

Estimating above ground biomass in a Salix plantation using high resolution UAV images

Simon Nåfält

2018
Department of
Physical Geography and Ecosystem Science
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden



Simon Nåfält (2018).

Estimating above ground biomass in a Salix plantation using from high resolution UAV images

Uppskattning av biomassa ovanför marken i en Salixplantering från högupplösta UAV-bilder

Master degree thesis, 30 credits in *Physical Geography and Ecosystem Science*

Department of Physical Geography and Ecosystem Science, Lund University

Level: Master of Science (MSc)

Course duration: *January* 2018 until *June* 2018

Disclaimer

This document describes work undertaken as part of a program of study at the University of Lund. All views and opinions expressed herein remain the sole responsibility of the author, and do not necessarily represent those of the institute.

Estimating above ground biomass in a *Salix* plantation using high resolution UAV images

Simon Nåfält

Master thesis, 30 credits, in *Physical Geography and Ecosystem Science*

Supervisors:

Per-Ola Olsson

Department of Physical Geography and Ecosystem Science
Lund University

Sadegh Jamali

Faculty of Engineering
Lund University

Exam committee:

Lars Harrie

GIS-Centre

Lund University

Wilhelm Dubber

Department of Physical Geography and Ecosystem Science
Lund University

Abstract

In forest biomass estimations, three dimensional (3D) canopy structure data derived from images captured by unmanned aerial vehicles (UAVs), also known as drones, has shown potential due to the flexibility and cost efficiency of the method. However, little research has been done for its applicability in bioenergy forest. In this study, a method was developed with the purpose of remotely estimating the above ground biomass of a bioenergy Salix stand in southern Sweden. The main aim was to design the method so that all the required input could be collected from a consumer grade UAV, making the application simple and at a relatively low cost. A 3D structure, or point cloud, of the Salix canopy was developed through structure from motion analysis of multiple overlapping aerial images. Images collected from both a RGB sensor and a multispectral sensor were tested when developing the point cloud. The biomass was estimated in each 3.55 meter cell of a grid by an allometric equation based on the structural characteristics of the canopy. The results were compared to the harvest yield. The obtained standing biomass showed an underestimation by 8%, of the 105 ton harvest yield, which indicates that the method performed well for the study site. However, it was concluded that more testing is needed to fully evaluate the method. This study provides a suggestion on how 3D data can be used for remotely estimating biomass in a bioenergy Salix forest which can be valuable information for land owners in management decisions to improve the economic viability.

Keywords: Biomass, Salix, Structure from motion, Unmanned aerial vehicle, Allometry, Point cloud

Sammanfattning

I uppskattning av biomassa har tredimensionell (3D) skogsdata som härrör från bilder tagna från UAVs (unmanned aerial vehicles), också kallade drönare, visat potential på grund av metodens flexibilitet och kostnadseffektivitet. Lite forskning har dock gjorts för tillämpligheten i bioenergiskog. I denna studie har en metod utvecklats med syfte att fjärr-uppskatta biomassan i Salixskog för bioenergi i södra Sverige. Huvudsyftet var att utforma metoden så att alla nödvändiga indata kunde hämtas från en UAV, vilket gör tillämpning enkel och till en relativt låg kostnad. En 3D-struktur, eller punktmoln, av Salixskogen utvecklades genom structure from motion analys av flera överlappande drönarbilder. Bilder insamlade från både en RGB-sensor och en multispektral sensor testades i skapandet av punktmolnet. Uppskattningen av biomassan gjordes i varje 3,55 meters cell i ett rutnät med hjälp av en allometrisk ekvation baserad på skogens strukturella karaktär. Den uppskattade mängden biomassa jämfördes med resultatet efter skörd. Den erhållna stående biomassan visade en underskattning med 8% av den 105 ton stora skörden vilket indikerar att metoden presterade väl i området som studerades. Dock drögs slutsatsen att mer testkörning behövs för att fullständigt utvärdera metoden. Denna studie ger ett förslag på hur 3D-data kan användas för att uppskatta biomassa i Salix-bioenergiskog som kan vara värdefull information för markägare i förvaltningsbeslut för att förbättra den ekonomiska gångbarheten av odlingen.

Nyckelord: Biomassa, Salix, Structure from motion, UAV, Allometri, Punktmoln

Acknowledgement

I would like to thank my supervisors Per-Ola and Sadegh for all the help I have received during the thesis, both during the method development, report writing and field data collection. I would also like to thank Göran who allowed me to use his Salix forest as a study area, as well as providing me with the harvest yield data which is the “true value” of the standing biomass and perfect for evaluation of the estimation. Lastly, thank you Cilla and Jep for reading through and providing feedback on my report during your summer vacation.

Table of Contents

1. Introduction.....	1
1.1 Aim	2
1.2 Disposition.....	3
2. Literature review	4
2.1 Background	4
2.2 Assessing above ground biomass.....	4
2.3 Bioenergy forest.....	7
3. Material and Method.....	10
3.1 Study area	10
3.2 Data/equipment	11
3.3 Experimental design	12
3.4 Field data collection	13
3.5 Point cloud creation.....	16
3.6 Development of the three parameter grids.....	17
3.7 Estimating Biomass	18
4. Results	20
5. Discussion.....	26
5.1 The experimental design	27
5.2 The field data	28
5.3 The point cloud	28
5.4 The parameters.....	30
5.5 The estimated biomass.....	31
6. Conclusion.....	33
References	34
Appendix I.....	36
Appendix II	39

List of abbreviations

AGB – Above ground biomass

ALS – Airborne laser scanning

TLS – Terrestrial laser scanning

VI – Vegetation index

Lidar – Light detection and ranging

UAV – Unmanned aerial vehicle

SFM – Structure from motion

GCP – Ground control point

DSM – Digital surface model

DEM – Digital elevation model

CHM – Canopy height model

SC – Stem count

1. Introduction

Monitoring the Above Ground Biomass (AGB) of an ecosystem can be a beneficial tool for decision making in different sectors of society. The AGB provide indications of the growth rate, estimations of yield and optimal timing for harvest in both agriculture and forestry (Li et al. 2016; Hawryło et al. 2017). In forests ecosystems the AGB can also be a sufficient indicator of the total biomass, which is being monitored and reported on national levels due to forests role of natural mitigation of climate change by sequestering and storing of carbon (Gibbs et al. 2007).

The direct method of measuring biomass of a plant is to harvest it and then measure the dry weight. This method is however not often a viable option on large temporal or spatial scales since it is destructive to the plants and time consuming (Li et al. 2016). Remote sensing is an efficient method of collecting data on the structural properties of plants on a large scale which greatly improves methods for estimating AGB (Van Leeuwen and Nieuwenhuis 2010). Airborne laser scanning (ALS) through Light Detection and Ranging (Lidar) is a common method of getting an accurate three-dimensional point cloud representation of a forest to provide information supporting management and monitoring (White et al. 2013). However, the ALS method is relatively expensive (Fassnacht et al. 2016) which has led to a growing interest in the alternative method of image-based point clouds through structure from motion (SFM) photogrammetry (Hawryło et al. 2017). Image-based point clouds contain information similar to ALS, but can be developed at a relatively low cost. Apart from the cost, the difference between ALS point clouds and image-based point clouds is that the image-based method only characterize the upper layer of e.g. a canopy, while the ALS method can detect structure below the canopy, since laser pulses can penetrate the surface (White et al. 2013). AGB cannot be directly measured from either ALS or SFM, but instead be deduced from directly measured forest characteristics, such as canopy height (Dubayah and Drake 2000).

The typical remote sensing platforms used for tree structure detection are manned aerial vehicles or a ground stationary platform (Dittmann et al. 2017). Recent advancement in unmanned aerial vehicles (UAV) systems, also known as drones, has led to a widespread employment in both forestry and agriculture due to their flexibility and cost efficiency (Li et al. 2016).

Bioenergy crops, such as willow (*Salix*), provide Sweden and several other European countries with low CO₂ emission heat energy (Aylott et al. 2008). The current methods of pre-harvest yield estimations are time consuming and limited in detecting spatial variations in the yield (Gaulton et al. 2015). The main expense in bioenergy forest production is the harvest procedure. It is therefore vital to identify the optimal harvest time and estimate the standing biomass to maximize profits (Verwijst and Telenius 1999; Hangs et al. 2013). A simple, non-destructive and cost efficient method is needed to improve the economic viability for farmers that cultivate bioenergy forests.

1.1 Aim

This study aims to use structure from motion photogrammetry over a *Salix* plantation to develop a point cloud that represents the structural properties of the canopy. The point cloud will then be used to develop three input parameters for an allometric equation to calculate the AGB of the plantation. Field data will be collected and used to develop the two input parameters that cannot be directly depicted from the point cloud. Figure 1 illustrates the general workflow of the study.

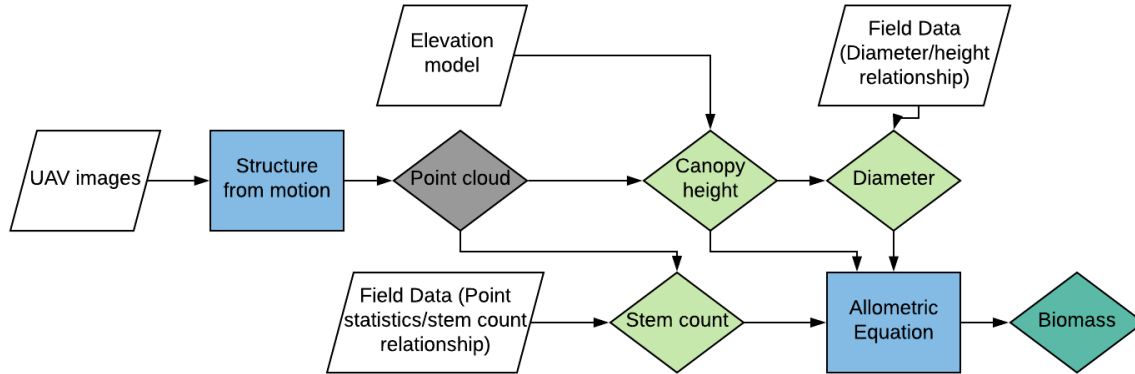


Figure 1: A flow chart describing the design of the method

The objectives are defined as:

- Develop a method for estimating the total standing biomass of a *Salix* plantation based on data acquired from a UAV platform.
- Investigate the accuracy of the canopy height model derived from a point cloud.
- Explore the use of point cloud statistics to determine the stem density.

1.2 Disposition

Following the first chapter with the introduction and aim, chapter two represents the background and available methods of biomass estimation and short introductions to Salix plantations. Chapter three represent the material used and a detailed description of the methodology. In chapter four the results are given. Chapter five and six include discussion and conclusion respectively.

2. Literature review

2.1 Background

Biomass is the mass of living biological organisms, i.e. plants, animals or microorganisms, in an area or at a given time (Hess and Tasa 2011). Biomass in forests is allocated both below ground in root systems and above ground in stems and canopy. Forest ecosystems provide mitigation against climate change by storing and sequestering significant amounts of carbon in its biomass. The ongoing deforestation, especially in tropical forests, and its impact on climate change has led to national incentives to monitor and report forest carbon stocks (Gibbs et al. 2007; Dittmann et al. 2017). The above ground biomass (AGB) represents the large majority of total forest biomass and is also most affected by deforestation. Quantifying AGB is thus a critical step in carbon stock monitoring (Gibbs et al. 2007).

Estimating AGB is also beneficial in commercial forestry management where it can be used to monitor tree size and density to identify areas ready for harvest or areas that are in need of thinning (Hangs et al. 2013; Nordkvist et al. 2013). Biomass in commercial terms is also a measure of bio energy where the harvests are turned into biofuel such as biogas or ethanol. In this type of forestry, routine monitoring can be beneficial for timing of harvest to maximize profit and productivity (Hangs et al. 2013).

2.2 Assessing above ground biomass

The only method to truly measure the biomass of a plant is to harvest, dry and weigh it (e.g. Clark and Kellner 2012). This method is expensive, time consuming and is not always a viable option, for instance in carbon stock monitoring of a forest. This has led to development of several non-destructive methods that attempt to accurately estimate biomass (Dittmann et al. 2017). Some common methods have been reviewed below.

Allometry

An allometric equation is a method of finding quantitative relationships between measureable characteristics of a tree, e.g. stem diameter at breast height or height, and relate this to characteristics that are more difficult to measure, like for instance the AGB. These relationships are usually both species and area specific (Muukkonen 2007) and do therefore need some destructive sampling to develop. Generalized equations may in some cases produce acceptable results across different species with small allometric

differences (Jacobs and Monteith 1981). Verwijst and Telenius (1999) compared site specific, diameter-to-weight allometric equations, to generalized equations on 124 commercial *Salix* plantations and concluded that destructive sampling and development of a site specific equation is preferred for accurate estimations of biomass. However, it was found that generalized equations deviated less than 10% from the site specific equations, which could be acceptable error margin when it comes to management decisions.

The allometric approach to estimate biomass is relatively accurate but time consuming and thus most suitable to implement over small areas (Muukkonen 2007; Dittmann et al. 2017).

Optical image processing

There are different methods to estimate forest characteristics through remote data collection. For coarse biomass estimations over large homogenous areas, optical image processing can be a suitable method (Muukkonen 2007; Dittmann et al. 2017). The pixels in an optical image contain spectral information in visible and infrared wavelength bands (Goetz et al. 1985). This information can be transformed into vegetation indices (VI) and correlated to biomass (Muukkonen and Heiskanen 2005). Optical image data is available from different service providers or can be collected with aerial vehicles or satellites (Dittmann et al. 2017).

Lidar

The use of Light Detection and Ranging (Lidar) sensors is a widespread practice within forest management and monitoring due to its efficiency to acquire information about the structural properties of a forest (Popescu et al. 2011). Lidar is an active remote sensing technology where a laser pulsates towards, and is reflected against, a target area. With the speed of light being known, the return time of the laser signal can be used to calculate the distance and thus the height of the reflected area (e.g. Dubayah and Drake 2000). By combining all the returns acquired from the lidar scanning, a so called point cloud can be formed. The point cloud contain height (z) and position (x,y) of all returns and is thus a three dimensional representation of the scanned area (White et al. 2013). In forest characteristics studies, lidar systems have been applied using terrestrial, airborne and space borne platforms (Popescu et al. 2011; Dittmann et al. 2017). In terrestrial laser scanning (TLS), a stationary scanner is placed on the ground and

measures laser returns horizontally to its target. TLS is relatively cost efficient on small scale scanning and can obtain highly accurate structural properties of individual trees (Raumonen et al. 2015; Li et al. 2016).

ALS, sometimes referred to as small footprint airborne lidar, is laser scanning from airplanes or helicopters that detects the vertical structure of vegetation and the ground surface. A typical ALS system used in forestry emits 50,000 to 150,000 pulses per second, where each pulse can get multiple (usually 1-5) returning echoes that are reflected from the top of the canopy or from the bare earth (White et al. 2013; Vauhkonen et al. 2014). The first return of a pulse is typically reflected from the top of the canopy and the last from ground surface (White et al. 2013). According to Popescu et al. (2011), ALS is considered to be the best method for estimating terrain and vegetation properties in terms of measurement accuracy.

Spaceborne lidar platforms can be used to measure terrain elevation and vegetation heights at large, up to global, scale. However, with large scale data acquisition, the accuracy is lower (Popescu et al. 2011).

Structure from motion

The science of measuring distance in images is called photogrammetry (Linder 2009). Structure From Motion (SFM) is a field in photogrammetry that utilizes the principles of stereoscopic viewing to construct 3D scenes through triangulation (Leberl et al. 2010; Westoby et al. 2012). The SFM technique was developed in the 1990s and originates in the field of computer vision (Spetsakis and Aloimonos 1991) and is today a highly automated process due to advancements in computer science (Snavely 2011). Westoby et al. (2012) describes the general workflow in SFM as i) keypoint extraction and image acquisition, ii) scene reconstruction and iii) post processing. The workflow is summarized below.

The keypoints are matching features that can be distinguished in multiple overlapping images taken from different camera locations. The amount of keypoints that can be distinguished depends on the image quality and resolution. The distance between the camera and the feature of interest determine the resolution of the image, where decreased distance yields a higher resolution. The amount of images and how much they overlap can also increase the number of keypoints that can be matched.

In the scene construction, the keypoints seen in individual images are matched with associated keypoints in the other images in a series. In traditional photogrammetric

methods, to determine the 3D location of a point in a scene, either the camera or ground control points are required to have a known 3D position to perform the triangulation. In SFM, neither of these has to be known prior to the construction of a scene. Instead, both camera position and feature position are reconstructed autonomously, and simultaneously, based on constraints from the keypoint associations. The scene geometry and the 3D location of features can then be estimated in a relative coordinate system through triangulation between camera positions and the feature of interest, where the camera angles towards the feature is known.

Post processing is required since the constructed scene only have a relative coordinate system which has to be transformed into a real-world absolute coordinate system. This can be accomplished through manual georeferencing of Ground Control Points (GCP) that need to be measured in field and identified in the images. The post processing can also include interpolation of the point cloud to create a Digital Surface Model (DSM) or other point cloud statistics.

The SFM point clouds are usually denser than the point clouds developed from lidar technology (Li et al. 2016). However, while lidar are able to detect both vegetation structure and the ground surface in the generated point cloud, the SFM point cloud only represents the upper layer of the canopy that is visible in the images. Therefore, to get the actual vegetation heights above the ground from a SFM-generated DSM, it is necessary to have a lidar-derived digital elevation model (DEM) as ground reference (White et al. 2013).

2.3 Bioenergy forest

Short rotation crop plantations in Europe is mainly grown with the purpose of being processed into low CO₂ emission bioenergy to substitute for fossil fuel based energy (Hollsten et al. 2012). Some of the most commonly grown species are willow (*Salix*), alder and poplar (Verwijst and Telenius 1999). In Sweden, *Salix* plantations used for bioenergy production has been cultivated as an agricultural crop for approximately 30 years (Mola-Yudego and Aronsson 2008). The *Salix* genus includes more than 350 different species and is native to the northern hemisphere (Mosseler et al. 2016).

The plants used in Swedish plantations are most commonly clones refined from two different species: *Salix viminalis* and *Salix dasyclados*. These clones are preferred due to their productivity, shoot straightness and resilience towards frost and pest

(Larsson 1998). The *Salix* plantations typically have a life cycle of 25 years where harvest occur every 3-5 years (Mola-Yudego and Aronsson 2008; Hollsten et al. 2012).

The shoots in a *Salix* plantation are often planted in the so called “double-rows” design (Figure 2). Each double-row contains two rows that are 0.75 meters apart, with 0.9 meters between the shoots. The distance between the double-rows is 1.5 meters. This planting design is implemented with regard to the design of the harvest machines (Hollsten et al. 2012; Castaño-Díaz et al. 2017).

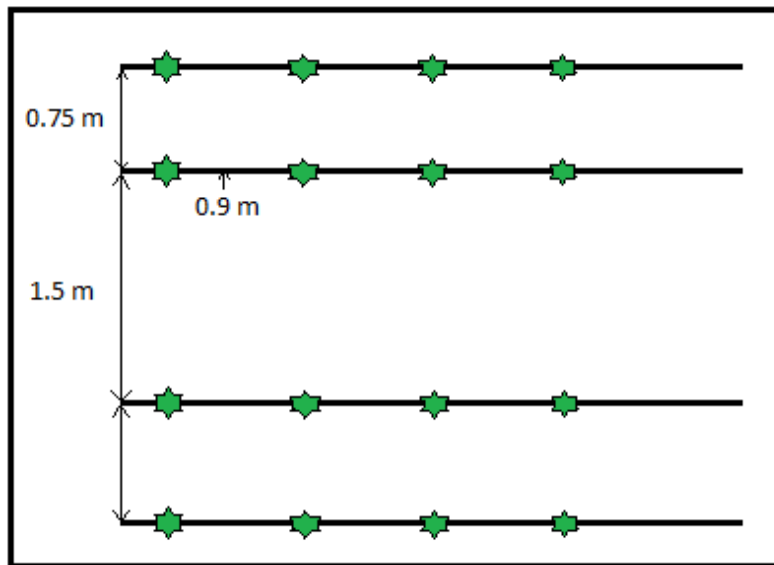


Figure 2: Diagram of the double-row planting design.
Modified from Castaño-Díaz et al. (2017).

The annual productivity of *Salix* plantations vary between growth cycles, location and management practices (Mola-Yudego and Aronsson 2008). Coppicing (cutting back) stimulates growth and thus the yield from the first growth cycle is generally lower than the future cycles (Hollsten et al. 2012; Mosseler et al. 2016). Coppicing of *Salix* often result in 20-25 new shoots per coppiced stem (Ceulemans et al. 1996). However, in dense coppice stands some self-thinning, or die-off, will occur and only 10-25% of the new shoots will subsist until harvest (Hansen and Baker 1979).

The annual production potential of short rotation *Salix* has been presented in numerous studies. Ceulemans et al. (1996) reviewed studies of *Salix* productivity in North America, Sweden, Finland and Ireland and found that an average annual growth of 10-20 tons per ha had been observed. Much higher and lower growth rates has also

been described. Christersson (1987) reported an annual growth rate of 36 t ha^{-1} in intensely irrigated and fertilized research plots in southern Sweden. Growth rates down to $7 \text{ t ha}^{-1} \text{ yr}^{-1}$ has also been found in unmanaged farm land in Finland (Hytönen 1988) .

The studies reviewed by Ceulemans et al. (1996) all estimated the standing biomass by extrapolation from small sample plots. Lindroth and Båth (1999) developed a model based on water availability to estimate potential yield in Swedish Salix plantations. The model predicted $8\text{-}9 \text{ t ha}^{-1} \text{ yr}^{-1}$ in the north east, $9\text{-}10 \text{ t ha}^{-1} \text{ yr}^{-1}$ in the east and $11\text{-}17 \text{ t ha}^{-1} \text{ yr}^{-1}$ in the south and south-western Sweden.

No published literature was found where the AGB in bioenergy forests is estimated using aerial data. Gaulton et al. (2015) present a pilot study where the potential in using SFM to estimate the biomass in a Salix plantation is examined. However, no result of the biomass estimation is presented in that study.

Using and image based point cloud to estimate the structural properties and biomass of different vegetation types have been addressed in several studies. Some example studies are presented in Table 1.

Table 1: Example studies where an image based point cloud is used to estimate the biomass

Study	Vegetation
Vastaranta et al. (2013)	Boreal forest
White et al. (2016)	Boreal forest
Goodbody et al. (2017)	Boreal forest
Ota et al. (2015)	Tropical forest
Kachamba et al. (2016)	Tropical woodland
Bedell et al. (2017)	Riparian forest
Li et al. (2016)	Maize

3. Material and Method

The theoretical framework, key words, definitions and the terminology in remote biomass estimation and bioenergy forests were established by reviewing published literature and reports. This knowledge was used to develop a model suitable for estimating the above ground biomass of a *Salix* plantation. The base of the model was an allometric equation for estimation biomass in a single stem, developed by Hytönen et al. (1995), which then was modified to be used for spatial analysis. The estimated biomass was then compared to the yield after harvest and reported yield numbers in published literature.

3.1 Study area

The study area is a 1.42 ha *Salix* plantation located in Billeberga, southern Sweden (Lat °55.8836, Lon °12.9862). The plantation started in late 1990s and shoots were planted according to the double-row design illustrated in Figure 2. The plants are a clone type that was commonly used for energy forest during the introduction of the plantation, but the exact species and clone name is not known. The current growth cycle has been standing for five years. The plantation is unmanaged, meaning no weed control, nutrients application or irrigation has been implemented. As a result of this there are some unwanted elder trees (*Sambucus nigra*) within the area (Figure 3). The owner of the plantation does not perform any estimation of the standing biomass.

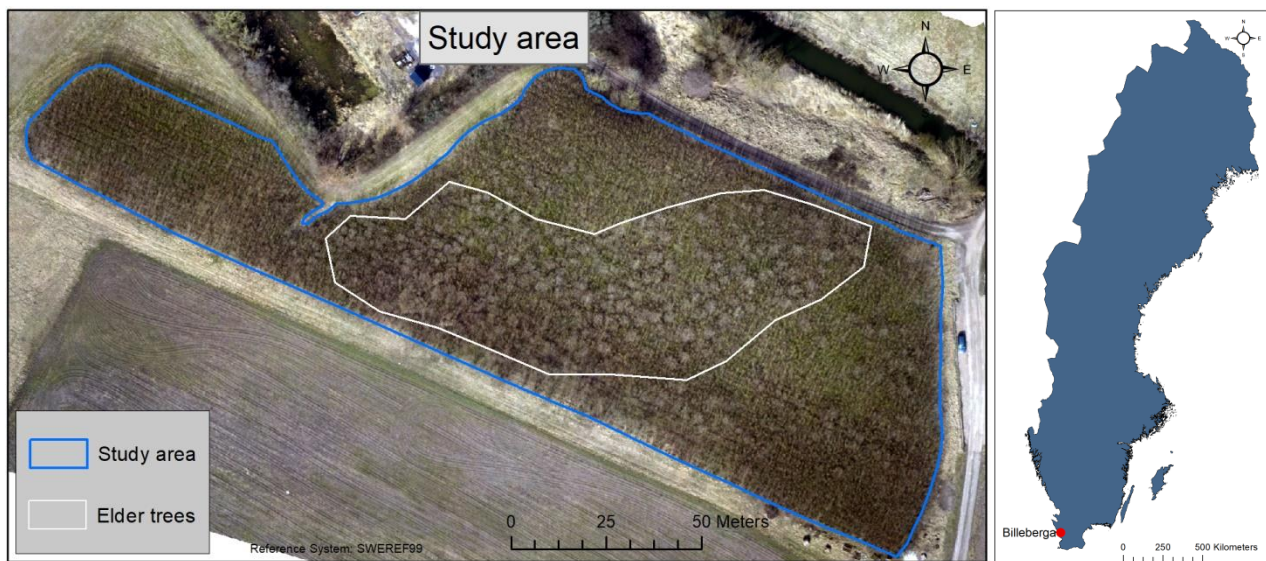


Figure 3: Aerial photograph of the unmanaged *Salix* plantation in Billeberga. The area marked out with a white line contains a relatively high amount of invasive elder trees. The elder trees are lighter and round in shape. Approved for publishing (Spridningstillstånd): Dnr.601-2018/8414.

3.2 Data/equipment

The following data and equipment were used for the analysis:

Data

UAV image data - Aerial image data in RGB- and multispectral image formats used as input for the SFM-analysis and development of the point cloud.

GSD-Höjddata, 2m - A two meter resolution digital elevation model (DEM) was acquired from Swedish national land survey (Lantmäteriet). Developed from Lidar and processed into grid format through Triangulated Irregular Network (TIN) interpolation.

Field data -

- 30 Salix stem were sampled and measured for height and diameter at the base and used to develop a height-diameter relationship
- Four height samples of objects surrounding the plantation used for evaluation of the developed height model
- 30 sample areas where all stems in a two meter radius were calculated and then plotted against various point cloud statistics to determine which statistics best describe the stem count.

Harvest yield data – A few days after the field data collection the plantation was harvested and the yield was used to evaluate the biomass estimation.

Equipment

UAV -

- Platform: 3D Robotics (3DR) Solo quadcopter that the sensors were mounted on.
- Sensors:
 - GoPro Hero4: Modified version without fisheye lens to remove distortion (PeauProductions). Captures 16MP RGB images.
 - Micasense Parrot Sequoia: 1.2MP/band, multispectral sensor. Captures imaged in red, near infrared (NIR), red edge and green spectral bands.

RTK-GPS – Topcon Real-time kinetic (RTK) GPS used to measure ground control points (GCP) and positions of sample areas with a high accuracy.

Totalstation – An optical/electronic land surveying instrument used to calculate height of objects in field through trigonometric rules. The calculations used are described in detail below in chapter 3.3.

Data processing software – The software programs used in the analysis where Agisoft Photoscan, Ardupilot MissionPlanner, Esri ArcGIS, RStudio and Microsoft Excel.

3.3 Experimental design

The allometric equation, which the method in this study is based on, was developed by Hytönen et al. (1995) and is used for estimating the biomass in a single stem of *Salix dasyclados* (Equation 1).

$$\text{Single Stem biomass} = a \times (D^2 \times H)^b \quad (\text{Eq. 1})$$

where a and b are constants, D is the diameter at the base in mm and H is the height of the stem in cm. The values of a and b are 0.0006 and 1.091 respectively. This equation was modified and used in a spatial approach by using the mean diameter and mean height in each cell of the study area to estimate the typical stem's physical characteristics in each cell. A stem count (SC) variable was multiplied to the equation to estimate the number of stems that can be expected in each cell. The modified equation can be seen in Equation 2.

$$\text{Stand biomass} = a \times (D^2 \times H)^b \times SC \quad (\text{Eq. 2})$$

where SC is the added stem count variable. The equation was implemented in a grid based analysis where each cell in the resulting grid represents the estimated biomass. The summed value of all the cells within the grid will then represent the total standing biomass. For implementation of this method, grid surfaces for the height, diameter and stem count parameters were created. The canopy height was directly measured from the point cloud heights. The stem diameter was indirectly estimated from the canopy heights based on the height-diameter relationship of the *Salix* plants on the site. The

stem count was estimated from the relationship between point cloud statistics and field samples. Development of the parameter grids are explained in more detail in chapter 3.6 below

3.4 Field data collection

UAV Image data was collected on two occasions in March and April (2018) roughly two weeks apart (23/3 and 9/4). This was prior to the start of the growing season and thus the images captured the Salix in leaf-off conditions (Figure 4). The flight paths were planned using MissionPlanner software developed by Ardupilot (2016). In MissionPlanner, the image overlap, flight speed, flight height and camera specifications are used as input to plan a flight. The planned missions were uploaded to the UAV-



Figure 4: An overview UAV-image of the study area and the conditions during image collection. Approved for publishing (Spridningstillstånd): Dnr.601-2018/8414.

platform which then sample images along the path at the required time interval without need for active piloting. Images were collected in a grid shaped flight pattern across the study area (Figure 5).

The image overlap was set to 80% in both flights to make sure that a sufficient amount of keypoints could be associated. The flight speed was set to 6 m/s and flight



Figure 5: One of the flight routes developed in MissionPlanner. The numbered points are route waypoints that the UAV navigated between while capturing images.

height to 40 meter for the first and 80 meter for the second flight occasion. Before the flight, six ground control points (GCP), to be used for georeferencing, were placed around the plantation in areas clearly visible from above. The northing, easting and altitude of the GCPs were measured with a Real Time Kinetic (RTK) GPS with sub-decimeter accuracy.

The diameter at the base and height of 30 Salix stems were measured using digital calipers and a totalstation. The calipers were used to measure the diameter with mm accuracy at the base of a stem, or just above the possible remnants of a stem from an older growth cycle that the current stem sprouted from. The totalstation utilizes trigonometric rules to determine heights of objects according to Equation 3, which is illustrated in Figure 6.

:

$$\text{Stem height} = x = HL \times (\tan(i_2) - \tan(i_1)) \quad (\text{Eq. 3})$$

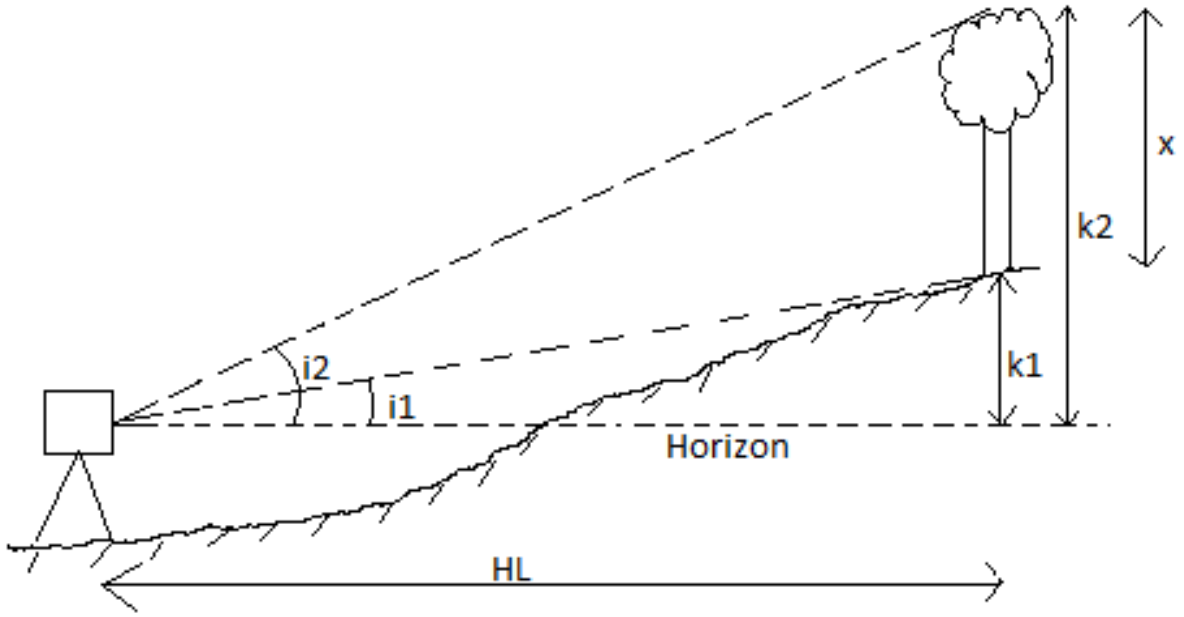


Figure 6: Illustration of the method used to calculate heights from the fields measurements using a totalstation.

The totalstation was first aimed towards a prism that was placed at the base of a stem. This process determined the horizontal distance (HL) to the stem and the angle between the horizontal line and base of the stem (i_1), making it possible to calculate the height difference between the instrument and the stem base (k_1). The same procedure was then done for top of the stem to calculate the height difference between the instrument and the top (k_2). The height of the stem (x) is then the difference between these two distances (k_1 and k_2). The totalstation requires a clear and direct view of the measured stem and thus the sampling was done in the edges of the plantation. The stems where selected randomly with some stratification based on aspect to account for sun exposure.

The totalstation was also used for height measurement of four additional objects in proximity to the plantation which were to be used for evaluation of the height model derived from the point cloud. Three larger deciduous trees and a metal hunting tower, which would be easily distinguished in the aerial images, were chosen for this.

Field data for the stem count parameter was collected in 30 randomly selected areas within the plantation. In each sample area a center point where marked and coordinates measured with the RTK-GPS. The number of Salix stems within a two meter radius from the center point was then counted.

3.5 Point cloud creation

The collected flight images consisted of RGB and multispectral images from the two different flight heights. Single spectral bands from the multispectral images could also be extracted and used separately. The SFM-analysis was carried out multiple times with varying input. Both separate image types and mixtures between different image types were tested as input. The resulting point clouds were examined visually to determine which input that produced the best representation of the forest stand structure.

Images out of focus or out of the area of interest were discarded before the images were loaded into Agisoft Photoscan. The images were aligned with the built-in algorithms to estimate the camera positions and orientation to further develop a sparse point cloud. There are five image alignment parameters in Photoscan and the input parameters used here can be seen in Table 2.

Table 2: The alignment parameter settings used in Photoscan

Parameter	Input
Accuracy	High
Reference preselection	Disabled
Generic preselection	Enabled
Key points	300,000
Tie point limit	4000

The accuracy input set to high means that each photos original resolution is used in Photoscan. This can be compared to the medium or low setting that downscales and uses 50% and 25% of the resolution respectively. Both the reference preselection and generic preselection options can be used to make pair selections of overlapping photos. This creates a rough location of the cameras prior to running the alignment algorithm to reduce the total processing time. The reference preselection parameter can be used for geotagged images which have the geographic location when the image was taken embedded in the metadata. The generic preselection parameter is matching pairs by using a lower accuracy setting before the alignment. The keypoints parameter is the maximum number of points that will be identified in each image. A number of 300.000 were chosen to make sure a sufficient number of points could be identified. The tie point limit defines the number of keypoints to extract, selecting the ones with the highest accuracy according to the program.

After the image alignment, and development of a sparse point cloud, a dense point cloud was developed. When building a dense point cloud, Photoscan calculates the distance to features in each image to create depth maps. The inputs for the parameters for building a dense point cloud are shown in Table 3.

Table 3: Parameters used for building a dense point cloud in Photoscan

Parameter	Input
Quality	High
Depth filtering	Mild

A high-quality setting was chosen as input for the dense point cloud. The higher quality results in more details and more accurate geometry but increases the processing time. The depth filtering is used to filter out outliers in the point cloud. The filtering can be set to mild, moderate or aggressive. The mild setting that was used is recommended if there are important small features in the scene (Agisoft Photoscan user manual v1.4).

Once the dense point cloud was built, the GCPs were identified in the images and markers were placed to georeference the scene into the SWEREF99TM reference system.

3.6 Development of the three parameter grids

Height

The point cloud was converted in to a digital surface model (DSM) by interpolation between the height values, using the built in function in Photoscan. The interpolation method used was inverse distance weighting (IDW) which is a method that assumes spatial autocorrelation, meaning that closer known values have greater influence than known values further away when predicting a unknown value (e.g. Huisman and De By 2009). This process resulted in a DSM with 14 cm resolution and cell values representing the height above sea level, in the national height system. The canopy heights were extracted by taking the difference between the height values in the developed DSM and the ground level DEM acquired from the Swedish national land survey, to develop a canopy height model (CHM). The four height evaluation objects that were measured in the field were compared to the height values in the CHM to get an idea of the accuracy of the SFM analysis.

Diameter

The field sample data on the diameter and height of 30 stems were used to develop the stem diameter parameter. RStudio (2015) and Microsoft Excel software were used for linear regression analysis to determine the significance of the relationship between height and diameter of a stem, as well as test for normal distribution of the sample. The equation from the fitted regression line was used to calculate the expected diameter in each cell, based on the height value in the CHM.

Stem count

To estimate the number of stems in a cell, the 30 stem count sample plots that were collected in the field were regressed against five different point cloud statistics: minimum point height, maximum point height, mean point height, standard deviation of the point heights and the point count. The ArcMap 3D-analyst toolbox was used to extract the point statistics in a two meter radius around the center point of each sample plot. The statistical analysis was done in RStudio and Excel where each different statistic was plotted against the stem count field data in a linear regression. Out of the five tested statistics, the strongest relationship to the stem count was found to be the minimum point height, which therefore was used to estimate the amount of stems in an area based on the point cloud height values. First a DSM grid, with each cell representing the minimum point cloud height found in that area, was developed using a custom ArcGIS tool in the LAStools-toolset, developed by Isenburg (2012). The cell values in the minimum height grid were then converted into estimated stem count values by using the equation from the fitted regression line.

3.7 Estimating Biomass

The three input parameters were converted to the units required in Equation 2 and resampled so all grids had the same cell size. A cell size of 3.55x3.55 meters was chosen since it is roughly the size of the two meter radius circles which was used for stem count field sampling and the basis of the minimum height-stem count relationship.

As will be described further in the result section, a visual inspection of the point cloud displayed distinct errors in the structural representation of the plantation versus reality. For example, some larger parts of the point cloud were covered by points with height values that were close to ground level even though aerial imagery of the same areas clearly displayed occurrence of stems. The SFM-analysis had therefore

underestimated the stem structure heights for some reason. These underestimation errors had also further been manifested in the parameter grids used as input for the biomass estimation. The errors-areas, that covered approximately 0.57 ha of the total 1.42 ha study area, were determined by visual analysis of the CHM and removed from the parameter data. The biomass was calculated for the remaining 0.85 ha using Equation 2 (see chapter 3.3) resulting in a grid where each cell represented the estimated biomass. The values in the cells in the smaller 0.85 ha area were summed to calculate the total biomass and then scaled up to the full 1.42 ha of the study area to get the estimation of the total standing biomass.

The result of the estimation was compared to the harvest yield and other yield numbers found in published literature.

4. Results

The point cloud with the best representation of the plantation in reality was found to be when using red-edge spectral images taken at a flight height of 80 meters. The SFM analysis of the images resulted in a dense point cloud consisting of 700.000 points with height values ranging between 15 and 27 meters in the national height system RH2000 (Figure 7). A visual inspection of the point cloud display distinct misrepresentations from what the plantation structure was in reality. Along the edges and western part of the study area the point heights are close to ground level and therefore the correct stem structure had not been detected in the analysis. Moreover, the same problem can be seen in some patches in the center of the eastern parts of the plantation that display height values close to ground level.

The points with the highest values are mainly found along the southern and south eastern parts of the area.

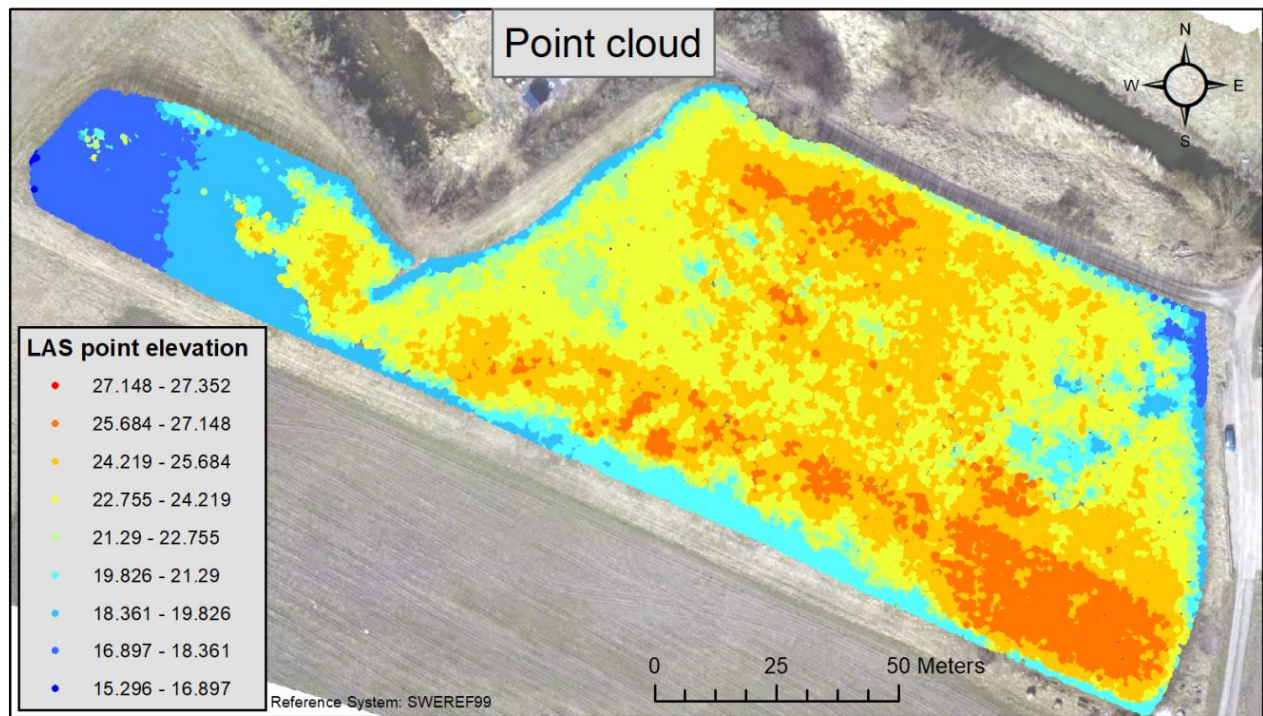


Figure 7: The point cloud of the Salix plantation with point heights displayed in meters in RH2000. The errors in the height representation, as a result of the structure from motion analysis, are mainly found in the western part and along the edges of the plantation, seen in blue colors.

In the canopy height model (Figure 8) the point cloud has been normalized into meters above ground level and converted into a grid surface with cell values representing the

mean height of the points. The errors in the point cloud resulted in height values below zero, meaning that the point height detected in the SFM analysis was in fact lower than the ground level elevation model acquired from Swedish national land survey. The negative values were removed for the remainder of the analysis. The difference between the highest and the lowest value is roughly 7 m which is substantially lower than the 12 m difference in the point cloud. This is a result of the averaging of the point values into 3.55 m cells, leading to a smoother surface. Due to the errors in the point cloud, the mean cell value in the CHM is 377 cm. The majority of the values are in the range 300 to 600 cm.

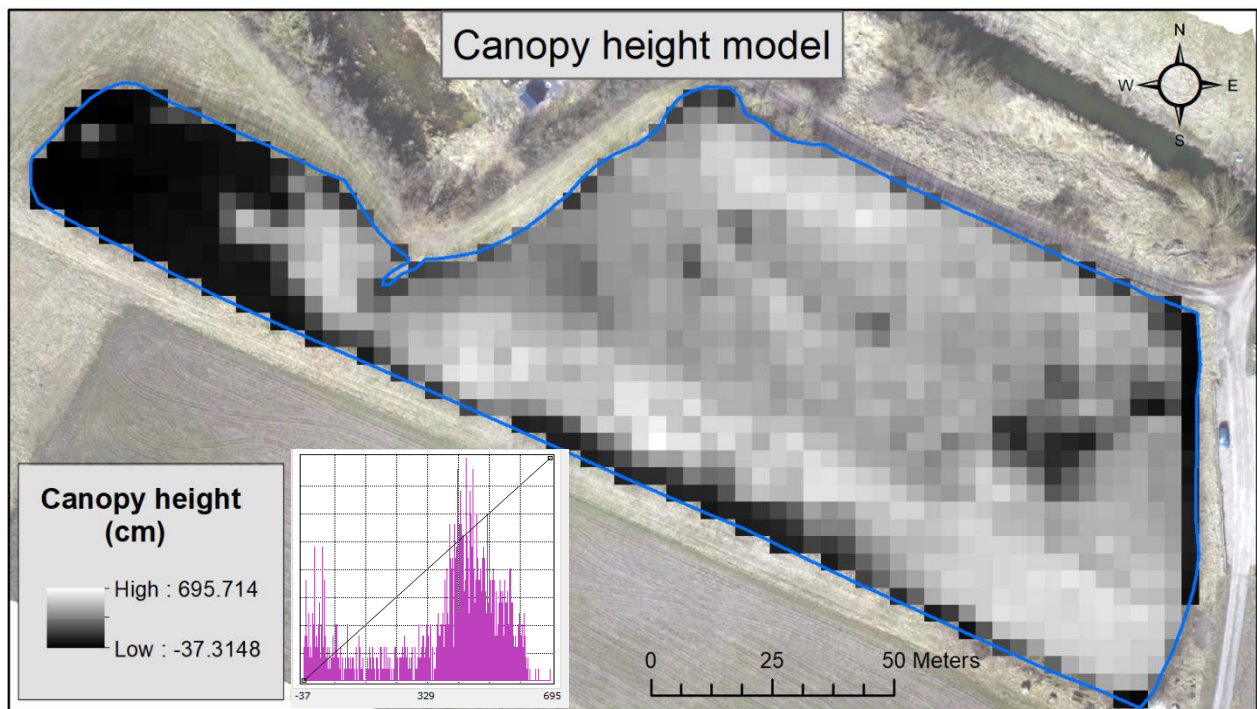


Figure 8: The Salix canopy height model, derived from the point cloud, in 3.55m cell resolution. The cell values represent the mean height above ground level in centimetres. Some cells display negative values since the value detected in the SFM-analysis were in some areas below the ground level.

The values in the CHM were compared to the height of the hunting tower and three deciduous trees that were measured in the field. The result from this comparison can be seen in Table 4. The difference between heights measured in the field and in the SFM-analysis was relatively large for the deciduous trees where the height model had detected heights that were between 1.7 and 3 m lower than what was measured in the field. The height of the hunting tower only differ 23 cm between measured in the field and estimated with SFM.

Table 4: Evaluation of the height model from the SFM-analysis. Unit in meters.

Measured Object	Height	CHM-Value	Difference
Tree	8.41	5.29	3.12
Tree	9.60	7.88	1.72
Tree	9.73	7.05	2.68
Tower	3.00	2.77	0.23

The linear regression analysis of the relationship between height and diameter of the sample Salix stems displays a positive relationship with an R^2 value of 0.6026 and a p-value of 0.00000029 (Figure 9). The R^2 describes the goodness of fit between the data and the regression model, and in this case that 60% of the data can be explained by the model. The sampled stems vary between 2.5 and 7 m in height and between 17 and 57 mm in diameter.

The stem diameter grid (Figure 10) has cell values ranging between 7 and 64 mm which were estimated from the height values in the CHM.. The mean value of the cells is 39 mm and most values are found between 25 and 56 mm.

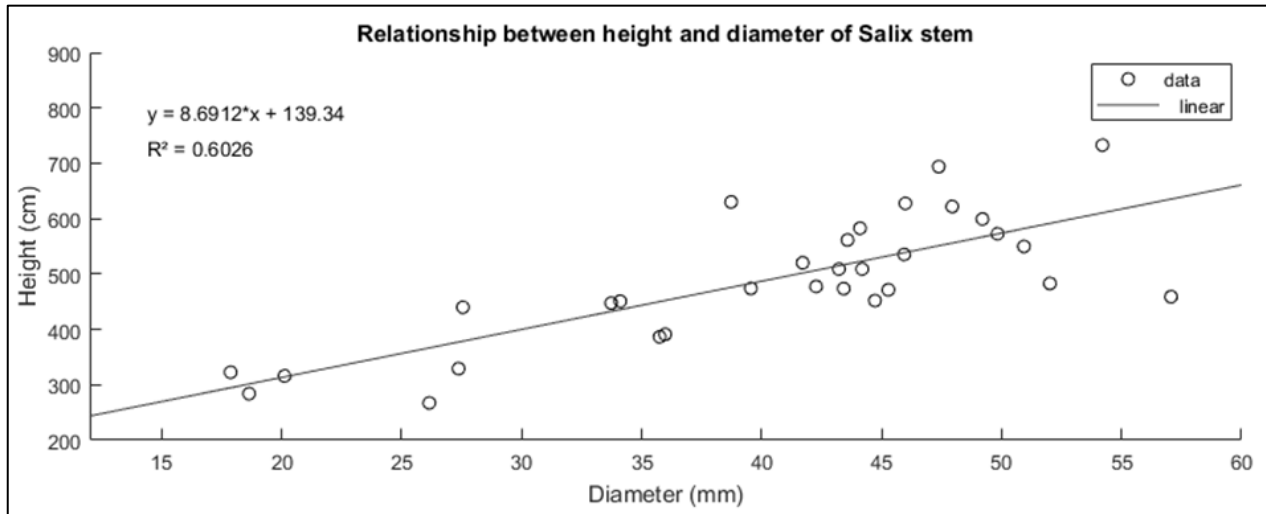


Figure 9: Linear regression analysis between height and diameter of the 30 field sample Salix stems. The equation of the regression line was used to develop a grid surface, with cells representing stem diameter, based on the values in the CHM. The relationship has an R^2 value of 0.6026 and a p-value of 0.00000029.

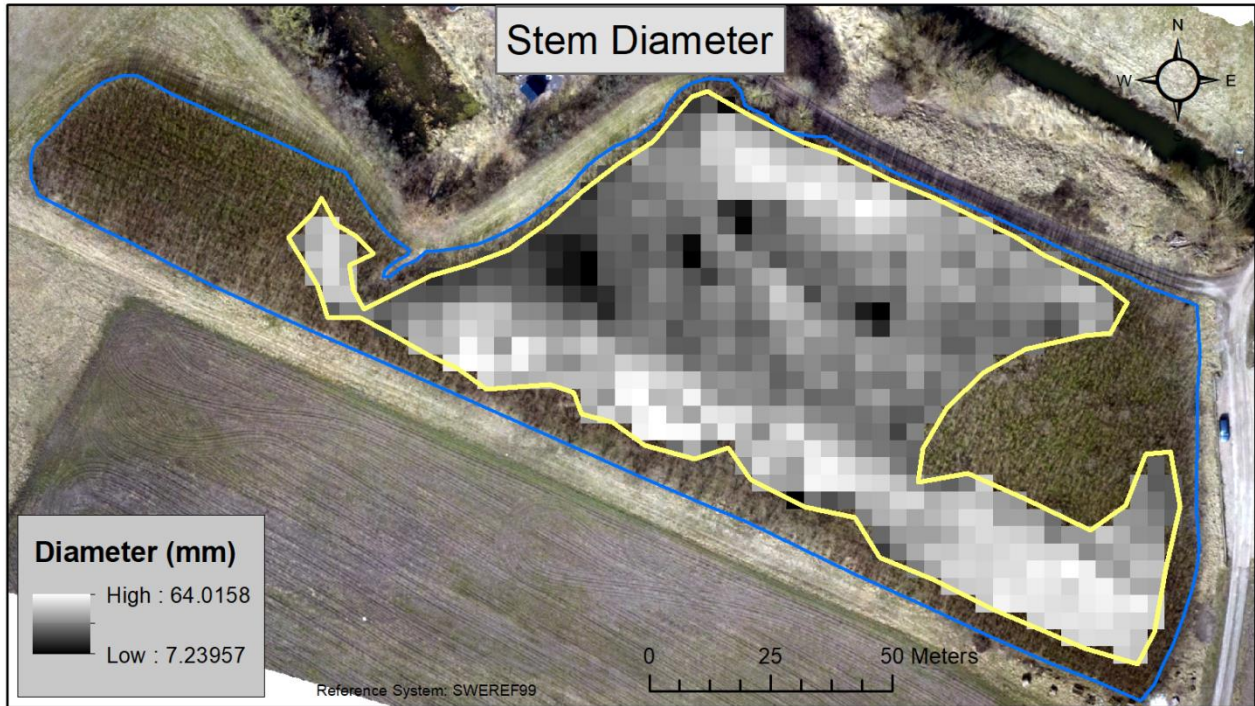


Figure 10: The stem diameter grid derived from the values in the CHM by using the regression line equation from the relationship between height and diameter of the sample *Salix* stems. The cell size is 3.55 m and cell values are displayed in mm.

As described in the methods section, chapter 3.6, the strongest relationship between point cloud statistics and stem count was the minimum point height (Figure 11). The relationship to the other tested point cloud statistics can be found in Appendix I.

The linear regression analysis between stem count and minimum point cloud height displays a positive relationship. The p-value was 0.0011 and the R^2 value (0.3293) describes that 33% of the data can be explained by the model. The field sampled stem count plots vary between 25 and 65 stems. The minimum point cloud heights in these sample plots vary between 20 and 25 m above the RH2000.

The cell values in the stem count grid (Figure 12) vary between 27 and 59 stems and have a mean value of 46 stems.

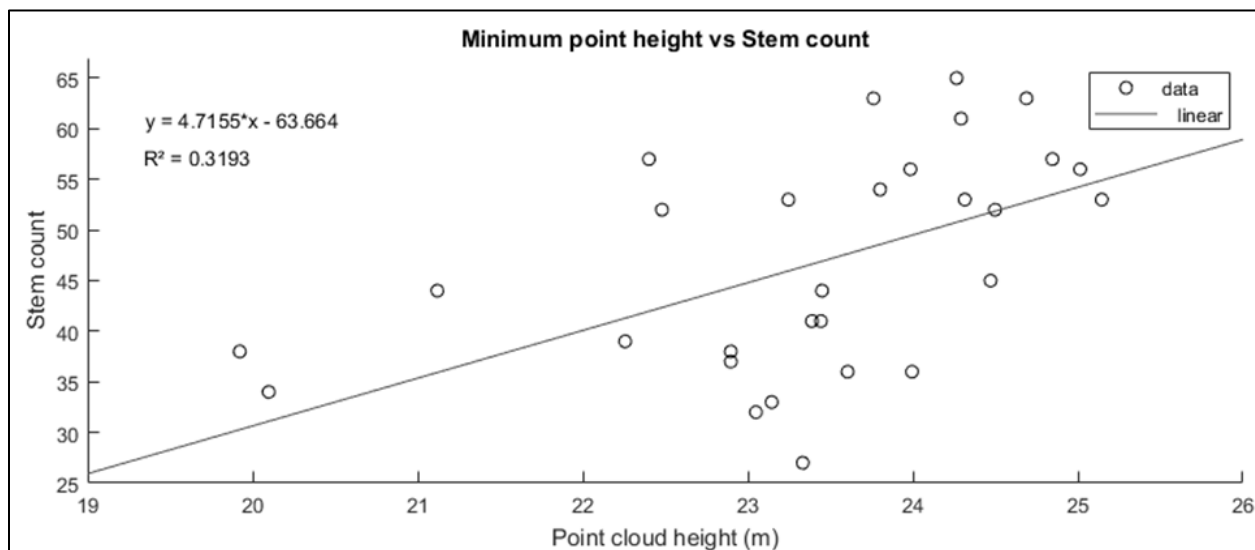


Figure 11: Linear regression analysis between minimum point cloud height and stem count of the sample areas measured in the field. The equation of the regression line was used to develop a stem count grid surface. The relationship has an R^2 value of 0.3193 and a p-value of 0.0011. Note that the values on the x-axis represent point cloud height and not heights above ground level.

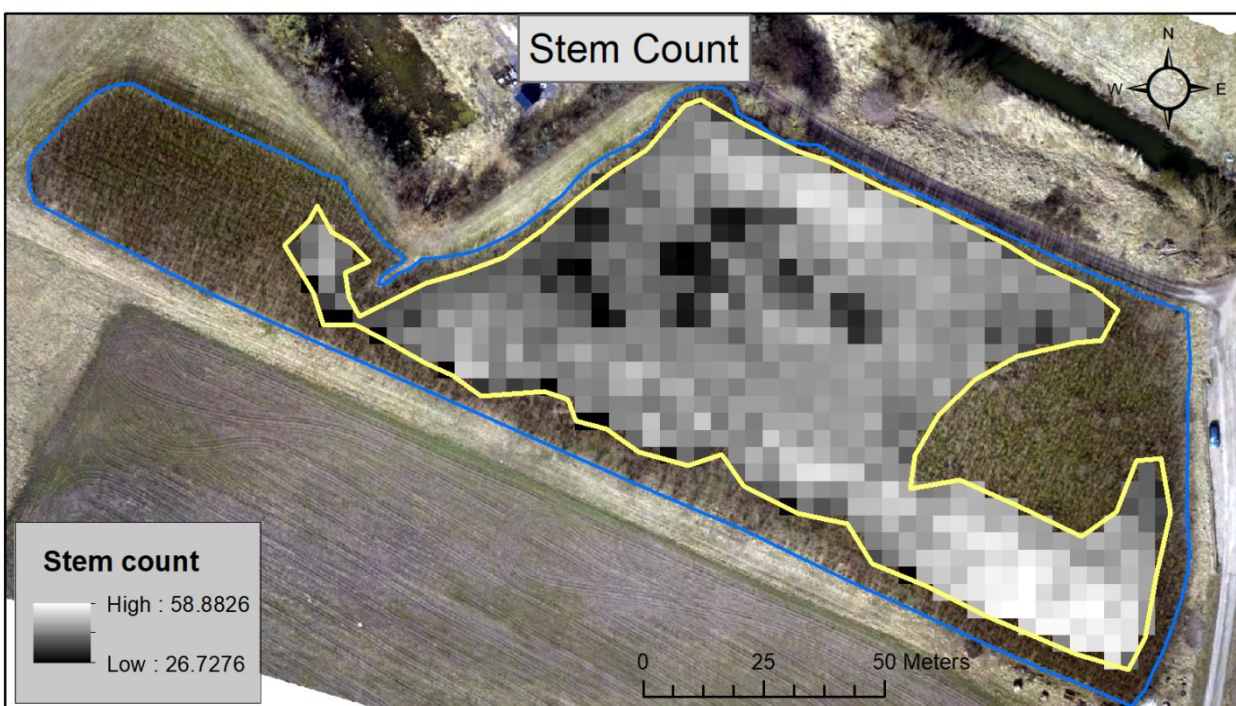


Figure 12: The stem count grid in 3.55 meter cell size. The cell values are estimations based on the minimum point height in the point cloud.

In Figure 13 the parameter grid has been combined using the Equation 2, described in section 3.3, to estimate the spatial distribution of biomass in the plantation. The areas with errors in the point cloud has been excluded from the analysis and as a result the biomass has been estimated in a smaller 0.85 ha area out of the total 1.42 ha of the study area. The range of the values is relatively large at 0.5 – 337 kg and the mean cell value is 85 kg. The histogram shows that there are a few high outliers and that the most common values are roughly in the range between 15 and 110 kg. The sum of all the cell values in the smaller 0.85 ha area is of 58000 kg. The areas with high amounts of biomass are mainly located along the southern part of the plantation. Cells with lower biomass amount are mainly found in the central and western part of the area.

Table 5 shows the result of the biomass estimation. The total biomass scaled up to the 1.42 ha of whole study area is then 96800 kg (96.8 tonnes). This gives an estimated annual yield of 19.4 ton of the whole study area which corresponds to about 13.6 ton per ha. The reported yield from the harvest of the plantation was 105 ton biomass which corresponds to an annual 21 ton in the whole study area and 14.8 ton/ha. The result from the method developed in this study is therefore an underestimation of about 8.2 tonnes, or 7.8%.

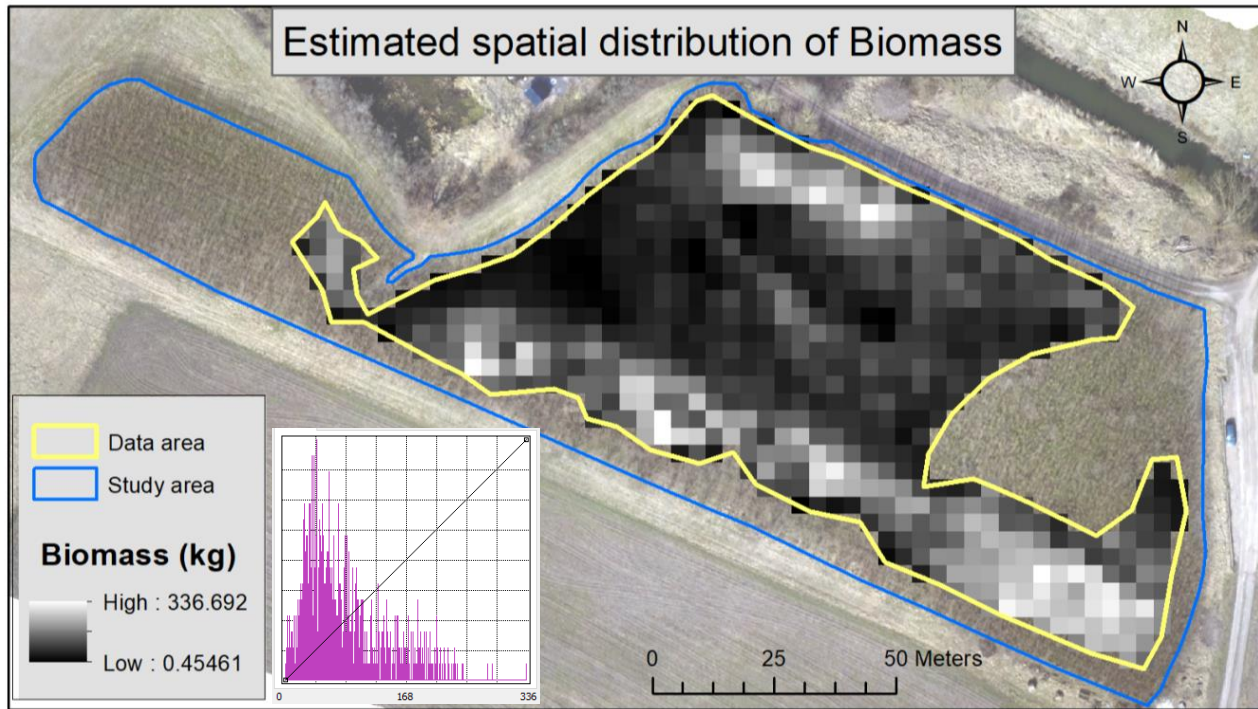


Figure 13: The estimated biomass in each 3.55x3.55 cell. The area within the yellow line is the remaining 0.85 ha after removing areas that had apparent errors in the point cloud data. The summed value of all the cells is the estimated standing biomass which was later scaled up to the full extent of the study area. The highest amount of biomass is located in the southern parts of the plantation.

Table 5: A comparison between the estimated biomass and the harvest result. The annual yield is the total estimated yield dividing by the age of the current growth cycle, five years, and converted to ton per ha

Category	Biomass (t)	Annual (t/ha)
Estimated	96.8	13.6
Harvest result	105	14.8

5. Discussion

The aim to develop a method for estimating the standing biomass in a *Salix* plantation based on UAV images resulted in a method with potential. However, there are weaknesses in the method that needs to be taken into account which are discussed in this chapter.

5.1 The experimental design

The equation developed by Hytönen et al. (1995), that is the base of the developed method, is for a specific species, *Salix dasyclados*, which is commonly used in bioenergy plantations (Hollsten et al. 2012). The *Salix* species in the study plantation is unknown and because of this two assumptions are made: i) the allometric difference between different species and clone types that are commonly used in bioenergy cultivation is small, and because of this, ii) the equation is relatively accurate for the study area regardless of species type. The equation was chosen due to its input parameters, height and diameter, which are compatible with the canopy structure data that can be collected with the use of a UAV platform. In order to use this method as a support in management decisions in other areas, it would be preferred to use a generalized equation developed from *Salix* samples that vary in location and clone type, so it could perform relatively well across different *Salix* species.

Developing a new allometric equation from destructive sampling of stems could have improved the results of the biomass estimation in the study area. However, this would result in a more site specific method that might not be applicable on plantations in different locations. Moreover, the aim of the method was to only use data that can be collected from an UAV platform. This also raises the question of the diameter-height relationship and the stem count-point cloud statistics relationships which were both collected in the field and not from the UAV platform. No existing equations on these relationships were found and therefore they had to be developed. The same issue as with the allometric equation is also valid in this case, that relationships based on larger samples from multiple locations would be preferred for the method to be applicable in other areas.

The equation by Hytönen et al. (1995) was developed by harvesting stems and then measuring the length and diameter. In this study the plants height above ground is used instead of stem length. These two are not perfectly equal since the stems usually don't grow in a straight vertical line. If a plant grows at a large angle, the difference

between height and length can be relatively large which will affect the resulting biomass estimation.

5.2 The field data

As explained in the methods section, the sample data used for establishing the relationship between diameter and length of *Salix* stems was based on 30 measurements done along the edges of the plantation. There is an uncertainty about whether these samples in fact are a suitable representation for the whole plantation. The reasoning behind this is that the stems along the edges are more exposed to the sun, wind and other external factors, and that these conditions might have led to differences in the structural characteristics of the stems. For example, plants along the edges might grow thicker, or not as high, to be more resilient against high wind speeds compared to stems in the central parts of the plantation which are less exposed. To avoid the influence of edge effect, the sampling could have been done for stems located within the central part of the plantation as well. However, the totalstation-based method that was used in this study is not suitable for measurements in a dense *Salix* plantation since it needs to be positioned with a clear and direct view to the base and top of the sampled stem.

The height measurements with the totalstation contained some aspects that affected the accuracy and needs to be taken into account. During the height sampling the totalstation was aimed toward the base and then top of the stem by looking through the instrument and aligning a crosshair on the target. There was no difficulty to aim at the prism that was placed in a steady position at the base of a stem. However, aiming at the top of a stem was not straightforward. During the field sampling there were strong winds which made the plants sway, making it difficult both to determine the exact natural position of the stems and also to distinguish the correct stem from a distance in an irregularly swaying canopy. The solution for this problem was to aim the instrument to the approximate position of the top of the stem which is not perfect and might have slightly affected the accuracy of the height measurements.

5.3 The point cloud

The height values in the point cloud were the base data that was used to develop the parameters and therefore has a high influence on the results. The SFM-analysis produced a point cloud with apparent errors. The canopy height where relatively homogenous across the plantation and yet some areas in the point cloud had height

values close to the ground level. SFM over a Salix forest is a relatively undocumented subject and therefore different sensors and flight height were tested. As explained in the methods section, the best point cloud was produced when using images from the red-edge spectral band from the multispectral sensor. Comparing images captured from different sensors showed that individual stems could be more easily distinguished and separated from understory vegetation in the multispectral images, especially on the red-edge and NIR bands. The RGB images had a relatively low contrast between the stems and the understory vegetation, making it difficult to detect objects that could be used as keypoints in the SFM-analysis. Example images from the RGB and red-edge band can be seen in Appendix II.

In this study, point clouds derived from two different flight heights were compared. The images captured at 80 m resulted in a point cloud with a better representation of the plantation compared to the images captured at 40 m. The main issue with using the 40 m images was the alignment, i.e. estimating the position of the images in relation to each other. This issue was prominent in images of the central part of the plantation where no borders of the plantation were visible. This could mean that borders could function as a reference when aligning the images. Flying at a higher altitude yielded a coarser resolution in the images but better alignment.

The extrapolation of the biomass that was needed, since the point cloud didn't represent the whole plantation accurately, introduce uncertainties in the results. To avoid this, a more accurate point cloud would be needed. There are some aspects of the image data collection that could be changed and might improve the resulting point cloud. The images were collected during leaf-off conditions. Viewing a Salix canopy from an aerial perspective during leaf-off conditions, as in this study, displays a relatively sparse forest and the understory is visible between the stems. Flying during the growing season might have added information to the images that could improve the keypoint detection and therefore the point cloud. Firstly, it would create a denser canopy surface making it easier to distinguish the canopy from the understory vegetation. Secondly, it would present an opportunity to utilize vegetation indices, e.g. NDVI, to detect patterns and reflectance differences in the canopy that could improve the detection of keypoints. Another method that might have improved the point cloud could be to include images of the Salix canopy not captured directly downwards from the UAV. Salix stems are relatively thin and straight growing, making them hard to characterize from directly above. Capturing images with camera positions and lens direction in a more hemispheric

pattern and including these images of the canopy in different viewing angles to the SFM-analysis might have improved the resulting point cloud.

5.4 The parameters

In the derived results of the CHM evaluation objects, that can be seen in Table 4 in the result chapter, there was a relatively large difference between the values measured in the field and the values estimated from the SFM-analysis for the deciduous trees, while the values from the hunting tower corresponded relatively well. The reason for the difference of the tree heights could be because the upper branches of the trees, which were measured with the totalstation, are relatively thin and hard to distinguish in images during leaf-off conditions. The CHM values are also an average value of the point cloud heights into 14 cm cells, which mean that the cells located at the tree top likely have values that are slightly lower than the actual height of the tree top. By comparing directly to the point cloud heights instead, the difference might have been smaller. However, the point values represent meters in RH2000 and had to be converted into a grid before the values could be normalized into meter above the ground level. The hunting tower, on the other hand, is a dense surface with constant height which can more easily be detected in the images and therefore its height is represented relatively well. This raises the question that maybe this issue with the tree heights coincides with the Salix stems as well and that their heights might be underestimated or even undetected by the SFM-analysis if they are too thin or sparse growing.

The diameter raster was developed by regressing height and diameter of Salix stems and using the relationship to derive the diameter from the CHM value. The linear regression that was used describes a relationship where, the higher a stem is, the larger diameter it has. This might not necessarily be true for the whole life cycle of a Salix plant. For example, the stems can't grow up to an infinite height and older plants might reach a point of maximum height where the continued growth mainly occurs in the circumference of the stem. The relationship might also vary with different conditions of sun exposure, nutrient availability or water availability. For this method to be applicable for monitoring the biomass in other areas, the diameter-height relationship should preferably be based on a larger field data sample that represents Salix stems in different growing conditions, growth cycles and ages.

The minimum point cloud height displayed the strongest relationship to stem count and was therefore used to estimate the number of stems in an area. In theory this

sounds like a viable predictor for stem count since the SFM-analysis in a dense canopy will unlikely detect points in the lower parts of the canopy and therefore the minimum height will be relatively high. This can be compared to a sparse canopy where it is more probable to detect lower points, maybe even the ground surface. One problem that might arise and has to be considered is that a cell that is mainly covered with a dense canopy, but with ground surface exposed, will be estimated to the same amount of stems as a cell which is mainly covered with ground surface because they both will have a minimum height value close to zero. Just as the height-diameter, minimum point height-stem count relationship is site specific and might not be applicable in other areas. For example, a one year old plantation might have a high stem density but the plants will be lower in general which would indicate a low stem count. A more general relationship that might be more applicable on various stages of a growth cycle could be to use both the minimum and the maximum point height, for example the difference between them, and relate this to the stem count.

5.5 The estimated biomass

The result for the biomass estimation was 96.8 tons or $13.6 \text{ ton ha}^{-1} \text{ yr}^{-1}$ which was an underestimation of about 8% of the harvest yield (105 ton or $14.6 \text{ ton ha}^{-1} \text{ yr}^{-1}$). The accuracy of the estimation is not perfect but still provides valuable information that can be used in management decisions. The result from the estimation corresponds well with the yield numbers reported by Ceulemans et al. (1996) and Lindroth and Båth (1999) which presented annual yields of $10\text{-}20 \text{ ton ha}^{-1}$ and $11\text{-}17 \text{ ton ha}^{-1}$, respectively, that can be expected from a *Salix* plantation in southern Sweden. The developed method therefore performed well for the study area even though it has weaknesses. There are uncertainties of how it would perform in other locations.

Since the *Salix* in the study area were planted in systematic double-rows at the same point in time the canopy characteristics should be relatively homogenous across the plantation. Because of this, the scaling up of the biomass to cover the full extent of the plantation might be a relatively accurate method. However, any spatial variation in the areas that were excluded from the analysis will be undetected. An accurate point cloud covering the whole area would be preferred to improve the estimation.

The elder trees that had started growing within the plantation were not removed prior to harvest and their biomass is included in the harvest result obtained. Elder trees grow lower and wider compared to the *Salix* and this might have affected the biomass

estimation by locally influencing the mean height and minimum point height. However, the shape of the elder trees is easily distinguished in the aerial images and might have added information in the images that improved the alignment and keypoint association. Another indication of this is that there were no elder trees growing in the western part of the plantation where the SFM-analysis could not detect any *Salix* structure. The full influence that the elder trees had on the biomass estimation is uncertain.

The reason of why the highest amounts of biomass were found along the southern parts of the plantation could be due to the higher sun exposure. The same areas are also closest to the neighboring agricultural field and therefore some nutrients might have leaked into the plantation. With higher growing plants along the southern border, the central part of the plantation is more shaded from the sun which might be the reason for why the biomass is lower there.

6. Conclusion

The developed method for estimating the standing biomass from UAV data performed well for the Salix forest in southern Sweden and therefore the method shows potential. An accurate point cloud representation of the structural properties of the canopy is essential for an accurate estimation of biomass but proved to be problematic to develop for the Salix forest in this study. Even though the method performed well for this study area, there are uncertainties how well it would perform in other locations and conditions. There are also uncertainties in the variables of the method which are based on the point cloud values. The total propagation of uncertainties was not evaluated in this study which raises the question whether the 8% underestimation that was found represents the actual performance of the method. More testing, in different locations and conditions, is needed to fully evaluate the method's applicability and usefulness for providing valuable information to farmers that cultivate Salix.

Future studies should investigate how to improve the point cloud representation of a Salix forest. Some suggestions to accomplish this are to collect images during the growing season and also examine to use of vegetation indices to improve the detection of keypoints in the SFM-analysis. Moreover, future studies should use larger and more spatially varied field samples when determining the allometric relationships of the method to get an accurate representation of the whole populations. It would also be interesting to develop a generalized equation for calculating the biomass of a Salix stem that performs well over various clone species that are commonly used in bioenergy forest plantations. To reduce the uncertainty of the method, the developed allometric equation would preferably only require height as input, since this can be directly measured from the images captured from a UAV.

References

- Ardupilot. 2016. Mission Planner Version 1.3.37. Indiana, USA.
- Aylott, M. J., E. Casella, I. Tubby, N. Street, P. Smith, and G. Taylor. 2008. Yield and spatial supply of bioenergy poplar and willow short-rotation coppice in the UK. *New Phytologist*, 178: 358-370.
- Bedell, E., M. Leslie, K. Fankhauser, J. Burnett, M. G. Wing, and E. A. Thomas. 2017. Unmanned aerial vehicle-based structure from motion biomass inventory estimates. *Journal of Applied Remote Sensing*, 11: 026026.
- Castaño-Díaz, M., P. Álvarez-Álvarez, B. Tobin, M. Nieuwenhuis, E. Afif-Khoury, and A. Cámara-Obregón. 2017. Evaluation of the use of low-density LiDAR data to estimate structural attributes and biomass yield in a short-rotation willow coppice: an example in a field trial. *Annals of Forest Science*, 74: 69.
- Ceulemans, R., A. J. S. McDonald, and J. S. Pereira. 1996. A comparison among eucalypt, poplar and willow characteristics with particular reference to a coppice, growth-modelling approach. *Biomass and Bioenergy*, 11: 215-231.
- Christersson, L. 1987. Biomass production by irrigated and fertilized *Salix* clones. *Biomass*, 12: 83-95.
- Clark, D. B., and J. R. Kellner. 2012. Tropical forest biomass estimation and the fallacy of misplaced concreteness. *Journal of Vegetation Science*, 23: 1191-1196.
- Dittmann, S., E. Thiessen, and E. Hartung. 2017. Applicability of different non-invasive methods for tree mass estimation: A review. *Forest ecology and management*, 398: 208-215.
- Dubayah, R. O., and J. B. Drake. 2000. Lidar remote sensing for forestry. *Journal of Forestry*, 98: 44-46.
- Fassnacht, F. E., H. Latifi, K. Stereńczak, A. Modzelewska, M. Lefsky, L. T. Waser, C. Straub, and A. Ghosh. 2016. Review of studies on tree species classification from remotely sensed data. *Remote Sensing of Environment*, 186: 64-87.
- Gaulton, R., J. Taylor, and N. Watkins. 2015. Unmanned Aerial Vehicles for Pre-Harvest Biomass Estimation in Willow (*Salix* spp.) Coppice Plantations. *ISPRS Geospatial Week*.
- Gibbs, H. K., S. Brown, J. O. Niles, and J. A. Foley. 2007. Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters*, 2: 045023.
- Goetz, A. F., G. Vane, J. E. Solomon, and B. N. Rock. 1985. Imaging spectrometry for earth remote sensing. *Science*, 228: 1147-1153.
- Goodbody, T. R., N. C. Coops, P. Tompalski, P. Crawford, and K. J. Day. 2017. Updating residual stem volume estimates using ALS-and UAV-acquired stereo-photogrammetric point clouds. *International journal of remote sensing*, 38: 2938-2953.
- Hangs, R., F. Stevenson, J. Schoenau, and K. Van Rees. 2013. Measuring harvestable biomass in short-rotation willow bioenergy plantations using light attenuation. *BioEnergy Research*, 6: 83-90.
- Hansen, E., and J. Baker. 1979. Biomass and nutrient removal in short rotation intensively cultured plantations. *Proceedings: Impact of intensive harvesting on forest nutrient cycling*: 130-151.
- Hawryło, P., P. Tompalski, and P. Wężyk. 2017. Area-based estimation of growing stock volume in Scots pine stands using ALS and airborne image-based point clouds. *Forestry: An International Journal of Forest Research*: 1-11.
- Hess, D., and D. Tasa. 2011. *McKnight's physical geography: a landscape appreciation*. Prentice Hall.
- Hollsten, R., O. Arkelöv, and G. Ingelman. 2012. Handbok för *Salix*odlare. Jordbruksverket (Swedish Board of Agriculture), Jönköping, Sweden.
- Huisman, O., and R. De By. 2009. Principles of geographic information systems. *ITC Educational Textbook Series*, 1: 17.

-
- Hytönen, J. 1988. Biomass production of *Salix' Aquatica'* on an abandoned field in south Finland. *Biomass production of Salix' Aquatica' on an abandoned field in south Finland.*: 74-90.
- Hytönen, J., A. Saarsalmi, and P. Rossi. 1995. Biomass production and nutrient uptake of short-rotation plantations.
- Isenburg, M. 2012. LAStools- Efficient tools for LiDAR processing. Access date: February 2018.
- Jacobs, M. W., and D. B. Monteith. 1981. Feasibility of developing regional weight tables. *Journal of Forestry*, 79: 676-677.
- Kachamba, D. J., H. O. Ørka, T. Gobakken, T. Eid, and W. Mwase. 2016. Biomass estimation using 3D data from unmanned aerial vehicle imagery in a tropical woodland. *Remote Sensing*, 8: 968.
- Larsson, S. 1998. Genetic improvement of willow for short-rotation coppice. *Biomass and bioenergy*, 15: 23-26.
- Leberl, F., A. Irschara, T. Pock, P. Meixner, M. Gruber, S. Scholz, and A. Wiechert. 2010. Point clouds: Lidar versus 3D Vision. *Photogrammetric Engineering & Remote Sensing*, 76: 1123-1134.
- Li, W., Z. Niu, H. Chen, D. Li, M. Wu, and W. Zhao. 2016. Remote estimation of canopy height and aboveground biomass of maize using high-resolution stereo images from a low-cost unmanned aerial vehicle system. *Ecological Indicators*, 67: 637-648.
- Linder, W. 2009. *Digital photogrammetry*. Springer.
- Lindroth, A., and A. Båth. 1999. Assessment of regional willow coppice yield in Sweden on basis of water availability. *Forest ecology and Management*, 121: 57-65.
- Mola-Yudego, B., and P. Aronsson. 2008. Yield models for commercial willow biomass plantations in Sweden. *Biomass and Bioenergy*, 32: 829-837.
- Mosseler, A., J. Major, and G. Larocque. 2016. Allometric relationships from coppice structure of seven North American willow (*Salix*) species. *Biomass and Bioenergy*, 88: 97-105.
- Muukkonen, P. 2007. Generalized allometric volume and biomass equations for some tree species in Europe. *European Journal of Forest Research*, 126: 157-166.
- Muukkonen, P., and J. Heiskanen. 2005. Estimating biomass for boreal forests using ASTER satellite data combined with standwise forest inventory data. *Remote sensing of Environment*, 99: 434-447.
- Nordkvist, K., E. Sandström, H. Reese, and H. Olsson, 2013. Laserskanning och digital fotogrammetri i skogsbruket.(2. uppl.). Report 1401-1204. [in Swedish, English summary]
- Ota, T., M. Ogawa, K. Shimizu, T. Kajisa, N. Mizoue, S. Yoshida, G. Takao, Y. Hirata, et al. 2015. Aboveground biomass estimation using structure from motion approach with aerial photographs in a seasonal tropical forest. *Forests*, 6: 3882-3898.
- Popescu, S. C., K. Zhao, A. Neuenschwander, and C. Lin. 2011. Satellite lidar vs. small footprint airborne lidar: Comparing the accuracy of aboveground biomass estimates and forest structure metrics at footprint level. *Remote Sensing of Environment*, 115: 2786-2797.
- Raumonen, P., E. Casella, K. Calders, S. Murphy, M. Åkerblom, and M. Kaasalainen. 2015. Massive-scale tree modelling from TLS data. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 2: 189.
- RStudio. 2015. RStudio: integrated development for R. *RStudio, Inc., Boston, USA*.
- Snavely, N. 2011. Scene reconstruction and visualization from internet photo collections: A survey. *IPSP Transactions on Computer Vision and Applications*, 3: 44-66.
- Spetsakis, M., and J. Y. Aloimonos. 1991. A multi-frame approach to visual motion perception. *International Journal of Computer Vision*, 6: 245-255.
- Van Leeuwen, M., and M. Nieuwenhuis. 2010. Retrieval of forest structural parameters using LiDAR remote sensing. *European Journal of Forest Research*, 129: 749-770.
- Vastaranta, M., M. A. Wulder, J. C. White, A. Pekkarinen, S. Tuominen, C. Ginzler, V. Kankare, M. Holopainen, et al. 2013. Airborne laser scanning and digital stereo imagery measures of forest structure: comparative results and implications to forest mapping and inventory update. *Canadian Journal of Remote Sensing*, 39: 382-395.
-

- Vauhkonen, J., M. Maltamo, R. E. McRoberts, and E. Næsset. 2014. Introduction to forestry applications of airborne laser scanning. In *Forestry applications of airborne laser scanning*, 1-16. Springer.
- Verwijst, T., and B. Telenius. 1999. Biomass estimation procedures in short rotation forestry. *Forest Ecology and Management*, 121: 137-146.
- Westoby, M., J. Brasington, N. Glasser, M. Hambrey, and J. Reynolds. 2012. 'Structure-from-Motion' photogrammetry: A low-cost, effective tool for geoscience applications. *Geomorphology*, 179: 300-314.
- White, J. C., N. C. Coops, M. A. Wulder, M. Vastaranta, T. Hilker, and P. Tompalski. 2016. Remote Sensing Technologies for Enhancing Forest Inventories: A Review. *Canadian Journal of Remote Sensing*, 42: 619-641. DOI: 10.1080/07038992.2016.1207484
- White, J. C., M. A. Wulder, M. Vastaranta, N. C. Coops, D. Pitt, and M. Woods. 2013. The utility of image-based point clouds for forest inventory: A comparison with airborne laser scanning. *Forests*, 4: 518-536.

Appendix I

Appendix I shows the results from the other tested point cloud statistics, apart from the used minimum point height, that were plotted against stem count field data. The tested statistics that are displayed in the figures below are maximum point height, mean point height, standard deviation of the points and the point count.

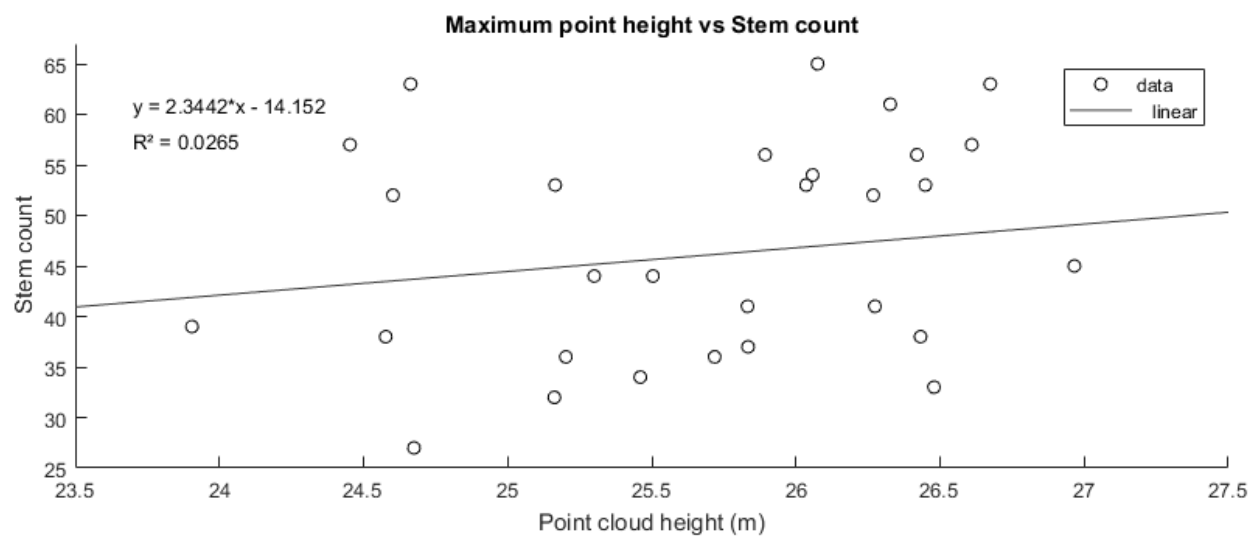


Figure i: Linear regression analysis between maximum point cloud height and stem count of the sample areas. The relationship has an R^2 value of 0.0265.

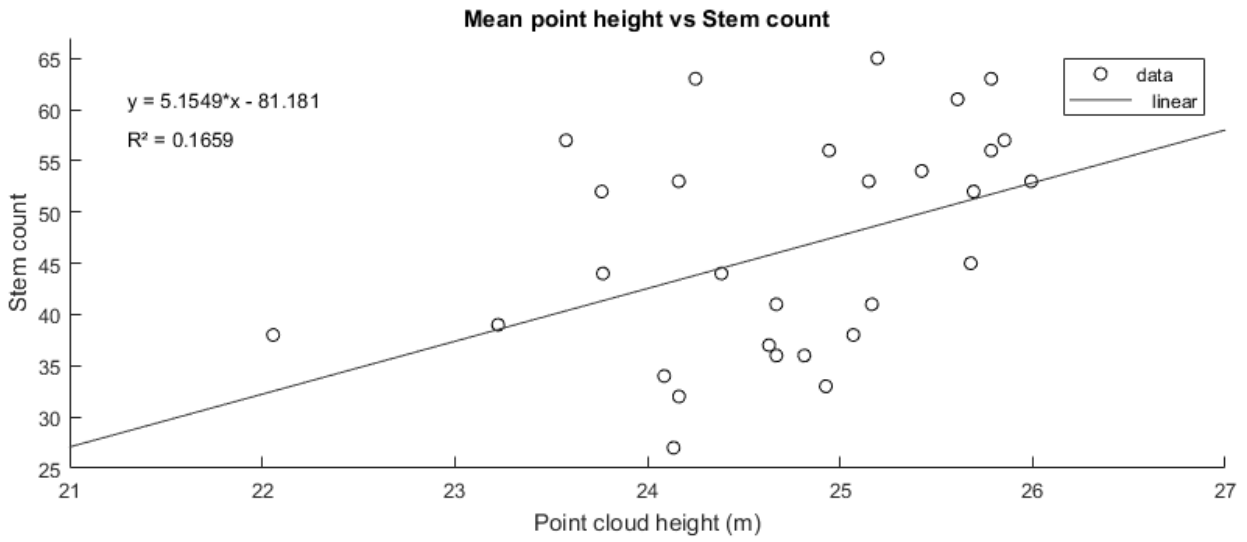


Figure *ii*: Linear regression analysis between mean point cloud height and stem count of the sample areas. The relationship has an R^2 value of 0.1659.

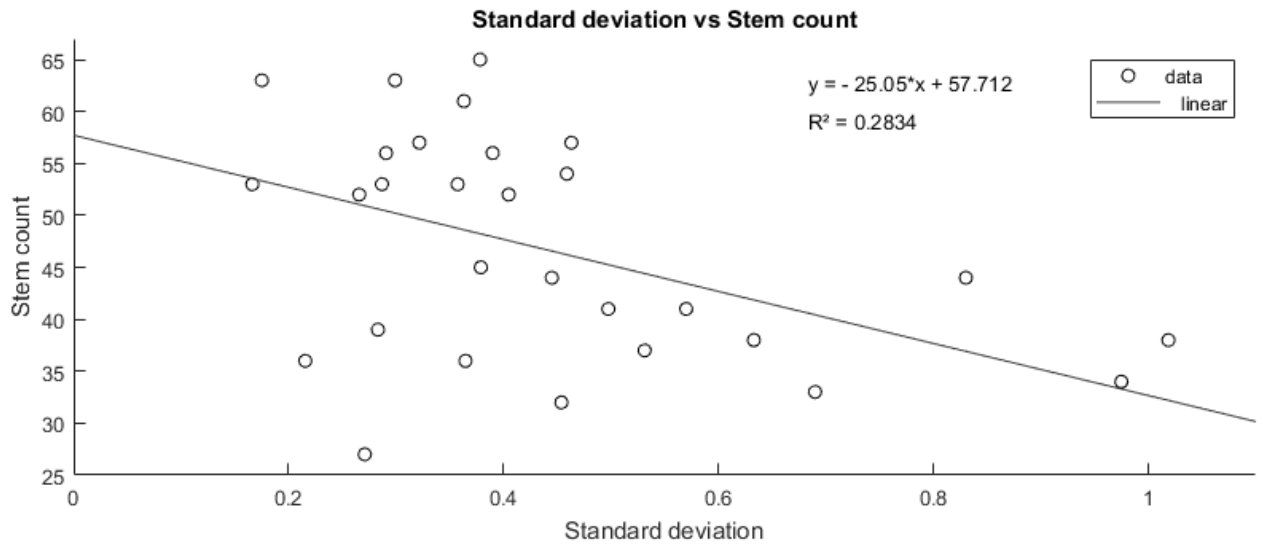


Figure *iii*: Linear regression analysis between standard deviation in point cloud heights and stem count of the sample areas. The relationship has an R^2 value of 0.2834.

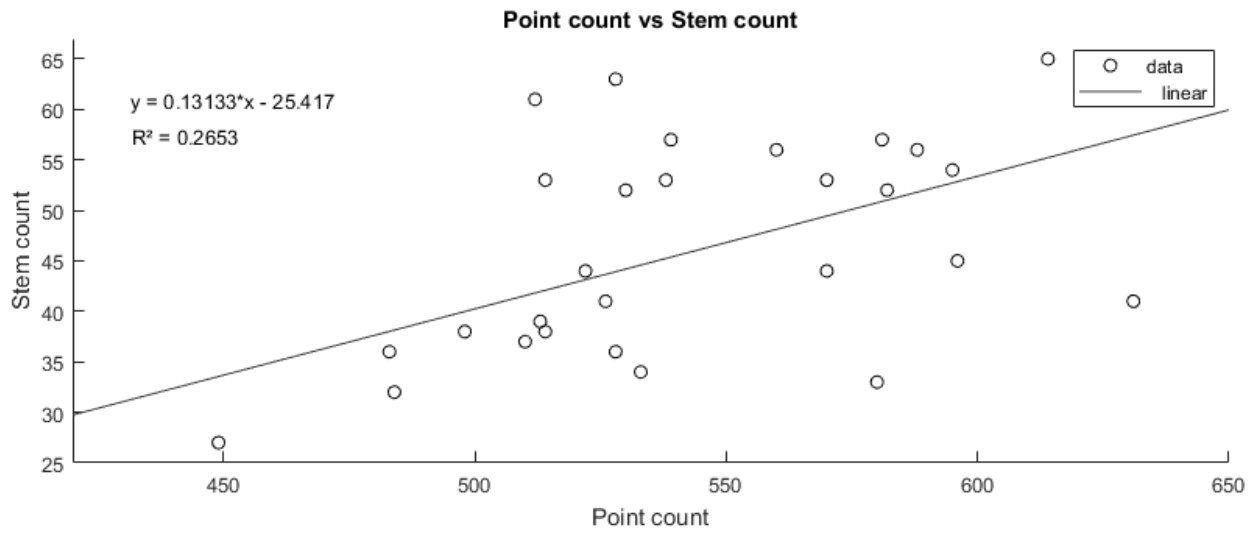


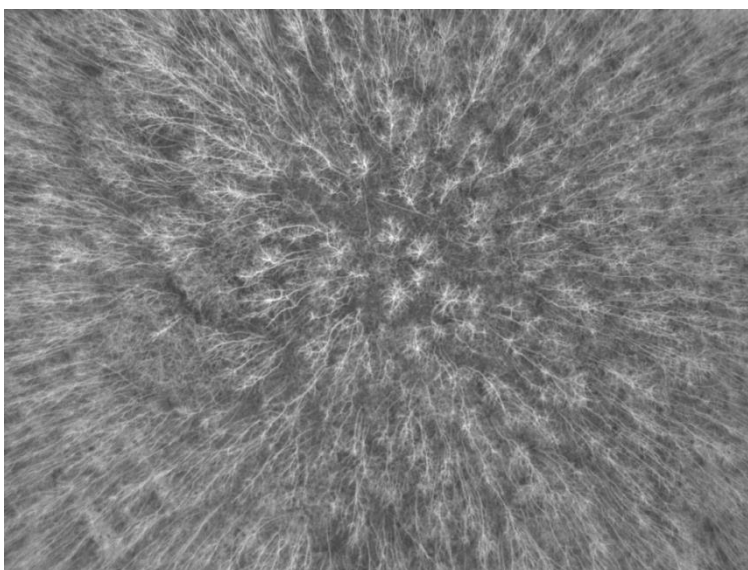
Figure *iii*: Linear regression analysis between point count and stem count of the sample areas. The relationship has an R^2 value of 0.2653

Appendix II

Appendix II shows example images that were used as input for the SFM-analysis to display the difference in details that are visible between the RGB images and multispectral images.



Example image 1: Captured with the RGB sensor at April 9, 2018



Example image 2: The red-edge spectral band of an image captured with the multispectral sensor at April 9, 2018