 2000), this estimate has about 26% difference being the general estimate for the Netherlands be about 59 Mg C/ ha (Nabuurs and Mohren 1993). Moreover, remote sensing technique based estimation of the carbon stock in woody biomass are in the ranges of 25 - 60 Mg C/ha for different countries, the average being 42.91 Mg C/ha (Figure 24). However, remote sensing estimates which are often made from very coarse satellites have larger uncertainties particularly due to occurrence of mixed pixels and a huge difference between the size of field-measurement data and pixel size (Lu 2006).

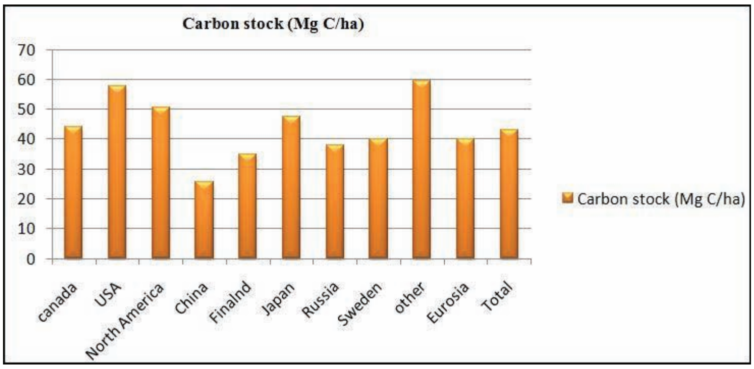


Figure 24: Remote sensing estimates of carbon pool (1995–1999) and sink in total woody biomass of temperate and boreal forests in North America and Eurasia (USDA 2003).

6.5. Uncertainities and sources of errors in tree crown delination and AGB carbon modelling

Tree crown delineation using high spatial resolution enabled us to estimate the AGB carbon at individual tree level. However, it has some uncertainties and sources of errors where further research and improvements are required. Most studies express the errors in regression modelling in terms of the root mean square error (RMSE) of the model (USDA 2003, Harrell et al., 1997). The RMSE error in this model is in the order of 0.084 and 0.19 Mg C / tree for coniferous and broadleaf trees, respectively. Moreover, as the confidence interval of estimation in Figure 25 indicated, coniferous trees are estimated with less uncertainty. For example, a tree with 20 m^2 CPA of coniferous and broadleaf trees will have an estimated carbon stock of 0.29 and 0.35Mg C, respectively. These are estimated by the models to be between 0.12 to 0.46 Mg C and -0.03 to 0.73 Mg C with 95% confidence interval for coniferous and broadleaf trees, respectively. Generally, the carbon estimation for coniferous and broadleaf trees laid between ± 0.17 and ± 0.38 Mg C with 95% confidence interval, respectively. This indicates the presence of much uncertainty in both models. However, comparing the results with previously done researches was not possible due to the scarcity of similar studies.

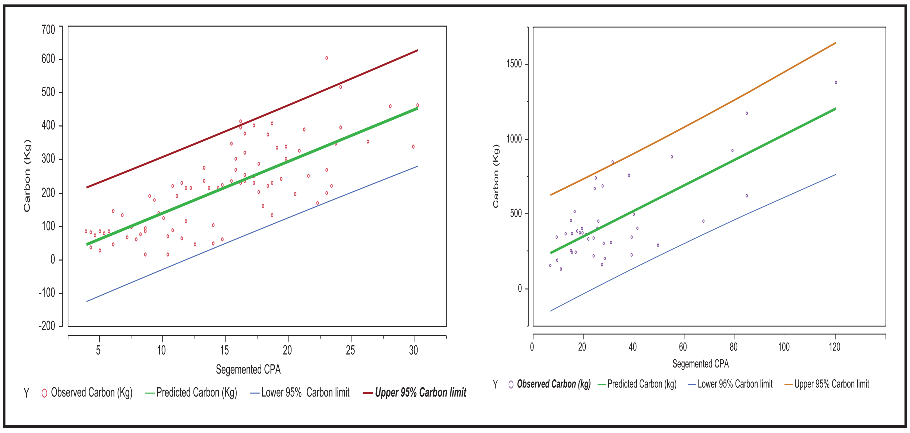


Figure 25: Confidence intervals of the model AGB carbon estimation for coniferous (left) and broadleaf (right) trees.

The sources of error may ranges from the data collection in the field to tree crown delineation phases. Sample tree location and DBH measurement in the field is mainly supported by Ipaq GPS and the printed image. The GPS signal can however be degraded by various factors such as by the satellite position, noise in the radio signal, atmospheric conditions and natural barriers to the signal. Noise can create an error between 1 to 10 meters and results from static or interference from something near the receiver or something on the same frequency. Barriers between the satellite and the receiver can produce error, sometimes up to 30 meters (www.maps-gps-info.com 2011). The most accurate determination of position occurs when the satellite and receiver have a clear view of each other and no other objects interfere. However, some degrees of uncertainties were prevalent as the GPS signal was degraded by forest canopies and clouds particularly in plots where there was overlapping crowns. Hence, if an error in tree DBH measurement is made the error in the AGB carbon will be inevitable. Therefore, some degrees of uncertainties which can be a source of error for the AGB carbon modelling are embedded on the difficulties of accurately identifying the sample trees. Moreover, field DBH measurements have systematic errors which can affect the quality of the regression model (Zhang et al. 2010).

The allometric biomass equation has also its own influence on the AGB carbon estimate of the model. Each tree species has specific allometric pattern and mostly species specific allometric equations are recommended. However, due to difficulties of classifying CPA for each tree species, all the CPA were classified into broadleaf and coniferous classes and general allometric equations were used. The general allometric equation however is developed from quite high number of coniferous and broadleaf tree species (Lambert et al. 2005), as result errors seems inevitable. As the comparison between the species specific and general allometric equation estimates of biomass carbon for coniferous and broadleaf trees indicated, there exist nRMSE of 22% and 42%, respectively. Both of the general allometric equations have underestimated the biomass carbon stock of coniferous and broadleaf trees (See Figure 26).

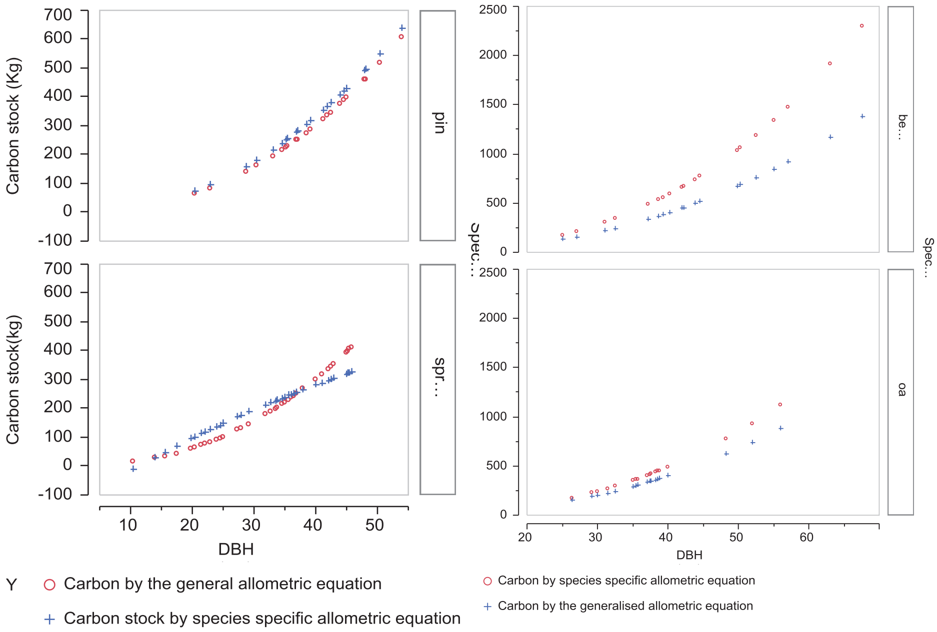


Figure 26: Comparison of the General and species specific allometric equation biomass carbon estimation

Accurate tree crown delineation is a key factor for estimating other variables based on CPAs derived from image segmentation (Ke 2008). A slight change in over segmentation and under segmentation can affect the relationship between AGB carbon and CPA. As indicated in Table 6, the goodness of fit reveals about 20 and 34% in the degree of mismatch between delineated and reference crowns due to over and under-segmentation for coniferous and broadleaf trees, respectively. This indicates the existence of random error in the model. However, the ordinary least square (OLS) regression used in this model assumes no error in both the response and the regressor variables (Zhang et al. 2010). Therefore, errors in the model can be attributed to the errors in the CPA delineations.

The form of relationship between CPA and carbon stock varies with different forest species. As indicated in Table 16, for most of the species there exists good relationship between CPA and carbon stock. However, for Scot Pine the CPA and carbon stock relationship is poor because the CPA does not increase with increasing DBH. As a result developing a model combining all the coniferous and broadleaf tree species influences the accuracy of the model.

Table 16: Relationship between CPA and carbon stock of different coniferous and broadleaf tree species

Forest tree types	Species	R^2
Broadleaf	Oak	61
	European beach	54
Coniferous	Scot pine	40
	Norway spruce	65
	Douglas fir	57

Omission and commission errors arising from misclassification of CPA are the other sources of errors. As the classification accuracy indicated in Table 9, there is 26 % total classification errors of CPAs which arises either due to omission and commission error for both types of forests. Thus, there exist some broadleaf trees whose carbon stock was estimated by the model developed for the coniferous forest and vice versa.

Generally, the errors associated with field sample DBH measurement and tree crown delineation error propagates to affect the accuracy of AGB carbon estimation. Figure 27 shows the summary of the error propagations.

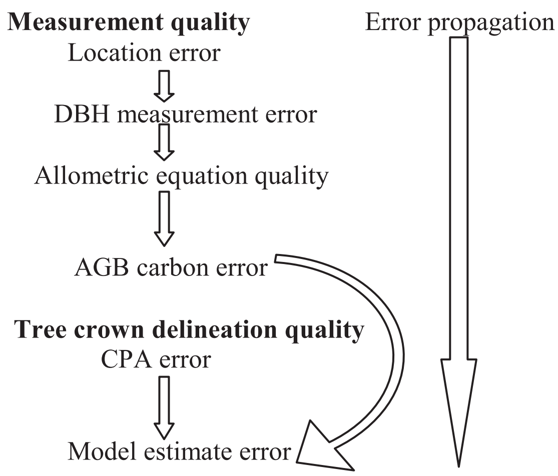


Figure 27: Error propagation.

7. CONCLUSION AND RECOMMNDATION

The general objective of this research was to assess the AGB carbon stock in coniferous and broadleaf forests using high spatial resolution images. To achieve this objective a new and robust method which enables carbon estimation at individual tree level is developed. The method overcomes the drawbacks of most of the conventional carbon estimation techniques. In times as today when forest carbon estimation is needed at higher accuracy, this method showed its potential in meeting this demand though the model needs further researches for improvement.

The study employed object based analysis on Quick-bird image with 0. 61 m spatial resolution and field measured DBH data. The CPA of trees was derived through tree crown delineation using ITC and eCognition software. This was followed by accuracy assessment, selecting the best tree crown delineation and object based classification, respectively. Eventually, the relationship between AGB carbon and CPA was investigated using a regression model. This model was then used to estimate the AGB carbon of individual trees in the study area. Hence the research questions defined in section 1.4 were properly answered.

1) **How accurately can tree crowns be delineated by eCognition and ITC software? Which method yields the best accuracy for coniferous and broadleaf trees?**

The accuracy and applicability of tree crown delineation varies depending on the forest type, the tree crown delineation algorithm, the image type used and the image pre-processing. Among different approaches of tree crown delineations in eCognition, multi-resolution segmentation algorithm was found to be appropriate. Using this approach 59 and 61% accuracy was obtained for coniferous and broadleaf trees, respectively. Whereas in ITC valley following approach is the only tree crown delineation approach. Hence, from this approach 75 and 65% accuracy was obtained for the coniferous and broadleaf trees, respectively. As compared with the multi-resolution segmentation in eCognition, the valley following approach gave better accuracy for both tree types. Despite this, the two software and algorithm yielded higher level of under segmentation for both forest types. The level of under segmentation however was overcome by applying the marker free watershed transformation to the CPAs obtained from multi-resolution and valley following approaches. As a result from multi-resolution segmentation and marker free watershed transformation the overall accuracy was improved from 59% to73% for coniferous trees and from 61 to 67% for broadleaf trees. Moreover in terms of correspondence 71 and 55% of the coniferous and broadleaf trees, respectively have 1:1 correspondence with reference tree crowns. Whereas the valley following approach in ITC software followed by partial marker free watershed transformation in eCognition have improved the accuracy from 75 to 80% for coniferous trees and from 65 to 66% for broadleaf trees. This algorithm combination however resulted 76 and 58% 1:1 correspondence for coniferous and broadleaf trees, respectively.

2) How accurately can the CPA of coniferous and broadleaf forests be classified?

The CPAs are classified with 74% overall accuracy. The coniferous trees are classified with 88% user and 71% producer accuracy. Whereas the broadleaf trees were classified with 55% user and 80% producer accuracies but the kappa coefficient of agreement of classes was only 45%.

3) How accurately can the AGB carbon of the study area be estimated using regression equation?

The linear regression models have explained about 58 and 55% of the variance in carbon stock for coniferous and broadleaf trees, respectively. Moreover, the models for the coniferous and broadleaf trees have RMSE of 0.084 and 0.19 Mg C/tree, respectively. The AGB carbon estimation in generally varies ± 0.17 and ± 0.38 Mg C with 95% confidence interval for coniferous and broadleaf trees, respectively.

4) How forest biomass and carbon stock can be mapped using Quick-bird satellite image?

The regression model developed for the coniferous and broadleaf trees is used to estimate the AGB carbon of each individual tree in the study area. As a result, the AGB carbon stock of each individual tree is estimated. The forest in general has about 26822 Mg C stock among which about 53% is found in coniferous trees. This is equivalent to 80 Mg C/ha. The private forest constitutes about 57% of the total carbon stock. The broadleaf trees generally have more than two times higher mean carbon stock than their counter part.

In general, High spatial resolution satellite images like Quick-bird are endowed with immense capabilities in providing information at individual tree level. These capabilities can however be tap whenever field measured data and object made analysis are made with caution by minimizing errors. So, In addition to GPS locations, field DBH measurements should be supported by existing documentary maps of the location and species of plantation. The sampling technique also should consider the density of the forest and the trees species types. This can help to accurately characterise the relationship between CPA and DBH. Moreover, locally adaptive allometric equations would be more appropriate than using general equations. Tree crown delineation should be done with much higher accuracy. This can be partly achieved by using appropriate filter window size, the appropriate tree crown delineation algorithm and accuracy assessment techniques.

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APPENDIXES

APPENDIX 1: DATA COLLECTION FORM FOR HAAGSE BOS

Name of recorder... **Date**.. **Plot radius size**.......12.62m.................

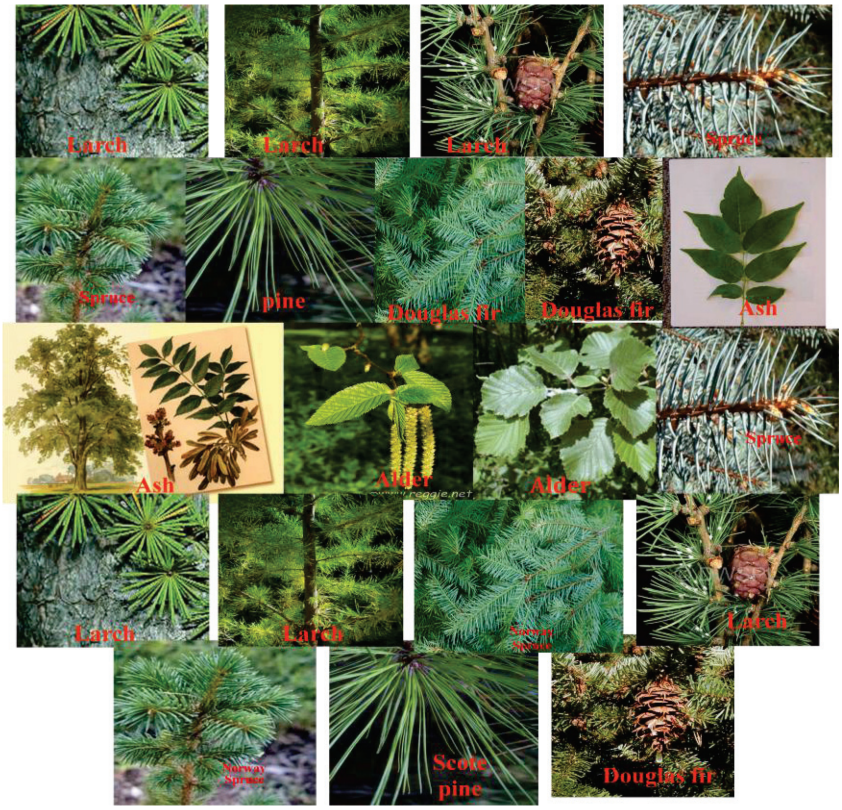
Sampling Plot No.	Map scale	Map No.	Grid ref. Land Mark X	Y	Dist. to centre of plot. (m)	Bearing to centre of plot.	Elevation	Slope (%)	Aspect
								0	0

Forest characteristics:

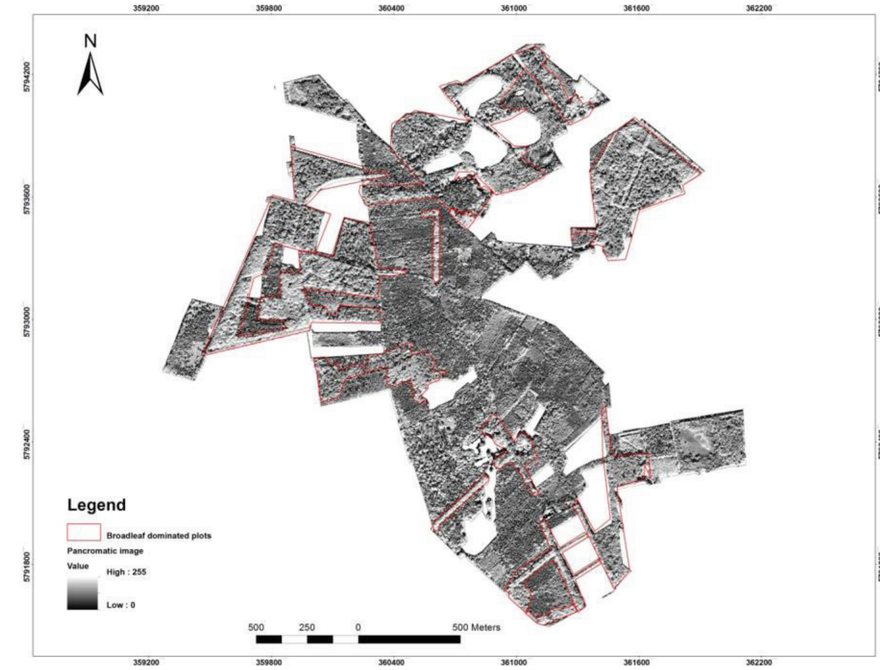
Land cover				Forest use type			Stand composition		Type of stand		Crown cover (%)	Undergrowth	
									P	N		G	N

Tree No.	Species	DBH (cm)	Height (m)	Crown diam.(m)	Remark	Tree No.	Species	DBH (cm)	Height (m)	Crown diam(m)	Remark
1						16					
2						17					
3						18					
4						19					
5						20					
6						21					
7						22					
8						23					
9						24					
10						25					
11						26					
12						27					
13						28					
14						29					
15						30					

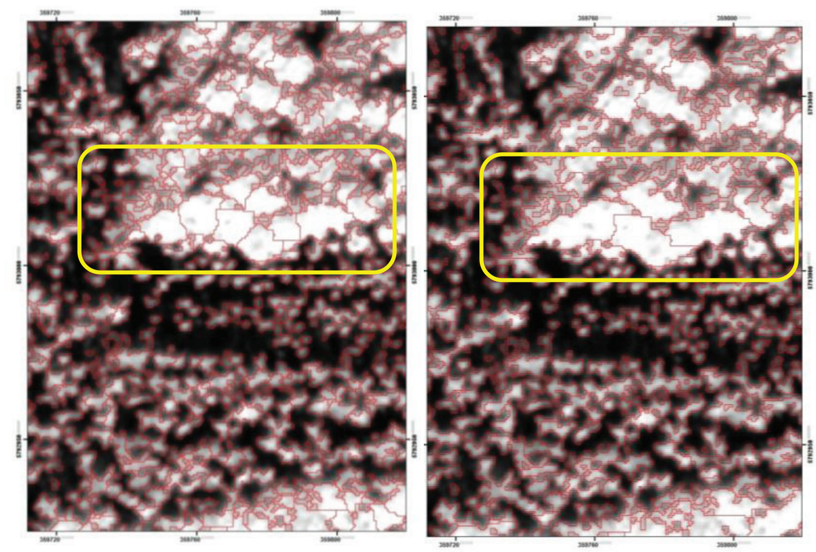
APPENDIX 2: Tree species picture index used for species identification during the field data collection.



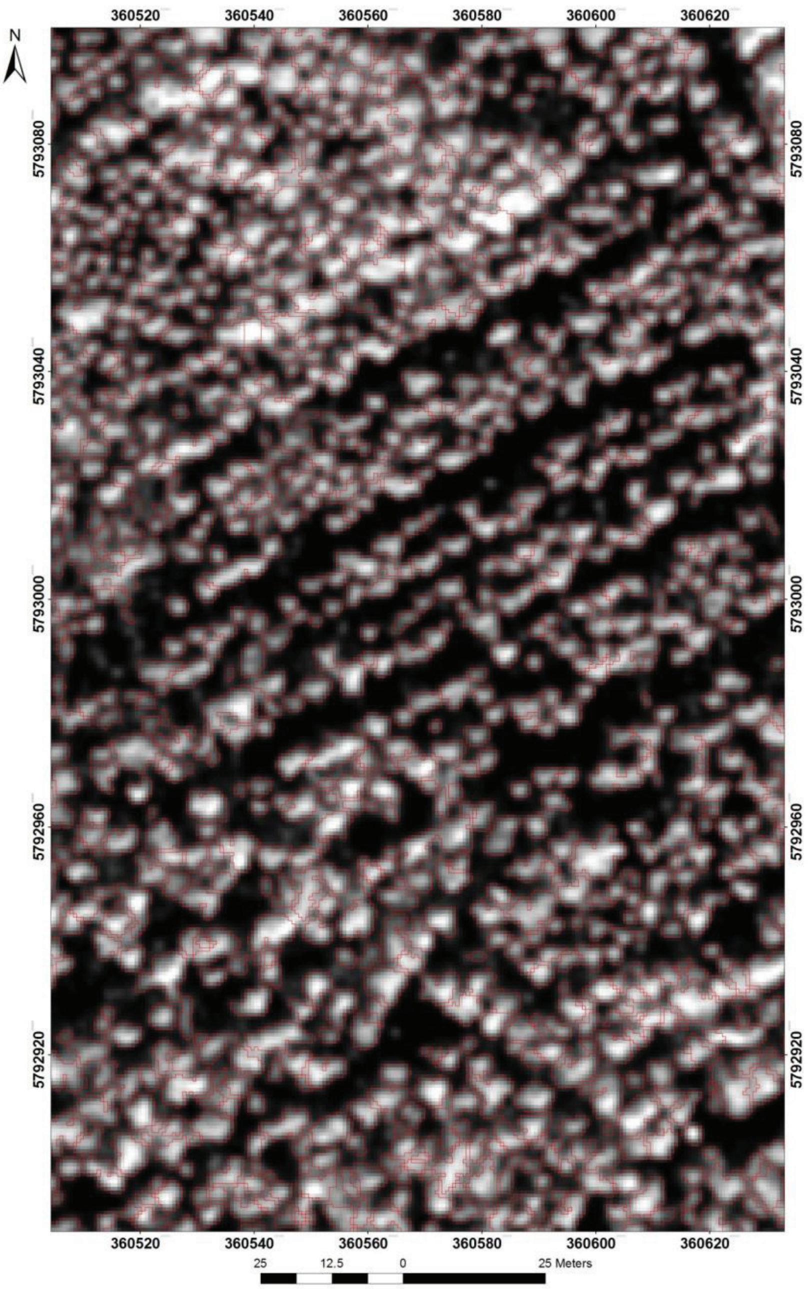
APPENDIX 3: Broadleaf and coniferous tree plots where a separate parameter combination of Multi-resolution segmentation was applied.



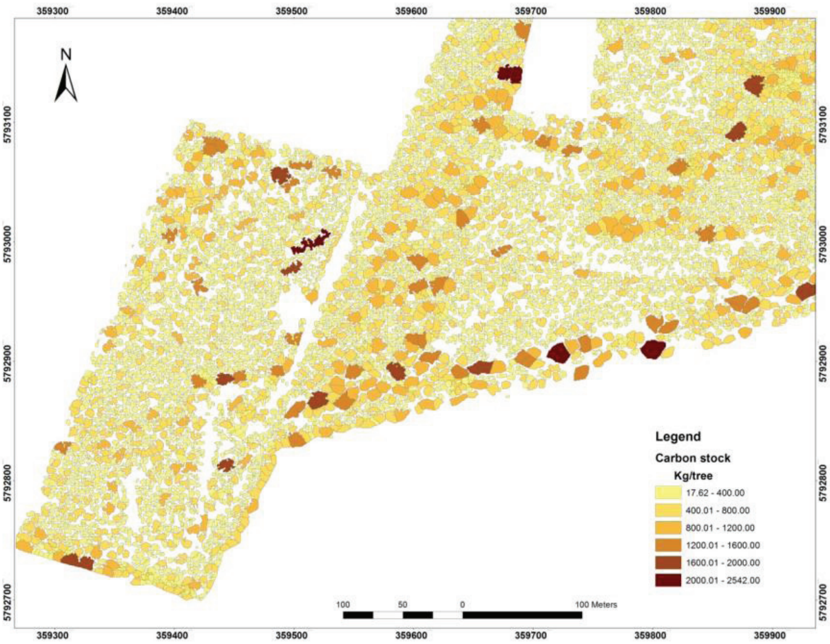
Appendix4: Multi-resolution segmentation image in west part of the nature monument forest (left) and the same image after watershed transformation.

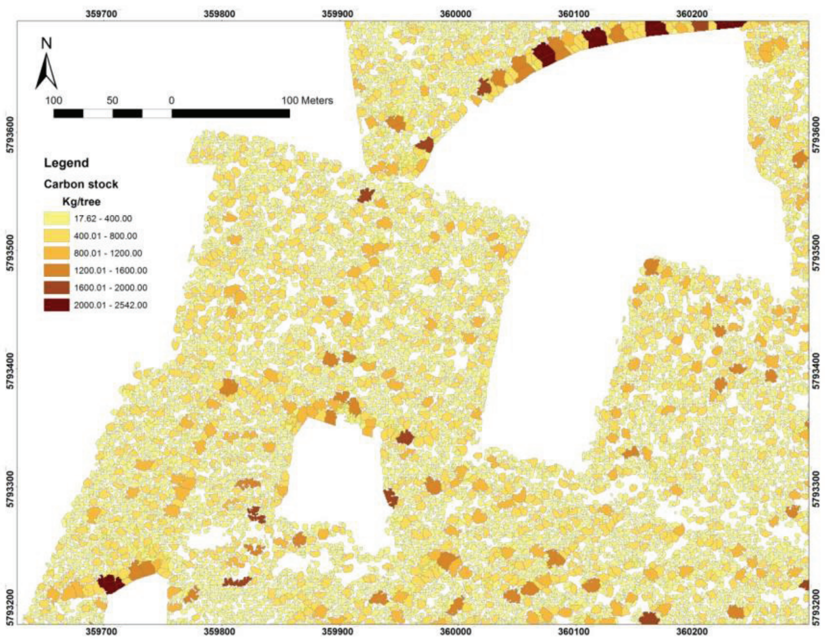


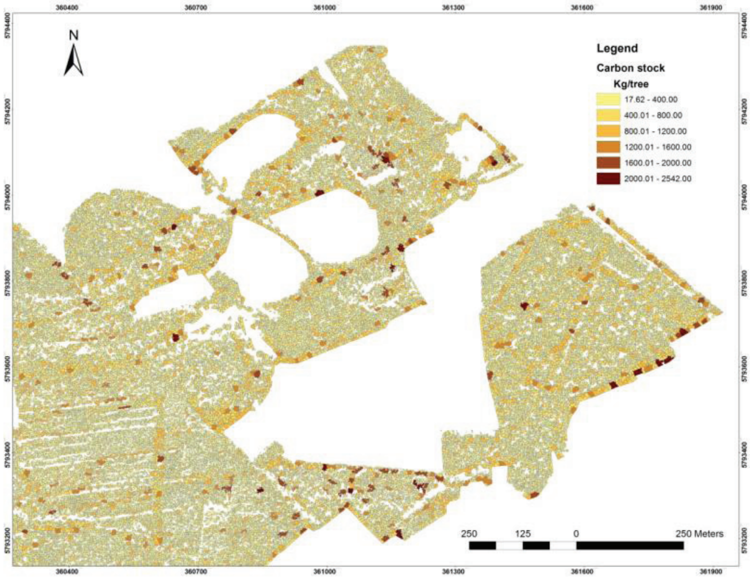
APPENDIX 5: Tree crown outlines obtained after tree crown delineation in ITC software for part of the study area.

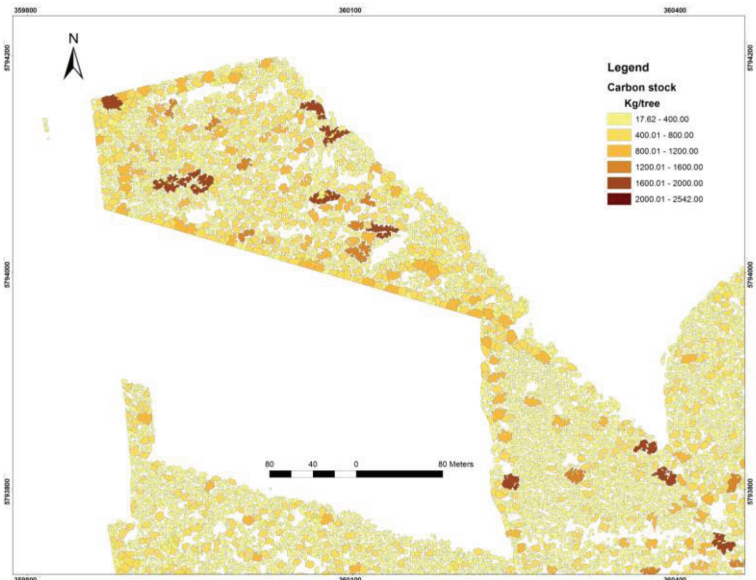


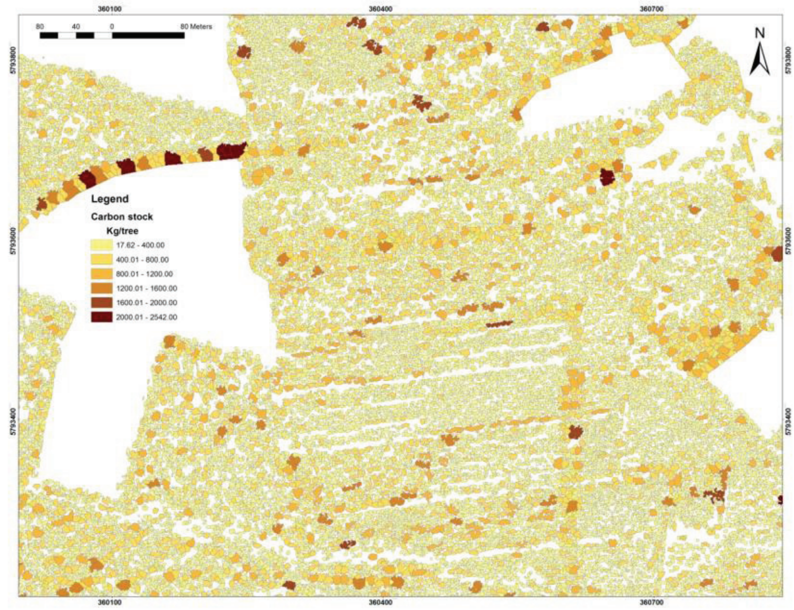
APPENDIX 6: Carbon stock estimate for different parts of the study area.

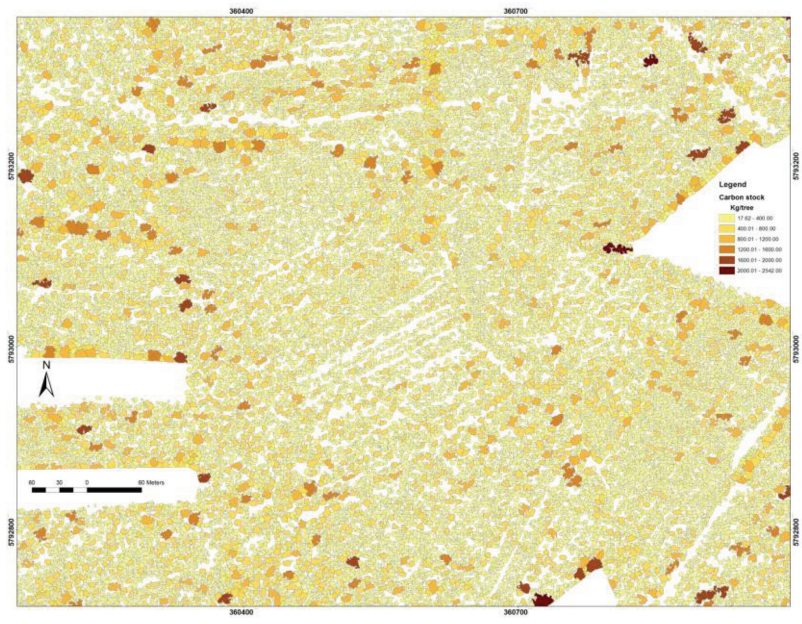


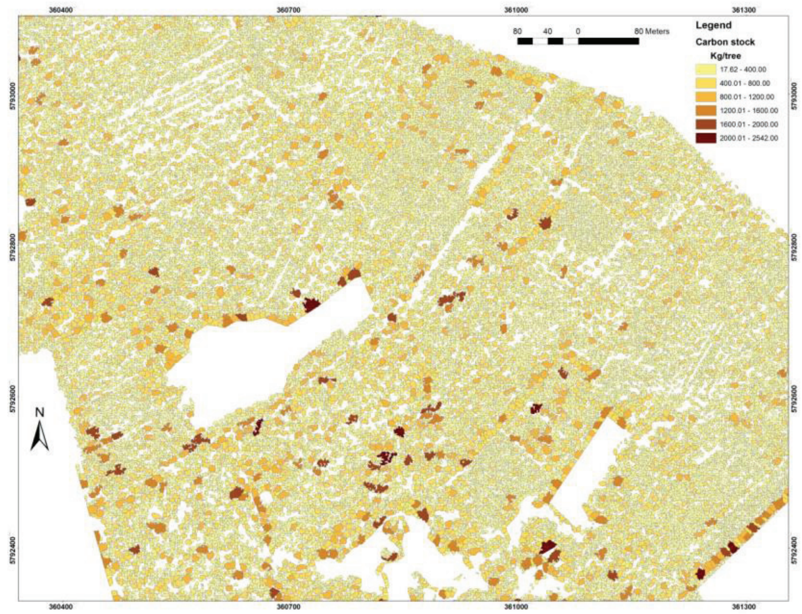



N
Legend
Carbon stock
Kg/tree
17.62 - 400.00
400.01 - 800.00
800.01 - 1200.00
1200.01 - 1600.00
1600.01 - 2000.00
2000.01 - 2542.00
250 125 0 250 Meters
360400
360700
361000
361300
361600
361900


N
Legend
Carbon stock
Kg/tree
17.62 - 400.00
400.01 - 800.00
800.01 - 1200.00
1200.01 - 1600.00
1600.01 - 2000.00
2000.01 - 2542.00
80 40 0 80 Meters
359800
360100
360400


360100
360400
360700
80
40
0
80 Meters
N
5793800
5793600
5793400
Legend
Carbon stock
Kg/tree
17.62 - 400.00
400.01 - 800.00
800.01 - 1200.00
1200.01 - 1600.00
1600.01 - 2000.00
2000.01 - 2542.00


360400
360700
5793200
5793000
5792800
N
Legend
Carbon stock
Kg/tree
17.62 - 400.00
400.01 - 800.00
800.01 - 1200.00
1200.01 - 1600.00
1600.01 - 2000.00
2000.01 - 2542.00



APPENDIX 7: MARKERS IDENTIFIED BY LOCAL MACIMA FILTER (RED COLOUR PIXELS) FOR SOME PORTION OF THE STUDY AREA.