Evaluating the need of cleaning using 3D point clouds derived from high resolution images collected with a drone

Lisa Wennerlund

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Handledare:
Jonas Bohlin
Jonas Jonzén

Swedish University of Agricultural Sciences
Department of Forest Resource Management
901 83 UMEÅ
www.slu.se/srh
Tfn: 090-786 81 00

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Supervisor: Jonas Bohlin, SLU, Dept. of Forest Resource Management, Remote Sensing
Asst. supervisor: Jonas Jonzén, SLU, Dept. of Forest Resource Management, Remote Sensing
Examiner: Håkan Olsson, SLU, Dept. of Forest Resource Management, Remote Sensing
External supervisor: Leif Johansson, SCA

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Department of Forest Resource Management
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Preface

First and foremost, I would like to thank my supervisors Jonas Bohlin and Jonas Jonzén for their help and support during this study. Their exchange of knowledge has been tremendously rewarding. The staff at the remote sensing department has also been helpful willing to share their knowledge. I would also like to thank SCA and Leif Johansson for the idea of this study. Lastly I would like to thank the Ljungberg foundation for their financial support to the Remote Sensing Lab at SLU which has made this study possible.

Summary

Management of young forest stands is important for the future economical outcome. Cleaning is a way to control the competition between plants and a total of 1 443 000 ha are in need of cleaning in Sweden. The cleaning is usually performed when the trees are 2 – 6 m high and the most common is to remove deciduous trees to favor coniferous species. To handle the amount of forests in need of cleaning there is a need for efficient inventory and planning of these areas. Remotely sensed data can be used to make these processes more efficient. Earlier studies have shown that variables that are commonly used for forest management planning can be accurately estimated when using photogrammetry with aerial images. In this study the use of 3D point clouds as an aid for field inventory when planning for cleaning has been evaluated. This was done by studying field inventoried sample plots and a 3D point cloud derived from high-resolution images collected with a drone in the county of Västerbotten. The need of cleaning was predicted with logistic regression with an overall accuracy of 82 %. Field attributes; average height, stem number and $\sum H^2$ was predicted using linear regression with a relative RMSE of 43.9 %, 44.4 % and 76.2 %, respectively. The results show that it is possible to estimate cleaning need and field attributes using 3D point clouds derived from high-resolution images collected with a drone. Cleaning need can be predicted with high accuracy. The method is time consuming, hence evaluations regarding costs and time compared to manual field inventory is required if the method is to be implemented in practical use.

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1. Introduction

1.1 Cleaning

Environmental resources such as nutrients, water and light are necessary for plant and tree survival. If the resources are limited, competition between plants will occur. The size of the plants will affect how the resources are distributed between plants (Canell et al., 1984). Larger plants will succeed better than smaller plants when competition occurs. Spacing between plants is another factor that can affect the plant development. If the spacing is too small the plant survival can be negatively affected (Ford, 1975).

Forest management affects the future economical outcome and is therefore meaningful. Management in young stands sets the basis for further development and therefore cleaning plays an important role (Huuskonen & Hynynen, 2006). Cleaning is a way to to control the competition between plants and results in that the main stems will have enough growing space to develop properly. The cleaning usually occurs when the trees are about 2 – 6 m high but in some cases the management is required when the tree height is lower than 2 m. If the first cleaning occurs early when the trees have a low height, there is usually a need for a second cleaning due to competition. The most common is to remove the deciduous trees to favor the coniferous species (Pettersson et al., 2012). The intensity and timing of the cleaning affects the results. If the management practice occurs early the volume growth is favored but quality parameters such as branch diameter and the amount of branches can be negatively affected. This is due to larger tree crowns since the growth of branches increases. (Varmola & Salminen, 2007). The amount of juvenile wood is another attribute that can be negatively affected by an early cleaning since the amount of the juvenile wood will increase. This is not a trait that is sought after since it usually gives a poorer wood quality (Pettersson et al., 2012). Cleaning is also used to remove trees that are not desirable due to less favorable properties or to achieve a certain mix of species (Ulvcrona et al., 2014).

Since 1950 the amount of areas in need of cleaning has increased in Sweden. This is due to the common silvicultural system, clear-cutting, which includes this management practice (Pettersson et al., 2012). According to Forest Statistics (2017), which is part of the official statistics of Sweden, 1 443 000 ha are in need of cleaning. To handle the amount of forests in need of cleaning there is a need for efficient inventory and planning of these areas. Manual ground inventory is the most common way to get information about forests by collecting ground measurements using circular field plots (Straub et al., 2010). Number of stems is collected at every field plot. To get the number of stems that are going to be removed, the number of future stems is also noted. The field data collected gives information about the likely duration for the cleaning, which sets the basis for the costs. Duration for the cleaning is mainly based on number of stems and height. Tree species composition, the terrain and other factors can also affect the time consumed for cleaning an area (Karlsson & Westman, 1991). According to Johansson[1], the inventory and planning of areas that are in need of cleaning can also be done from a helicopter and is the common way when planning on forests held by the forest company SCA. The inventory is done by an ocular assessment if the area is in need of cleaning or not when flying over the area with a helicopter.

[1] Leif Johansson, SCA, 2017-06-20

Today the use of remotely sensed data can improve the results of the inventory. The development of remote sensing techniques has led to more valuable information favoring forest management and planning (Straub et.al., 2010).

1.2 Remotely sensed data

In a wide perspective, remote sensing means that data of an object is collected without making physical contact with it (Rees, 2001). Lillesand et al. (2008) defines remote sensing as “The science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation”. When collecting data with remote sensing techniques it is possible to get wall-to-wall information about the study area. Compared to manual field inventory where information is only obtained from sample plots, inventory with remote sensing techniques also yields information about the areas outside the sample plots. Remotely sensed data can be used for several purposes. Some examples are agriculture, cartography, climatology and forestry. With remote sensing techniques it is possible to collect information about objects that are difficult or dangerous to access for ground sampling (Rees, 2001).

Some examples of techniques to collect remotely sensed data is through satellites, laser scanning and aerial images (Harrie, 2013). When planning for sustainable forest management, it is crucial to have qualified information about the forest stands. To achieve this with remote sensing techniques it is important to have high resolution approaches. Drones that collect aerial images can be an option since they are affordable and able to collect data in an efficient way (Tang & Shao, 2015).

1.3 Drones

According to the Swedish Transport Agency (2018) a drone is described as “an unmanned air vehicle capable of flying by itself or remotely controlled by an operator in a different location”. UAV (Unmanned Aerial Vehicle), UAS (Unmanned Aircraft System) and RPAS (Remotely Piloted Aircraft System) are examples of other names that drones are referred to (Tang & Shao, 2015). Compared to a manned aircraft, drones can fly at lower altitudes which allow collection of high resolution data and some opportunities to fly during cloudy weather conditions when visibility is low. Drones are also more affordable than manned aircrafts, for example they do not have to be moved from an airport to the site which is going to be flown over. Another advantage with drones compared to manned aircrafts is that the drone can fly a more consistent flight path which results in that the image acquisition is more consistent (Watts et al., 2010).

Drones are classified according to their attributes. Two attributes that separates the different drone types are weight and maximum kinetic energy evolved. There are some rules to be aware of when flying with a drone. For example, if flying will occur within an airport control zone it is required to have a permit if the flying will occur within 5 kilometers from the start and landing strip. It is also required to have a permission when flying if the drone has a weight of more than 7 kg. While flying the drone it always has to be in sight for the operator. It is also important to be aware that some areas, such as national parks and prisons, are prohibited to fly over (Swedish Transport Agency, 2018).

1.4 Drones in forestry

There are some studies regarding forestry that have used drones. For example, Koh & Wich (2012) used a drone as a tool for mapping tropical forests in Indonesia. These forests are often covered with clouds which make a drone a suitable tool since it can fly at lower altitudes. Images from satellites were not useful due to the cloud cover. The researchers concluded that using drones could lead to less expensive inventories since it is less time consuming and less labor is required. Another study conducted by Zarco-Tejada et al. (2013) showed that heights, which is an important parameter for planning, could be quantified using a drone for the data acquisition. They used a large overlap, 80 %, in both along- and across-track directions and the images acquired were in a very high resolution. Digital surface models (DSMs) that were generated had a resolution of 5 cm pixel $^{-1}$.

1.5 Photogrammetry

Photogrammetry has many applications, for example to produce different types of GIS data products. Topographic maps, digital elevation models (DEMs), orthophotos and spatially referenced GIS data in 2D or 3D are examples of different products derived from photogrammetry. According to Lillesand et al. (2008), photogrammetry can be described as "the science and technology of obtaining spatial measurements and other geometrically reliable derived products from photographs".

When collecting data for photogrammetry, flying with a high overlap between the photographs comes with some benefits. If the overlap is large the chances of matching tie-points successfully will increase. The unit errors of measurements will be smaller as a result of an increased image overlap (Leberl et al., 2010). One disadvantage with large overlaps is that the flying route will be more expensive since it will take longer time to fly the area (Lantmäteriet, 2013). Another variable that will influence the accuracy of the 3D data is flight altitude (Bohlin et al., 2012). Light condition and sun angle are also variables that might have an effect on the results (Gobakken et al., 2015). Compared to laser scanning, photogrammetry is more restricted to the top of the tree canopies. It is not possible to get as good information of the ground surface as with laser scanning. But photogrammetry can yield very dense point clouds and it has been widely used in forestry (Ackermann, 1999). Forest mapping, stand attribute estimation and forest damage evaluation are some examples where photogrammetry has been applied (Willingham, 1957; Nyssönen et al., 1968; Murtha, 1975). Since point clouds derived from photogrammetry gives great information about the top of the tree canopies, Canopy Height Models (CHM) can be computed. This allows individual trees to be detected (Nevalainen et al., 2017). The CHM is produced by combining an accurate Digital Elevation Model (DEM), which is derived from Airborne Laser Scanning (ALS), and 3D data derived from digital aerial images (Bohlin et al., 2012).

Studies have shown that variables that are commonly used for forest management planning can be accurately estimated when using photogrammetry with aerial images. The accuracy has shown to be higher than from field methods that are commonly used in forestry today. It has also shown to be similar to the results achieved with methods using ALS (Bohlin et al., 2012). Altough, the ALS method can yield more information about the tree canopy and vegetation as the laser can penetrate through the canopy cover and thus this method can result in slightly better results if kind of data is favorable (Ackermann, 1999). The photogrammetric approach can tough be performed at a lower cost than the ALS, therefore this method may be suitable in forestry (Bohlin, et al., 2012). Puliti et al. (2015) showed that loreys mean height could be predicted with adjusted R^2 of 0.71 and a relative RMSE of 13.3 % when using photogrammetry with areal images collected with a drone. Stem number could be predicted with adjusted R^2 of 0.57 and a relative RMSE of 38.6 %. The accuracy was validated at a plot-level. They used an area-based-approach and when collecting field data they used a plot-size of 400 m^2. Næsset & Gobakken (2009) showed that the size of the field sample plots will affect the accuracy of the results. If the sample plots are small, the positioning error of the plots is greater than if the sample plots are large and thus the accuracy of the predicted stand properties will be affected. In their study they used ALS data and three different sample plot sizes for the field plots; 200 m^2, 300 m^2 and 400 m^2. Overall, the standard deviation was larger for smaller sample plots than for larger sample plots. The variation in standard deviation showed the same pattern; larger for smaller sample plots and smaller for large sample plots. Stand attributes can also affect the accuracy of the results. If the stand is on a poor site with few stems it is required to have larger sample plots to cover all of the varieties than if the forest is dense and homogenous. Næsset & Bjerknes (2001) used ALS data to estimate tree height and stem number in young forest stands using an area-based-approach resulting in an R^2 of 0.83 for tree height and 0.42 for stem number. The size of their sample plots were 200 m^2.

1.6 Density measurements

To describe the need of cleaning, density measurements can be used. Elfving (1982) used the parameter $\sum H^2$ (sum of the quadratic heights) as a measure of congestion, i.e. how much growing space that is available for the trees. This parameter has also been shown to estimate the need of thinning with success (Halvarsson, 2008). The parameter can be calculated based on both field measurements and remote sensing data. Halvarsson (2008) used laser data to estimate the need of thinning with the density index $\sum H^2$. The study showed that it was possible to estimate $\sum H^2$ from both sparse and dense point clouds. Bohlin (2017) used the parameter for point clouds derived from photogrammetry with the aim to improve the information about forest density.

Another density measurement that is commonly used is the proportion of points at a certain height to the total number of points. This results in a vegetation quota which can be a good density measurement (Næsset, 2002). This density measurement is based on remote sensing data and not field measurements.

1.7 Cleaning need interpretation using remote sensing techniques

Earlier studies have used different remote sensing techniques to evaluate the possibilities of interpretation of the cleaning need with remote sensing data. Pouliot et al. (2006) studied seedling stands and the need for cleaning. They estimated the need for cleaning based on the amount of deciduous species which was derived using high-resolution leaf-off images. Need of cleaning was based on stem competition. The images were collected using a helicopter with a flying altitude of 185 m. Predicted competition and thus need of cleaning based on the images agreed well with the field measurements. Korpela et al. (2008) studied seedling stands using both images and LiDAR data. They used textural and spectral information from the images and geometric and radiometric information from the LiDAR data with the aim of classifying different vegetation compositions and their heights. They tried to classify trees, shrubs and low vegetation canopies. With this information they aimed to identify areas that are in need of management such as cleaning, for example if a conifer seedling area is dominated by overgrown deciduous trees. The results from their study showed that the classification could be performed with an overall accuracy varying from 61 % to 79 %. The results showed that it could be possible to detect the distribution of deciduous forests and thus could work as an aid when planning for management of these areas. Although they suggest that further studies are required before practical implementations can be done. Another study that examined the possibilities of using ALS data to find areas in need of cleaning was conducted by Nivala (2012). He used three classes for the classification; need of cleaning, need of fuel wood thinning and no need for management. This resulted in an overall accuracy of 76.9 %. The results were improved when only using two classes; need for cleaning and no need for management. Another example of research regarding cleaning need interpretation using remote sensing is the study which Korhonen et al. (2013) conducted. They used both airborne laser scanning data and aerial images to estimate the need of cleaning. Attributes such as height and density was extracted from the airborne laser scanning data and spectral and textural information from the aerial images. They used logistic regression when classifying the need of cleaning resulting in an overall accuracy of 77 % with training data and 71 % with validation data. Their conclusion was that the modelling prediction of cleaning need could not totally replace field inventory.

Earlier studies that have evaluated the possibilities of using remote sensing data when planning forests in need of cleaning shows that it is possible to get quite good results (Korhonen et al., 2013; Nivala, 2012; Pouliot et al., 2006; Korpela et al., 2008). Although the results indicate that the methods can not totally replace manual field inventory and thus there is a need for more research. Young forest stands that are in need of cleaning are difficult to handle with remote sensing data due to their attributes. The areas are often very dense and clustered with small tree crowns and thus difficult to manage (Hall & Aldred, 1992). High-resolution data is required to handle these types of forests. Drones are well developed systems that can be used to collect very high-resolution data and also at lower costs than satellites, airborne sensors and manual field inventory (Koh & Wich, 2012). Since the amount of areas in need of cleaning in Sweden are very extensive, there is a need for efficient inventory and planning of these areas and thus minimizing expensive costs for manual field inventory. If methods for drone systems are developed with success, it might be possible to apply these methods on other platforms such as on helicopters to improve the efficiency and economy.

1.8 Objective

The overall aim of the study is to evaluate the use of drones as an aid for field inventory when planning for cleaning on forests held by SCA. The hypothesis for this study is that a 3D point cloud derived from high-resolution images taken by a drone can be used to evaluate the need of cleaning. The following will be carried out:

1. Need of cleaning will be predicted wall-to-wall using 3D data from high-resolution images using an area based approach. The performance of the prediction will be estimated.

2. Wall-to-wall raster of field surveyed height and density variables ($\sum H^2$ and number of stems) will be predicted from 3D data to be used for manual interpretation of the need of cleaning. The performance of the prediction will be estimated.

3. Wall-to-wall raster of descriptive height and density metrics (height, vegetation quota, $\sum H^2$, number of stems) will be generated from 3D data to be used for manual interpretation of the need of cleaning.

4. The usefulness of aerial images for manual interpretation will briefly be discussed.

2. Material and Method

2.1 Study area

The stands that have been studied are located in the county of Västerbotten and they are owned by the forest company SCA. 14 stands of different forest types have been studied and a total of 198 sample plots have been collected (Figure 1). The size of the study areas varied from 1.53 – 26.65 ha (Table 2).

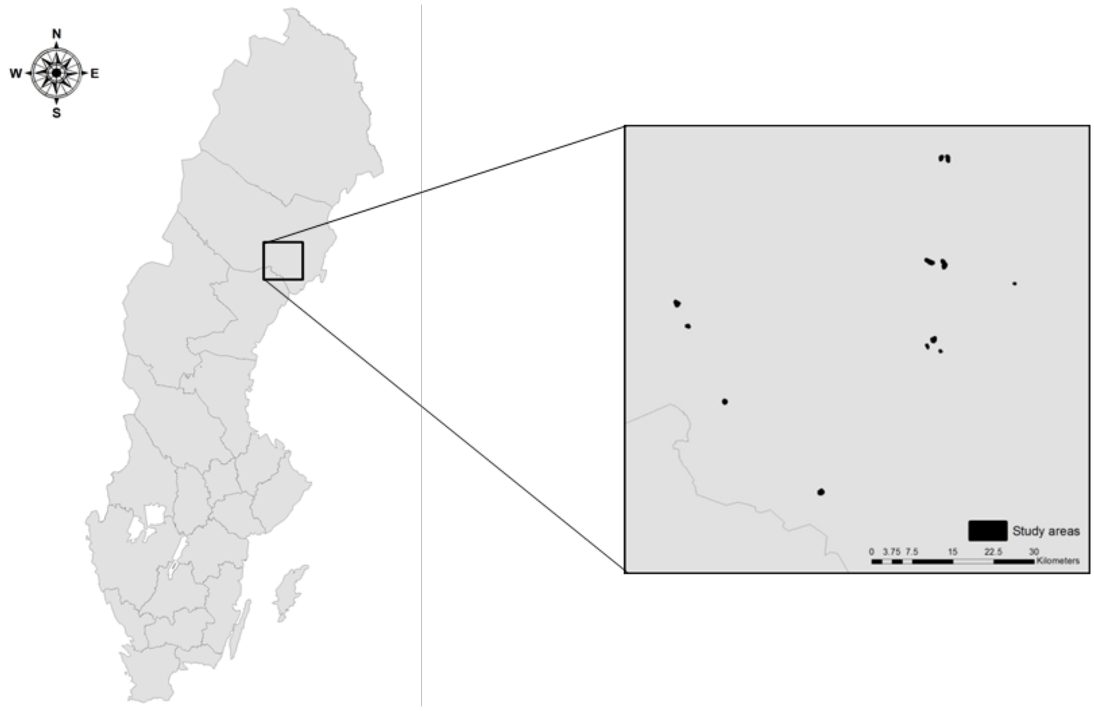

Figure 1. Map showing the location of the 14 study areas within the county of Västerbotten.

2.2 Data collection

2.2.1 Ground sampling inventory

The field data collection was configured as a cluster design. At every stand, one or two clusters were laid out. Within each cluster nine plots were distributed in a 3x3 grid. The grids were always laid out facing the northern direction; which was confirmed using a compass. To get comprehensive data for different types of objects the inventoried areas were subjectively chosen. The center sample plot was tough chosen objectively by throwing an item a couple of meters, marking the center of the center plot. The shape of the sample plots was circular with a radius of 3.99 m and the distance between the sample plots was 10 m (Figure 2). Variables collected at every plot were total stem number (>0.5 m), mean height and mean diameter at breast height (1.3 m) for every tree species. The tree diameter was measured using a caliper and the height with a height pole. If the trees were greater than the height pole, Haglöfs hypsometer was used. Number of main stems on each plot was also collected, this information was used to facilitate the assessment if the plot was in need of cleaning or not. A subjective assessment if the plot was in need of cleaning or not (yes or no) was also done at every sample plot. The need of cleaning was based on competition between the trees; which was based on how much growing space that was available for the future stems. A short description of the cluster was written down and a number of images of them were taken with a phone camera. The sample plots were used as both reference and validation data. A subjective assessment if the inventoried forest stand was in need of cleaning or not was also done based on the collected field plots and a visual assessment of the forest stand.

To identify the field plots positions in the point cloud, some of the field plots were marked. To be able to find the field plots in the drone images three of the plots within each grid of plots were marked with a paper plate mounted on a wooden stick. These paper plates were colored in three different colors; red, blue and yellow, depending on their position. The red marker was placed in the center sample plots, the blue one in the North West sample plot and the yellow one in the South East sample plot (Figure 2).

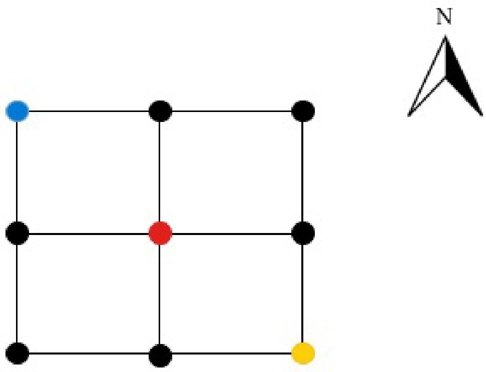

Figure 2. The arrangement of the field plots in a 3x3 grid. Three of the field plots marked with a colored paper plate mounted on a wooden stick. The radius of the circular plots was 3.99 m and the distance between the plots was 10 m.

2.2.2 Inventory with drone

The drone used in this study was a DJI Phantom 4 Pro (Table 1). Flying altitude was 80 m and both front overlap and side overlap was 80 %. The angle of the camera was 90º i.e. the camera was facing down (nadir). Pix4Dcapture was used when planning the flying routes. All of the objects were flown over and inventoried with the drone after ground sampling inventory had been done. To ensure the quality of the further processes of the images, the collection of images was done with a buffer around the stands.

Table 1. Specification for DJI Phantom 4 Pro (Source: DJI (2017), Swedish Transport Agency (2018))

DJI Phantom 4 Pro	
Weight	1388 g
Maximum flight time (No wind)	30 min
Maximum flight speed	72 km/h
Drone category	1
Control range	7 km
Camera sensor	20 mp
Operating temperature range	0˚C – 40˚C

2.3 Data processing

Agisoft PhotoScan Professional Version 1.2.6 (64 bit) was used to create the dense point clouds. The software has shown to be effective when working with forest areas and was therefore chosen (Dandois & Ellis, 2013). There were several steps in the process of generating point clouds in Agisoft PhotoScan. The first step was to load all of the images in to PhotoScan and once that was done, the images could be aligned. That included finding the camera position and orientation for each image, using automatically generated tie points. Based on the camera positions derived from the alignment the program calculated depth and generated a dense point cloud. The dense point cloud was set in the coordinate system SWEREF99 TM and exported as a .las file. After the dense point cloud was built it was possible to build a mesh. The last step was to create an orthomosaic and export the results as an orthophoto. The generated point clouds were studied within Agisoft PhotoScan and QTModeler to see if the generation of the points had been complete.

Within Agisoft PhotoScan the sample plots for each stand marked with a paper plate were identified in the images collected with the drone. This generated coordinates for the sample plots and with this information, the coordinates for the rest of the sample plots could be computed.

The next step was to classify all of the points in the dense point cloud within Agisoft PhotoScan. They were classified as either ground points or points above ground. With this information a digital elevation model was created based on the ground points. The digital elevation model was processed to make it smoother. The heights of the points within the point clouds were height above sea level. To be able to measure the height above ground the point clouds were normalized according to the digital elevation model created. LasTools (Rapidlasso, 2017), which is a well-used software, was used to normalize the data and extract all of the sample plots.

FUSION (McGaughey, 2016) was then used to get different metrics of the data. The software is primarily a research tool. However, large sets of LIDAR data can be processed using the program. The program was used to get information about heights, such as different height percentiles. It was also used to get a vegetation quota by getting the percentage of all returns above 1,3 m.

To estimate the field variables; number of stems and the quadratic height sum, local maxima was identified in the canopy height model (CHM). This was done by creating a CHM with a 0.2 m cell size assigning the maximum height within each cell. All of the pixels that due to occlusion had no-data was included and set as zero. When finding the local maximum, a 3 x 3 cell window was used which means that only one local maximum was allowed within 0.6 m x 0.6 m in this study. The metrics was also produced with a CHM that had been smoothed by a mean filter with a 3 x 3 cell window (Bohlin, 2017). This resulted in four different metrics; number of local maximum, number of local maximum of filtered CHM, sum of quadratic height and sum of quadratic height of filtered CHM. A threshold for the minimum height of the local maximum was set to 1.3 m, i.e. all of the local maximum below 1.3 m was not included in the calculations.

2.4 Statistical analysis

2.4.1 Prediction of the need of cleaning

Logistic regression was used to estimate the need of cleaning, yes or no. Logistic regression is a method that is suitable when there is a binary response, i.e. the response is a two-class response (in this study it can either be "cleaning" or "no cleaning"). Therefore, logistic regression is commonly used as a classification method (James et al., 2013). Several different combinations of metrics derived from FUSION and from the CHM were tested to find the best model. The best model was chosen based on the lowest Akaike Information Criterion (AIC). The metric describing the need of cleaning most accurate was chosen and additional metrics were added if they improved the model. To avoid overfitting, a maximum of three metrics was chosen.

When using logistic regression, the function gives outputs between 0 and 1 (Equation 1) (James et al., 2013). In this study the outputs will be values indicating the "need of cleaning". The outputs between 0 and 1 are a measure that indicates whether p(X) should be classified as cleaning or no cleaning

$$p(X) = \frac{e^{\beta 0+\beta 1x1+\beta 2x2+\ \dots +\ \beta nxn}}{1+e^{\beta 0+\beta 1x1+\beta 2x2+\ \dots +\ \beta nxn}}\,, \qquad (1)$$

where *p(X)* is the modeled probability of X belonging to a particular category, β_0 is the intercept and β_n is the estimated constant for the variable x_n that describes the need of cleaning. If it is classified as 0 it is classified as "no need of cleaning" and if it is classified as 1 it is classified as "need of cleaning". The threshold was set to 0.5 which means that if p(X) is larger than or equal to 0.5 it is classified as 1 (need of cleaning) and if it is less than 0.5 it is classified as 0 (no need of cleaning).

The performance of the prediction of need of cleaning was estimated with a confusion matrix.

2.4.2 Prediction of field surveyed height, number of stems and $\sum H^2$

Linear regression was used to analyze the stand attributes height, quadratic height sum and stem number and to produce wall-to-wall raster with this information. The metric describing the stand attributes most accurate was chosen and additional metrics were added if they improved the model. To avoid overfitting, a maximum of three metrics for each model was chosen. The performance of the predictions was estimated with adjusted R^2 derived from the linear regression, RMSE and relative RMSE using leave-one-out-cross-validation (LOOCV):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}\,, \qquad (2)$$

where n is the number of sample plots, y_i is the field surveyed value for sample plot i and $\hat{y}_i$ is the estimated value for sample plot i.

$$Relative\ RMSE = \left(\frac{RMSE}{\overline{X}}\right) * 100\ , \qquad (3)$$

where $\overline{X}$ is the average of field surveyed stand attribute.

The best models were chosen based on the highest R^2adjusted value.

2.5 Generation of wall-to-wall rasters for manual cleaning need interpretation

LasCanopy was used to generate rasters with the different metrics used for the wall-to-wall products. The pixel size of the rasters was set to 7 m x 7 m to correspond to the field sample plots (Magnussen & Boudewyn, 1998). Within the statistical software R, the logistic regression model and the linear regression models were applied to the rasters. This generated one raster with estimated need of cleaning and different wall-to-wall rasters for manual interpretation of cleaning need. The generated wall-to-wall rasters for manual interpretation had information about height, vegetation quota, $\sum H^2$ and number of stems. The height, $\sum H^2$ and number of stems are estimated field variables whereas the vegetation quota is a FUSION metric derived from the point cloud. ArcMap was used to visualize the results and to generate maps with this information.

3. Results

3.1 Field data and generation of point clouds

A total of 12 stands were chosen for the study which is a total of 18 clusters and 162 sample plots. 14 different stands were inventoried (Table 2) but two of the stands were not included for the further analysis due to poor light conditions during the data collection with the drone, which resulted in deceptive generated point clouds. They were pure pine stands on poor sites with ground lichens dominating the ground cover. The 12 studied stands that were included for further analysis was of different character such as in heights, tree species composition and if they were in need of cleaning or not etc. This resulted in different types of point clouds generated from Agisoft PhotoScan. Normalized point clouds for stands that was in need of cleaning (Figure 3) and for stands that was not in need of cleaning (Figure 4) was computed.

Table 2. Information about the stands that was inventoried.

Stand	**Area (ha)**	**Number of stems/ha**	**Average height (m)**	**Average diameter (cm)**	**Number of clusters**
1	11.33	1567	4.88	7.58	2
2	1.53	5633	4.89	4.68	2
3	1.58	6578	8.59	7.21	1
4	24.14	8563	2.29	1.65	2
5	4.75	2889	3.33	4.30	1
6	26.65	2422	4.44	7.60	1
7	4.00	3489	3.52	4.90	1
8	19.94	7456	2.25	2.05	2
9	3.42	13778	3.85	2.89	2
10	7.08	10989	3.00	2.23	2
11	24.29	2467	5.41	6.83	1
12	19.42	8200	3.40	2.52	1
13*	20.94	4789	3.83	4.08	2
14*	20.16	3953	4.07	4.42	2
Average	13.52	5912	4.13	4.49	

*Forest stand that was not included for the further analysis

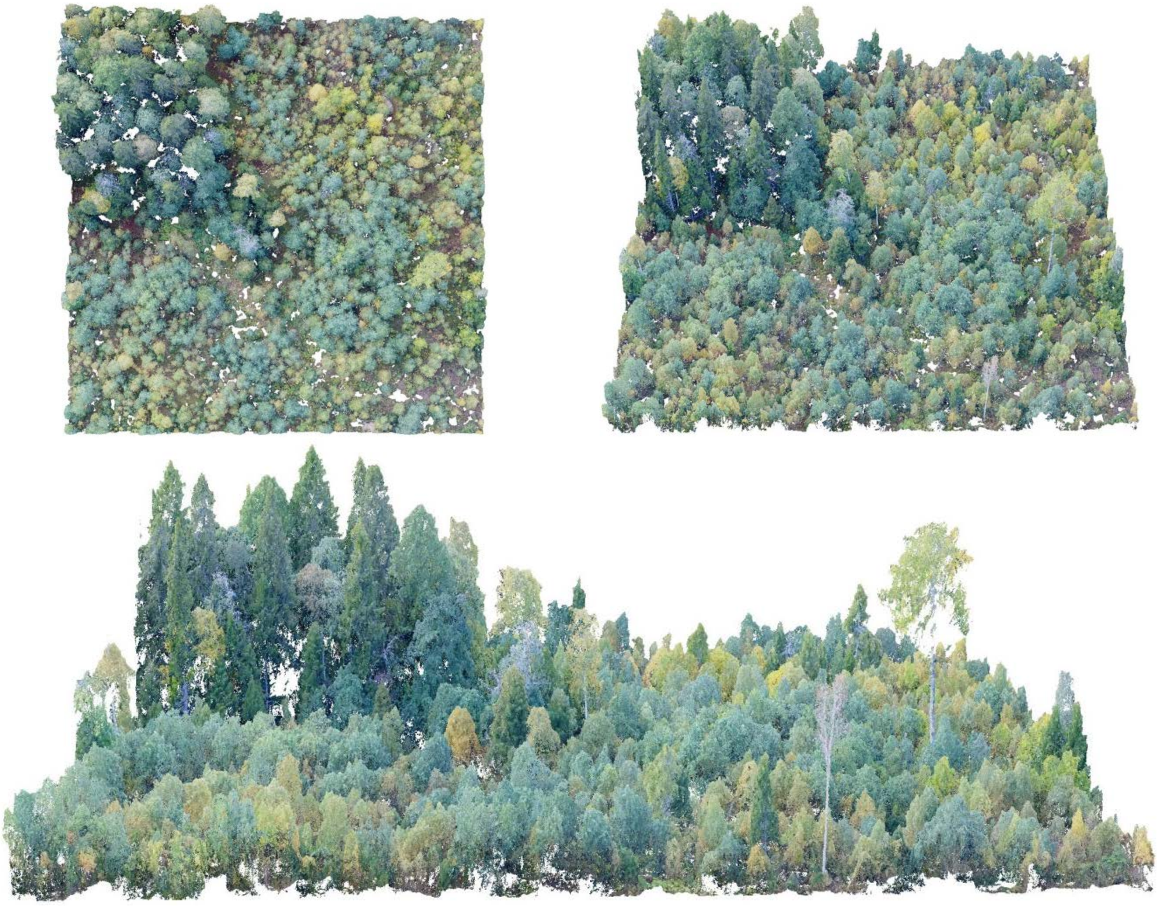

Figure 3. Normalized point cloud generated from Agisoft PhotoScan for a stand (number 12 in Table 2) that is in need of cleaning, visualized in QTModeler.

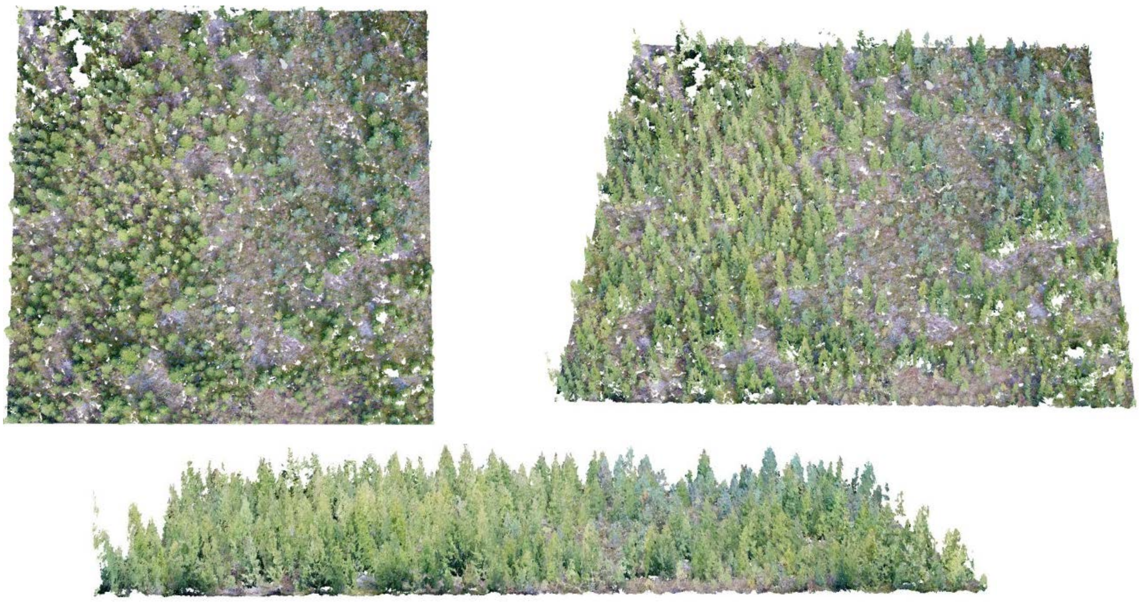

Figure 4. Normalized point cloud generated from Agisoft PhotoScan for a stand (number 1 in Table 2) that is not in need of cleaning, visualized in QTModeler.

The point clouds derived from Agisoft PhotoScan had low geometric accuracy in height compared to the DEM's from the land survey. The difference in the z-coordinates could differ up to more than 100 m (Figure 5). To solve this problem, the data were normalized based on DEM's created from the generated point clouds.

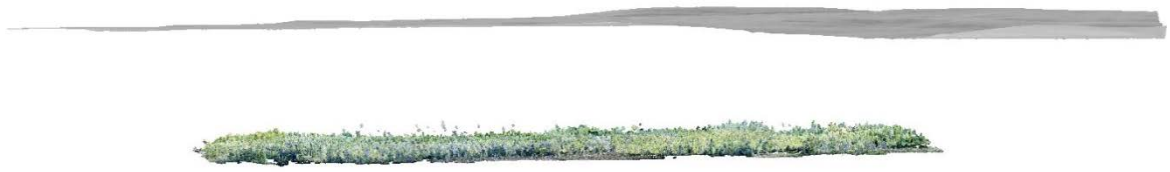

Figure 5. One of the point clouds generated visualized in QTModeler with a DEM from the land survey. The point cloud (the lower part) is not in line with the DEM from the land survey (the upper part).

3.2 Metrics

FUSION metrics and CHM metrics was derived and used to find the best model fit. A total of six different metrics was used for the different statistical analysis (Table 3).

Table 3. Information about the metrics used for the statistical analysis and a description of them.

Metric	Description	Unit
Elev_P20	Height percentile 20	m
Elev_stddev	Standard deviation of the height values	m
Percentage.all.returns.above.1.3	Percent all returns over 1,3 m (canopy cover estimate)	%
N.local.max	Number of local maximum	Number
N.local.max.f	Number of local maximum smoothed with a mean filter	Number
Sum.H2.f	The quadratic height sum smoothed with a mean filter	m

3.3 Prediction of the need of cleaning

The best logistic regression model, based on the lowest AIC, for predicting the need of cleaning was achieved when using the metrics Elev_stddev, N.local.max.f and Percentage.all.returns.above.1.3. The accuracy of the model was evaluated using LOOCV reported in a confusion matrix (Table 4). Overall accuracy for the model was 82 %, producer's accuracy was 82 % for both class 0 and 1 (i.e. no need of cleaning and need of cleaning) and user's accuracy was 81 % for class 0 and 83 % for class 1. The validation was done on plot level.

Table 4. Confusion matrix presenting the classification accuracy from the logistic regression model for the need of cleaning. Whereas class 0 is no need of cleaning and class 1 is need of cleaning.

		Field surveyed class			
	Need of cleaning	0	1	Total	User's accuracy
Estimated class	0	63	15	78	81 %
	1	14	70	84	83 %
	Total	77	85	162	
Producers's accuracy		82 %	82 %		**Overall accuracy = 82 %**

3.4 Prediction of field surveyed height, number of stems and $\sum H^2$

The best models to use for different stand attributes was evaluated based on the highest adjusted R^2 (Table 5). To estimate average height, Elev_P20 was most suitable. The best model fit for estimating stem number was achieved when using the metrics N.local.max, SumH2.f and Percentage.all.returns.above.1.3. The best model fit for $\sum H^2$ was achieved when using the metrics Sum.H2.f and Percentage.all.returns.above.1.3. The estimation of the average height had an adjusted R^2 of 0.68 and the relative RMSE was 23.9 %.

Table 5. Accuracy of the estimated values for average height, stem number and quadratic height sum2.

Stand attribute	**Metrics**	**R^2adjusted**	**RMSE**	**RMSE (%)**
Average height	Elev_P20	0.68	0.94	23.9
Stem number	N.local.max, SumH2.f, Percentage.all.returns.above.1.3	0.53	15.0	44.4
$\sum H^2$	Sum.H2.f, Percentage.all.returns.above.1.3	0.59	409.0	76.2

The results of the estimated stand attributes compared to the field surveyed stand attributes are visualized in a scatterplot (Figure 6).

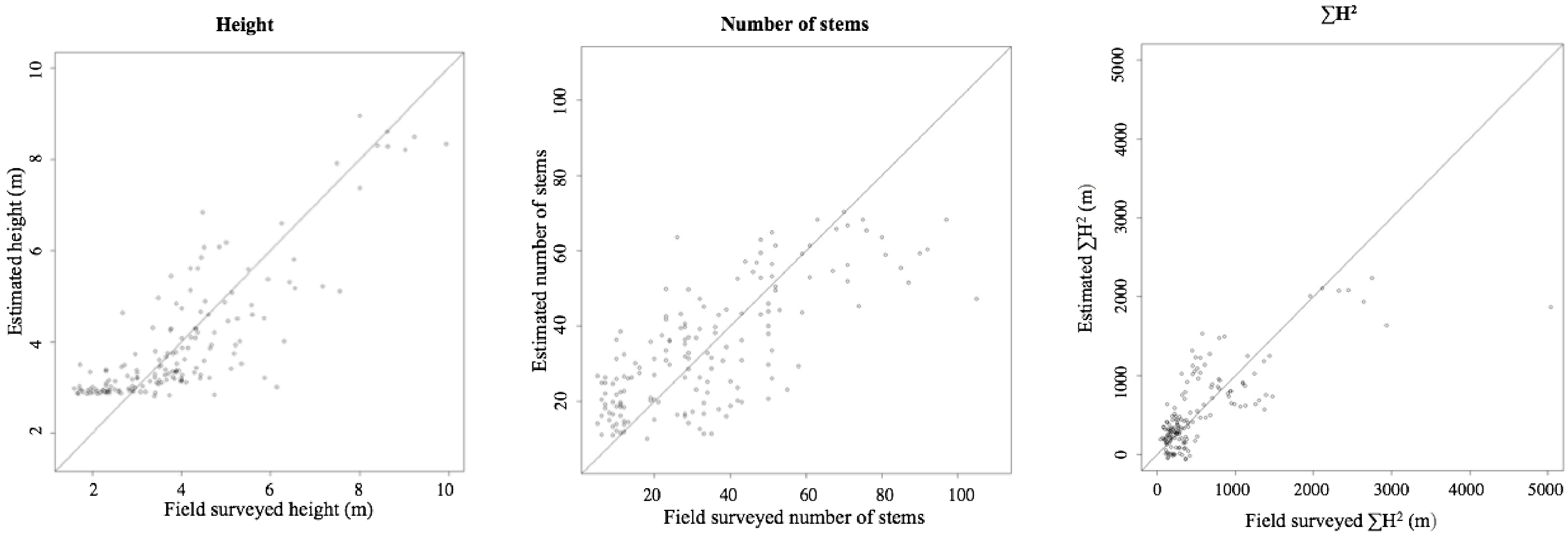

Figure 6. Scatterplots with information about the estimated stand attributes compared to the field surveyed attributes. The attributes shown are height (left), number of stems (middle) and quadratic height sum (right).

3.5 Wall-to-wall rasters for manual cleaning need interpretation

Wall-to-wall rasters for manual interpretation of the cleaning need was created for each stand. Orthophotos was created within Agisoft PhotoScan (Figure 7 and Figure 12). The logistic regression model was used to create wall-to-wall rasters with information about the estimated cleaning need (Figure 8 and Figure 13). Wall-to-wall rasters with the estimated field variables height and $\sum H^2$ derived from the linear regression models was also computed (Figure 9, 11, 14, 16). The vegetation quota and density metric "Percentage.all.returns.above.1.3" was also visualized with wall-to-wall rasters (Figure 10 and Figure 15).

Figure 7. Orthophoto of a stand (number 1 in Table 2) that is not in need of cleaning.

Figure 8. The predicted need of cleaning for a stand (number 1 in Table 2) that is not in need of cleaning.

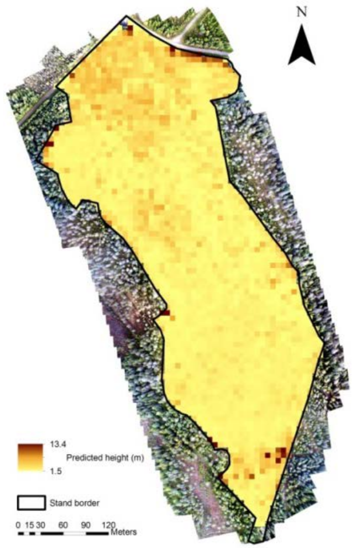

Figure 9. Predicted tree height, using the metric Elev_P20, for a stand (number 1 in Table 2) that is not in need of cleaning. Darker color indicates higher objects.

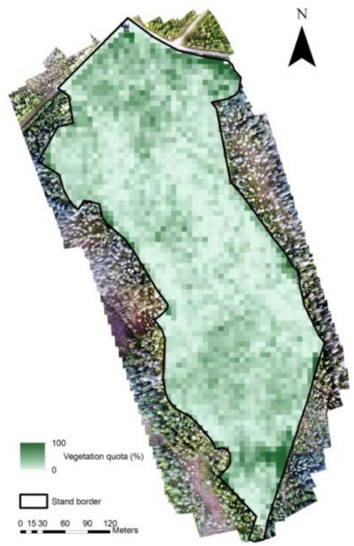

Figure 10. Metric (Percentage.all.returns.above.1.3) from FUSION showing the vegetation quota for a stand (number 1 in Table 2) that is not in need of cleaning. Darker color indicates a higher vegetation quota, i.e. denser area.

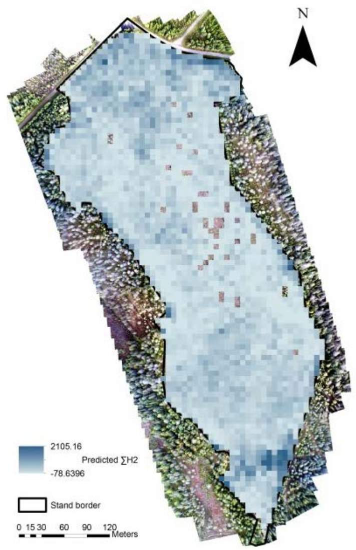

Figure 11. Predicted $\sum H^2$, using the metrics Percentage.all.returns.above.1.3 and Sum.H2.f, for a stand (number 1 in Table 2) that is not in need of cleaning. Darker color indicates a higher quadratic height sum.

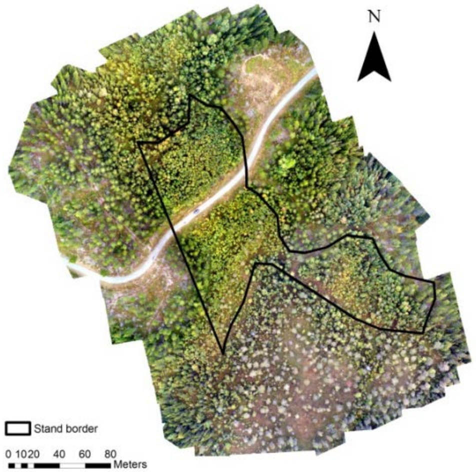

Figure 12. Orthophoto of a stand (number 3 in Table 2) that is in need of cleaning.

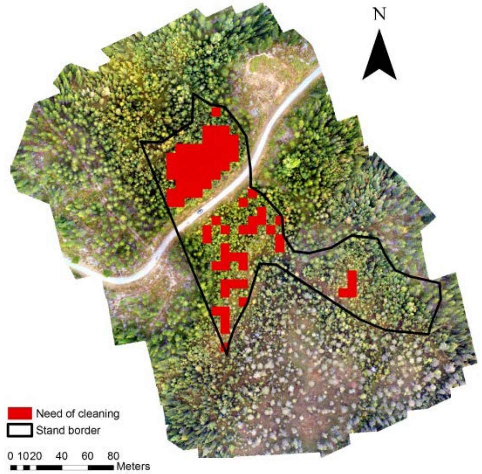

Figure 13. The predicted need of cleaning for a stand (number 3 in Table 2) that is in need of cleaning.

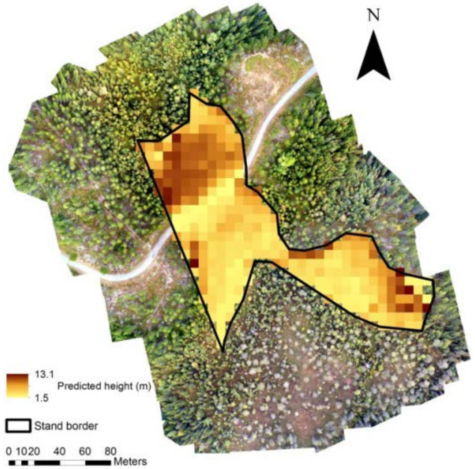

Figure 14. Predicted tree height, using the metric Elev_P20, for a stand (number 3 in Table 2) that is in need of cleaning. Darker color indicates higher objects.

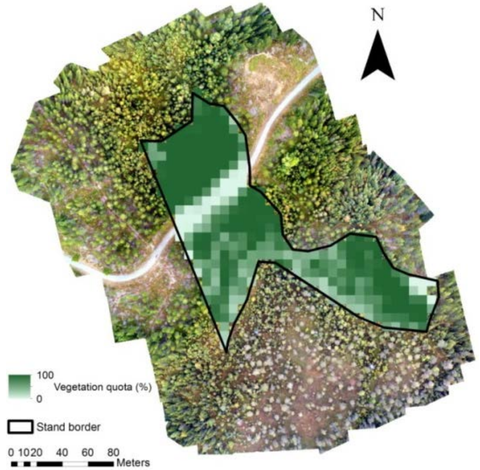

Figure 15. Metric (Percentage.all.returns.above.1.3) derived from FUSION showing the vegetation quota for a stand (number 3 in Table 2) that is in need of cleaning. Darker color indicates a higher vegetation quota, i.e. denser area.

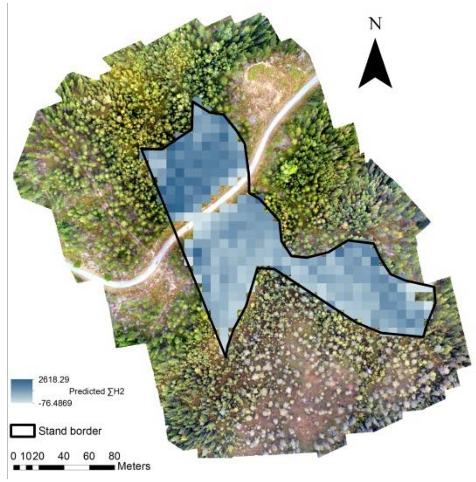

Figure 16. Predicted $\sum H^2$, using the metrics Percentage.all.returns.above.1.3 and Sum.H2.f, for a stand (number 3 in Table 2) that is in need of cleaning. Darker color indicates a higher quadratic height sum.

4. Discussion

The aim of this study was to evaluate the need of cleaning using 3D point clouds derived from high resolution aerial images collected with a drone. Field variables such as height and different density variables were also predicted from the same 3D point cloud.

4.1 Prediction of the need of cleaning

The results show that when using logistic regression, the need of cleaning can be predicted with an overall accuracy of 82 %. Number of local maximum with a smoothed filter, the standard deviation of the elevation and the vegetation quota "percentage all returns above 1.3 m" was found to be the best variables to use within the logistic regression. Earlier studies show that this vegetation quota has been a good metric when estimating the density, i.e. the canopy cover (Næsset, 2002). The overall accuracy within this study is slightly better than the overall accuracy that Korhonen et al. (2013) received. They used both aerial images and airborne laser scanning data and achieved an overall accuracy of 77 % when classifying the need of cleaning using logistic regression. Compared to the study conducted by Korpela et al. (2008) this study performed better with the resulted overall accuracy of 82 %. Korpela et al. (2008) achieved overall accuracies varying from 61 % to 79 %. Nivala (2012) did not meet the same overall accuracy as within this study, he achieved an overall accuracy of 76.9 %. The results from this study indicates that the use of high-resolution images collected with a drone performs better when classifying the need of cleaning compared to other methods such as ALS or ALS combined with aerial images.

This study and the study conducted by Korhonen et al. (2013) indicates that field inventory cannot be replaced totally by modelling the predicted need of cleaning since some of the stands were classified incorrectly.

When classifying the need of cleaning, in some cases the model classifies areas that are obviously not in need of cleaning when looking at the orthophoto as cleaning (Figure 7 and Figure 8). This might indicate that there is a need for more data to make the model better. Due to the time limit of this study, it would not have been possible to collect much more data. But to make the model even better, it would probably be necessary with more sample plots of different character such as open areas that are clearly not in need of cleaning.

4.2 Prediction of field surveyed height, number of stems and $\sum H^2$

Puliti et al. (2015) used the metric Elev_P20 to estimate Lorey's mean height, Elev_P20 was also used in this study to predict the average tree height. In this study the accuracy of the estimated average tree height was 0.68 in R^2adjusted and RMSE of 23.9 % (Table 5). This is not as good as earlier studies have resulted in. Puliti et al. (2015) received an R^2adjusted of 0.71 and RMSE of 13.3 %. The difference in the results might be explained by the different sizes of the sample plots. Within this study the size of the sample plots was 49 m^2 and in Puliti et al. (2015) they used a size of 400 m^2. As Næsset & Gobakken (2009) showed, the size of the sample plots will affect the accuracy of the predictions. In general, larger sample plots result in more accurate predictions than smaller sample plots and thus this could explain the difference of the results within this study and Puliti et al. (2015). Næsset & Bjerknes

(2001) did also achieve results with higher accuracy than within this study. The size of their sample plots were 200 m^2, i.e. larger than within this study. Another thing that might have had an effect on the results of the predicted heights is the DEM used within this study. Photogrammetry gives good information about the top of the canopy which is why information from laser scanning is commonly used for creating DEM's since it can penetrate through the canopy cover (Ackermann, 1999). In this study, a DEM created from the aerial images and photogrammetry was used. When flying at low altitude and high overlap, such as within this study, a DEM can be created.

The stem number was predicted with an accuracy of 0.53 and 44.4% in adjusted R^2 and RMSE within this study. This is similar to the results of Puliti et al. (2015), which got 0.57 and 38.6 % in adjusted R^2 and RMSE. Næsset & Bjerknes (2001) predicted stem number with an R^2 of 0.42. The high value of RMSE and low adjusted R^2 indicates that stem number is not that well predicted with neither aerial images and photogrammetry nor ALS data.

4.3 Aerial images and wall-to-wall rasters for manual cleaning need interpretation

Different attributes of the stands will affect when and how to do the cleaning to optimize the outcome. The size of the trees and how much growing space that is available is crucial when planning for cleaning management (Ford, 1975). Therefore, maps with height and density metrics could act as an aid for manual cleaning need interpretation (Figure 9, 10, 11, 14, 15, 16). When studying the density maps it is possible to see that there is a big difference between the densities for a stand that is not in need of cleaning (Figure 10) compared to a stand that is in need of cleaning (Figure 15). The density is much higher for the area that is in need of cleaning. It is also possible to get a good overview of the tree heights studying the wall-to-wall rasters (Figure 9 and 14) and thus use it for manual interpretation of cleaning need. The maps showing the predicted need of cleaning (Figure 8 and 13) can also work as an aid for manual interpretation. With this kind of data, it is possible to get an overview of the stands and use the data for manual interpretation of the cleaning need. The overall accuracy of 82% for the prediction of cleaning need indicates that it is possible to estimate the cleaning need directly from remotely sensed data with good results at plot level. The collection of data with drones can also minimize the costs compared to manual field inventory (Koh & Wich, 2012). Using wall-to-wall rasters with this information and information about height and density variables could be used for manual interpretation of cleaning need. Even if it probably can't replace field inventory totally, it can give a good overview of areas that might need field visits respectively areas that don't need field visits. The maps with cleaning need information could also work as an aid when pricing the cleaning based on the distribution of the pixels classified as cleaning.

4.4 Data collection and processing

When collecting the field data, three of the sample plots were marked with a paper plate mounted on a wooden stick so that they could be found in the images collected with the drone (Figure 3). The expected distance between the sample plots was 10 meters. At some stands, it was very difficult to walk exactly 10 meters in a straight direction with the help of a compass. Some stands were very dense which made it difficult to walk in a straight direction. The sample plots that were not marked with a paper plate were identified based on the coordinates of the marked sample plots. In some cases, this might have led to that some sample plots were given the wrong coordinates. This would have led to that the wrong information within the point clouds has been extracted and thus this information might not match the ground information. Although, at the very dense stands, the stands were quite homogeneous and therefore the wrong positioning of the sample plots should not have affected the results that much. In sparse stands it could have been a larger effect if the sample plots from field do not match the sample plot from the remote sensing data (Næsset & Gobakken, 2009). But in the sparser stands it was easier to walk in a straight direction and thus this should not have had such an effect on the results either. To improve the accuracy of the position of the sample plots, all of the sample plots should have been marked with a paper plate mounted on a wooden stick. One aspect to consider in that case is that it would be rather time consuming since it is quite difficult to carry large wooden sticks through a stand in need of cleaning. It is also important to consider that the sample plots within the clusters used in this study might be dependent due to their spatial distribution, i.e. 10 m between the centers of the sample plots. This might also have had an effect of the results. To handle this it would have been possible to use the whole clusters as one unit for the statistical analyses. This would tough probably require a larger data set than collected within this study and thus it would have been very time consuming considering the time limit for this master thesis.

Collecting data with a drone is quite simple and it can give a good overview of the area. There is though some information that with today's technology is not possible to get, for example information about some damages on forests. This information can be valuable since it can affect the timing of the management of the forests. For example, fungi diseases can be hard to see from images collected from above. This is a drawback with this kind of data collection technique.

When using a drone, it is possible to fly at low altitudes to get high resolution data. Photogrammetry requires large overlaps to get good 3D point clouds (Leberl et al., 2010). Due to the requirement of large overlaps the flight time will be affected. If the aim is to just get a good overview of the area, and not to get 3D point clouds from the aerial images acquisition, it is possible to fly with small overlaps or no overlaps. This will minimize the flight time and it is still possible to get a good overview of the stand by studying aerial images.

The processing of the data within Agisoft PhotScan was very time consuming. It was very large data sets that were handled and the generation of the point clouds took almost 14 days to complete for all of the stands. If the settings was set to lower quality than within this study, the process would probably have been faster. But then one has to take into count the possible losses due to lower quality. Another option to speed up the process is to use the cloud service integrated in Pix4Dcapture. This allows the user to upload the images collected with the drone to the cloud service where the images can be processed. This approach could make the data processing less time consuming since the process can start directly after the flying is finished.

The time during the day the flying was done could have affected the results. As Gobakken, et al. (2015) indicates, the results might differ due to sun angle and light conditions. Within this study the flying was done during the whole day. Therefore, the images collected during mid-day and in the afternoon might differ due to the sun angle and more shadows. The amount of clouds varied during the days and thus might have had an effect on the results.

To improve the results and minimize the errors, it might be beneficial to compute regression models depending on what type of stand it is. For example, it could be better to compute different regression models for coniferous and deciduous forests. The tree crowns differ depending on if it is a coniferous or deciduous species and this might affect the results. It could be better to compute one model for pure coniferous cleanings, one for pure deciduous cleanings and one for mixed etc. It should also be taken into count that different types of stands might require different sample plot sizes. For example, on poor sites with few stems it will be necessary to have larger sample plots compared to more dense and homogenous stands to improve the results (Næsset & Gobakken, 2009).

4.5 Conclusions

The results of this study show that cleaning need can be predicted using logistic regression with an overall accuracy of 82 % when using 3D point clouds derived from high resolution images collected with a drone. Tree height was predicted with an R^2adj of 0.68 and a relative RMSE of 23.9 %. This study shows that it is possible to estimate the cleaning need with 3D point clouds derived from high resolution images collected with a drone with high accuracy. Drones can therefore be used to collect data for manual interpretation of cleaning need and produce wall-to-wall rasters with this information. The low accuracy of the predicted tree height can probably be explained by the small sample plot size used within this study since large sample plots yields higher accuracy than small sample plots.

The process of generating 3D point clouds is very time consuming due to large data sets. This is a draw back with this method. It is though possible to perform the photogrammetric process outside working hours since it can be automatically done on a computer. This can make the whole process more effective. It could also be possible to use the cloud service provided by Pix4Dcapture and thus start the processing directly after the flying is done which could make the whole process less time consuming. If the aim is not to produce 3D data from the aerial image acquisition, it is possible to just fly over the area with the drone and still get a good overview of the area.

This method results in cleaning need predictions with high accuracy. Since the method is quite time consuming it would be good to evaluate the time and costs compared to manual field inventory and also compared to inventory with helicopter, if the method is to be implemented in practical use.

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