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Assessing tree modeling algorithm from terrestrial laser scanning in Rumperöd mixed forest

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Assessing tree modeling algorithm from terrestrial laser scanning in Rumperöd mixed forest

Utvärdering av algoritm för trädmodellering från TLS i Rumperöds blandskog

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Abstract

Recent technological advancements have revolutionized tree inventory methods for the forest industry. The development of terrestrial laser scanning (TSL) and automatized tree recognition software to estimate crucial tree parameters such as diameter at breast height (DBH) has made the inventory work faster and more reliable. Forest managers can quickly acquire large amounts of data to safely estimate timber yield and effectively use the resources of the forest. This study assesses the Hough transform algorithms (TreeLS) performance to acquire DBH and tree height in the Rumperöd mixed forest in Scania, Sweden, with continuous cover forestry management. Few studies have been made evaluating the Hough transform script under these challenging conditions with uneven terrain and irregular spatial tree density and dense understory vegetation. The result showed large difficulties for the Hough transform algorithm to correctly identify the trees in the plot due to stones, boulders, and uneven terrain. Only 25% of the trees in the plot were identified correctly. The algorithm also returned artefacts that further impaired the results of the TLS measurements to traditional field measurements. The mean difference in DBH between TLS measurement and field measurement in the plot was 115 mm and for tree height, the mean difference was 7.35 m. This difference in DBH and tree height would have overestimated the timber yield and made this algorithm unsuitable for the forest industry in the conditions present in the Rumperöd mixed forest.

Table of Contents

1. Introduction

Terrestrial laser scanning (TLS) is a remote sensing technology where recent technological advancements have opened new possibilities to provide reliable data for forest management. Accurate and detailed forest inventories of forest-stands of different age, volume and health are essential information for decision-makers to effectively use the forests resources. Continuous monitoring of forest properties also provide information about regional growth patterns and expected timber yields, necessary to ensure profitability of financial investments and sustainability. TLS is not only important for forestry with its great economical values, but it can also be an effective tool for environmental monitoring of forest ecosystems and carbon cycle modeling by detecting changes in forest structure and composition over time (Hackenberg et al., 2014; Raumonen et al., 2013).

Diameter at breast height (DBH) is the most significant and most commonly used key feature for forest managers to estimate values such as timber yield (Yang & Swenson, 2023; Zhang et al., 2023). But also tree height is commonly used in forest management to determine e.g. stand structure and productivity (Xu et al., 2019). Traditionally forest inventories use tape measure and inclinometer to measure those parameters on individual trees. DBH and tree height are used in combination with allometric functions to calculate above-ground biomass (AGB). The problem with traditional forest inventories is that it is time-consuming and associated with field measuring errors. Height is generally more prone to errors than DBH because of the more advanced measuring methods and difficulties to identify the highest branch of the tree leading to underestimations of the height, especially in species with large crown diameters (Srinivasan et al., 2015). Allometric functions also need to be verified, which normally means cutting down the trees to dry them and weigh them. This generates allometric functions that show an increasing error with increasing DBH due to low sample sizes of collected data on large trees (Demol et al., 2021; Stovall et al., 2018, 2023). This means that the allometric functions may need to be calibrated with additional samples to fit the environmental properties and climate in a specific region (Pandey et al., 2022). TLS has many advantages over traditional forest inventory methods because it reduces human errors, is fast, is a non-destructive method, and makes it easy to expand sample sizes to improve the allometric functions (Raumonen et al., 2013).

TLS creates 3D models with very high accuracy that consist of a point cloud. The 3D model needs to be processed where the data points of the trees need to be separated from the data points of the terrain and other objects. Also, the individual trees need to be identified and processed. There are several different types of software developed to calculate the properties of the trees in the point cloud and they use different methods with corresponding advantages and disadvantages (Liu et al., 2018). For the forest industry, the computationally demanding cylinder fitting methods are too time-consuming and disregarded in favor of less demanding shape recognition algorithms. There are many different algorithms, and they perform differently when applied to different types of forests. There are no comprehensive studies of all the algorithms and different forest types due to endless combinations of varying conditions of species, tree density, understory vegetation, terrain, etc. Neither is there any algorithm with superior performance when applied to a variety of forest conditions (Liu et al., 2018).

In this study tree properties used in allometric functions were collected with traditional inventory methods and compared with the same tree properties obtained from TLS point clouds to assess their performance. The tree properties from the point cloud used in this comparison are calculated with TreeLS, an R package vision algorithm designed to detect tree-like geometric shapes (*RStudio. 2020*, n.d.; *TreeLS*, 2020). The study is conducted in a mixed forest with continuous cover forestry management in the Northeast of Scania, Sweden. There are few studies to be found with similar forest type assessing algorithms on irregularly spatial distributed trees. Most of the previous studies have focused on sites with planted forests with equal distribution and with thinned branches and understory. Numerous of the studies of irregularly distributed trees are in climates which are not similar to Swedish conditions.

1.1 Study aim

Due to the limited amount of information on how algorithms designed to detect tree-like geometric shapes performs under Swedish conditions this study aims to assess how the shape recognition function TreeLS will perform in a Swedish forest site with continuous cover forestry management. Another aim is to evaluate its functionality and effectiveness when applied to challenging forest conditions such as varied terrain and irregular spatially distributed trees, typically found in these sites the derived tree properties will be compared to traditionally collected tree properties.

I hypothesize that the traditionally collected tree properties will be underestimated compared to TLS acquired tree properties in the Rumperöd mixed forest with continuous cover forestry management due to two problems associated with manually collected measurements. First, failure to visually identify the highest branch of trees with large crown sizes. The TLS measurements should generate a 3D-model with the highest branch available for detection by the TreeLS algorithm. Secondly, cone-shaped trees will appear closer to the inclinometer due to their tapering shape when the transponder is placed in front of the tree. The measured angle is then smaller than the real angle and the tree height will then be underestimated.

2. Methods and Material

2.1 Study site

The study site was the Rumperöd Forest which is located in northeast of Scania in Sweden (56° 19′ 58.52′′ N, 14° 6′52.58′′ E) (Figure 1). The site is a mixed forest with a long heritage of continuous cover forestry management. The site was chosen because of its composition of trees of different ages, their irregular spatial orientation, and variety of tree species. The most prominent tree species in the Rumperöd forest are *P. abies* (Norway spruce), *F. sylvatica* (European beech), *B. pendula* (Silver birch), *P. sylvestris* (Scots pine) and *Q. robur* (Pedunculate oak) and a variously dense understory.

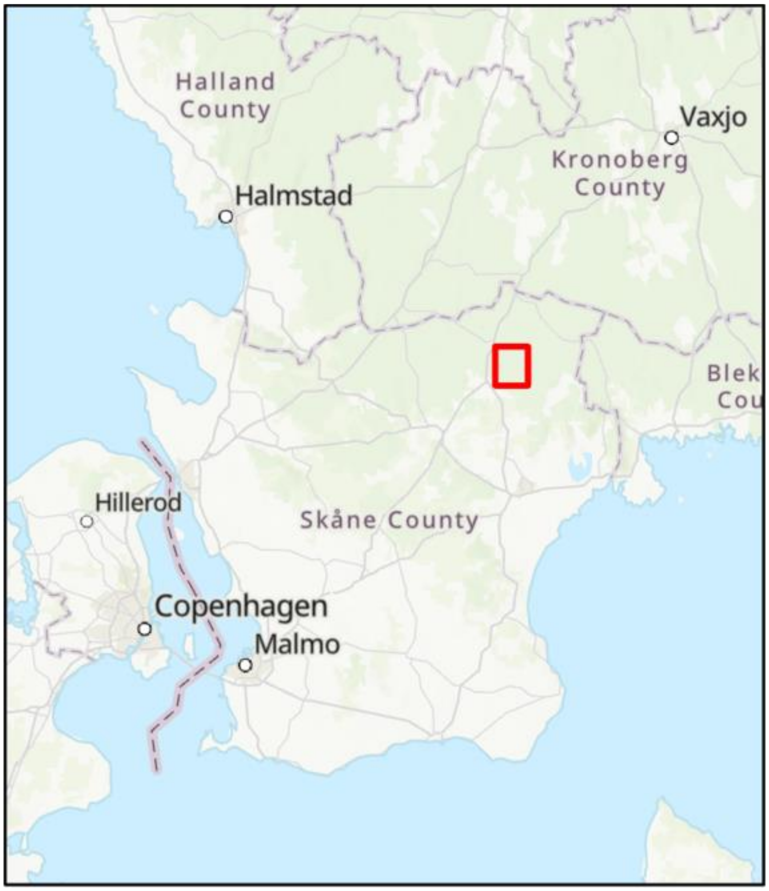

Figure 1. The red square marks the location of the study site in the northeast of Scania, Sweden.

2.2 Terrestrial laser scanning

TLS instruments emit laser pulses that are reflected back and detected by the sensor of the instrument. By measuring the time for a laser pulse to be reflected back to the sensor, the distance to objects can be determined and the environment can be calculated into a 3D-model. 3D-models are point clouds that consist of millions of data points in a three-dimensional coordinate system.

Aggregated data points represent the shape and structure of objects in the model with very high detail and accuracy.

The terrestrial laser scanner used to collect cloud points is a RIEGL VZ 400i, it is a high pulse repetition laser suitable for vegetation scanning (*RIEGL*, 2021b). The scanner is mounted on a tripod and manually transported in the field (Figure 2).

Figure 2. Terrestrial laser scanner RIEGL VZ 400i in the field mounted on a tripod during a test run in Rumperöd, these measurements were not used in the study due to the snow conditions. The red pole in the background marks the center of one of the scanned plots.

2.3 Measurements

The plot in Rumperöd were scanned on 21 March 2023. It was a circular plot with a diameter of 7.98 meters which equals 200 m^2. In each plot there were 6 scans equally distributed at the circumference around the plot 10 meters from the center. Starting at the north and rotating clockwise with a new scan position every 60° and one final scan performed in the middle. At each scan position there were two scans performed, one vertical and one horizontal. This equals 7 scan positions and 14 scans at each plot in total. The horizontal scan was always positioned with a 90°angle of the scanning axis towards the center of the plot so the instrument was always scanning towards the center of the plot.

Other requirements that have to be fulfilled and settings of the scanner to ensure good quality of the point clouds when performing the scans are:

- Wind speed must not exceed 2.5 m/s. Too high wind will cause the trees to move and result in point clouds of low quality by inducing motion blur in to the scans.
- No raining or snowing. Rain and snow will induce noise into the point cloud and reduce the performance of the TreeLS algorithms.
- No snow lying on the ground or on branches that can compromise the point clouds. Snow on branches or on the tree trunk can give false readings to the diameter of the tree. Snow lying on the ground can also compromise the signal by returning false echoes due to the high reflectance of the snow.
- Scan position must be at least 1.5 meter from the nearest tree. Trees close to the scanner will be ineffective due to the tree will shadow big portions of the plot.
- Angular sampling interval: 0.04 degrees
- Laser Pulse Repetition Rate: 300 kHz. This is the number of pulses emitted every second.
- Minimum range: 0.5m

The scanned plot in Rumperöd fulfill all the above-mentioned conditions to generate an accurate point cloud.

The traditional inventory, henceforth referred to as field measurements (FM), was conducted on 24 August 2022 on all trees in the plot (34 trees). The DBH was measured with a measuring tape at 1.30m above ground and the height of the trees was measured using a VERTEX IV with a transponder at 1.30m above ground (*Haglof Sweden AB*, n.d.).

2.4 3D-Modeling

To process the scanned data and create a 3D model the RiSCAN PRO software was used (RIEGL, 2021a). It is RIEGLs own software to develop and process the 3D-model into a georeferenced point cloud (Figure 3). The point cloud was trimmed down to fit the boundaries of the scanned plots in Rumperöd to reduce the amount of data for each plot. This is necessary because each scanned plot with point cloud from multiple scans contains a large amount of data and requires vast computer resources and is very time consuming. The software was also used to visually inspect the point clouds to make sure that all scans were aligned with each other and there was not too much noise from the understory. Then a Laser-file (LAS) was exported from the software, that is the file type that is used to further process the point cloud in R.

Figure 3. Image of the 3D-model showing the centre of the scanned plot in Rumperöd when processed in RiSCAN. The point cloud was later further processed by TreeLS in R.

2.5 TreeLS

When the LAS-file was imported into R it was processed with the R package TreeLS. The TreeLS is a script that is based on the Hough transform script (*TreeLS*, 2020), that is an algorithm design for detecting geometric shapes such as lines or circles (Liu et al., 2018; *TreeLS*, 2020). The Hough transform algorithm was first proposed in 1962 and it's a well-proven algorithm with many applications. It is used in many different tree-based modeling scripts and in many other fields of science such as geospational analyses and autonomous robotic systems. TreeLS is also a free software and easily accessible and therefore chosen in this study. In TreeLS the Hough transform algorithm is used with many more algorithms to specialize the script to be a customized tree modeling function (De Conto et al., 2017; *TreeLS*, 2020).

The first operation of the TreeLS script that is essential for the script to perform is the normalization of the ground. This part of the script flattens out the whole point cloud so the script can start identifying the trees at the same level above the ground. To verify that the normalization of the ground succeeded, the point cloud generated by the R script was extracted and put back into RiSCAN and visually compared to the original non-normalized point cloud.

When the point cloud was successfully normalized and for the script to start search for trees it needs to cut the point cloud into thin slices parallel to the ground. Where the script starts to cut, and the thickness of the slices is determined by the settings. The sliced-up point cloud is where the Hough transform algorithm starts identifying tree stems, when looking from above is represented as circles in the point cloud and eventually measures its DBH at 1.30m above ground.

In the TreeLS script there are a number of settings that need to be tuned for the script to successfully identify the trees.

- minh - minimum height above ground where to look for tree stems.
- maxh - maximum height above ground where to look for tree stems.
- maxd - maximum DBH in meters.
- mindensity - minimum density to consider data points as tree stems.
- minres - minimum density to consider data points as ground.
- hstep - slice thickness to look for tree trunks in meters.

When maxd, minres and hstep were tuned in the remaining 3 parameters was set to different values and run in the script to identify the trees. To successfully identify most of the trees the values of the parameter were set according to the table below (Table 1). The most crucial parameter here is the mindensity because it decides where the Hough algorithm will look for circles. Because only dense aggregations of data points will undergo circle search with the Hough algorithm (Figure 4).

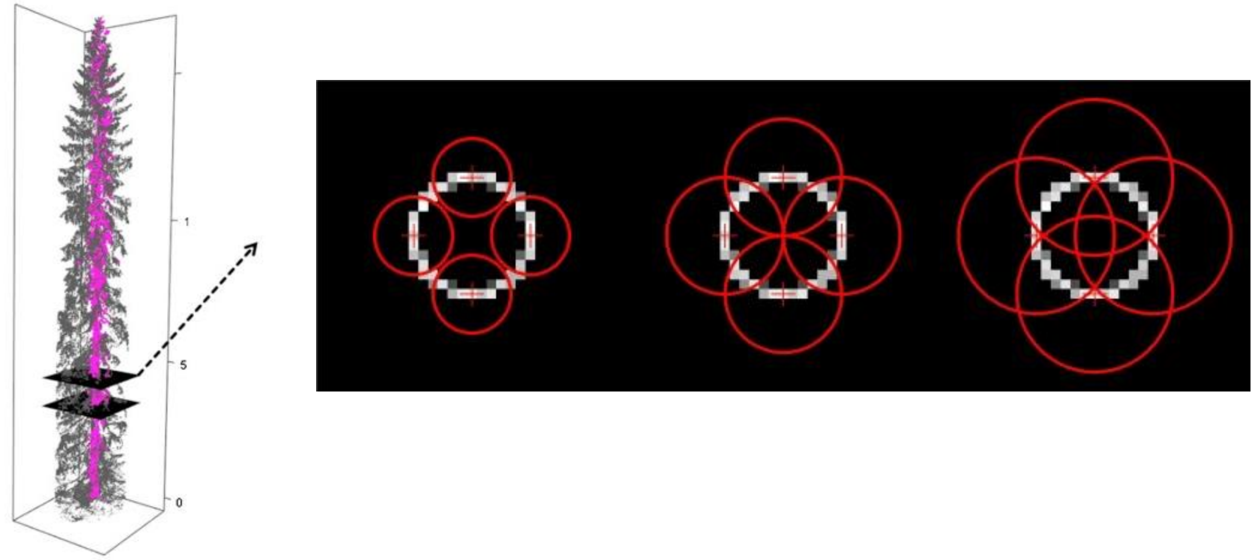

Figure 4. TreeLS algorithm slices the 3D-model parallel to the ground (left) and then perform its circle search (right) and later finds the circle diameter that best fits the tree trunk. Image from De Conto et al. (2017).

Table 1. Parameter thresholds to successfully identify most of the trees in the plot.

Properties	Threshold
minh	0.5-1.5
maxh	1-2
maxd	0.55
mindensity	0.03-0.06
minres	0.05
hstep	0.25

The resulting data from the script contains maps of the plot and a table with coordinates for each tree with its corresponding height and DBH. Visual comparison between the generated maps and a plotted map from the traditionally collected field data was made to validate the performance of the script.

3. Results

3.1 Visual inspection of point clouds

First step in the TreeLS script is the normalisation of the ground and to visually inspect it in RiSCAN. When comparing the two point clouds in RiSCAN, the normalized point cloud is flattened out compared to the non-normalized point cloud where the irregularities of the ground can clearly be seen (Figure 5 and Figure 6).

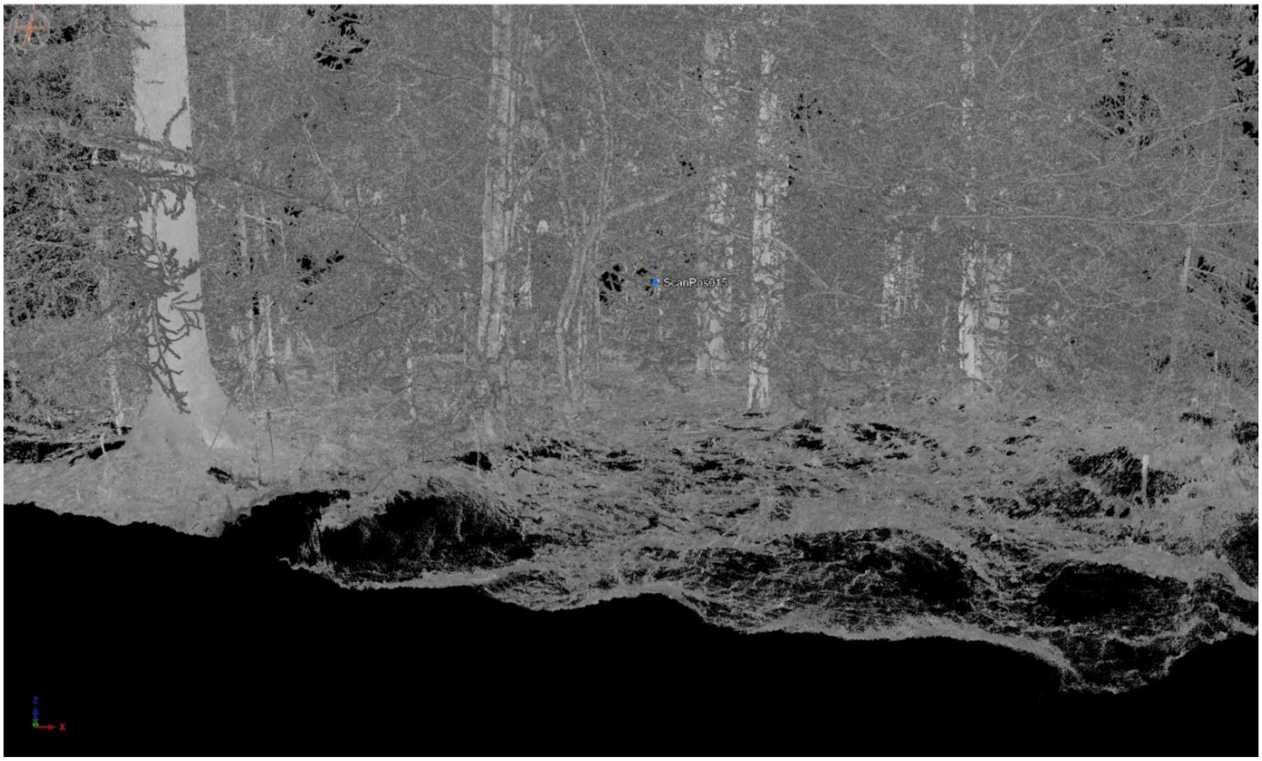

Figure 5. The non-normalized point cloud still containing the irregularities of the terrain, peaks and cavities of the ground can still be seen when inspected in RiSCAN.

Figure 6. The normalized point cloud with the irregularities of the terrain flattened out when inspected in RiSCAN.

The second plot to be processed with TreeLS failed in the normalisation step. The point cloud was partially flattened but when inspected in RiSCAN the whole plot was split in two halves and settled at two different levels. The output from TreeLS from the second plot where therefore deleted and not accounted for in the results (Figure 7).

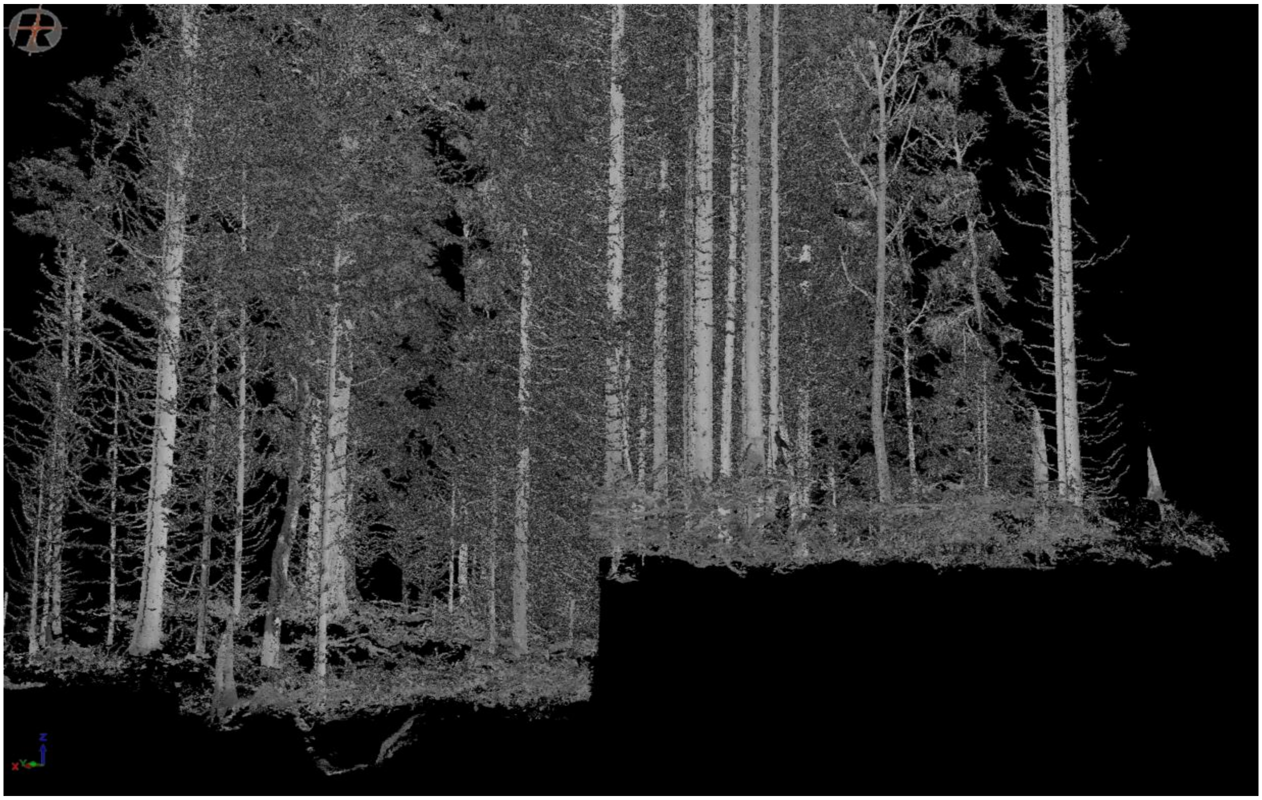

Figure 7. This image show when normalisation of the ground has failed. The irregularities has been flattened to some extent but then the whole plot have been split in two pieces and settled at two different levels.

3.2 Tree identification

When comparing the output from the TreeLS script to the field measurements most of the trees where not identified at all by the script, only 25% of the trees in the plot were identified correctly by the TreeLS script. But the script also created artefacts, indicating trees where there are no trees probably because of noise in the point cloud caused by dense vegetation. Artefacts with very unrealistic values were considered outliers and taken out from the results i.e., trees with DBH of more than 0.5m.

The trees correctly identified by the script did however match well with DBH when plotted in a regression model with a R^2 value of 0.93 and the slope indicates a strong relationship. The tree heights do not show the same strong relationship as the DBH and have an R^2 value of 0.76 (figure 8 and figure 9).

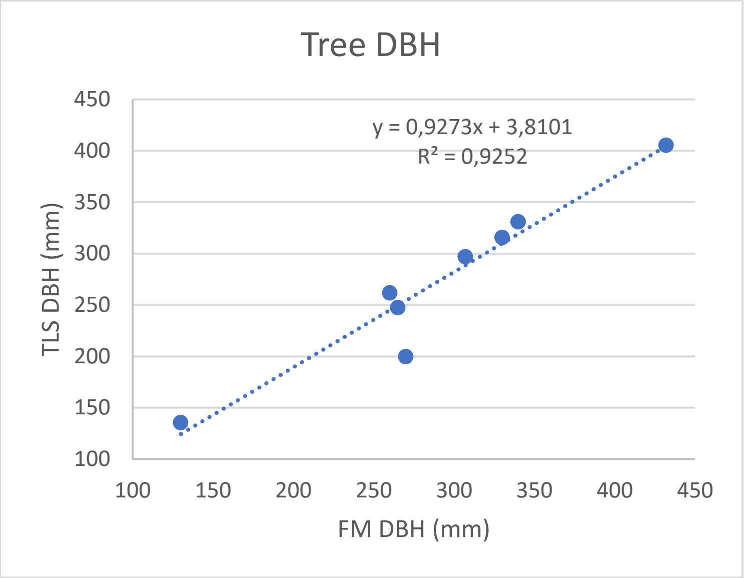

Figure 8. Tree DBH comparison of the correctly identified trees from FM and TLS measurements with an added trendline.

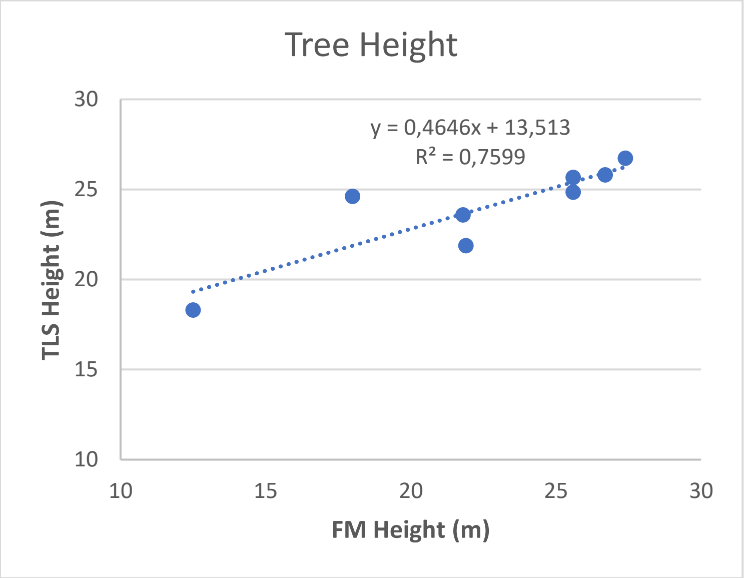

Figure 9. Tree height comparison of the correctly identified trees from FM and TLS measurements with an added trendline.

3.3 Plot comparison

When comparing the whole output from the TreeLS script to the field measurements there is a huge discrepancy in the values indicating the difficulties of the Hough transform algorithm in the TreeLS script to correctly identify the trees (Table 2). Here the difference between TLS measurements and field measurements in both DBH and tree height indicates the difficulties of the Hough algorithm to correctly identify all trees and measure them correctly.

Table 2. The table shows plot mean and standard deviation of TLS DBH and tree height (21 trees) measuments and field measurements of DBH and tree height(34 trees).

	TLS Height (m)	**FM Height (m)**	**TLS DBH (mm)**	**FM DBH (mm)**
Plot mean	22.66	15.31	301	186
SD	3.52	7.53	148	112

4. Discussion

4.1 TreeLS Performance

The performance of the TreeLS script in the Rumperöd forest site shows both the strength of the Hough transform algorithm but it also shows its weaknesses. The correctly identified trees show great resemblance with DBH (R^2 of 0.93) and the slope of the regression model indicates a strong relationship. The tree height measurements do not show as strong resemblance as the DBH. Here the R^2 value is a weaker as it is down to 0.76. Also, the slope of the regression model is considerably lower indicating a much weaker relationship between the measurements. This can be explained by the functionality in the TreeLS script. To cut the normalized point cloud into slices parallel to the ground and identify the stem circles at 1.30 above ground level and calculate them is a much simpler operation than calculating the height of the tree. Calculating the tree height requires many more steps in TreeLS which means there are many more potential sources of error. Normally the point cloud also gets noisier above breast height with increasing numbers of branches. Here the crowns of the trees can intersect with each other and further complicate it for the TreeLS script. Another point here is that it is possible that more effort has been made in the TreeLS software to correctly identify DBH as this tree parameter is the most essential to the forest industry.

The weaknesses of the TreeLS script are shown by the poor number of identified trees ranging to only 25%. The numbers in table 2, show a great discrepancy in the means of the plot when comparing the TLS measurements and the field measurements. There is a mean difference of 115 mm in DBH and a mean tree height difference of 7.35 m. This discrepancy could probably be explained by the many trees the TreeLS algorithm failed to identify and the high number of created artefacts. It was clear from the output that the script missed many of the smaller trees existing in the plot, which explains the considerably higher tree heights from the TLS measurements. This also explains the large difference in DBH, but here the created artefacts also are important. The artefacts were all trees with very large DBH. Even if the artefacts with unrealistically large DBH were taken out of the results it is likely that they have affected the result to some extent. The difference in both DBH and tree heights shows a clear overestimation of the TLS measurements compared to the field measurements.

The performance of the TreeLS algorithm in this study is very low when looking at the number of identified trees. When comparing it to other studies made with the Hough transform algorithm the result is very varying. Some studies have result similar to this study ranging between 20 – 50% (Brolly & Király, 2009; Liu et al., 2018) correctly identified trees while others have reported up to over 95% of the trees correctly identified (Olofsson et al., 2014). Most studies have concluded the same problem with the Hough transform algorithm and that is its sensitivity to noise. The algorithm seems to work very well in planted and thinned forests but when the forest site becomes a little bit more challenging the percentage of correctly identified trees sinks rapidly. The different conditions at the different study sites makes it difficult to compare them in detail. But there is also another aspect to comparing the performance of the algorithms. The Hough transform algorithm is a basic principle of a shape detecting function. There have been many improvements made over the years and often have the users improved the algorithm by themselves. There are also different combinations of algorithm and setups in the scripts making the results very hard to compare.

It is clear that the script runs into problems when the terrain of the plot this uneven. But also, when the understory is dense and trees are standing closely together creating a dense forest with protruding branches. The densely packed vegetation creates a noisy point cloud which the Hough transform algorithm has problems to handle. The Hough transform algorithm also seems to have problems to handle stones and big boulders in the terrain. Close to big boulders, artefacts also seem to occur more frequently. The script works much better in areas of the plot with flat terrain and with trees not that densely packed.

4.3 Comparison of TLS and traditionally collected tree properties

Even if the scanning itself at the forest site is very fast it is associated with some time-consuming work with data processing. The process of creating a point cloud in RiSCAN is time-consuming but also to cut down the point cloud and make it suitable for TreeLS script take a lot of time. The processing in R is also very time consuming. This is because it's computationally intense but also the need to run the script more than once with different settings to be sure to identify all the trees. There is also an uncertainty with running the TreeLS script with different settings because when changing the mindensity or minh/maxh the resulting tree heigh may vary in magnitude. The DBH was robust and did not change between the different runs with the different settings as the tree height did. The tree height varied with up to 2.9 meters when using different settings in the TreeLS script showing that the Hough transform algorithm is potent in estimating DBH but not as good at estimating the height of the trees.

There is one of the correctly identified trees that stands out from the rest. The tree shares the same coordinates in the TLS and field measurements, but it shows some differences in tree properties especially in tree height, 18m in the field measurements compared to 24.6m in the TLS measurements. This could be an outlier regarding the difficulties in measuring tree height manually in the forest which is known to induce errors in the readings. Tree height is measured with a VERTEX IV and that is a handheld device and not mounted on a tripod, meaning there could be an offset if not carefully handled (Ganjalipour, 2021). This could count for at least some part of the deviation of the measurements but there is also a small deviation in DBH in this tree that is not seen in the other trees. This could mean that the Hough transform script has not worked perfectly for this identified tree. There are many possible explanations for this, already mentioned, but there is also one possibility for this particular tree and that is that it is leaning a little bit. Inclined and crocked trees are known to show incorrect results with the Hough transform algorithm (Brolly & Király, 2009; Stovall et al., 2023).

To answer the hypothesis in this study the numbers in table 2 have to be considered carefully due to the many artefacts. The correctly identified trees also show a great deviation in height between the TLS measurements and the field measurements but the eventual outlier earlier mentioned counts for most of the deviation between the measurements. If the eventual outlier is taken out the remaining difference between the field measurements and TLS measurements is 0.8 m. But here the number of identified and measured trees is too low to support and answer the hypothesis. There are also too many uncertainties in the measurements to conclude that the underestimation is due to not identifying the highest branch of the tree and not just a random variation because of the handheld instrument. Another potential uncertainty is that the TLS actually misses scanning the absolute highest branch of the tree. This could happen when the top of the tree is shadowed by other trees and not visible to the scanner. This risk increases in this type of mixed forest with spatially irregular densities of the trees. This could lead to an underestimation of tree height by the TLS measurements (Srinivasan et al., 2015). However, in this case with the very high number of scans on a plot of a radius of only 7.98 m the risk of that the highest branch should not have been accounted for in the multiple scans is not likely. Due to time constraints and failure to normalize the second plots point cloud more data could not be added to the results to increase the sample size of measured trees.

5. Conclusion

Even if the Hough transform algorithm (TreeLS) is well-established, and has been shown to be a powerful tool for estimating DBH and tree height under certain conditions. This study found the algorithm not suitable for continuous cover forestry management in the Rumperöd mixed forest in Scania, Sweden. The shifting terrain with many stones and boulders combined with irregular spatial tree density made the performance of the TreeLS algorithm to produce very unsatisfactory results. The Algorithm only identified 25 % of the trees correctly, and it also created a lot of artefacts compromising the result. This difference would in turn have vastly overestimated the timber yield and made this method unusable to the forest industry under the conditions present at the Rumperöd site.

The hypothesis of that traditionally collected tree properties will be underestimated compared to TLS acquired tree properties in the Rumperöd mixed forest with continuous cover forestry management due to two problems associated with manually collected measurements, failed to be validated. This is due to too small sample sizes of correctly identified trees to answer the hypothesis.

To further strengthen the conclusions of this study, more work with additional plots is recommended to better understand the functionality and limitations of the TreeLS algorithm under the challenging conditions present in Rumperöd. There are also other types of tree recognition algorithms that could be tested and compared to the TreeLS algorithm.

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