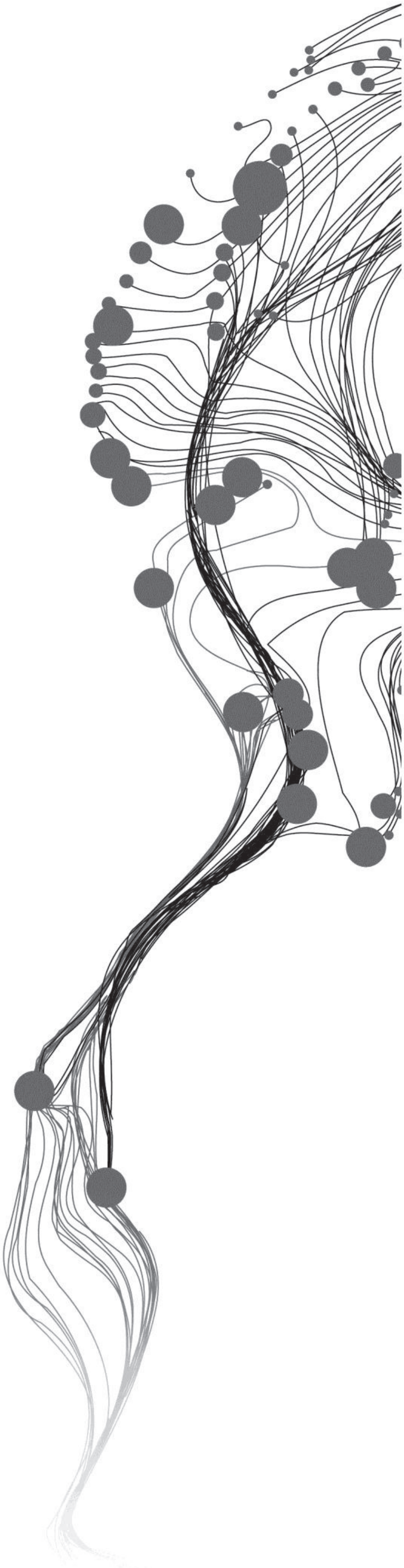
CARBON ESTIMATION OF INDIVIDUAL TREES USING HIGH LASER DENSITY DATA OF AIRBORNE LIDAR

(A CASE STUDY IN BOIS-NOIR, FRANCE)

FATEMEH HATAMI
February, 2012

SUPERVISORS:
Dr. H.A.M.J. van Gils
Dr. Y. A. Hussin



CARBON ESTIMATION OF INDIVIDUAL TREES USING HIGH LASER DENSITY DATA OF AIRBORNE LIDAR

(A CASE STUDY IN BOIS-NOIR, FRANCE)

FATEMEH HATAMI
Enschede, The Netherlands, February, 2012

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

SUPERVISORS:
Dr. H.A.M.J. van Gils
Dr. Y. A. Hussin

THESIS ASSESSMENT BOARD:
Dr. A.G. Toxopeus (Chair)
Dr. Ir. R. van der Velde (External Examiner, ITC)

ABSTRACT

Airborne lidar (Light Detection And Ranging) is a proven technology which can be solely used to accurately assess aboveground forest biomass and carbon stock. The overall goal of this study was to develop a model for assessing carbon stock for individual trees of *Pinus uncinata* and *Pinus sylvestris* using high density of LiDAR data for extraction of forest biophysical metrics such as tree height and crown projection area (CPA).

The novelty of this research lies in comparing original canopy height model (CHM) derived from highest point density (164 point/m^2) of LiDAR data with four CHMs with lower point density generated using simple thinning algorithm in order to investigate how the average point density of lidar data affect the accuracy of forest biophysical models. Two methods, 'TreeVaw' and 'Region Growing' applied to detect trees and delineate the crown of individual trees.

The overall accuracy of tree detection from TreeVaw and Region Growing approaches were compared. It was found that tree detection and crown delineation using Region Growing gives a better result with accuracy of 79.0% comparing to TreeVaw approach with accuracy of 72.6% while there was no significant difference for the accuracy of extracted tree height between two approaches.(R^2= 82.5, RMSE=1.8 m R^2= 0.80, RMSE=1.2 m respectively).

Overall accuracy and D value for segmentation result for four CHMs derived from thinned LiDAR data revealed a decrease in accuracy of tree detection and height extraction when point density between CHMs declines. This decrease of density from 164 to 4 point/ m^2 has a declined trend of accuracy from 79.0% to 66.1% for tree detection and from R^2= 0.80 to R^2=0.63 for tree height. In addition, D value for segmentation accuracy revealed an increase from 0.18 for CHM with highest point density to 0.33 for CHM with lowest point density.

A multi linear regression model was developed using height and crown area as predictors to estimate carbon stock of pine (R^2= 0.56). The validation of the model found that the 65% (RMSE=22.83 kg/tree) of calculated carbon can be explained by the developed carbon model.

ACKNOWLEDGEMENTS

Apart from the efforts of me, the success of any project depends largely on the encouragement and guidelines of many others. I would like to take this opportunity to express my special gratitude to all people whose efforts and contributions were valuable for me to accomplish my study. This has been a major achievement of my life.

First and foremost I would like to gratefully acknowledge the enthusiastic supervision of Dr. H.A.M.J. (Hein) van Gils for his continuous and creative guidance, constructive feedback, critical suggestion and words of encouragement. Many thanks goes to my second supervisor Dr. Y.A. (Yousif) Hussin for bringing ideas to shape my work and his support to me from inception till the end of my work.

A special gratitude goes to my Course Director, Dr. M.J.C. (Michael) Weir, for his support, advice during my research period and his sincere concern for welfare of all NRM students throughout the course. I am also thankful to NRM department faculty member who supported my study.

I would like to acknowledge the sponsorship I received from Erasmus Mundus funed by European Union who provided me the access to the latest developments in this thematic field of technology and sciences.

Besides, my appreciation goes to Dr. M.W. (Menno) Straatsma from Earth System Analysis Department for his valuable support and his help to get start with soft ware used is this research.

I am very grateful to Khamarrul Azahari Razak, PhD student for his sincere help and valuable suggestion from the very beginning till the end of my work.

My appreciation goes to Jean-Philippe Malet from University of Strasbourg, School and Observatory of Earth Sciences, Strasbourg, France for his warmly consideration to provide useful information for me.

And I would like to express my special thank to my all classmates who were always there for me in my hard time and your willingness to help each other during the research period especially Vinod Kumar and Ameya Gode, my team's members, for their support throughout the research and field work. Besides, my deepest appreciate goes to my parents who always give me the strengths and support during my life, finally an honourable mention goes to Alwin, my beloved partner, for his constant love and his understanding. He has always encouraged me towards excellence.

Lastly, I offer my regards and blessings to all of those who supported me in any respect during the completion of the research.

Without helps of the particular that mentioned above, I would face many difficulties while doing this study.

"This work is dedicated to my beloved partner, Alwin, without whose caring support it would not have been possible"

Fatemeh Hatami
13-02-2012

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Background

Forests have major roles in mitigating climate change by sequestering carbon. They absorb CO2 from atmosphere and store carbon through photosynthesis process in their leaves, stem, roots and branches. Forest biomass is organic matter resulting from primary production through photosynthesis minus consumption through respiration and harvest. Biomass estimation provides information on the structure and fictional attributes of a forest. Relatively 50% of dry forest biomass comprised of carbon (UNFCCC, 2010b). Forest contribute about one-sixth of global carbon emissions when cleared, overused or degraded (FAO, 2011). Forests are the largest global terrestrial carbon, 650 Giga tone, of which 44 % in the biomass, 11 % in dead wood and litter and 45 % in the soil (FAO, 2010). Globally, carbon stocks are decreasing at about 10 Giga ton for the period 1990-2010 as a result of forest fire, over logging or land use change. At a regional level, the South America suffered the largest net loss of forest between 2000 and 2010 followed by Africa and Oceania whereas the forest area in Europe continued to expand (FAO, 2010).

The Kyoto Protocol, linked to UNFCCC, request all member countries to assess and report national greenhouse gas emission regularly including carbon emission reflected at carbon stock changes in forests. They have been identified the need to establish an accurate inventory of forest carbon stocks.

The Clean Development Mechanism (CDM) is one of the mechanisms of the Kyoto Protocol by which carbon emission reduction and its estimation took on economic value. This in turn allows emission-reduction projects such as afforestation/reforestation projects in developing countries, that are particularly vulnerable to the adverse effects of climate change, to earn Certified Emission Reduction (CER) credits, each equivalent to one ton of CO2. These credits can be traded and sold and used by industrialized countries to meet their emission reduction targets under the Kyoto protocol (UNFCCC, 2010a). Therefore having accurate estimation of carbon stock of forest biomass is increasingly necessary.

Remote Sensing (RS) has been confirmed as an important mapping technique to estimate biomass in a larger area. Forest biomass measurement is required input to estimate carbon stock. Allometric equation is a direct field-based method by which wet and dry biomass of different part of trees (branch biomass, total foliage biomass, crown biomass, biomass of root and stem volume) are estimated. Though the direct way to quantify biomass by measuring sample trees in the field is an accurate approach for a particular location; it is time consuming, expensive, destructive and impractical in larger areas. The strengths of RS technique are to provide spatially and temporally explicit information of large areas as well as remote areas which may be hard to access and also data with spatially high resolution contributed to provide detail information at individual tree scale. Different RS techniques including Optical, SAR (Synthetic Aperture Radar) and LiDAR data can be considered.

Optical data (e.g. Landsat, MODIS) uses visible and infrared wavelengths to measure spectral indices and correlate to ground based forest carbon measurements. Its limitation is that spectral indices saturate at relatively low carbon stocks (Gibbs et al., 2007). In addition they are more accurate for biomass estimation of simple forest stand structure (Lu, 2005). However, this data is limited by cloud cover which mostly observed in the tropical forest landscape (Thenkabail et al., 2004). Coarse resolution optical data, for example NOAA, AVHRR, have very limited application for biomass estimation because of the mixed pixels and the huge difference between the support of ground reference data and pixel size of the satellite data (Lu et al., 2003).

Synthetic Aperture Radar (SAR) is an active remote sensing technology that has been shown to be sensitive to biomass levels at higher values than passive sensors (optical sensors). It provides three-dimensional information on canopy structure. These kind of data estimate biomass accurately of relatively young and open conifer forest (Gibbs, et al., 2007) but less accurate in complex canopies of mature forests. Moreover, the SAR signal saturates at a low level of biomass.

Airborne Light Detection and Ranging (LiDAR) is an active remote sensing system which uses its own energy sources. LiDAR system has three main components: laser sensor for distance measurement; Global Positioning System to determine the position of each laser reflection point; Inertial Measurement Unit (IMU) to record orientation of the system. LiDAR system emits laser pulse and measures return time for each beam to travel between the sensor and a target object. LiDAR data comprises 3-dimension point data (x, y, z coordinates) with associated data such as intensity and images. LiDAR systems used in forestry application can be categorized as either 'discrete returns' system or 'full waveform' systems and differ one from another with respect to how they vertically and horizontally sample a canopy's three dimensional structure (Lim et al., 2008). Development of lidar models for estimating forest structure and biomass relies on the assumption that the vertical distribution of lidar returns is related to the vertical distribution of vegetation(Magnussen & Boudewyn, 1998). Discrete-return systems have been used to successfully estimate aboveground biomass at individual tree level and up to stand levels (Lim & Treitz, 2004; Næsset & Gobakken, 2008; Bortolot & Wynne, 2005; Popescu, 2007). These systems have been used either alone, or in combination with passive optical or RaDAR data (Hyde et al., 2007; Lucas et al., 2008).

LiDAR system is capable of achieving high vertical and horizontal accuracies because all the measurements are individually geo-referenced (Suárez et al., 2005). As opposed to optical remote sensing methods, airborne LiDAR has certain characteristics such as high sampling density, direct measurement of heights, precise geo-location and automated processing that make it useful for retrieving vegetation characteristics (Popescu, 2007) and deriving forest biomass at multiple scales, from individual trees to regional extents (García et al., 2010). The strong relationship between these direct measurements and other biophysical parameters, such as above-ground, provide critical information about the function and productivity of forest ecosystems. Dubayah (2000) figures out potential contribution of LiDAR remote sensing (Table 1) for forestry applications as shown in Table 1 (Dubayah & Drake, 2000):

Table 1: potential contribution of LiDAR remote sensing for forestry applications

Forest characteristic	LiDAR derivation
Canopy height	Direct retrieval
Sub canopy topography	Direct retrieval
Vertical distribution of intercepted surfaces	Direct retrieval
Above-ground biomass	Modeled
Basal area	Modeled
Mean stem diameter	Modeled
Vertical foliar profile	Modeled
Canopy volumes	Modeled
Large tree density	Inferred
Canopy cover, leaf area index	Fusion with other sensor
Life form diversity	Fusion with other sensor

There are different methods using LiDAR data to estimate above ground biomass with high accuracy and low uncertainty (Gibbs, et al., 2007). LiDAR-derived tree height and LiDAR-derived crown diameter are applied in order to calculate stem volume and biomass of individual trees (Brown, 2002; Suárez, et al., 2005). High sampling density (number of points) of LiDAR data makes it possible for more accurate detection of the height and crown dimensions of individual trees. In a study (Persson, 2002) using high density of points, 71% of position of the trees (x and y coordinate) were correctly detected. Height and crown diameter of detected trees were estimated with RMSE of 0.63 and 0.61 meter, respectively. Leaf less individual trees were detected using a spatial resolution of 10 cm for LiDAR poitns (approximately 12 points/m^2) to retrieve the morphology of individual trees (Brandtberg et al., 2003). Six to ten laser hits per tree crown needed to detect individual trees (Magnussen et al., 2010) while detection quality was best on homogenous high-resolution data (Rossmann et al., 2007).

In addition to the position of an individual tree other forestry attributes can also be extracted by LiDAR data. Attributes such as the height, crown area and also type of species (using intensity of LiDAR data) can be determined producing digital canopy model using LiDAR data.
In many research LiDAR data fusion (especially low point density) with passive optical sensors is considered to be effective. For example estimation of carbon stock in coniferous forest using a fusion of aerial photography and LiDAR data (Kim et al., 2010; Suárez, et al., 2005).

There are also reliable outputs of studies which applied pure LiDAR data with different point density to obtain biomass of trees. For instance, estimating biomass of loblolly pine plantation in Virginia, USA in which individual tree-based algorithm for determining forest biomass using small footprint LiDAR data was developed and tested (Bortolot & Wynne, 2005). Estimation of stem volume and biomass of individual *Pinus koraiensis* using LiDAR data with density of 5-7 point/m^2 (Kwak et al., 2010). Brandtberg (2003) analyzed individual tree crown and height of deciduous forest with a point density of approximately 12 point/m^2. The coefficient of determination was 69% (Brandtberg, et al., 2003). It is feasible to obtain suitable estimates of forest inventory variables at stand level using low sampling density and higher sampling point density may add little value to forest attributes (Lim, et al., 2008). Thomas (2006) shown that high density models are well correlated with mean dominant tree height, basal area, crown closure and average above ground biomass (R^2 =0.90, 0.91 and 0.92 respectively) whereas low-density models could not accurately predict crown closure (Thomas et al., 2006).
In many research tree height under-estimation has been reported for individual tree level (Gaveau & Hill, 2003; Næsset & Økland, 2002). According to these studies it was reported that under-estimation of tree height is affected by the density and coverage of laser pulses, algorithm used to obtain the canopy height model and some other factors (Hyyppä et al., 2008). However, the vast size and complexity of forest introduces a number of challenges to the implementation of LiDAR for forest inventory mapping at different scales. In an study it was concluded that examination point density specifically on the performance of LiDAR models is required (Thomas, et al., 2006).

1.2. Review of Allometric equations

Most important independent variables which are frequently applied in biomass allometric equations are “diameter at breast height (DBH)” and “height of the trees”. Database of European biomass and volume stem equations (Zianis et al., 2005) showed that 39 tree species applied for developing 607 biomass allometric equations and 55 tree species for developing 230 stem volume equations.
This research is started on the assumption that the local Forest Department of Barcelonnette (study area) would be able and willing to provide biomass figures or at least the local species specific allometric equation, if not according to the above database, available equations which can be applied for estimating

biomass for dominant tree species in the study area, are used that originally comes from the Netherlands and Italy which developed for *Pinus nigra* and *Pinus sylvestris* based on DBH and tree height.

1.3. Problem statement and justification

Previous studies that focused on estimation of forest biophysical variables with LiDAR scanning data carried out with either relatively low point density of all returns or high density with only one laser return. Density of LiDAR data in these works varies between <1 and 60 points/m^2. Generally it can be said that <1-2 points/m^2 considered as low and more than that identified as high density LiDAR data. However, before this technology can be adopted with confidence for long-term monitoring applications in forestry, robust models must be developed that can be applied and validated over large and complex forested areas. This will require scaling-up from current models developed from high density lidar data to low density data collected at higher altitudes(Thomas, et al., 2006).

Density of point is expected to be principal issue determining accuracy of tree height and tree crown area (Hyyppä, et al., 2008; Lefsky et al., 2002). However, the relationship between LiDAR sampling point density (which is directly related to acquisition and processing costs) and accuracy and precision of forest variables at individual tree level estimation has not yet been established across a range of forest ecosystems (Lim, et al., 2008).

In this study, a high density of LiDAR data with an average of 164 points/m^2 available for the Bois-Noir catchment, France will be utilized. "How does the average point density of lidar data affect the accuracy of forest biophysical models?" In other words, "can lidar data be collected at higher altitudes (i.e., lower average point density) for greater and more cost-effective ground coverage and still maintain the accuracy of the biophysical variable estimates?" is a question which this research focuses on it. A simple thinning is applied (Isenburg, 2012; Pirotti & Tarolli, 2010) to obtain lower sample density of available LiDAR points. Besides, developing regression models for aboveground carbon stock estimation, using discrete lidar data acquired for the study area is examined.

1.4. Research objectives

1.4.1. General objective

To model spatial distribution of carbon stock in aboveground biomass of *Pinus uncinata* and *Pinus sylvestris*, dominant tree species in the study area, using high density airborne LiDAR data

1.4.2. Specific objectives

- To analyze the relationship between DBH, crown area and height as predictors for estimating carbon stock in pine forest
- To estimate the amount of carbon stock of individual tree based on allometric equations and field measurement
- To assess the effect of point density on the accuracy of estimation of above-ground biomass
- To develop a species-specific equation to estimate carbon stock of pines using LiDAR derived height and crown area as an explanatory variables

1.5. Research Questions:

(1) Is there a significant relationship between forest biophysical parameters?

(2) Is it feasible to estimate carbon stock for individual tree of pine forest using solely high density LiDAR data?

(3) How does the different point density of LiDAR data affect the accuracy of forest biophysical model?

(4) How significant are the variables (height and crown area derived from LiDAR data) to estimate the above-ground biomass and carbon stock?

1.6. Research hypothesis

- There is a significant relationship (95% confidence level) between DBH, crown diameter and height measured in the field(Q1)
- High density LiDAR data solely provides high accurate ($R^2 > 80\%$) carbon stock estimation using regression between carbon, height and crown area (Q2)
- Decreasing point density of LiDAR data affects the accuracy of canopy height model to estimate carbon stock (Q3)
- There is a significant relationship (95% confidence level) between carbon stock, height and crown area from LiDAR that provides a reliable allometric model (Q4)

2. STUDY AREA

2.1. Geographic location

The Bois Noir catchment (3 km²) is located in the north-facing slope of the Barcelonnette Basin in the South-western French Alps, a tributary of the Ubaye River, 2.5 km to the southeast of Jausiers.
The Barcelonnette Basin is representative of climatic, lithological, geomorphological and land cover conditions common to many regions of the South French Alps. It is located at 1130 m average elevation. The basin extends over an area of 200 km², with a length of 22 km (from Jausiers to the east to Les Thuiles to the west), and a maximum width of 10 km (Theiery et al., 2007).
The area of study is 1.3 km² of south and east part of the catchment showed in Figure 1.

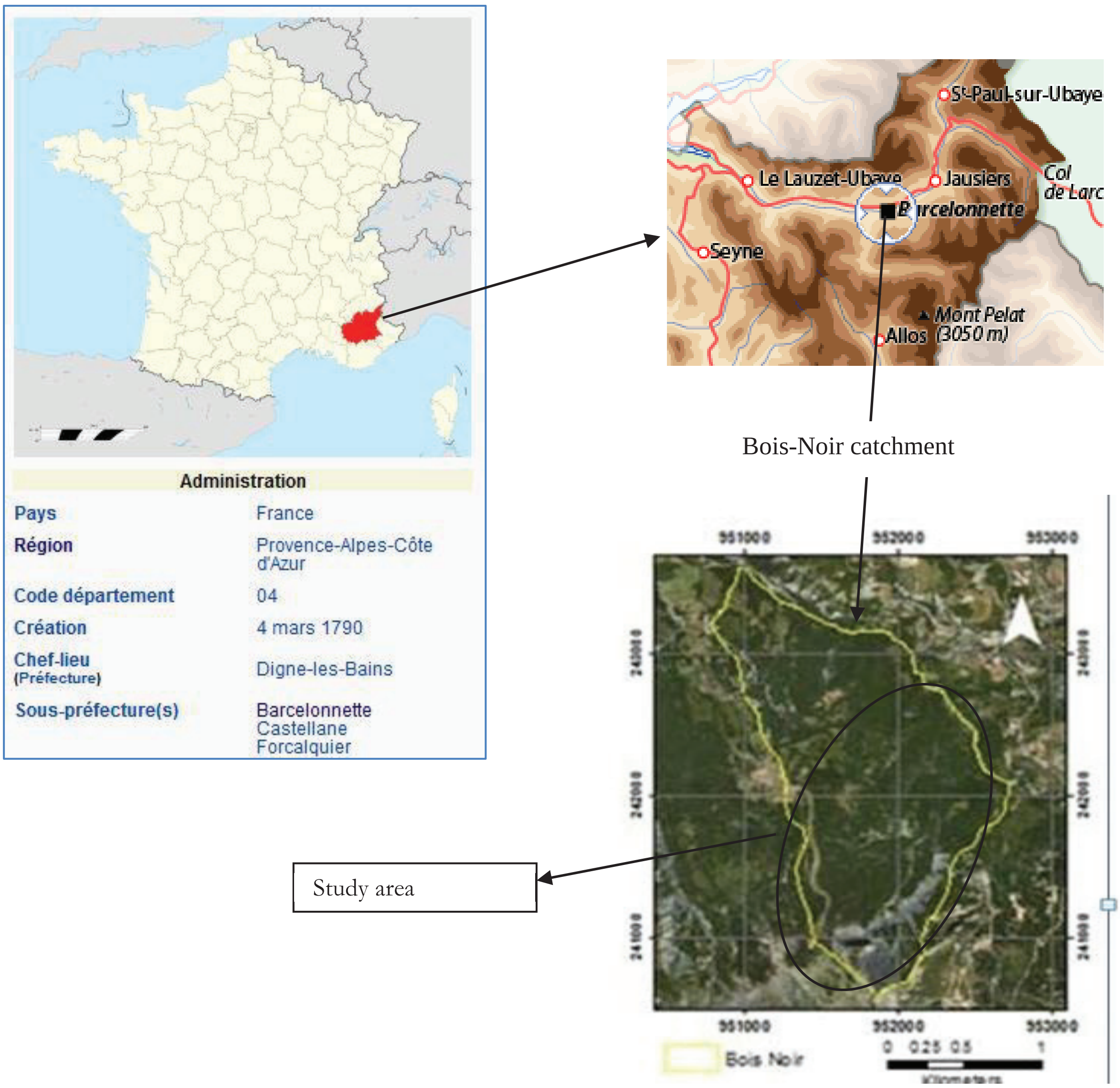


Figure 1: Geographic location of study area

2.2. Climate and topography

The basin has a dry and mountainous climate with strong inter-annual rainfall variability (e.g. annual rainfall may vary between 400 and 1400 mm) based on the rainfall records from 1928 till 2009, measured at the Barcelonnette station, (Hosein 2010; Mountain Risks 2010). Summers are usually dry though some random storms may happen in the season. The lower parts of the watershed receive more rainfall than snow during winters while in the upper parts; precipitation is in form of snow. Most of rainfall occurs in autumn and spring (Flageollet, Maquaire et al. 1999).

In the study area elevation range relatively from 1400 to 2038 and up to more than 70^0 steep slopes can be found. In the south-eastern side highly steep rock walls and in the north and north-eastern side it connects to river.

The area consists of Callovo-Oxfordian unstable black marls, overlaid by deposits of reworked glacial till.

Predisposing geomorphic and climatic influences triggered various types of landslides (Appendix 1). All the landslides (appendix 1) composing the landslide complex are typically shallow and occur at the interface between the bedrock and the surface deposits (Razak et al., 2011; Theiery, et al., 2007).

2.3. Vegetation cover

Forest covers 92% of the total surface area of Bois Noir catchment (Theiery, et al., 2007) (Figure 2) and consists mainly of *Pinus uncinata* , *Pinus sylvestris*, *Larix deciduas* and a few *Picea abies* (Appendix 2). Some broadleaves such as *Fraxinus* sp*., Alnus* sp*., Juniperus* sp. have been observed in lower part of the study area. Broadleaves and bare areas have been masked for this research, therefore total area of 1.01 km^2 which fully covered by high density of LiDAR data comprise the study area. More explanation about dominant tree species(van Gils, 2011) is given below:

Pinus uncinata Mill. ex Mirb.(Le Pin à crochet):The Mountain pine (*P. uncinata*) is found naturally at the tree line and from there down slope in scree slopes in the Pyrenees and the Western Alps. *P. uncinata* is aka is a subspecies of *P. mugo* found in the Central- to Eastern Alps and the Balkan in such sites. Plantations of *P. uncinata* are used for land rehabilitation in France. *P. uncinata* is distinguishable from the other pines by the hooked bracts (scales) of its cone ("uncinata'= hooked). We have collected extremely hooked cones in pine plantations in the research area.

Pinus sylvestris L. (Le Pin sylvestre): The Scotch pine (*P. sylvestris* L.) is indigenous in, among others, the mountain forest belt (<1700 m a.s.l.) of the dry inner-alpine valleys and the (dry) Western Alps, mostly as a mono-specific forest. The Scotch pine is distinguished from other pines by its orange and peeling bark in the upper half of the stem. The Scotch pine in the Alps is locally infested with *Viscum album* L. In Barcelonette this infestation is quite dramatic.

Larix decidua Miller:The larch (*L. decidua*) is a deciduous coniferous tree indigenous in the Alps and found often up to the alpine timberline also at the pass heights close to the Barcelonette research area.

Picea abies L. (Karsten): The spruce (*P. abies*) is indigenous in Northern Europe and throughout the Alps in the mountain belt often up to the tree line. It is widely planted outside its native distribution area.

The forest plantations: The research area is covered by pine plantations. All four coniferous trees have been observed to regenerate spontaneous from seed. The Larch mostly shows signs of stress in the research area, but appears healthy at higher elevation in the Ubaye valley. In the lower part, roughly coinciding with the *P. sylvestris* distribution, relics of crop farming are common including terraced fields and cairns (pile of stones removed from crop fields). These crop farming practices have been abandoned at least a century ago as elsewhere in the Alps. Locally relics of intensive livestock grazing (dense *Juniperus communis* or *J. sabina)* were observed.

First generation *P. uncinata* plantations dating from the early 20th century have often not been thinned, resulting in a high density of tall, even-aged trees with a low DBH without any shrub or forest flora understory. Such unthinned pine plantations are also common in the Netherlands and Germany dating back to the same period. The even-aged, low DBH pine trees represent an unusually ideal indicator of landslides; more so since fallen or drunken tree are not removed.

The Scotch pines, including its *Viscum album*, constitute indigenous forest at lower elevations (<1660 m) in the research area. The more natural tree distribution in the Scotch pine forest is less suitable as land slide indicator.

The Larch and Spruce at higher elevation in the research area occur in small open groups of trees much taller than the surrounding pine plantations. The Larch could represent forest remnants predating the pine plantations.

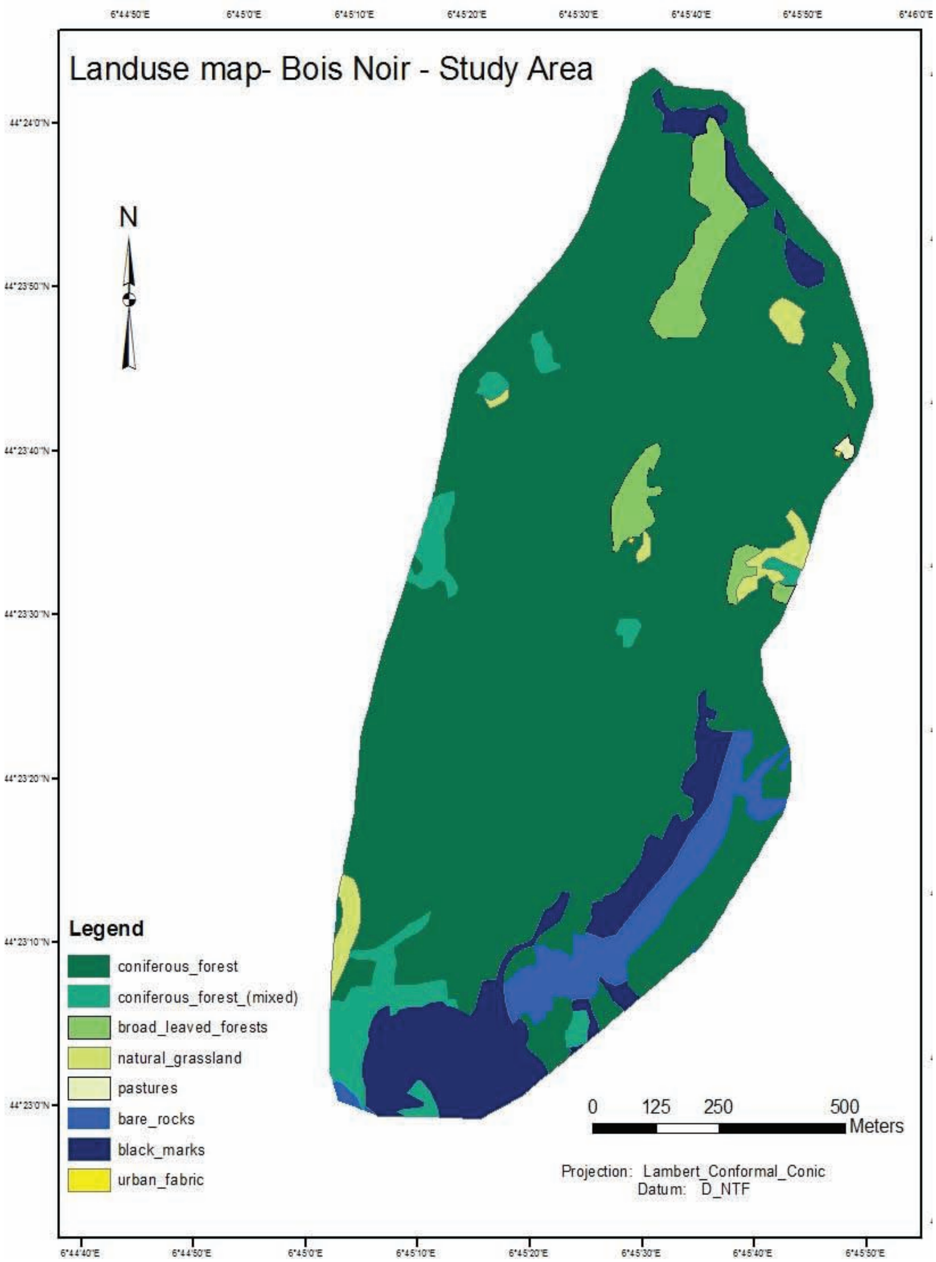


Figure 2: Land use map of the study area

3. METHODS AND DATA

3.1. Material

3.1.1. LiDAR and Photography

A high density airborne LiDAR dataset of Bois- Noir catchment was acquired in July 2009 using a handheld airborne laser scanning system. In order to increase the point density, seven flight lines were flown resulting in 214 million points, with mean density of 164 points/m². The dataset was primarily acquired for the study of the landslide activities in the study area. An aerial photograph of 30 cm resolution was co-acquired during the same campaign along with LiDAR data. More detailed of this campaign can be found in Table 2.

Table 2: Airborne LiDAR data characteristics

Acquisition (month/year)	July2009	
Laser scanner	RIEGL VQ 480i	
IMU system	IMAR FSAS (record up to 500 Hz)	
Positional system	Topcon legacy(record up to 5Hz)	
Laser pulse repetition rate	300kHz	
Beam divergence	0.3 mrad	
Laser beam footprint	75mm at 250m	
Field of view	60^{o}	
Scanning methods	Rotating multi-facet mirror	
Mean Density of points of raw data	164 points/m²	
Projection system	Lambert-conformal_ Conic	
Minimum and Maximum coordinates	951515.83	240850.96
	952589.91	242834.76
Min & Max elevation (above sea level)	1398.90	2040.10

3.1.2. Other data

The research was carried out on coniferous forest; therefore other land uses were masked based on the available land use map (Figure 2). Other data used for the research listed in Table 3.

Table 3: Other data used in this study

No	data	purpose	data type	data source
1	land use map	stratification area	shape file	(Theiery, et al., 2007)
2	land slide map	stratification area	shape file	(Theiery, et al., 2007)
3	allometric equations	estimating AGB	NL& Italy	(Zianis, et al., 2005)
4	train and test dataset	model validation	numeric /Data sheet	fieldwork
5	aerial photo 2009	Navigation	ortho-rectified (TIF)	ITC

3.1.3. Software and fieldwork equipment

Main soft ware and equipment which used in the fieldwork listed in Table 4 and 5. TreeVaw and Lastools were free software's. The first works in MS dos prompt and the later works under IDL virtual machine

Table 4: Software applied

No	software	purposes
1	ArcGis 10	Image processing, map production, generation sample points
2	Erdas Imagine 11	filtering
3	TreeVaw 1.0	Detection of tree and extraction of tree crown diameter and height
4	Lastools (October 2011)	Managing, analysing 3D point clouds; producing DSM, DTM
6	eCognition developer 8.7	Delineation of tree crown
7	Intersector.jar	validation

Table 5: List of equipment used in the fieldwork

1	Leica Differential GPS system 1200
2	Clinometer Suunto
3	Compass Suunto
4	Diameter tape 3 meter
5	Forestry rangefinder 550
6	GPS Garmin 12xl
7	Measuring tape 50 meter
8	Stereoscope pocket small
9	Tripod
10	Caliper 60cm
11	iPAQ

3.2. Methods

The method for predicting above ground carbon using LiDAR data in the research area can be subdivided into three major steps: 1. Canopy Height Model (CHM) preparation; 2. Image partitioning in more or less homogenous objects representing individual tree canopies; 3. Carbon modelling and application of the model to the tree canopy map.

In this research original LiDAR dataset with density of 164 point /m^2 was used to generate the first CHM. The main product of the LiDAR dataset is CHM which comprises the absolute height for each pixel. CHMs with lower point density were generated after thinning LiDAR dataset as well. Individual tree crown delineation was done based on two approaches namely Tree Variable window (TreeVaw) processing implemented in IDL Virtual Machine which focusing on locating and measuring individual trees (Popescu et al., 2003) and 'Region Growing' using eCognition tool. Tree species classification was based on the brightness and crown size of species in the study area. Tree height and canopy projection area (CPA) were calculated for each CHM and used to predict the amount of carbon stock per tree. The method to carry out this research is described in the flowchart in Figure3. Detailed explanation is described in the following subsections.

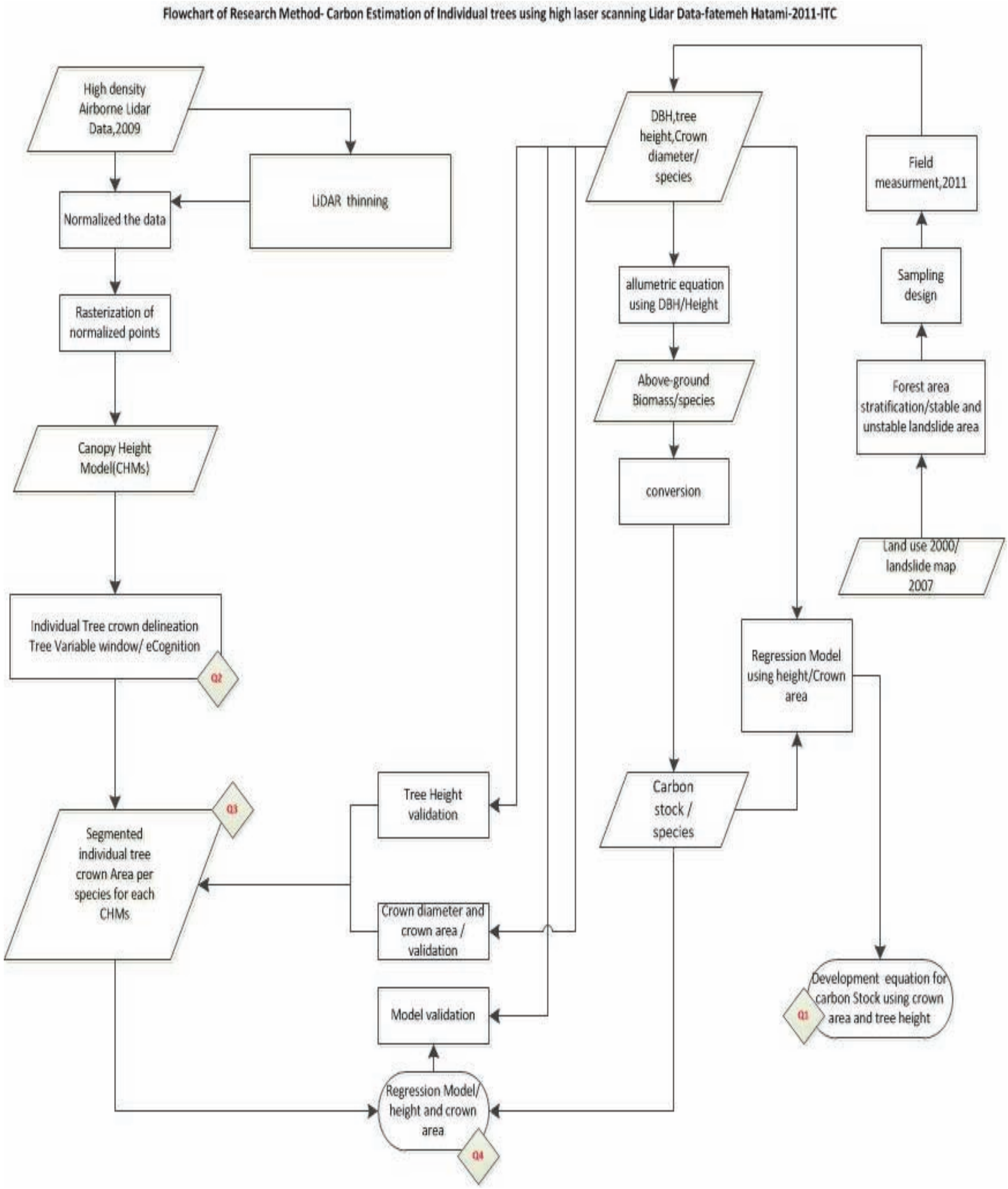


Figure 3: Flowchart of methodology

3.2.1. Canopy Height Model from LiDAR data

The airborne LiDAR dataset is in point form, and consists of X, Y, Z and intensity. As a first pre-processing step, LiDAR dataset has to be normalized in order to view the absolute elevation or height of the objects (e.g. trees). Lastools software is capable to do it (Figure 4).

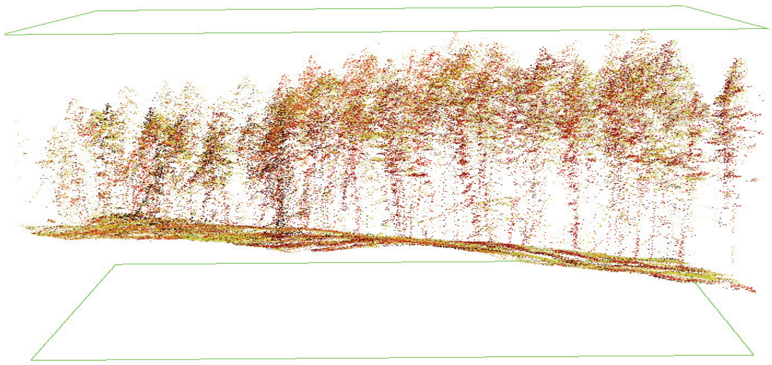


Figure 4: A small subset of point cloud befor normalizing displaying by Lastools 'View' - each color refers to return pulse

LiDAR dataset which is used in this research includes five returns for each pulse. The first returns refer to canopy hits and the last returns mostly refer to the ground. The LiDAR data was already classified into two classes in which the points corresponding to the ground level classified as class 2 extracted by the data provider and the rest kept as unclassified. The assumption that ground points would be the last returns (Thomas, et al., 2006) was considered in this study. All five returns were used to generate CHMs. In order to make CHM, there are different ways applying different commands in "Lastools". Using Lastools software which is command prompt format makes it possible to produce CHM directly from LiDAR data in a quick way. The steps of making CHM can be simplified as below:

- Normalizing the data:

  This command computes the height of each LiDAR point above the ground. This assumes that ground points have already been classified so they can be identified and used to triangulates the ground points into a triangulated irregular network (TIN), a digital data structure used in a geographic information system for the representation of a surface ,and then calculated the elevation of each point with respect to this TIN.

- Remove noise points:

  After visualizing the result from the previous step, any point as noise observed in the data information file removed in this step. According to the field observation, points with absolute height above 40 m and below zero removed in this step.

- Gridding step: This tools reads LiDAR points and grids them onto a raster. The output as TIF format was selected. The tool takes the elevation of each point and stores the highest, lowest or average elevation for inside each grid cell. In order to keep as much as point information from point cloud as well as to prevent making a huge raster file in processing , the grid size of 25 cm and highest value in order to achieve the canopy height was selected. However the size of the pixel and the total area of the study area make a limitation of resolution selection. For any grid cell in which there is no point an interpolation by number of grid cell (4 grid cells) applied. So by this, the original height information for each given pixel saved and only the pixel without value were interpolated. That means generated CHM has highly original height value derived from point cloud.

- Merging point files: The study area covers 17 huge single point files. Any previous step has been done for single file of point cloud. By this tool which simultaneously applied with previous step all the files merged and one raster file which covers the whole study area came out.

Commands used for above mentioned steps can be seen in Appendix 3.

3.2.2. LiDAR Thinning

Suitability of the LiDAR point density for producing CHM is done using different methods of thinning (Pirotti & Tarolli, 2010). Point cloud thinning is a process to give another dataset with a lower point density. The method of thinning (Isenburg, 2012) used in this research is: '-keep_every_nth 2' which says: keep every nth point. This option is possible because the original LiDAR points are recorded in the same order as they were sampled with the laser sensor (Pirotti & Tarolli, 2010). This method that basically considers every nth point from the whole point dataset ordered by time taking every nth point which simulates a survey taken at higher flying altitude and therefore giving a lower point density (Pirotti & Tarolli, 2010).

Subsequently, 17 thinned LiDAR datasets generated of which four datasets (Table 6) selected for generating new CHMs (Figure 2, 3, 4 & 5). Dataset with minimum point density of $4/m^2$ as used in other studies (Ke et al., 2010; Lim, et al., 2008; Parker & Glass, 2004) as well as three intermediate densities between minimum (4 point/m^2) and available maximum datasets (164 point /m^2) were selected.

Table 6: CHMs generated after thinning

No.	algorithm	Point density for all return	Point density of first return	CHM
1	----	164	115	CHM0
2	-keep_every_nth 2	82.3	58.1	CHM1
3	-keep_every_nth 5	32.9	23.2	CHM2
4	-keep_every_nth 15	11.7	8.3	CHM3
5	-keep_every_nth 25	4.7	3.4	CHM4

However a side view of point cloud before and after thinning helped to better understanding of changes in generated CHMs (Figure5).

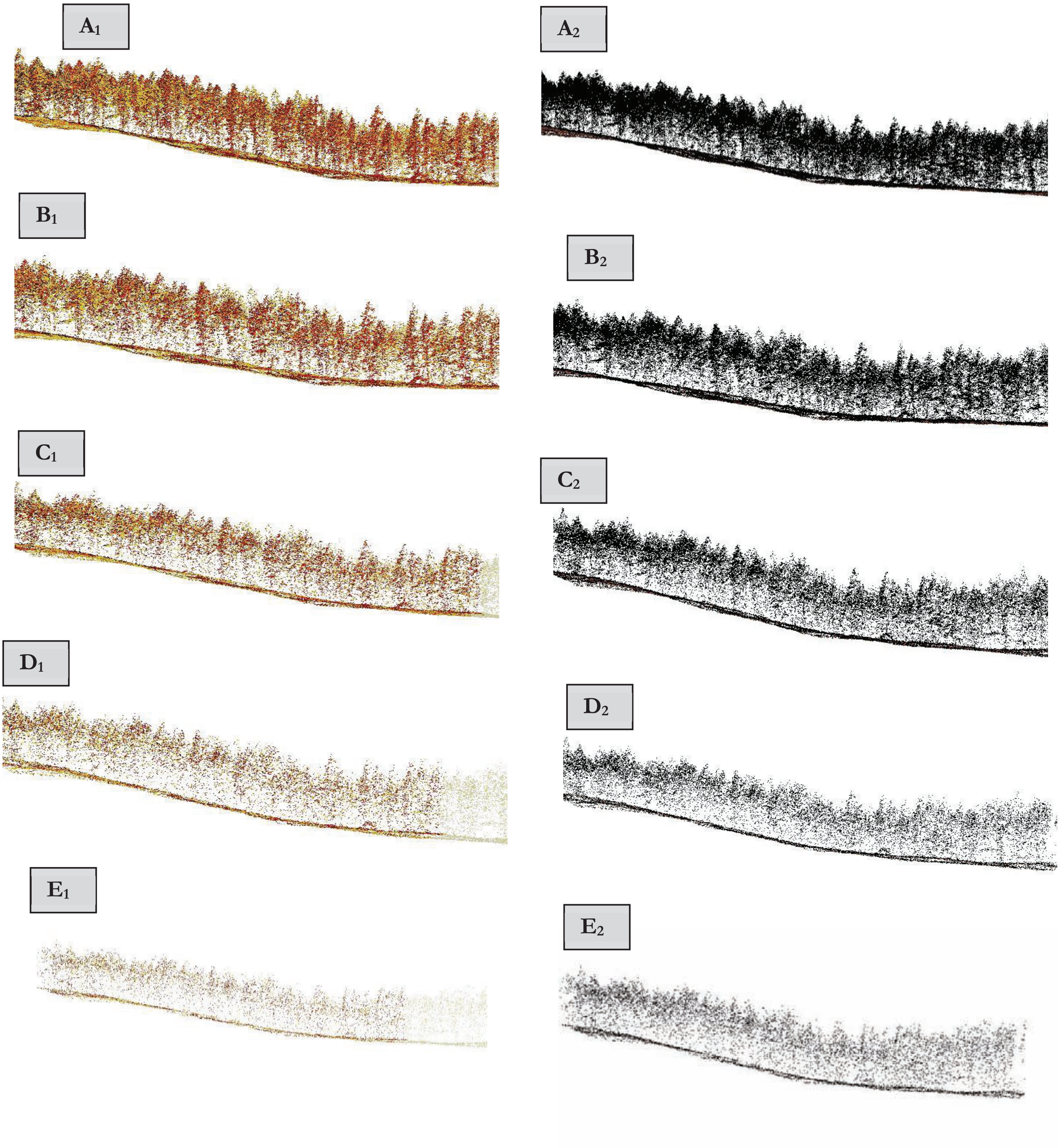


Figure 5: Color (1) and black-white (2) 2D views of point clouds before and after thinning - A_1 &A_2) before thinning- point cloud with 164 p/m^2, B_1 & B_2) after first thinning- point cloud with 82 p/m^2, C_1 &C_2) after second thinning- point cloud with 32 p/m^2, D_1 & D_2) After third thinning- point cloud with 11 p/m^2, E1 &E2) after fourth thinning- point clouds with 4 p/m^2

3.2.3. Tree height and Tree crown delineation

Two approaches TreeVaw (Popescu & Wynne, 2004) and 'Region Growing', one of the available algorithm in eCognition, (Rossmann, et al., 2007) applied for extracting tree location, tree height, tree crown diameter /tree crown area. Explanation for each approach is as follows:

a) Individual Tree Height and Tree Crown Diameter using TreeVaw:

In TreeVaw the input is a LiDAR-derived CHM in ENVI image format (image binary file and header)(Popescu & Wynne, 2002). The output consists in individual tree positions, tree height, and crown radius as a text file. Using this approach trees were identified and located based on local maximum adaptive filtering using continuously varying windows of circular shape (Figure 6). The filtering window size is based on mean, minimum and maximum of tree height that is inherently present in the LiDAR CHM. TreeVaw uses focal filtering with a dynamically varying window size to automatically locate trees and extract tree heights and tree crown radius (Figure 7). This analysis is based on the assumption that a relationship exists between tree height and crown size- the taller the tree, the larger the crown size(Niemann, 1999; Popescu, 2003).This method is capable to detect individual trees and estimates the dominant tree height. CHM derived from highest point density (CHM0) was used and the parameter such as minimum crown diameter of 2 m, maximum crown diameter of 7.5 m, and minimum tree height of 6 in order to eliminate the effect of shrubs and understory vegetation and median filter size 3*3 was applied.
Based on this information, the window size varied between 3*3 and 31*31 pixels. TreeVaw allows the user to specify a height-to-crown diameter relation that best describes the CHM under consideration. The best prediction for crown size based on tree height, with an R^2 value of 0.14, was obtained when using linear regression with a polynomial model as shown below:

$Y= 0.0168*X^2 -0.3404*X+ 4.7902$

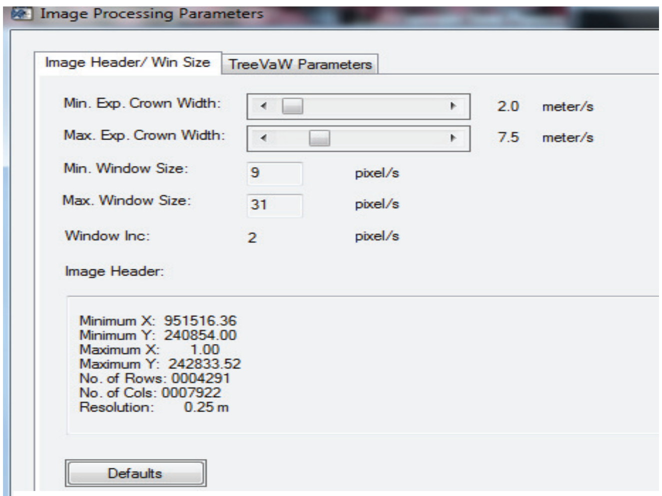


Figure 7: Window view of TreeVaw to set Min. and Max. of crown width

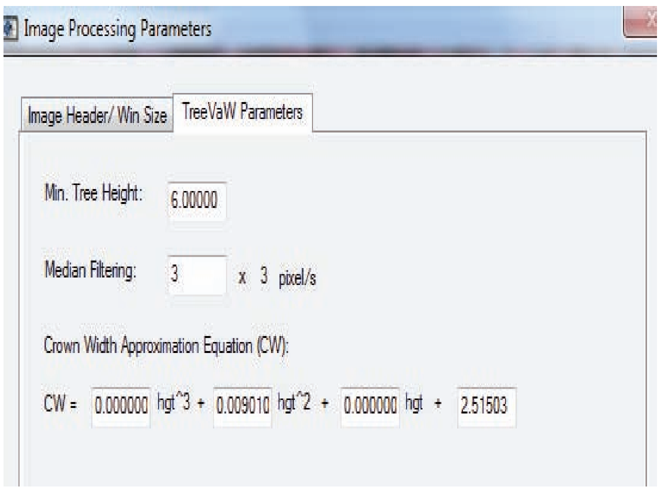


Figure 6: Window view of treeVaw to set Min. tree height and equation

The output of TreeVaw which was a text file converted to a shape point file (Figure 8) with a circle buffer for each tree as crown area (Figure 9) in Arc GIS in order to assess the accuracy of tree detection and crown diameter.

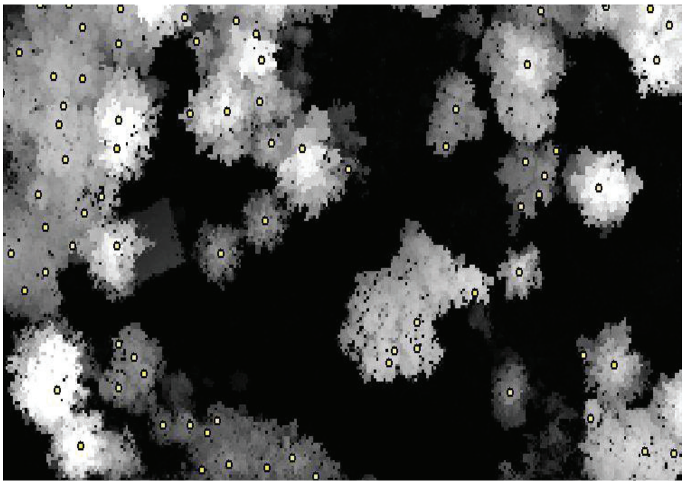


Figure 8: A subset of TreeVaw result overlaid on CHM0, each point refer to a detected tree associated with height and crown diameter value

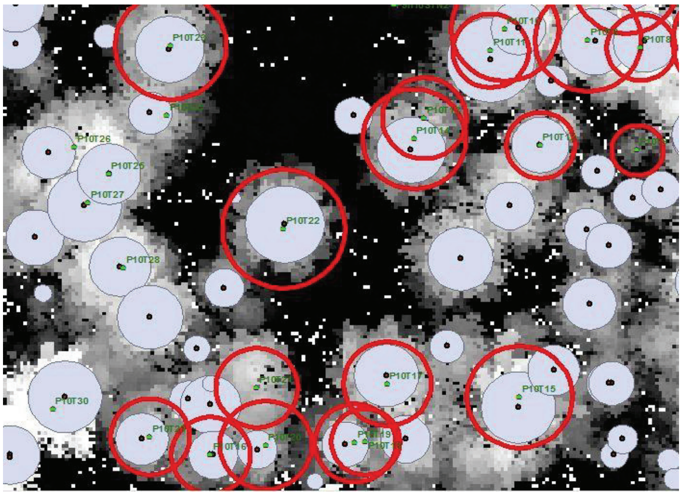


Figure 9: A subset of TreeVaw result overlaid on CHM0, each point refer to a detected – filled-circle in light blue color is a buffer of crown diameter for each tree and line-circle in red color is tree crown diameter measured in the field

b) Individual Tree crown delineation and Tree Height using Region Growing approach in eCognition:

"Region Growing" is a bottom up approach in eCognition whereby more or less homogeneous objects are created through gradual expansion, 'growing', starting from the smallest unites, and gradually growing into larger units until distinct boundaries are met, based on predefined criteria. Start with a single pixel (seed) and add new pixels slowly (1) Choose the seed pixel, (2) Check the neighbouring pixels and add them to the region if they are similar to the seed, (3) Repeat step 2 for each of the newly added pixels; stop if no more pixels can be added.

Region Growing approach applied for individual tree segmentation using local maxima as tree top and local minima as tree crown edge which called 'seeds' in rule set (Figure 10) . Average crown diameter of *P. sylvestris* and *L. decidua* in the study area is larger than average crown diameter of *P. uncinata*. Therefore to improve detection, the study area divided into two zones: High elevated zone, here after is called zone 1, upper than 1660 meter above sea level in with dominantly (>90% *P. uncinata)* and lower zone (zone2) in which the dominant tree species is *P. sylvestris*. *L. decidua*, was presented in both zones with lower density.

Region Growing algorithm (Figure 10) has been applied for both zones. To find open areas between trees, chessboard segmentation and shadow masking were applied. Chessboard segmentation creates identical sized objects. 2*2 pixel sized objects was found to appropriate based on processing capability of eCognition. In shadow masking any pixel with height value equal or less than 3 meter assigned as shadow or open area. They were not participated in segmentation. Furthermore the rest of area as vegetation area assigned, in zone 1 the "search range window" size of 4 for finding local minima (tree top) and local maxima was calculated. This size of search window is quite good for *P. uncinata* but neither appropriate for segmenting *P. sylvestris* nor for *L. decidua* which having larger crown. Therefore in zone 2 "search range window" of 7 pixels specified.

To remove false tree top and false seeds, all tree tops and seeds which neighbours to one another were merged. Then growing from tree top was started until significant boundaries of tree crowns found. The maximum height for each segment as tree height was extracted using "find enclose by image object" function (Kwak et al., 2007).

These steps of segmentation applied for other four CHMs with lower density as well and output were exported to ArcGIS for visualisation and validation.

Canopy Projection Area (CPA) were calculated for all segmented trees then any trees below 5 meter of height and less than 2 meter of CPA removed in order to have trees with significant stem volume for biomass calculation. Polygon Smoothing has been done for CPA with peak tolerance of 2 meter.

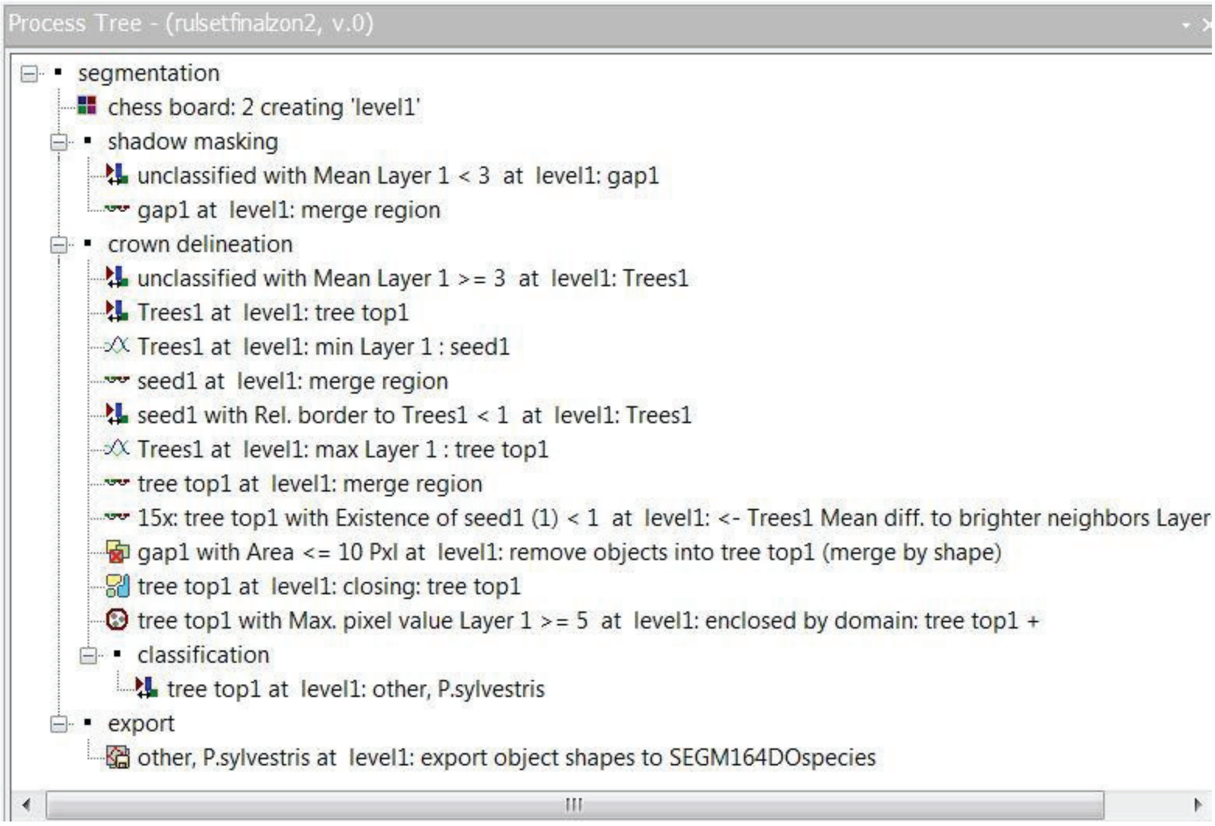


Figure 10: Tree crown segmentation using Region Growing algorithm in eCognition- Rule set

3.2.4. Object based image classification

A "nearest neighbour" classification using eCognition algorithm applied to classify species into three classes as *P. uncinata* and "others" in zone 1 and *P. sylvestris* and 'others' in zone 2. "Others" is mostly *L. decidua* in both zones. Assessment of accuracy for *L. decidua* was not possible due to low sample numbers. The output of classification exported as a raster layer to assess accuracy in Erdas Imagine software. This layer in a vector format associated with attribute table including height of each individual tree and name of species as well.

The nearest neighbour classification in eCognition was applied to selected object features and was trained by 70% samples of field data. Crown of the trees delineated manually on the CHM0.

Parameter (Figure11) which considered for classification were maximum pixel value as tree height, area of segment as crown area , brightness of pixels as difference between tree top and tree crown edge and species name as well.

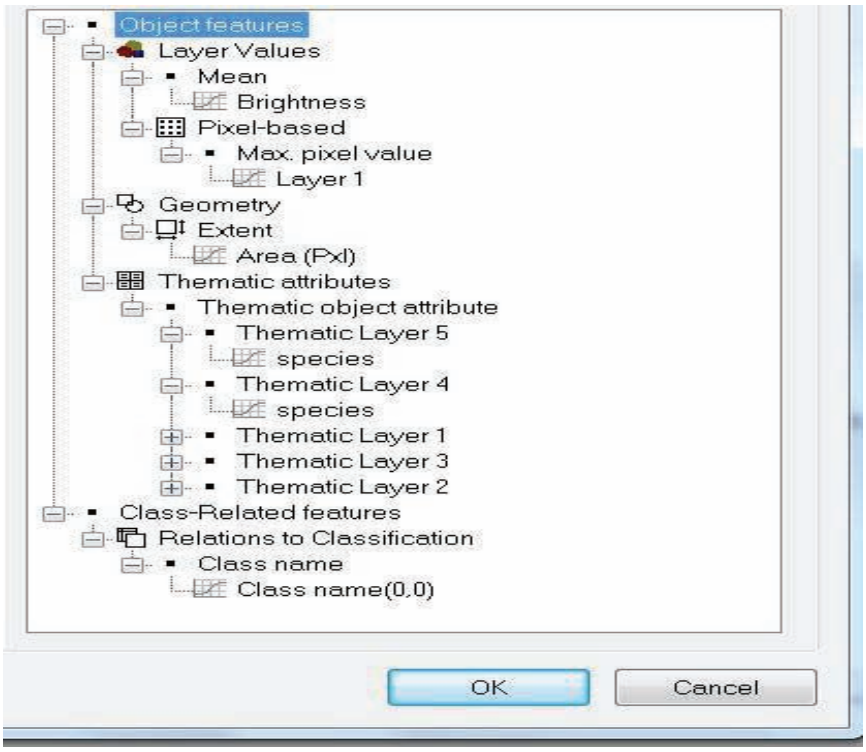


Figure 11: setting parameters for species classification

3.2.5. Validation for Tree attributes

Validation of tree detection and tree crown delineation were done for both approaches (Rahman et al., 2009). The result of tree height and crown diameter/ crown area evaluated using a coefficient of determination and root mean square error comparison while the results of tree detection and crown delineation were validated based on two approaches in which topological and geometric relationships were considered for segmented trees with reference trees (Moller et al., 2007):

- Relative area of intersection between segmented objects and reference objects
- 1:1 Spatial correspondence (Gougeon & Leckie, 2006; Li et al., 2009)

The overall accuracy, the omission error and the commission error for tree detection and crown delineation quantified as follow:

Comission error: $(N_d - N_m)/ N_d * 100$

Ommission error: $(N_r - N_m)/ N_r * 100$

Overall Accuracy$= (N_m) / (N_r + N_d - N_m)*100$

Where N_m is the total number of matched trees, N_r is the total number of reference trees measured or delineated in the plot in the field and N_d is the total number of trees detected by both approaches

It was considered that the matched detected tree should fulfil the following condition (Rahman, et al., 2009):

1- Two segments are considered matched if their overlap is larger than the overlap of either segment with other segments

2- The area of intersection should comply with > 60% of the area of reference segment and the area of detected segment from both approaches as well

Furthermore, second approach was resulted to over segmentation and under segmentation as defined by Clinton et al (2010). The value range of over segmentation and under segmentation is between 0 and 1, where over segmentation is equal to 0 and under segmentation is equal to 0 define a perfect segmentation. Combination of over segmentation and under segmentation is interpreted as 'D value' which used here. D value means "goodness' measure to an ideal segmentation result. Equation for D value is shown in figure12:

$$D = \sqrt{\frac{over\ segmenation^2 + under\ segmenation^2}{2}}$$

Figure 12: D value which quantify the closeness measure of segmentation

3.2.6. Field work

Because the study area was affected by landslide so the probability of getting difference data in stable and unstable area was considered. Therefore based on Landslide map (Figure 13) purposefully 13 sample plots were distributed in the area.

The data were collected during September 2011 by measuring tree location (X, Y, and Z) using DGPS and total stations with average 8 hours static observation for each geodetic station. The average accuracy of GPS stations was about 4 mm for horizontal and 7 mm for vertical components.

DBH> 7.5cm (Vallet et al., 2006) using calliper 60cm, tree height using forestry rangefinder, crown diameter using measuring tape and tree species identification collected. Crown diameter was determined as the average of two perpendicular crown width (south to north and east to west) (Appendix 4). In each plot measurement carried out for the trees which were visible through DGPS located in geodetic station. In Total 288 trees measured. A routine and navigating facility such as iPAQ, Garmin GPS, maps and aerial photo map prepared for the field orientation as well.

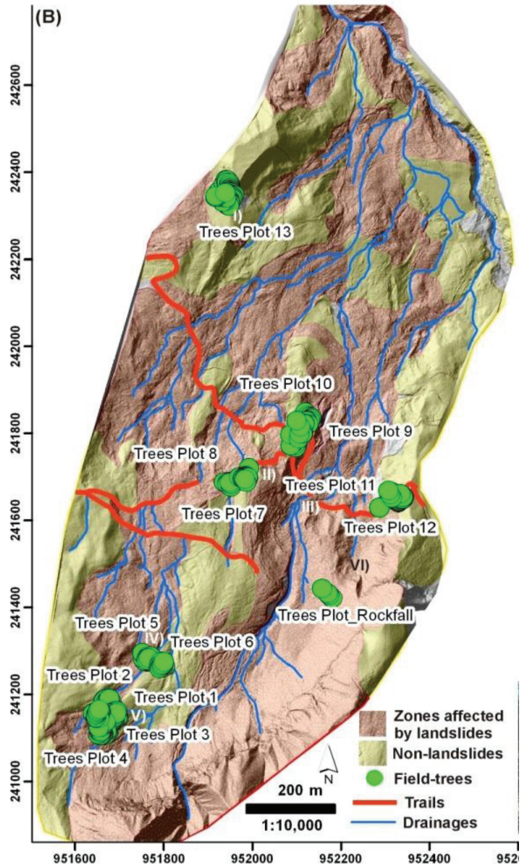


Figure 13: sample plot distribution on Landslide map (Razak, 2011)

Fieldwork data analysis

Multi-collinearity of independent variables which may be a problem for dependent variable if any pair wise correlation is > than 0.5 was calculated. To this, VIF which stands for Variance Inflation Factor applied. VIF is a measure of strength of the relationship between each covariate and all other covariates. The strength of relationship between different part of tree (DH, tree height and CPA) were examined.

For biomass and carbon stock calculation, the research was started on the assumption that biomass figures or the local species specific allometric equation would be provided by the local Forest Department. In the absence of both, Allometric volume equations (Figure 14) for taxonomically- related pine species were evaluated in France (Vallet, et al., 2006). Three volume equations were available for pine species(Zianis, et al., 2005) as below:

Equatio(1)
origin Country=The Netherlands
Stem $Volume = [\![DBH]\!]^a * [\![Height]\!]^b * \exp(c)$
a=1.89192 , b=0.95374 , c=-2.72505
species=Pinus nigra var maritima
unit= volume=dm3 , DBH=cm, Height=m
No. of Trees=798 trees
R square=0.997

Equation(2)
Origin country=Italy
Stem Volume $= a * [\![DBH]\!]^b$ *Height^c
a=1.480589 b=1.982459514 c=0.742674501
Species=Pinus sylvestris
unit: volume=dm3 , D=dm H=dm
No. of Trees114 trees
R square not mentioned

Equation (3)
origin Country=The Netherlands
Stem $Volume$=a*⟦DBH⟧^(b+c) *⟦$Height$⟧^d
a=0.00042613 , b=2.066225947 , c=-0.001926657 d= 0.80636901
speceis=Pinus spp.
unit= biom=dm3 , DBH=mm, Height=m
No. of trees=798 trees

Figure 14: Allometric equations for estimating stem volume of pines

Furthermore, the stem volume was converted into carbon stock using the carbon fraction of 0.5 (FAO, 2010). Wood density convertor (0.5) for *P. uncinata* (AFIB, 2004) was applied as well.

3.2.7. Regression analysis

Standard practice in establishing LiDAR-based models for estimating forest attributes involves the use of regression analysis for relating LiDAR metrics to the spatially in-situ measurements. Upon validation and calculating aboveground carbon stock using DBH and height information and allometric equations, relationship of carbon stock with height and CPA were analysed using regression analysis. These regressed models was applied to the rest of LiDAR data for carbon stock prediction (Naesset, 2002). The equation with higher R^2 was selected for carbon estimation for whole study area.
Tree crowns (delineated from eCognition approach) which have 1:1 spatial correspondence with reference CPA (Crown Projection Area) correctly were used for modelling. Validation of the model was carried out using 30% of field data to determine significance and strength of the relationship.

4. RESULT

4.1. Descriptive statistics of field data

Samples from 13 plots were collected in the study area (Figure13). In total 292 trees measured including 204 *P. uncinata*, 50 *P. sylvestris* and 34 *L. decidua*. Four pines were extremely tilted and removed from the sample.

Descriptive statistics for three species have been given in following tables (Table1 to Table3). On average *P.uncinata* has the smallest mean DBH followed by *P. sylvestris* and *L. decidua* while P. *sylvestris* is the shortest tree (1 m < *P. uncinata*) followed by *P. uncinata* and *L. decidua*. *P. uncinata* has the smallest mean crown diameter among the species. Moreover the variation in crown diameter for this species is relatively small.

Table 7: Descriptive statistics of *P. uncinata*

	DBH (cm)	Height (m)	Crown diameter (m)
Mean	19.4	11.7	3.2
SE	0.4	0.2	0.1
Median	19	11.6	3.2
SD	4.2	2.4	0.9
Minimum	10	7	1
Maximum	30	17	6.1
n	204	204	204

Table 8: Descriptive statistics of *P. sylvestris*

	DBH (cm)	Height (m)	Crown diameter (m)
Mean	23.9	10.9	5.7
SE	0.8	0.3	0.2
Median	24	11	4.6
SD	6.0	2.4	1.2
Minimum	11	6.5	2.3
Maximum	36	15	6.9
n	50	50	50

Table 9: Descriptive statistics of *L. decidua*

	DBH (cm)	Height (m)	Crown diameter (m)
Mean	31.9	16.4	6.3
SE	1.7	0.4	0.4
Median	30	17	6.4
SD	11.6	2.9	1.7
Minimum	15	7.8	3
Maximum	61	22	9
n	34	34	34

4.1.1. Testing normality of forest Tree attributes

All tree attributes of *P. uncinata* and *P. sylvestris* (Figure 1 to Figure 6) shows a normal distribution. All median values are quite close to mean values that is interpreted the normalisation of distribution as well.

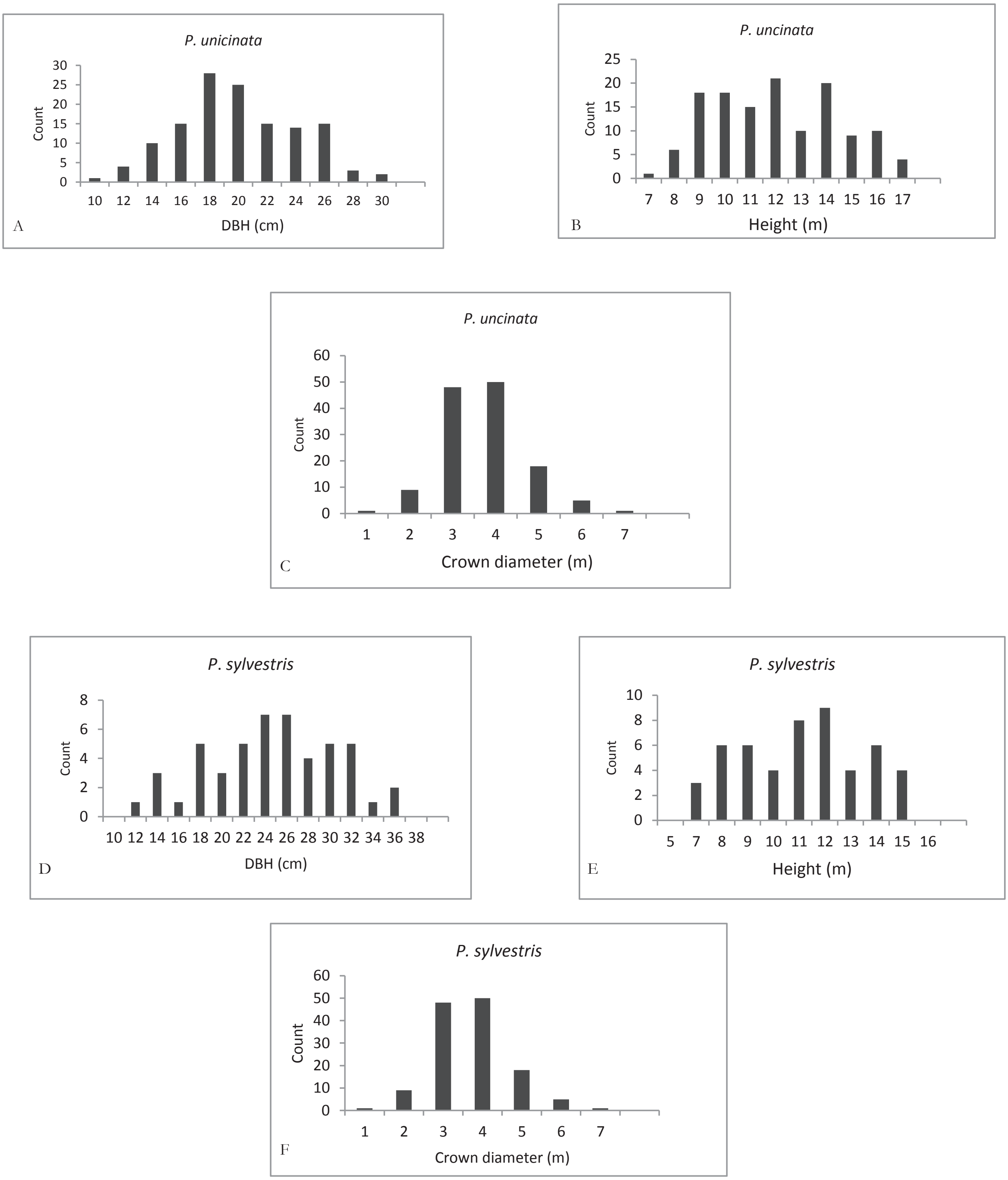


Figure 15: A, B and C Histograms of tree attributes of *P. uncinata* - D, E and F Histogram of tree attributes of *P. sylvestris*

4.1.2. Multi collinearity verification

All VIF are < 10 (Table 10 and 11), so all the explanatory variables can be used in regression.

Table 10: Multi collinearity for *P. uncinata*

	R^2	VIF
DBH (cm)	0.63	2.67
Height (m)	0.27	1.37
Crown diameter (m)	0.54	2.15
n	204	

Table 11: Multi collinearity for *P. sylvestris*

	R^2	VIF
DBH (cm)	0.52	2.1
Height (m)	0.27	1.36
Crown diameter (m)	0.44	1.77
n	50	

The strength of relationship between tree biophysical variables at the level 0f 95% confidence examined as showed in Table 12 &13.

Table 12: Relationship between tree attributes in the field – *P.* spp

Tree attribute	R^2
DBH and Height	0.32
DBH and Crown diameter	0.37
Height and Crown diameter	0.15

Table 13: Relationship between tree attributes in the field– *L. decidua*

Tree attribute	R^2
DBH and Height	0.76
DBH and Crown diameter	0.64
Height and Crown diameter	0.53

Weaker linear association between variables for *P. uncinata* and *P. sylvestris* has been found than *L. decidua*. Height and Crown diameter had the least relationship followed by DBH and height for pines.

4.2. Canopy Height Model (CHM)

CHMs with different point density of LiDAR data were generated. Non-forest and broadleaves forest areas were masked on the CHM. Crown area of tree is recognizable in CHMs especially for those trees which are taller and isolated. The brighter set of pixels, the taller the tree (Figure 16). Tree crown were manually delineated for trees measured in the field. A subset of each CHM was showed in Figures 17, 18, 19 and 20.

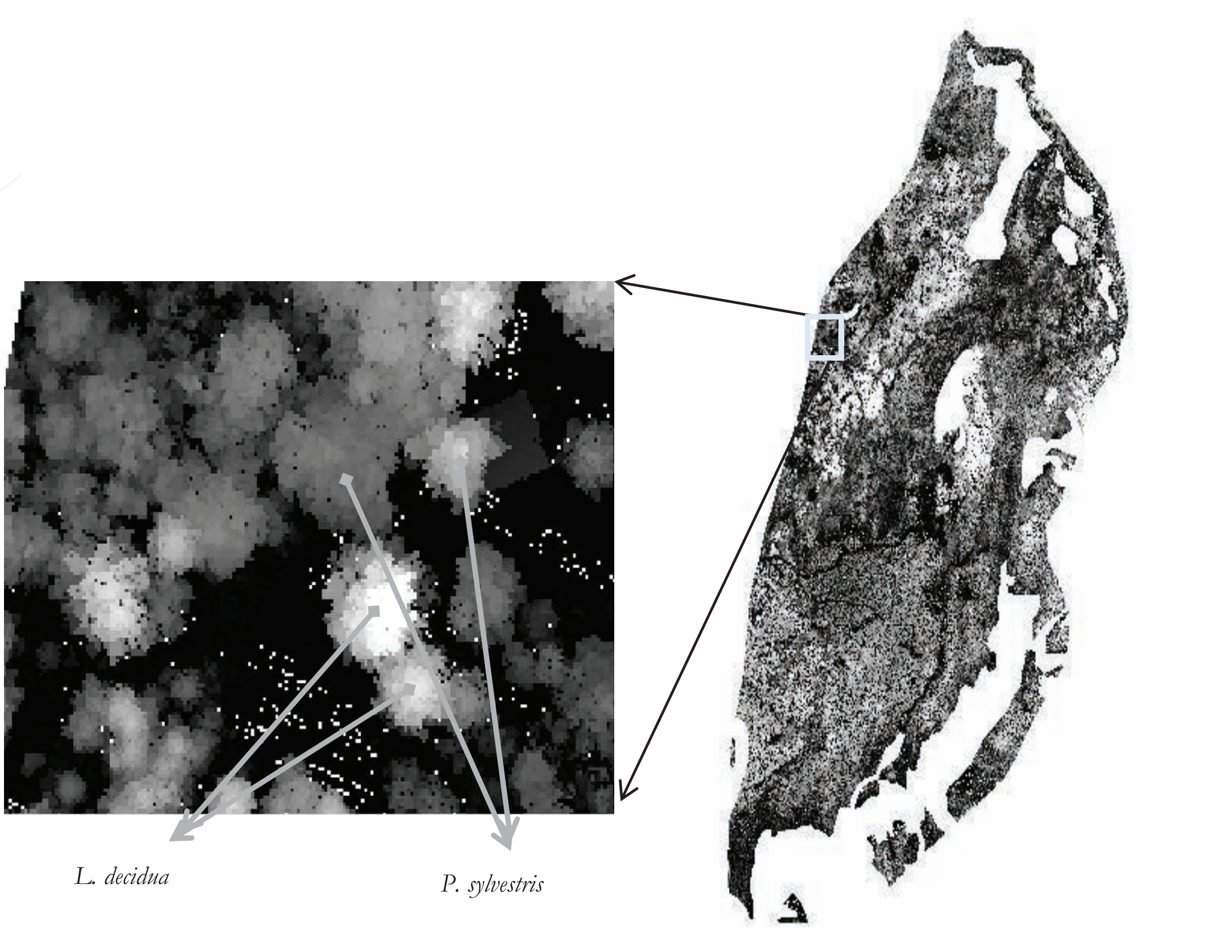


Figure 16: On the right showing a full raster of CHM0 - 164 point /m^2 and on the left a subset of CHM0 showing how recognizable the tree crown is.

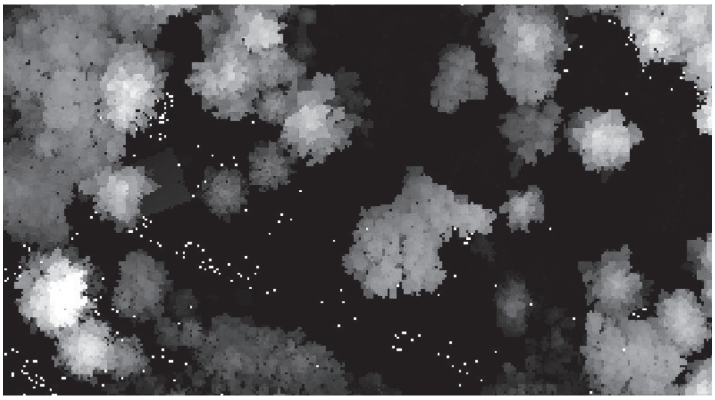


Figure 17: a subset of CHM1 derived from LiDAR dataset with density of 82 point/m^2

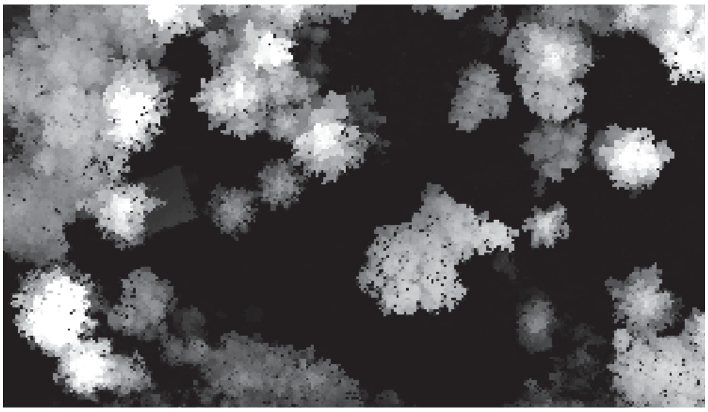


Figure 18: a subset of CHM2 derived from LiDAR dataset with density of 32 point/m^2

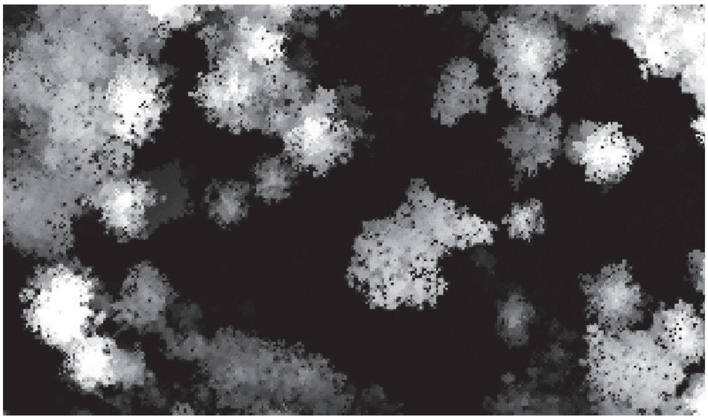


Figure 19: a subset of CHM3 derived from LiDAR dataset with density of 11 point/m^2

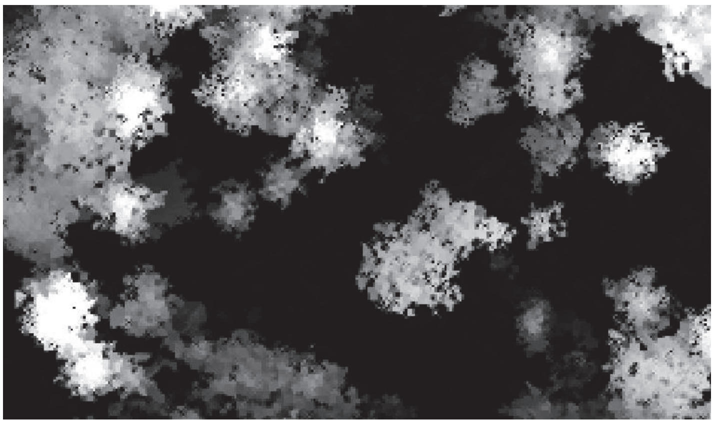


Figure 20: a subset of CHM4 derived from LiDAR dataset with density of 4 point /m^2

4.3. Tree height and tree crown delineation

4.3.1. Tree height and tree crown diameter using TreeVaw

After pre-processing 67,518 detected trees remained (Figure 21).

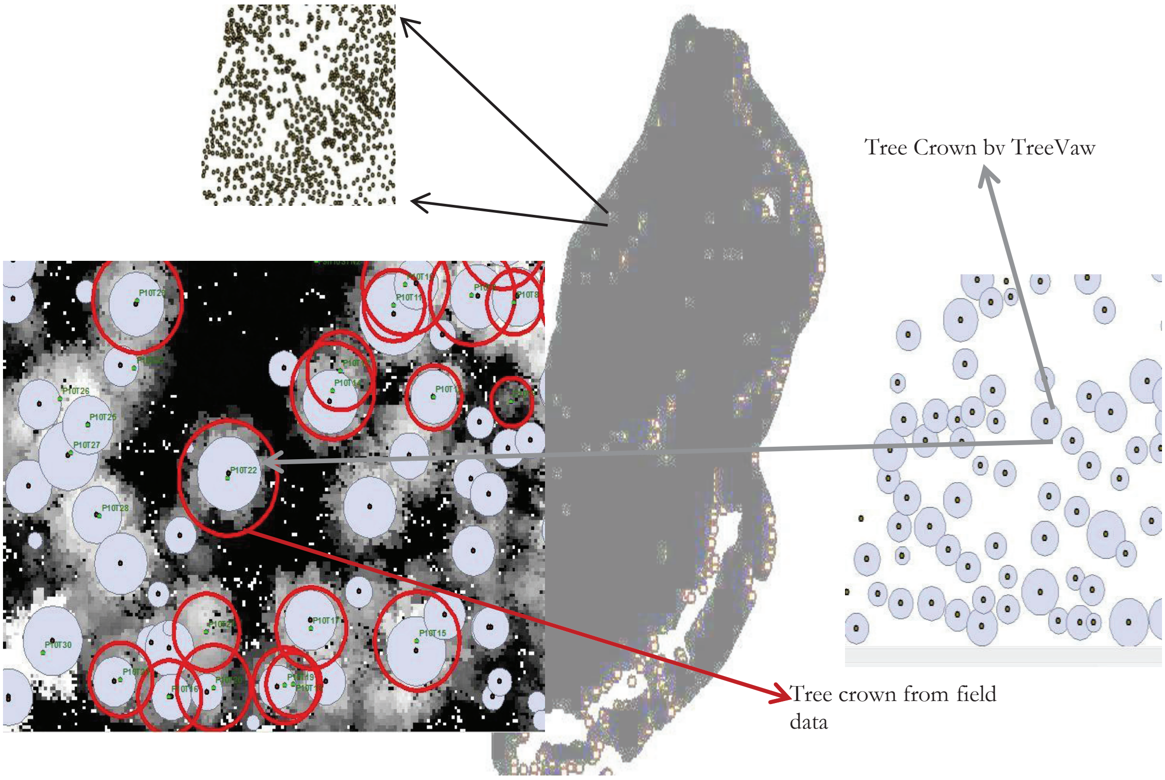


Figure 21: on the centre, a full point shape file for the study area is shown, on the left top, a subset of point is displayed – on the right, a subset of point with buffer of crown diameter for each tree. On the left down, overlaying of TreeVaw result, field data with CHM

Tree Height and Crown diameter validation from TreeVaw:

A high R^2 and a low RMSE for tree height showed a good fit of extracted height with reference height from ground measurements (Figure 22).The crown diameter cannot be extracted by this approach. Four values of height and crown diameter recognized as outliers were removed from the scatter plots (Appendix 2).

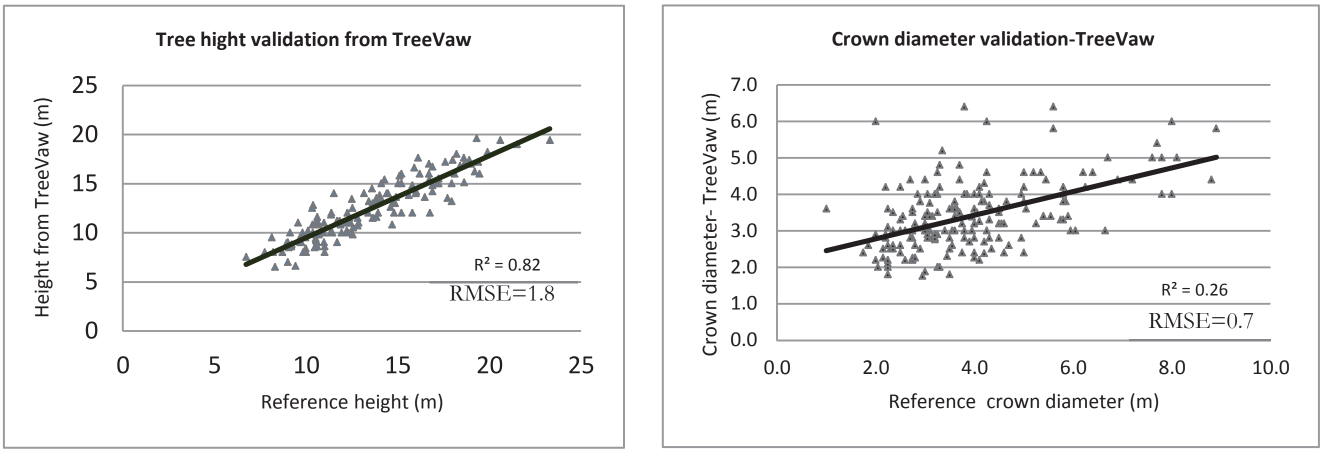


Figure 22: Tree height and Crown diameter validation –TreeVaw approach

Accuracy assessment of tree detection and tree crown area of TreeVaw approach was analysed using reference tree crowns. Overall accuracy varies from low accuracy 36.4% in plot 9 to 100% in plot 7, both located in unstable areas, though total accuracy of 13 plots is promising 72.6% (Table 14).

Table 14: Overall accuracy for tree detection and tree crown area using TreeVaw, St=Stable area, Ust=Unstable area

Plot No.	1 St	2 Ust	3 St	4 Ust	5 Ust	6 St	7 Ust	8 St	9 Ust	10 St	11 Ust	12 St	13 St	Total
N_m	20	16	21	13	14	11	10	9	4	27	7	16	44	212
N_r	22	17	41	18	18	16	10	13	11	30	11	30	51	288
N_d	22	16	21	14	14	11	10	9	4	27	7	16	45	216
Omission error	9.1	5.9	48.8	27.8	22.2	31.3	0.0	30.8	63.6	10.0	36.4	46.7	13.7	26.4
Commission error	9.1	0.0	0.0	7.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.2	1.9
overall accuracy	83.3	94.1	51.2	68.4	77.8	68.8	100.0	69.2	36.4	90.0	63.6	53.3	84.6	72.6

** N_m is the total number of matched trees, N_r is the total number of reference trees measured or delineated in the plot in the field and N_d is the total number of trees detected by TreeVaw*

4.3.2. Tree height and tree crown delineation using Region Growing in eCognition

Tree crown delineation resulted in segmented trees for each CHM. As in following figures (Figure 23, 25, 26, 27 and 28) segmentation for different CHMs are displayed. In the crown isolation process some of crowns were broken into more than two crowns where as some of the overlapped tree crowns could not be separated. It was also noticed that some of the small crowns were delineated to one bigger crown. Thus the problem of over-segmentation and under-segmentation persists in the segmentation Figure24.

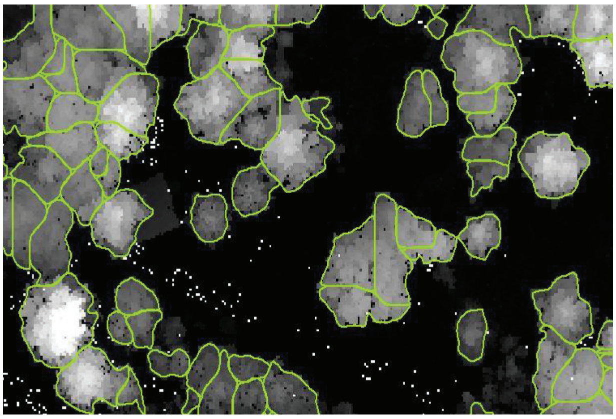


Figure 23: crown delineation on CHM0 derived from LiDAR dataset with density of 164 point /m² - the yellow polygons are segmented trees overlaid on CHM0

Figure 24: Errors occurred during segmentation

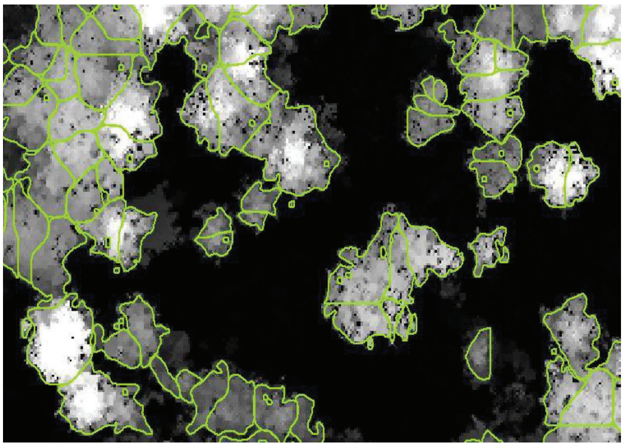


Figure 28: crown delineation on CHM4 derived from LiDAR dataset with density of 4 point/m^2

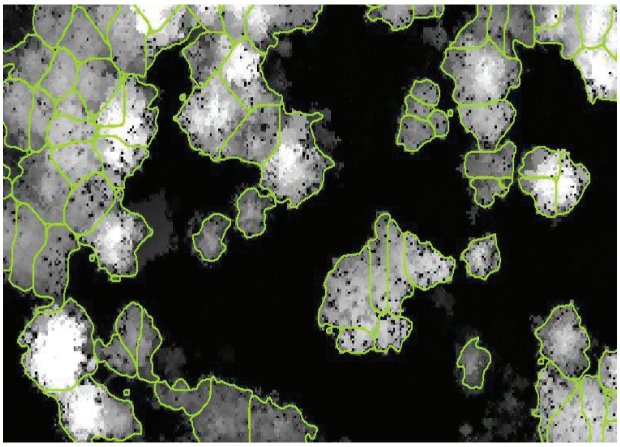


Figure 27: crown delineation on CHM3 derived from LiDAR dataset with density of 11 point/m^2

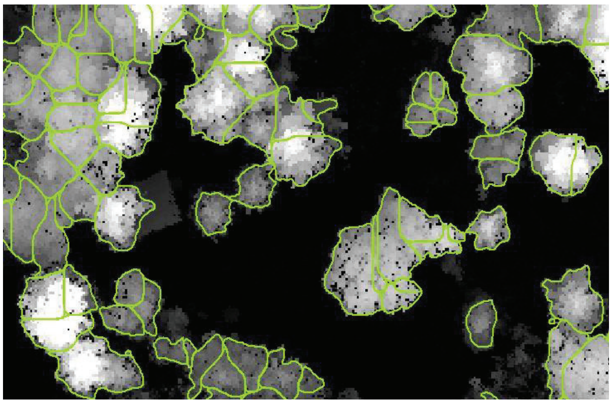


Figure 25: crown delineation on CHM1 derived from LiDAR dataset with density of 32 point/m^2

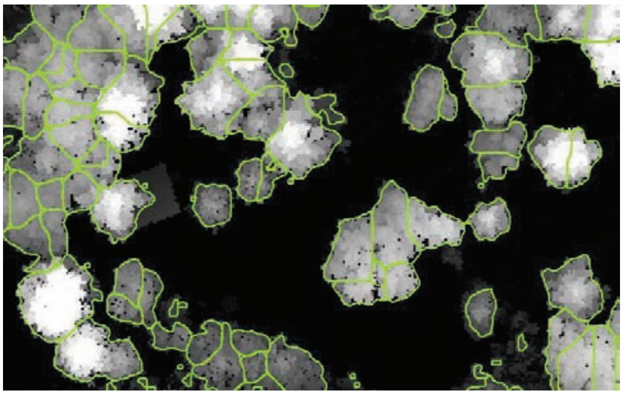


Figure 26: crown delineation on CHM2 derived from LiDAR dataset with density of 82 point/m^2

Tree Height and CPA validation from Region Growing in eCognition:

The extracted height and crown area (CPA) from Region Growing approach for CHM0 were plotted against reference data (Figure29). R^2 and RMSE for both variables explained how the extracted variables fit to reference variables.

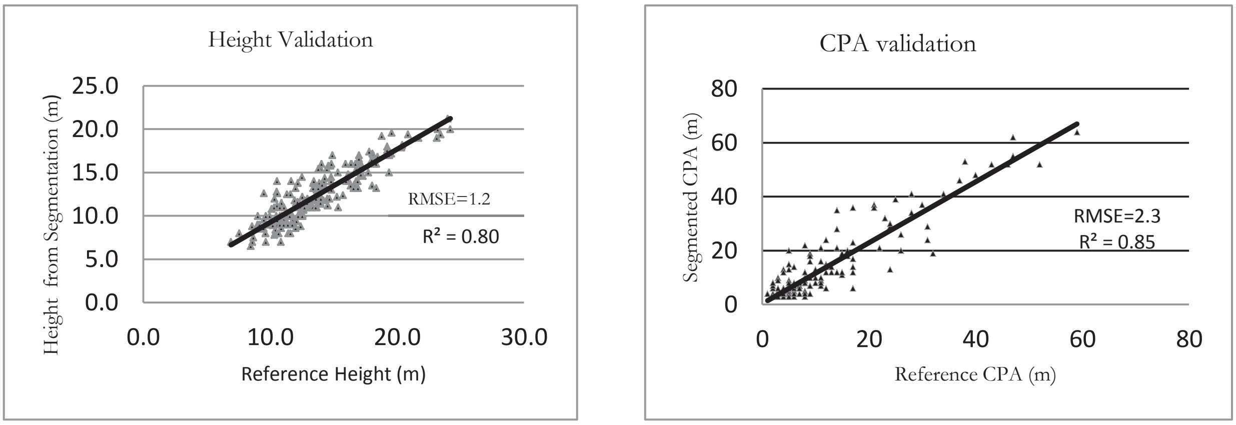


Figure 29: Tree height and CPA validation of Region Growing approach

The accuracy assessment of tree detection and tree crown delineation per plot (Table 15) carried out for result from segmentation of CHM0. The accuracy value varies from 63.6 in plot 12 located in stable areas to high accuracy of 94.9 in plot 2 located in unstable areas. The overall segmentation accuracy was found to be 79%. This implies that 79% of the CPA-segment had good match with the manually delineated CPA. The missing tree was accounted as 16% for all plots out of which plot 3 has the highest value.

Table 15: Accuracy assessment of tree detection and tree crown delineation of Region Growing on CHM0 in eCognition , St=Stable area, Ust= Unstable area

Plot No.	1 St	2 Uns	3 St	4 Ust	5 Ust	6 St	7 Ust	8 St	9 Ust	10 St	11 Ust	12 St	13 St	Total
*N_m	18	17	29	14	15	15	10	12	10	28	10	22	45	244
*N_r	22	17	41	18	18	16	10	13	11	30	11	30	51	288
*N_d	18	18	30	15	15	15	14	12	11	35	13	24	42	262
Omission error	18.2	0.0	29.3	22.2	16.7	6.3	0.0	7.7	9.1	6.7	9.1	26.7	11.8	15.3
Commission error	5.3	5.6	3.3	6.7	0.0	0.0	28.6	0.0	9.1	20.0	23.1	8.3	2.2	6.9
Overall accuracy	78.3	94.4	69.0	73.7	83.3	93.8	71.4	92.3	83.3	75.7	71.4	68.8	86.5	79.0

** N_m is the total number of matched trees, N_r is the total number of reference trees measured or delineated in the plot in the field and N_d is the total number of trees detected by TreeVaw*

Tree height validation (Table 16) for all CHMs is done using R^2 and Root Mean Square Error calculation (Table16).
The accuracy of height varies from 0.75 to 0.63 when the density decreases from 82 point/m2 to 4 point/m2. RMSE value is similar for the last three CHMs but the least for CHM with density of 82 point/m2.

Table 16: Height accuracy for different CHMs

	R2	RMSE	Point density of LiDAR dataset/ m^2
CHM1	0.75	1.4	82
CHM2	0.73	1.8	32
CHM3	0.65	1.9	11
CHM4	0.63	1.9	4

Accuracy assessment for all tree crown segmentations resulted for different CHMs done and omission and commission errors were calculated (Table17). This accuracy varies between 80% and 66%. It has a negative trend when the density of point of CHMs decreases.

Table 17: accuracy assessment of segmentation of Region Growing Approach in eCognition for five CHMs

CHM- SEGMENTED	CHM0	CHM1	CHM2	CHM3	CHM4
N_m	244	240	238	238	234
N_r	288	288	288	288	288
N_d	267	257	258	293	300
Omission error	14.9	16.7	17.4	17.3	18.8
Commission error	8.2	6.6	7.75	18.7	22.0
overall accuracy	79.0	78.7	77.3	69.5	66.1

** N_m is the total number of matched trees, N_r is the total number of reference trees measured or delineated in the plot in the field and N_d is the total number of trees detected by Region Growing*

Moreover, the goodness of segmentation measured using D value for all segmented results of Region Growing approach as given in Table18. D value varies from 0.18 to 0.33 when density decreases from 164 point/m^2 to 4 point/m^2.

Table 18: D value for Tree segmentation in eCognition for CHMs derived from thinned LiDAR dataset

	CHM0	CHM1	CHM2	CHM3	CHM4
Over segmentation	0.19	0.21	0.23	0.25	0.36
Under segmentation	0.16	0.21	0.20	0.23	0.29
D Value	0.18	0.21	0.22	0.24	0.33

Assessment result of Overall accuracy and D value plotted in order to have a better understanding of variation of accuracy for different CHM (Figure29). The accuracy in both methods (Overall accuracy and D value) has a slightly decrease and increase respectively.

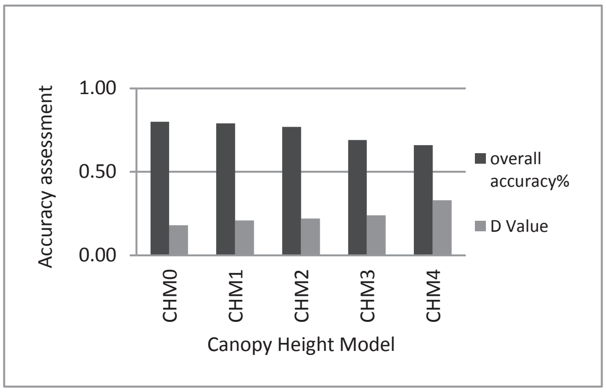


Figure 30: Variation of segmentation assessments for 5 CHMs

4.4. Object based image classification

4.4.1. Species classification

The segmentation result was classified into three dominant species classes including *P. uncinata* and *P. sylvestris* and the rest of segmentation classified as *Others* (figure 17). The result showed *P. uncinata* as dominant species in case of number of trees with density of 1,397 trees/ha while *P. sylvestris* is dominant in case of crown area covered (Table19). In total tree density is 731.

Table 19: Area of each species class and number of trees

Species	Counts	Total Crown area-CPA (ha)	Mean (CPA) (m^2)	Min. of CPA (m^2)	Max. of CPA (m^2)	Total gap area (ha)	Tree density (ha)
P. uncinata	44988	22.0982	4.9	3	12	10.3	1,397
P. sylvestris	22906	33.2802	14.5	3	67	20.4	429
Others	6111	10.8817	17.8	3	86	5.3	381
Total	74005	66.2501	9.0	3	86	45	731

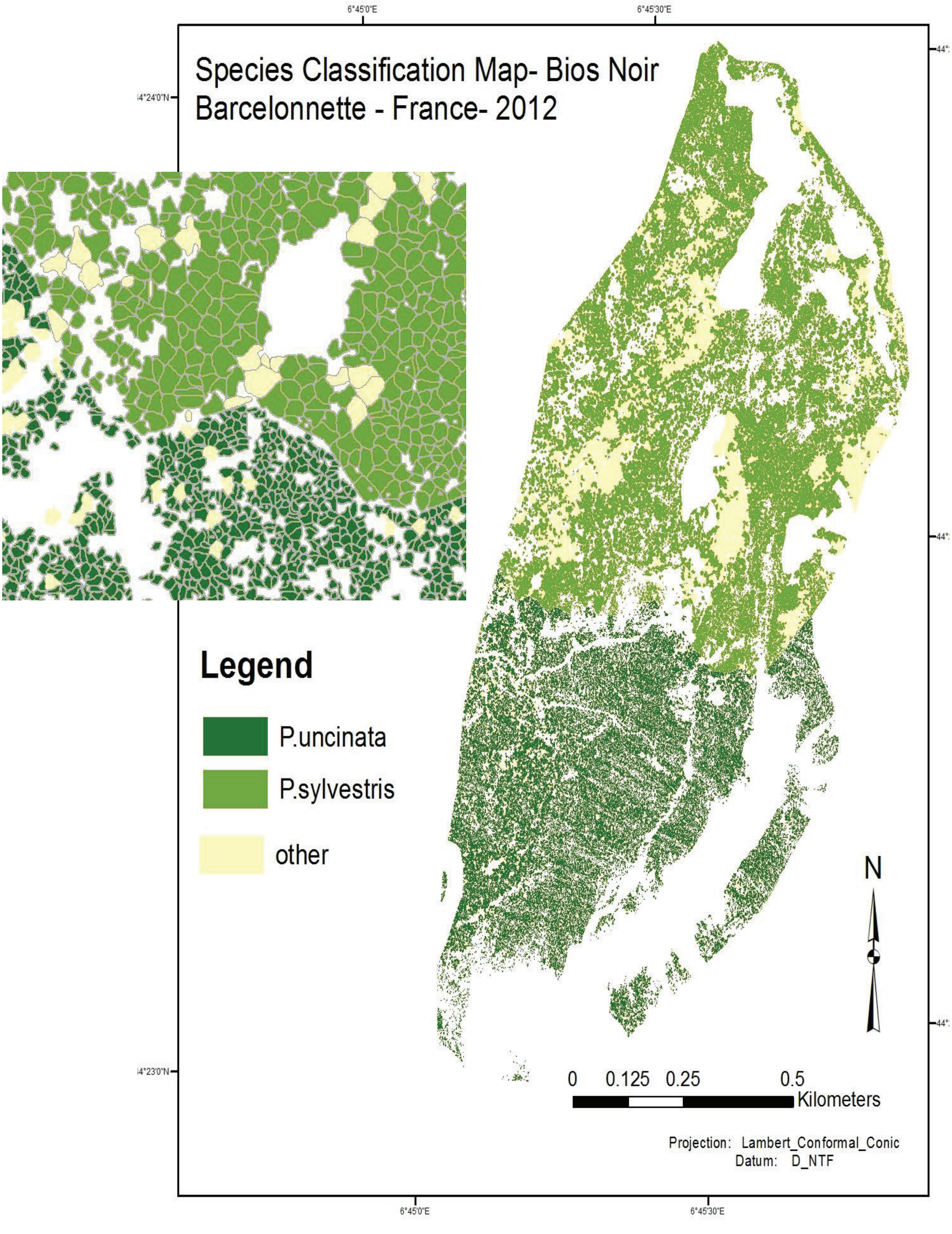


Figure 31: (on the right) Tree Species map, (on the left) a subset of the map displaying individual trees

4.4.2. Object Based Image Classification Accuracy

In order to classification validation 85 trees (30%) of field data was selected in which there were 61 *P. uncinata*, 15 *P. sylvestris* and 9 Others (*L. deciduas)*.
Confusion matrix of error and accuracies calculated as shown in Tables 20 and 21.

Table 20: Confusion matrix of errors of tree species classification

Species	*P. uncinata*	*P. sylvestris*	*Others*	Total
P. uncinata	56	3	0	59
P. sylvestris	4	11	3	18
Others	1	1	6	8
Total	61	15	9	85

Table 21: Accuracy assessment for tree species classification

Species class	Reference total	Classification total	Correct total	Producer's accuracy %	User's accuracy %	Kappa
P. unciata	61	59	56	91.80	94.91	0.71
P. sylvestris	15	18	11	73.33	61.11	0.60
Others	9	8	6	66.00	75.00	0.58
Total	85	85	73			
Overall Accuracy: 81.1%						0.62

As the result of classification showed *P. uncinata* was classified the most correctly with higher user's and producer's accuracy following by *P. sylvestris* and others. Overall accuracy and Kappa coefficient was found to be 81.10% and 0.62 respectively. This means that 81% of the CPA-segments were correctly classified. It can explain the capability of CHM for species classification in this forest.

4.5. Model development and Validation

4.5.1. Relationship between height, CPA and Carbon

The comparison of coefficient of determination for three equations presented in Table 22 showed that equation 1 provided the best fit. Besides, multi linear regression resulted in a higher coefficient of determination for carbon modelling than simple linear regression (Figure 32). Therefore, Carbon model was developed for pines through multi linear regression using height and CPA.

Table 22: Multi linear regression analysis for three allometric equations using height and CPA and carbon stock

	Coefficient of determination (R^2)	Standard error	T Statistic	P Value
Equation 1	0.56	23.72	-4.49	1.28E-05
Equation 2	0.49	23.36	-3.62	0.0004
Equation 3	0.51	25.35	-3.23934	0.00143

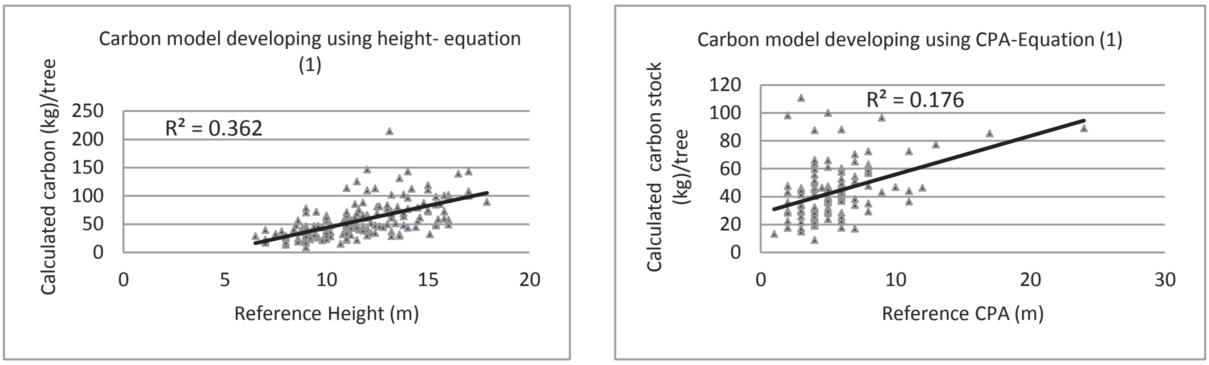


Figure 32: Simple linear regression model for carbon estimation

As it is clear in Table 22, T Statistic for all equations is not equal to 1 and the p-value as well is less than 0.05. Therefore one way ANOVA was applied to test the significance of coefficient of determination and results in Table 23 showed that the regression was statistically significant at 95% level of confidence.

Table 23: ANOVA test result of *P. uncinata* and *P. sylvestris*

	df	S	MS	F	Significance F
regression	2	84978.94	42489.47	75.51541	1.79E-24
residual	178	400613.6	2250.638		
total	180	740529.4			

So the model developed for carbon stock estimation in both pines in the study area is given as below:

*Carbon Estimation Model = -38.17 +7.91*Height+1.74*CPA*

Applying the model for estimating carbon for the whole study area gave some information of carbon as showed in Table 24.

Table 24: carbon information in the study area

Species	Counts	Tree density / ha	Mean Carbon kg/tree	Mean Carbon tonne/ha
P. uncinata	44988	1397	55.59	77.659
P. sylvestris	22906	429	65.49	28.10

4.5.2. Model validation

The predicted values were plotted against calculated carbon stock. The model resulted of coefficient of determination of 0.65 using 132 trees of *P. uncinata* and *P. sylvestris* (figure 33). So it is interpreted that 65 % of calculated carbon from the field was explained by predicted carbon using model. The test of goodness of fit was done using RMSE of this validation which is 22.83 kg per tree. It was noticed that the model calibrated with calculated carbon with unknown error.

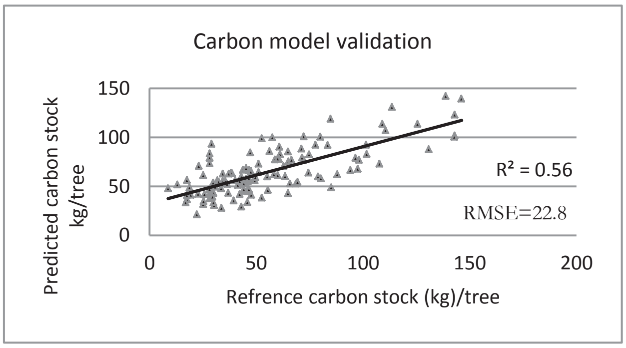


Figure 33: Carbon Model Validation

5. DISCUSSION

5.1. Tree Attributes

Though the field data showed normal distribution for all attributes the relationship between tree attributes is not strong for pine species. They are not comparable with the result of other studies which found allometric relationship among different parts of trees. The R^2 >0.70 between DBH, height, crown area/crown diameter was found in those studies (Bartelink, 1996; Fang & Bailey, 1998; Hall et al., 1989 ; Hemery et al., 2005). The condition of this anomalous forest, dense tree plantation especially *P. uncinata* with a tree density of 1,397 /ha (Table19) resulted in low correlation between tree variables.

In addition, when LiDAR data are applied for measuring trees and stands in a forest, the DBH-height relationship should be functionalised (Kwak, et al., 2007) while the R^2 doesn't show a strong function. Besides, the relationship between height and crown diameter is significantly low (R^2= 0.15).

5.2. Tree detection and extraction of forest attributes in TreeVaw

An average of 72% of tree was detected correctly in TreeVaw approach at the highest point density. This result is comparable with the result with lower point density of 70 point /m^2 with the same method of assessment with 63 % accuracy with 4 % of commission error, and 36 % omission error. On comparison to the result from another study in the same area (Razak, et al., 2011) with accuracy of 80% to 94% with the same method of assessment is not promissing.

This overall accuracuy varies from 36% to 100 % between plots. This high variation rises from some factors. One is that tree detection method is tree species dependent, for example, in plot 10, 95% of trees are *L. deciduas* which are large, tall and isolated trees, or plot13 all trees are *P. sylvestris*. That means they are easily visible by even low point density of LiDAR data but in other plots which mostly covered by *P. uncinata* trees which they don't have large crown planted in a very close to each other and their crown has a large overlay, so in this case intermingle trees make low accuracy in tree detection. It can be interpreted that tree detection accuracy influenced by tree density, in plot where the number of trees are low detection accuracy is significant acceptable (plot 7 and Plot 2) while other reason may affect the accuracy even in plot with low tree density. It may be because of the inclination and orientation of tilted trees. For example in plot 9 which located in unstable area and most of the trees tilted and number of intermingled trees is high, so accuracy is low, though number of trees in the plot is also low. Furthermore, Variation of accuracy between stable and unstable plots shows that the accuracy is not affected significantly by stability of the land. It implies that single reason couldn't explain the detection accuracy. Lower commission errors compare to omission errors imply that TreeVaw approach was able to correctly detect trees but not all measured trees in the field.

5.2.1. Tree height

The accuracy of the tree height estimates (R^2= 0.82, RMSE=1.8 m) is also comparable to the accuracy of the estimations achieved by Razak (et al., 2011) with R^2=0.72 -0.91 and RMSE=1.07- 1.28 m) while in other research with very lower point density accuracy of tree height is also similar(Kwak, et al., 2007; Leckie et al., 2003; Popescu, 2005). As height error (RMSE) could be closely correlated with slope(Véga & Durrieu, 2011) in the study area which is highly steep >60% and measuring tree height in dense steep forest is associated with error as we had already in the field.

5.2.2. Crown diameter

As expected, the tree crown diameter is less accurately estimated than the tree height. This result (R^2=0.27 and RMSE=1.4 m) is not in agreement with the result by Popesco (2003) for pines and deciduous trees with R^2 values 0.62-0.63 respectively and RMSE 1.36 and 1.41 m. The reason might be due to that the algorithm to calculate crown diameter in TreeVaw is based on the relationship between crown size and height of the trees (Popescu, et al., 2003) as this relation is not significant in this forest (R^2 = 0.14). Other part of the unexplained variance associated with crown diameter can be attributed to the fact that the algorithm for calculating crown diameter aimed at measuring the non-overlapping crown diameter and individualized crowns on the CHM, while the field measurements considered crowns to their full extent and therefore measured overlapping crown diameters (Popescu, 2003)

5.3. Thinning method

The issue of whether or not different density of point affects the accuracy of forest biophysical model is a controversial one (Lim, et al., 2008). Some would argue that because many parameters such as scan angle, scan frequency, aircraft velocity and repetition frequency could contribute to determine point density, so it is counterintuitive to conclude that one of those parameter itself resulted different point density (Lim, et al., 2008). However the advantage of the simple thinning method used in this study which more likely is a kind of filtering is that the variation of point density used here didn't derive from different survey parameters, so the influence of sampling point density could have been argued with this assumption that all above mentioned parameters were constant but flight survey done in different altitude.This methd of thinning filters the point based on the time they recorded though the distribution of the points before and after thinning were not examined in this research. Larger point density provide more detail about the vertical canopy structure whinin a given area.

5.4. Tree detection and extraction of forest attributes in Region Growing approach

Several methods exist for detecting and segmenting trees on the image. In a study by Larsen and Erikson (2011) different approaches (6 individual tree crown detection algorithms) for segmenting crowns of individual trees has been fully compared(Larsen et al., 2011). The study shows that no algorithm is optimal for all types of images and forest type. He concluded that the optimal approach in a specific situation depends on various characteristics of the image and forest stand, such as crown closure, regularity and species mixture. However a comparison of Region Growing method with other approaches (Erikson, 2003; Eriksson et al., 2004) showed superiority of Region Growing method for dense forest with correct delineation as much as 95% of all visible tree crown segmentation of images.

An average of ~80% of trees in Region Growing approach was correctly detected for CHM0. Though this result is higher than result from TreeVaw approach and is with agreement of the result of other study in the same area (Razak, et al., 2011), higher accuracy was expected because of high point density. Variation of detection accuracy between plots is also less than TreeVaw approach (63.6 – 94.40). D value of 0.18 as well explained an acceptable detection of trees. However this accuracy came out from the condition which researcher assigned for tree detection (> 60% of intersection area for true detected tree) though this condition is more flexible in other researches (Brandtberg, et al., 2003; Rahman, et al., 2009). Furthermore, function of Local Maxima in Region Growing approach may not be able to find all true tree tops, so the segmentation result was influenced by this function. Applying a height filter may give a better result as Leckie (et al., 2003). As mentioned before, structure of forest also influences the accuracy of tree detection. As in the study area *P. uncinata* was planted in a very high density and most of trees are in a same level of height while crown's overlap is very high which affects tree detection accuracy. Furthermore the same finding as similar as in previous approach regarding difference of accuracy between stable and unstable plots was found.

5.4.1. Tree height and crown area

Examination of the height and crown area delineation derived from LiDAR using Region Grwoing approach for ground reference data demonstrated the effectiveness of the approach. The coefficients of determination for tree height estimations ($R^2 = 0.80$, RMSE =1.2 m) and CPA ($R^2 = 0.85$, RMSE =2.3 m^2) are in an agreement with other researches (Kim, et al., 2010; Leckie, et al., 2003; Suárez, et al., 2005) and higher than found with the TreeVaw approach as well.

5.5. Influence of point density on tree segmentation:

As density of point decrease between CHMs, accuracy of tree detection resulted two methods of assessment (Overall accuracy and D value) declines generally. There was a slight drop in overall accuracy when the density decrease from 164 to 32 point / m^2 followed by a significant decline when density goes down to 4 point /m^2. This trend has been occurred in D value in an inverse direction as well. Therefore It can be interpreted that point density of >11/m^2 does neither influnce tree detection nor crown delineation. The higer ommision error than commission errors for all CHMs imply that number of trees which were not detected are higher than the number of tree detected wrongly. As tree detection accuracy is based on intersection area of matched trees, the accuracy of tree detection relies on the quality of crown delineation. As the density of points decreases, the probability of finding correctly tree top and seeds comes down in Region Growing and numbers of points which are detected as crown edge also decrease.

It is clear that the loss in vertical accuracy (height) has significant (75%- 63%) effects especially at lower density (CHM4). This result is in agreement with the result in a study (Yu et al., 2004) on effect of flight altitude on tree height estimation. His results indicated, in general, that tree height estimation accuracy and number of detectable trees decreases with the increase in flight height and point density (10, 5 and 2.5 point/ m^2 were output of three flights in 400, 800 and 1500 m of altitude, respectively) has more influence on tree height than other factors. The forest tree species were *Picea abies* and *P. sylvestris*.

Besides, this result can be supported by the result of an study in which a slightly similar method of thinning but with lower LiDAR point density applied (Pirotti & Tarolli, 2010).

Furthermore, in an study (Lim, et al., 2008) the effects of sampling point density on canopy height was examined and was concluded that though minimum and maximum canopy height affected by sampling density but mean canopy height is insensitive to density of point across different types of forest plots. The study area was planted by *P. resinosa* and *P. strobus* while Thomas examined the scanning density for stand-level mapping and revealed high-density models are well correlated with mean dominant height and crown boundary (R^2=0.84 , 0.91 respectively) and low density couldn't predict crown boundaries. The maximum point density in this study was 8 point/m^2 (Thomas, et al., 2006).

Therefore it implies that CHMs derived by at least 11 point density of LiDAR data/ m^2 to be capable to achieve an accurate tree detection ,tree height and tree crown delinieation . It has to be noted that segmentation algorithm as a function also influence the accuracy of tree detection and tree crown delineation.

5.6. Tree species identification

Recently the LiDAR data has been tested for tree species classification (Brandtberg, 2002; Holmgren & Persson, 2004). Holmgren classified *P. sylvestris* and *Picea abies* using LiDAR of density of 0.5 point/m^2 with overall accuracy of 95%. In another study (Persson et al., 2006) *P. sylvestris* and *Picea abies* and *Betula* spp. were identified with an accuracy of 87% using laser scanning data of 50 point/ m^2. The result of species classification accuracy in this study is similar to the result of researches mentioned above.

Tree species classification has an overall accuracy of 81% with Kappa statistics of 0.62. It was also observed that user's accuracy for *P. uncinata* was even as high as 94%. The reason is that 71% of the trees sampled in the field belonged to this species. Low user's accuracy in classifying the other two species is mainly attributed to fewer samples for training and validation of the result. Short time field work resulted in having not enough samples of all dominant tree species in the study area. Also the training and validation data for *P. sylvestris* all belongs to a single plot in zone 2 which may not represent this species adequately.

5.7. Carbon model development

LiDAR-measured height and LiDAR-measured CPA used for developing carbon model are high correlated to reference data (80% and 82% respectively) so examining how good CPA itself can be applied to estimate carbon stock associated with height which both can be extracted from CHM was considered. If local allometric equation was used for calculation of above ground carbon, the findings would be largely narrow down the uncertainty of this model for prediction. Whereas untested equation used in this research has an unknown error. This represents error propagation.

In addition the type of forest in the research area is too anomalous (century-old abandoned plantations with very thin, very dense trees) unlikely to fit to any allometric equation developed in production forests elsewhere. Besides, when LiDAR data are applied for measuring trees and stands in a forest, the DBH–height relationship should be functionalized. This relationship also is not strong in this forest ($R = 0.57$).

A limitation of the allometric equation is that it was developed from DBH with a narrow range. So the model may produce extrapolation errors when applied beyond the range of model development data(Anderson et al., 2000).

The validation accuracy for the carbon model with R^2 of 0.65 means 65 % of calculated carbon can be explained by predicted carbon/tree implying an error of 22.83 kg per tree. However the mean carbon/tree is 55.6 and 65.5 kg for *P. uncinata* and *P. sylvestris* respectively which is comparable to 193 kg for *P. densiflora* with mean DBH 40 cm and mean height 17.2 m (Kim, et al., 2010).

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

In this work, LiDAR point density and accuracy of LiDAR derived height and LiDAR derived CPA to develop a biophysical model for estimating carbon stock was tested. In general it was found that the forest is too anomalous for fundamental research on biomass and carbon estimation. However, with respect to this, following conclusions were drawn for each research question.

(1) Is there a significant relationship between forest biophysical parameters measured in the field to obtain an allometric equation?
Significant (<0.05) but not high correlated relationship (> o.37) was found between DBH, crown area and height of pine trees

(2) Is it feasible to estimate carbon stock for individual tree of pine forest using solely high density LiDAR data?
Using a developed model of carbon prediction by LiDAR measured height and LiDAR measured CPA provided carbon stock of individual trees with R^2 of 0.56. Though the relationship of this model is not strong it is feasible to estimate the amount of carbon using solely and effectively high density airborne LiDAR data.

(3) How does the different point density of LiDAR data affect the accuracy of forest biophysical model?
In this research the assessment of segmentation result from Region Growing approach was considered to answer to the above question. It was found that the density >11 point/m^2 gives more accurate of tree segmentation result on CHM with overall accuracy of > 70% and D value of <0.24.
The research indicated that LDAR point density to be used for CHM generation can be as low as 11 point density/m^2 so the ability of low-density models to accurately map key biophysical variables of forest is a positive indicator for the utility of lidar data for monitoring forested areas

(4) How significant are the variables (height and crown area derived from LiDAR data) to estimate the above-ground biomass and carbon stock
LiDAR derived tree height and Lidar derived tree crown area do not show a highly significant correlation (R2=0.32, 0.18 respectively) with calculated carbon though they are highly correlated with the height and crown area measurements in the field (R^2 of 0.80 and 0.85 respectively).

6.2. Recommendation

During this work several points were discovered which will need ongoing work and attention

- The availability of such high density LiDAR data in forest area gives the opportunity of direct measurement of tree variables on the point clouds. So carrying out studies for extracting more accurate forest biometrics information which more contribute to estimate aboveground biomass and carbon stock such as crown volume, crown base height.
- Species identification found the effectiveness of high density LiDAR for one of the species. More field data needed for identifying other dominant tree species.
- Improving individual tree crown segmentation in eCognition using such as 'marker-control watershed segmentation' or 'Region Growing' based on Density of High Points (DHP) is recommended.

- Testing thinning method considering the first returns which refer to the canopy surface is recommended in further studies.

- The information of influence of point density derived from this research can be of interest when planning LiDAR flights for this specific purpose.

References

AFIB, C. (2004). wood density Conversion tables. In D. o. W. M. a. Biomass (Ed.), *AFIB-CTFC from SIBosC(CREAF-DMAH,2011) and CPF (2004).* Catalunya, Spain: Department of Wood Mobilisation and Biomass.

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

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

Bortolot, Z. J., & Wynne, R. H. (2005). Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. *ISPRS Journal of Photogrammetry and Remote Sensing, 59*(6), 342-360.

Brandtberg, T. (2002). Individual tree-based species classification in high spatial resolution aerial images of forests using fuzzy sets. *Fuzzy Sets and Systems, 132*(3), 371-387.

Brandtberg, T., Warner, T. A., Landenberger, R. E., & McGraw, J. B. (2003). Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. *Remote Sensing of Environment, 85*(3), 290-303.

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

Dubayah, O. r., & Drake, J. B. (2000). Lidar remote sensing for Forestry applications.

Erikson, M. (2003). Segmentation of individual tree crowns in colour aerial photographs using region growing supported by fuzzy rules. *Canadian Journal of Forest Research, 33*(8), 1557-1563.

Eriksson, M., Perrin, G., Descombes, X., & Josiane, Z. (2004). A COMPARATIVE STUDY OF THREE METHODS FOR IDENTIFYING INDIVIDUAL TREE
CROWNS IN AERIAL IMAGES COVERING DIFFERENT TYPES OF FORESTS. Retrieved from http://www-sop.inria.fr/ariana

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

FAO. (2010). *Global Forest Resource Assessment 2010 ,Main report*
Rome,Italy: Forestry Department.

FAO. (2011). Roles of forests in climate change. Retrieved 26-05-2011, 2011, from http://www.fao.org/forestry/climatechange/en/

García, M., Riaño, D., Chuvieco, E., & Danson, F. M. (2010). Estimating biomass carbon stocks for a Mediterranean forest in central Spain using LiDAR height and intensity data. *Remote Sensing of Environment, 114*(4), 816-830.

Gaveau, D. L. A., & Hill, R. A. (2003). Quantifying canopy height underestimation by laser pulse penetration in small-footprint airborne laser scanning data. *Canadian Journal of Remote Sensing, 29*(5), 650-657.

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

Gougeon, F. A., & Leckie, D. G. (2006). The individual tree crown approach applied to Ikonos images of a coniferous plantation area. *Photogrammetric Engineering and Remote Sensing, 72*(11), pp.1287-1297.

Hall, R. J., Morton, R. T., & Nesby, R. N. (1989). A comparison of existing model for DBH estimation from large scale photo. *The Forestry Chronicle* pp. 114-120

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

Holmgren, J., & Persson, Å. (2004). Identifying species of individual trees using airborne laser scanner. *Remote Sensing of Environment, 90*(4), 415-423.

Hyyppä, J., Hyyppä, H., Leckie, D., Gougeon, F., Yu, X., & Maltamo, M. (2008). Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *International Journal of Remote Sensing, 29*(5), 1339-1366.

Isenburg, M. (2012). thinning algorithm. In Martin.Isenburg@gmail.com (Ed.).

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

Kim, S.-R., Kwak, D.-a., Olee, W.-K., & Son, Y. (2010). Estimation of carbon storage based on individual trees detection in pinus densiflora stands using a fusion of aerial photograghy and LiDAR data. *science China Press and Springer-Verlag Berlin Heidelberg 2010, 53,No.7*, 885-897.

Kwak, D.-A., Lee, W.-K., Cho, H.-K., Lee, S.-H., Son, Y., Kafatos, M., et al. (2010). Estimating stem volume and biomass of Pinus koraiensis using LiDAR data. *Journal of Plant Research, 123*(4), 421-432.

Kwak, D.-A., Lee, W.-K., Lee, J.-H., Biging, G. S., & Gong, P. (2007). Detection of individual trees and estimation of tree height using LiDAR data. *Journal of Forest Research, 12*(6), 425-434.

Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T., & Gougeon, F. A. (2011). Comparison of six individual tree crown detection algorithms evaluated under varying forest conditions. *International Journal of Remote Sensing, 32*(20), 5827-5852.

Leckie, D., Gougeon, F. A., Hill, D., & Armstrong, L. (2003). Combined high-density lidar and multispectral imagery for individual tree crown analysis. *Can. J. Remote Sensing, , Vol. 29,No. 5,*, pp. 633–649.

Lefsky, M., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies. *BioScience, 52 no.1*, 19-30.

Li, Z. R., Hayward, R., Zhang, J. L., Liu, Y. E., Walker, R., & Ieee. (2009). *TOWARDS AUTOMATIC TREE CROWN DETECTION AND DELINEATION IN SPECTRAL FEATURE SPACE USING PCNN AND MORPHOLOGICAL RECONSTRUCTION.*

Lim, K., Hopkinson, C., & Treitz, P. (2008). Examining the effects of sampling point densities on laser canopy height and density metrics. *Forestry Chronicle, 84*(6), 876-885.

Lu, D. (2005). Integration of vegetation inventory data and Landsat TM image for vegetation classification in the western Brazilian Amazon. *Forest Ecology and Management, 213*(1-3), 369-383.

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2003). Classification of successional forest stages in the Brazilian Amazon basin. *Forest Ecology and Management, 181*(3), 301-312.

Magnussen, S., & Boudewyn, P. (1998). Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. *Canadian Journal of Forest Research, 28*(7), 1016-1031.

Magnussen, S., Næsset, E., & Gobakken, T. (2010). Reliability of LiDAR derived predictors of forest inventory attributes: A case study with Norway spruce. *Remote Sensing of Environment, 114*(4), 700-712.

Moller, M., Lymburner, L., & Volk, M. (2007). The comparison index: A tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation, 9*(3), 311-321.

Naesset, E. (2002). Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. [Article]. *Remote Sensing of Environment, 80*(1), 88-99.

Næsset, E., & Økland, T. (2002). Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. *Remote Sensing of Environment, 79*(1), 105-115.

Niemann, K. O., Adams, S., Hay,G. (1999). Automated tree crown identification using digital orthophoto mosaiccs. In: processings of the International Forum on Automated interpretation of High Spatial Canadian forest Service. *Pacific Forestry Center*, 105-113.

Parker, R. C., & Glass, P. A. (2004). High- versus low-density LiDAR in a double-sample forest inventory. [Article]. *Southern Journal of Applied Forestry, 28*(4), 205-210.

Persson, A., Holmgren, J., & Söderman, U. (2006, 14-15 Febraury 2006). *Identification of Tree Species of Individual Trees by Combining Very High Resolution Laser Data with Multi-Spectral Images.* Paper presented at the International Workshop on 3D Remote Sensing, Vienna, University of Natural Resources and Applied Science,.

Persson, A. J. H. a. U. S. (2002). Detecting and measuring individual trees using an airborne laser scanner. *Photogrammetric Engineering and Remote Sensing 68*, 1–8.

Pirotti, F., & Tarolli, P. (2010). Suitability of LiDAR point density and derived landform curvature maps for channel network extraction. *Hydrological Processes, 24*(9), 1187-1197.

Popescu, S. C. (2003). Forest measurment with airborne and Ground based Laser Scanning. *Geospatial solution*. Retrieved from www.geospatial-online.com

Popescu, S. C. (2005). *When Every LiDAR Point Counts:Analyzing the Point Cloud with a Height Bin Approach to Assess Forest Parameters*. Paper presented at the LiDAR applications in Forest Assessment and inventory.

Popescu, S. C. (2007). Estimating biomass of individual pine trees using airborne lidar. *Biomass and Bioenergy, 31*(9), 646-655.

Popescu, S. C., & Wynne, R. H. (2002). Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *computer and electronics in agriculture, 37*, 71-95.

Popescu, S. C., & Wynne, R. H. (2004). Seeing the trees in the forest, using Lidar and Multispectral data fusion with local filtering and variable window size for estimating tree height. *Photogrammetric Engineering & Remote Sensing, 70,No.5*, 589-604.

Popescu, S. C., Wynne, R. H., & Nelson, R. F. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian journal Remote Sensing,, Vol. 29,*(No. 5), pp. 564–577,.

Rahman, M. Z. A., Gorte, B. G. H., & Bucksch, A. K. (2009). A new method for individual tree measurement from airborne LIDAR. *-silvi2009*.

Razak, A. R., Bucksch, A., Damen, M., van Westen, C., & Straatsma , M. (2011). *Characterizing tree growth anomaly induced by landslides using LiDAR*. Paper presented at the Second World Landslide Forum, Rome, Italy.

Rossmann, J., Schluse, M., Bucken, A., & Krahwinkler, P. (2007, 12-14 September, 2007). *Using Airborne Laser Scanner Data in Forestry Management:A novel approach to single tree deliniation.* Paper presented at the ISPRS Workshop on Laser Scanning 2007 and SilviLaser 2007,Espoo, Finland.

Suárez, J. C., Ontiveros, C., Smith, S., & Snape, S. (2005). Use of airborne LiDAR and aerial photography in the estimation of individual tree heights in forestry. *Computers & Geosciences, 31*(2), 253-262.

Theiery, Y., Malet, J. P., & Maquaire, O. (2007). *is it possible to link statistical and deterministic models for assessment landslide hazard.* Paper presented at the poster.

Thenkabail, P. S., Enclona, E. A., Ashton, M. S., Legg, C., & De Dieu, M. J. (2004). Hyperion, IKONOS, ALI, and ETM+ sensors in the study of African rainforests. *Remote Sensing of Environment, 90*(1), 23-43.

Thomas, V., Treitz, P., McCaughey, J. H., & Morrison, I. (2006). Mapping stand-level forest biophysical variables for a mixedwood boreal forest using lidar: an examination of scanning density. *Canadian Journal of Forest Research-Revue Canadienne De Recherche Forestiere, 36*(1), 34-47.

UNFCCC. (2010a). About CDM.pdf. Retrieved 26-05-2011, 2011, from http://cdm.unfccc.int/about/index.html

UNFCCC. (2010b). Greenhouse Gas Inventory Data. Retrieved 27-05-2011, 2011, from http://unfccc.int/ghg_data/items/3800.php

Vallet, P., Dhôte, J.-F., Moguédec, G. L., Ravart, M., & Pignard, G. (2006). Development of total aboveground volume equations for seven important forest tree species in France. *Forest Ecology and Management, 229*(1-3), 98-110.

van Gils, H. A. M. J. (2011). Trees_Forests_Barcelonette. Faculty of Geo-Information Science and Earth Observation of the University of Twente.

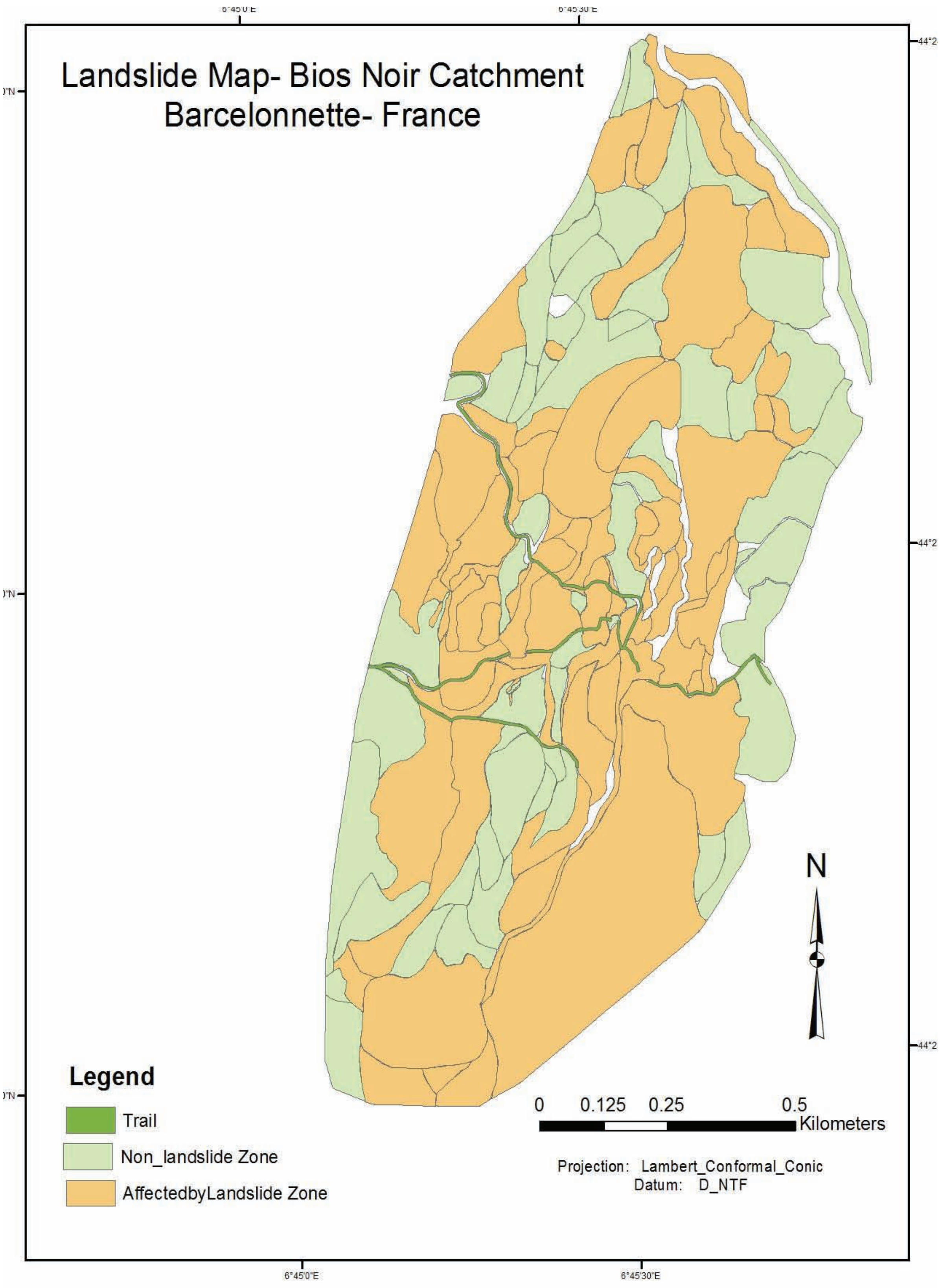
Véga, C., & Durrieu, S. (2011). Multi-level filtering segmentation to measure individual tree parameters based on Lidar data: Application to a mountainous forest with heterogeneous stands. *International Journal of Applied Earth Observation and Geoinformation, 13*(4), 646-656.

Yu, x., Hyyppa, j., Hyyppa, h., & Maltamo, M. (2004). *EFFECTS OF FLIGHT ALTITUDE ON TREE HEIGHT ESTIMATION USING AIRBORNE LASER SCANNING*. Paper presented at the International Conference NATSCAN 'Laser-Scanners for Forest and Landscape Assessment – Instruments, Processing Methods and Applications'.

Zianis, D., Muukkonen, P., Raisa, M., & Mencuccini, m. (2005). *Biomass and stem Volume equations for Tree species in Europe* (Vol. Monograohs4): Tammer-Paino Oy, Tampere, Finland, 2005.

Appendices

Appendix 1



Appendix 2

List of species observed in the Bios Noir catchment		
	Specie name	Generic name
1	*Pinus uncinata*	Mountain pine
2	*Pinus sylvestris*	Scotch pine
3	*Larix decidua*	Larch
4	*Picea abies*	Spruce
5	*Alnus* spp	----
6	*Fraxinus* spp	Ash
7	*Juniperus communis*	---
8	*Juniperus sabina*	-----

Outlier trees which removed from data				
Plot nomber- Tree Nomber	Reference Crown diameter (m)	Extracted crown diameter (m)	Reference height (m)	Extracted height (m)
P11T3	4	4	11	15.4
P13T13	3.5	2	15.3	17
P13T20	3.8	2	13.66	6.1
P12T28	-	4	11	16

Appendix 3

Generating CHM directly from Lidar Data:

In order to make Canopy height model there are different way. The simple way that used in many research is making Digital Train Model and Digital Surface Model and by subtracting these two raster file , the CHM will be provided.
Using lastools make it possible to produce CHM directly from LiDAR data. Using "lasheight" function for two times , the first for normalizing data and the second time for dropping height less than and above than minimum and maximum expected height (here minimum is zero and maximum 40 as the highest tree height) . Then by merging simultaneously when executing the second "lasheight " function (we can merge the 17 files of data as a separate function after doing "lasheight" , that is called "merge") a merged file is provided that will be used in generating CHM by applying "Blast2dem" function.
The output of this step can be tif, img or other extension. But when we are going to visualize in ArcGIS first we should be sure that the pixel depth is 32 bit not 8 bit. (In source), then should be done some raster calculation for displaying the maximum and minimum value of height in the ArcGIS as below

Generating CHM using blast2dem, example name: CHMBlfirstret20, 15, 10, 25:

1- lasheight -lof file_list.txt -olaz -replace_z
2- lasheight -lof file_list.txt -merged -o Height_040_BN.laz -drop_below 0 -drop_above 35
3- lasmerge -lof file_list.txt -merged -o Merg_2lasheight.laz *(if you don't merge in previous step then this command should be done otherwise from step 2 goes to step 4)*
4- blast2dem -i Merg_2lasheight.laz-o CHMBlfirstret10.tif -step 0.1 -first_only -kill 50
5- blast2dem -i Merg_2lasheight.laz-o CHMBlfirstret25.tif -step 0.25 -first_only -kill 50

1. Generating CHM using Grid , example name :CHMGrid15,10,20)

1. lasheight -lof file_list.txt -olaz -replace_z
2. lasheight -lof file_list.txt -olaz -drop_below 0 -drop_above 40 or
3. lasheight -lof file_list.txt -olaz -drop_below 0 -drop_above 35
4. lasgrid -lof file_list.txt -merged -o CHM_Grid15.tif -step 0.15 -elevation -highest -fill 15 -mem 1500 -temp_files g:\temp\temp or
5. lasgrid -lof file_list.txt -merged -o CHM_Grid20.tif -step 0.2 -elevation -highest -fill 15 -mem 1500 -temp_files g:\temp\temp or
6. lasgrid -lof file_list.txt -merged -o CHM_Grid10.tif -step 0.1 -elevation -highest -fill 20 -mem 1500 -temp_files g:\temp\temp

2. Generating CHM using substraction DTM from DSM :

2.1. Generating DTM

In Lastools using lasground takes all of points and try to find the ground points (class 2 if it has beeb classified by vender) and then applying 'lasmerge' then blast2dem we can make a DTM:

1-lasground -lof file_list.txt -olaz
2-lasmerge -lof file_list.txt -merged -o DTM_G_merg.laz
3- blast2dem -i DTM_G_merg.laz -o DTM_GMB_BN_15.tif -step 0.15 -keep_class 2 -kill 10

Problem: DTM with high resolution of 10 cm makes some pixles without data, so it is better to have a resolution bigger than 20cm.

- This way there will be some missed data inside the area but by "grid command" there is an option called "fill" that solves this problem.

Or

DTM_10_low_grid.tif

1-lasground –lof file_list.txt –olaz ……….

2-lasgrid -lof file_list.txt -merged -o DTM_10_low_grid.tif -step 0.1 -elevation -lowest -fill 8 -mem 1500 -temp_files i:\temp\temp

(Problem; so empty pixels, number of fill pixel should increase up to 20)

2.2. Producing DSM10_BN: (Command with all raw data)

lasgrid -lof file_list.txt -merged -o DSM_Highs_25.tif -step 25 -elevation -highest -fill 10 -mem 1500 -temp_files i:\temp\temp

Or merging all of 17 files then by applying Blast2dem and –first_only a new DSM will be provided

Making Intensity Map:

1. lasheight -lof file_list.txt -olaz -replace_z
2. lasheight -lof file_list.txt -olaz -drop_below 0 -drop_above 40
3. blast2dem -i Height_040_BN.laz -o Intensity_10cm_BN.tif -step 0.1 -intensity -kill 5050

Thinning command:

For Single file boinoi009:

1-1- las2las -i boisnoir000009_L3.las -o boi009_thinalleve10.laz -keep_every_nth 10

1-2- las2las -i boisnoir000009_L3.las -o boi009_thinfirsev10.laz -first_only -keep_every_nth 10

Appendix 4

Sampling Plot No.		**Elevation**		**Slope (%)**	**Aspect**
Forest characteristics:					
Landslide type		**Type of forest**			

Tree No.	**X coordinate**	**Y Coordinate**	**Z coordinate**	**species**	**DBH(cm)**	**Height (m)**	**CROWN Width (m)**		**Tree inclination**				**Tree orientation**			
							South-North	**East- West**	**0**	**0.5**	**1.3**	**2**	**0**	**0.5**	**1.3**	**2**
1																
2																
3																
4																
5																
6																
7																
8																
9																
10																
11																
12