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joint project of EuroSDR and ISPRS

Part I: Objective, Datasets, Evaluation Criteria and Methods

Xinlian Liang, Juha Hyyppä, Harri Kaartinen, Jiri Pyörälä, Matti Lehtomäki, Markus Holopainen, Ville Kankare, Ville Luoma, Ninni Saarinen, Liang Chen, Yunsheng Wang

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INTERNATIONAL BENCHMARKING OF TERRESTRIAL LASER SCANNING APPROACHES FOR FOREST INVENTORIES

joint project of EuroSDR and ISPRS

PART I: OBJECTIVE, DATASETS, EVALUATION CRITERIA AND METHODS

With 9 figures and 2 tables

Xinlian Liang [1, 2], Juha Hyyppä [1, 2], Harri Kaartinen [1], Jiri Pyörälä [1, 2], Matti Lehtomäki [1, 2], Markus Holopainen [2, 3], Ville Kankare [2, 3], Ville Luoma [2, 3], Ninni Saarinen [2, 3], Liang Chen [1, 2], Yunsheng Wang * [1, 2]

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ABSTRACT

The last two decades have witnessed increasing awareness of the potential for terrestrial laser scanning (TLS) in forest applications in both public and commercial sectors, along with tremendous research efforts and progress. It is time to inspect the achievements of and the remaining barriers to TLS-based forest investigations, so further research and application are clearly orientated in operational uses of TLS. In such context, the international TLS benchmarking project was launched in 2014 by the European Spatial Data Research Organization and coordinated by the Finnish Geospatial Research Institute. The main objectives of this benchmarking study are to evaluate the potential of applying TLS in characterizing sample plots, to clarify the strengths and the weaknesses of TLS as a measure of forest digitization, and to reveal the capability of recent algorithms for tree-attribute extraction. The project was designed to benchmark the TLS algorithms by processing identical TLS datasets for a standardized set of forest attribute criteria and by evaluating the results through a common procedure respecting reliable references. Benchmarking results reflect large variances in estimating accuracies, which were unveiled through the 18 compared algorithms and through the evaluation framework, i.e., forest complexity categories, TLS data acquisition approaches, tree attributes and evaluating procedures. The results also reveal some best available forest attribute estimates at this time achieved by a couple of groups using their algorithms, which hints at the potential of TLS in forest environments with the hardware currently available. Some results are well expected, while some are new, e.g., the variances of estimating accuracies between single-/multi-scan, the principle of the algorithm designs and the possibility of a computer outperforming human operation. This paper focuses on the conceptual schema to promote the understanding of the benchmarking results, the potential of TLS in forest modelling, and the fundamental components, i.e., the selection of sample plots, the collection of TLS data, the acquisition of reference datasets, the definition of evaluation criteria (including three criteria proposed in this benchmarking), and the development of evaluation structures (e.g., the algorithm performances are investigated through combining two or more criteria). The TLS datasets are set to open data for further research purposes. New developments can be linked to the eighteen algorithms reported in this benchmarking.

Keywords: benchmarking, forest inventory, point cloud, terrestrial laser scanning, TLS

1 INTRODUCTION

Forest-field inventory holds a central role in all forest research, monitoring and managements that rely on knowledge of forest structure, distribution and dynamics over time. Field inventories are conducted in sample plots, where tree information is usually collected through tree-by-tree measurements (i.e., plot-level inventory). Forest field inventories can be costly since the field measurements require many efforts and resources, consequently limiting the amount of field inventories that can afford to be made. Attempts to improve the field inventory efficiency started ever since field inventory began. Countless techniques, instruments, and protocols have been introduced, e.g., (Clark et al., 2000), yet progress has been slow, until a laser-based measuring instrument called terrestrial laser scanning (TLS) became practically available.

TLS automatically measures the surrounding three-dimensional (3D) space using millions to billions of 3D points. The major advantage of applying TLS in forest inventories lies in the digitization of the forest plots accurately, rapidly, automatically and in details at millimeter-level. In addition to the regular tree attributes measured in practical field inventories, e.g., the diameter at breast height (1.3 m, DBH) and tree height, more detailed tree attributes, such as the stem curve or taper curve (stem diameter as a function of height) that reveals the wood productivity and quality yet difficult to acquire non-destructively in the field, can be derived from TLS with high degrees of accuracy and cost efficiency (Liang et al., 2014).

Tremendous efforts have been put into research to investigate the automated interpretation of TLS data and to establish best practices for using TLS. In the past 20 years, significant progress has been made in deriving tree- and stand-level attributes from TLS data to depict forest productivity, evolution and ecological functions. In general, sufficient evidence has shown that TLS can improve the quality of quantitative forest measurements. However, it will take some time before foresters start using TLS operationally, since acceptable results obtained from TLS for forest inventories, from a forester’s perspective, have only recently been presented and it takes time to develop software and best practices.

In addition, a proper understanding of TLS performance in forest field inventories is still missing. The results of estimating forest attributes from TLS data varied in previous studies. For example, the rate of correctly extracted trees has ranged from 20% to 100% (Thies and Spiecker, 2004; Maas et al., 2008; Strahler et al., 2008; Brolly and Kiraly, 2009; Murphy et al., 2010; Lovell et al., 2011; Yao et al., 2011; Liang et al., 2012; Lindberg et al., 2012; Liang and Hyyppä, 2013; Astrup et al., 2014; Olofsson et al., 2014). The high variety of the data collection equipment and methods, the forest type and stand situation, and the processing and evaluation procedures in the reported studies have made it different to compare results and approaches, which also hinders a convincing analysis on the status quo of TLS application in forest field inventories.

To reveal the state of TLS-based forest field inventories and to orient further investigation, an international benchmark study of TLS in forest inventories (TLS benchmarking) was launched in 2014, led by European Spatial Data Research Organization (EuroSDR) and partly funded by the European Community’s Seventh Framework Programme. The TLS benchmarking aims to clarify the potential and current status of the TLS application in field inventories by evaluating methodologies on the basis of a standard evaluation procedure and a common dataset, thereby paving the way for further research and developments.

The forest sample plots in the benchmarking project are selected by foresters to reflect different stand conditions in boreal forests. Considering the development stage, stem density, and density of the sub canopy vegetation, sample plots are classified into three complexity categories in the context of TLS-based forest inventories. Both single- and multi-scan approaches are employed to acquire the sample plot TLS datasets. The TLS dataset was disseminated to all the benchmarking project partners, who processed the data utilizing their own algorithms and delivered the required products. All of the partners results were then evaluated using a standard evaluation procedure, so a comprehensive understanding can be achieved on the capacity of recent algorithms for extracting important forest attributes from TLS data. In particular, the influence of forest conditions and data acquisition methods on the algorithm performance can be investigated and interpreted from a practical perspective.

This paper summarizes the benchmarking project's conceptual schema. Section 2 describes the benchmarking project's main objectives and the data schema fundamental concepts to support the main benchmarking objectives. Descriptions about the common TLS datasets of the forest sample plots representing different forest stand situations for the benchmarking are given in sections 3.1 and 3.2, which explains the variety in the accuracy of tree attribute estimations across forest complexity categories, across algorithms and across the TLS-measurement approaches. The reference information and the evaluation procedures, which lay down the bases of the benchmarking, are detailed in sections 3.3 and 4. A couple of new evaluation criteria for tree attribute estimates were introduced to analyze the TLS performances.

2 THE INTERNATIONAL TLS BENCHMARKING PROJECT

Accurate forest inventories with strong degree of time and cost efficiencies have been long awaited by multiple forest-related applications and users. The TLS technology introduced 20 years ago was anticipated to have the potential to provide a high-quality solution that was highly automated for plot-level forest measurements. It is time to inspect the achievements of and the remaining barriers to the TLS-based forest investigations. This section summarizes the benchmarking project and the project's conceptual schema.

2.1 The project

The TLS benchmarking project was launched in 2014 by EuroSDR and hosted by the Finnish Geospatial Research Institute (FGI). The FGI is responsible for the benchmarking processes' architecture; the development of the evaluative criteria and procedures; the collection of participants; and the implementation, coordination and dissemination of the project. Forest researchers from the University of Helsinki (UH) selected the sample plots and measured tree attribute using calipers and clinometers in the field. The TLS data and other field measurements were a joint effort of FGI and UH.

The benchmarking project's targeted participants include national mapping agencies, companies, universities and research organizations, which develop their own processing methods or modify existing methods. Meanwhile, the project is open for techniques that are in the development phase. The project was actively advocated to potential participants, reached through research networks, during conferences and via various social media tools.

Twenty-four partners from three continents (Asia, Europe and North America) participated in the benchmarking. The partners agreed to process the TLS data provided by the project using their own methods and to deliver the standardized results. The required criteria comprised the tree location, tree height, DBH, stem curve of each individual tree in a sample plot, and a Digital Terrain Model (DTM) of the sample plot. Partners were encouraged to process both single- and multi-scan data, but had the option to process data according to their preference. Among twenty-four partners, eighteen successfully provided their results following the project guidelines, which were used in the following evaluation processes, as listed in Table 1. Of the 18 partners, 12 provided all requested parameters from both single- and multi-scan data, 2 provided results from either single- or multi-scan data, and 4 provided part of the results. All the results were evaluated using the same reference data (Section 3) and evaluation methods (Section 4).

Table 1: List of participants

Full name	Country
Chinese Academy of Forestry	China
Delft University of Technology	Netherlands
Finnish Geospatial Research Institute	Finland
Institut Français de Pondichéry – Laboratoire des Sciences de l'Information et des Systèmes	India/France
INRA Biogéochimie des Ecosystèmes Forestiers – ING Laboratoire d'Inventaire Forestier	France
Institute of Remote Sensing and Digital Earth	China
Korea Univeristy	South Korea
Nanjing University	China
Shinshu University	Japan
Swedish University of Agricultural Sciences	Sweden
Technical University in Zvolen	Slovakia
Technische Universität Wien	Austria
The Silva Tarouca Research Institute for Landscape and Ornamental Gardening	Czech Republic
Treemetrics	Ireland
University of Lethbridge	Canada
University of Padova	Italy
University of Sopron	Hungary
Wuhan University	China

2.2 Conceptual Schema

The benchmarking is carried out from two equally important perspectives: the capacity of the TLS data to digitize the forest plots and the performance of the data processing algorithms for attribute extractions. TLS digitization capacity in recording forest is influenced by the stand condition and scanning pattern, which determine what can best be achieved by a particular feature extraction method. In evaluating an algorithm's performances, two major tasks are to establish a standardized criterion and to develop an evaluation procedure. This section details the benchmarking design.

2.2.1 To evaluate the capacity of the TLS to digitize a forest plot

The strength of TLS in forest field inventory lies in its capacity to record the forest environment automatically, accurately and rapidly. Two essential factors addressing the TLS-data quality are the spatial precision and completeness of tree information in the point-cloud data. The spatial precision is determined by the system calibration and by the registration of multi-scan data if applicable, which are typically sufficiently accurate for forest applications. The tree-information completeness is determined by the forest conditions and the field-inventory design but is however not guaranteed. The forest stands' complexity, the scanning patterns applied in the field and the distance/geometry between a tree and the scanning position(s) are the issues that determine the completeness of trees in the point-cloud data of a forest sample plot.

The accuracy of tree attributes' extraction can only be meaningfully discussed when the completeness of tree information in the data is clarified. Therefore, the impacts of different stand situations and scanning pattern to the quality of the collected TLS data and, as a consequence, to the results of attribute extraction are investigated in this benchmarking. The stand conditions of the sample plots, as well as the applied scanning pattern for the TLS data collection is in Section 3.

2.2.2 To evaluate the algorithm performances

A foundation in evaluating the performance of attribute extraction is to establish a series of standardized criteria that suits most of the currently existing algorithms. Evaluation criteria are selected based on five main considerations: firstly, a criterion is of high interest and importance in forest inventories; secondly, the criterion's measurement is within the capacity of TLS equipment commonly available; thirdly, the criterion estimates can be evaluated against the corresponding references; fourthly, multiple algorithms for the criterion extraction from TLS data have been reported in previous studies; fifthly, for practical applications, such as forest inventories, the criterion is measurable with reasonable costs in practical inventories at a large scale, e.g., national forest inventories (NFIs).

Among various forest attributes, the most interested tree-level attributes in conventional field inventory include the tree height, DBH and species, which are widely used in estimating tree volume and biomass. However, plausible results on species classification based on TLS merely exist until recently. Other highly interested tree-level attributes, e.g., tree class, canopy layer and age, lack sufficient evidences to be measureable from TLS; therefore are not included in the benchmarking criteria.

A couple of other tree attributes are highly important but not conventionally measurable due to the large amount of required resources, but lie in the strengths of TLS: the stem curve, a long awaited tree-level attribute that has been difficult to measure non-destructively; tree position, a parameter that reveals forest structure and bridges observations from different perspectives, e.g., terrain and airborne; and the digital terrain model (DTM) that is essential for measuring tree height and DBH from the TLS point cloud. Furthermore, two indirect attributes that requires allometric model, i.e., the volume and the biomass at tree- and plot-level, should also be investigated since they are of high importance for various applications.

Based on these factors, this benchmarking project's criteria consist of one plot-level attribute, i.e., the DTM; four direct tree-level attributes, i.e., tree location, tree height, DBH and stem curve; and two indirect tree-level attribute, i.e., stem volume and the biomass. Figure 1 illustrates five direct attributes that are taken as the criteria of this benchmarking.

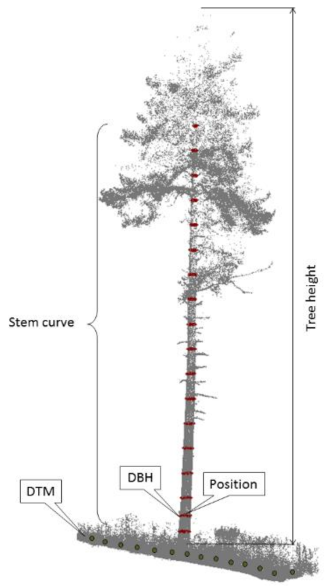


Figure 1: The five criteria extracted from TLS data at the plot- and tree-level

In addition to standardized evaluation criteria, credible evaluation also requires robust evaluation procedures. To minimize the human-introduced influences, a series of fully automated procedures are developed to evaluate the attribute extraction, and a same set of parameter settings is applied for all the evaluated results. Thus, all the evaluations are solely based on the comparisons between the reference and the results delivered by the project partners. Details of the evaluation procedure for each criterion are given in section 4.

In brief, all algorithms evaluated in this benchmarking project process a unique set of TLS data providing the attribute extraction results of a standardized set of criteria are projected to a common frame of reference and are independently evaluated by a series of automated evaluation.

3 DATASETS

The data acquisition approaches are designed to support the main objectives of the benchmarking project. Thus, 24 sample plots are selected from varying forest-stand conditions representing developing stages, stem densities and richness of sub canopy growth in boreal forests. The forest plots are scanned from 5 positions and the data for processing are delivered in both single- and multi-scan format. Reference datasets for the benchmarking were collected by integrating manual measurements from the TLS data and the conventional field measurements.

3.1 The sample plots and complexity categories

The 24 sample plots were selected by foresters to represent different stand situations, which vary in species, growth stages and management activities including both homogenous and less-managed forests. The sample plots are distributed in a southern boreal forest in Evo, Finland (61.19ºN, 25.11ºE). Each plot has a fixed size, 32-by-32 m. The main tree species are Scots pine (Pinus sylvestris L.), Norway spruce (Picea abies (H.Karst.) L.) and silver (Betula pendula Roth) and downy (Betula pubescens Ehrh.) birches.

The sample plots were classified into three complexity categories: “Easy”, “Medium” and “Difficult”. The complexity categories were defined intuitively on stem visibility (the level of possible occlusion effects) at the ground level, stem density and DBH distribution in the sample plots. The category “Easy” represents a clear visibility with minimal understory vegetation and low stem density (~600 trees/ha); “Medium” represents sample plots with moderate stem densities (~1000 trees/ha) and sparse understory vegetation; and “Difficult” represents those plots having high stem densities (~2000 trees/ha) and dense understory vegetation. TLS data completeness in the three categories is expected to decrease as the complexity increases. Figure 2 illustrates the examples of the three complexity categories.

(a) Easy (b) Medium (c) Difficult

Figure 2: Three complexity categories of the sample plots in the TLS benchmarking. The category “Easy” represents sparser stem densities and little understory vegetation, “Medium” represents moderate stem densities and sparse understory vegetation, and “Difficult” represents high stem densities with dense understory vegetation.

The sample plots statistics are summarized in Table 2, where the plot attributes’ mean and standard deviation values are presented by complexity categories. As the complexity categories increase, the stem density increases sharply, the mean DBH and tree height decrease clearly and the basal area increase marginally, suggesting that, as the complexity level increases, the amount of young and small trees within a plot grows, the age of the forest stand decreases and human intervention in forest management also drops.

Table 2: The statistics of the forest plots in three complexity categories, i.e., mean and standard deviation values of the stem density (stems/ha), basal areas (m^2/ha), diameter at the breast height (cm) and tree height (m)

Complexity categories	Stem density (stems/ha)	DBH (cm)	Tree height (m)	Basal area (m^2/ha)
Easy	592+/-189	20.7+/-8.5	18.4+/-6.4	23.2+/-5.9
Medium	968+/-370	17.2+/-10.7	16.2+/-7.3	31.2+/-8.6
Difficult	2021+/-553	12.3+/-7.2	13.2+/-5.9	32.3+/-7.1

The differences between the three complexity categories are illustrated in more detail by the DBH distribution of each difficulty category in Figure 3. For each difficulty category, the DBH is grouped at intervals of every 2 cm. The number of trees in each DBH group is separated and counted per difficulty category. In the category “Easy”, most of the trees are mature with a DBH between 15 and 35 cm. The amount of small trees increases clearly in the “Medium” category, with most of trees having a DBH less than 21 cm. Meanwhile, in the category “Difficult”, the majority of trees have a DBH of approximately 10 cm and the total population of trees in the plots increases significantly.

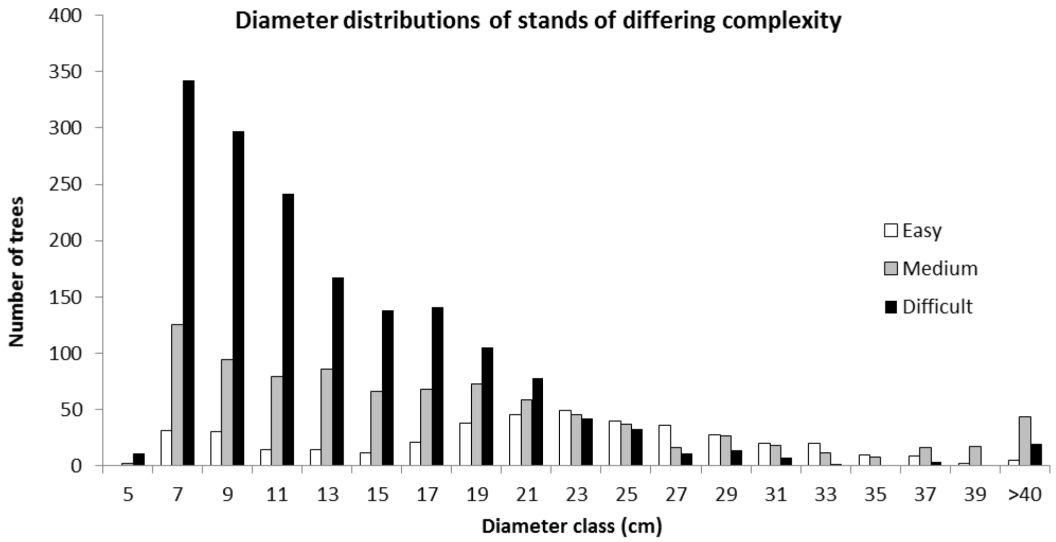
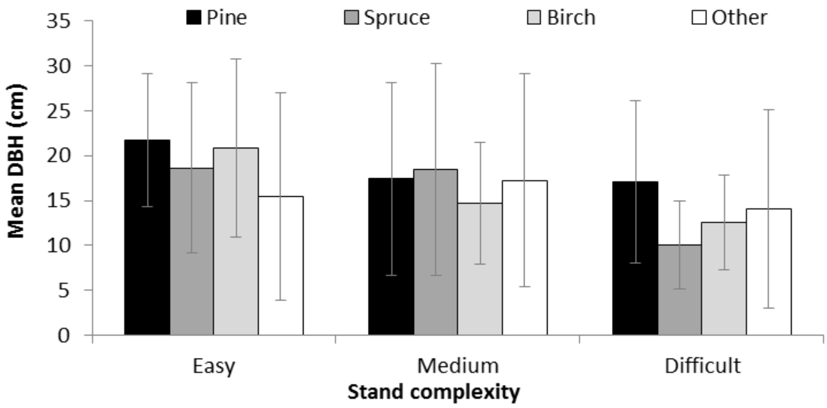
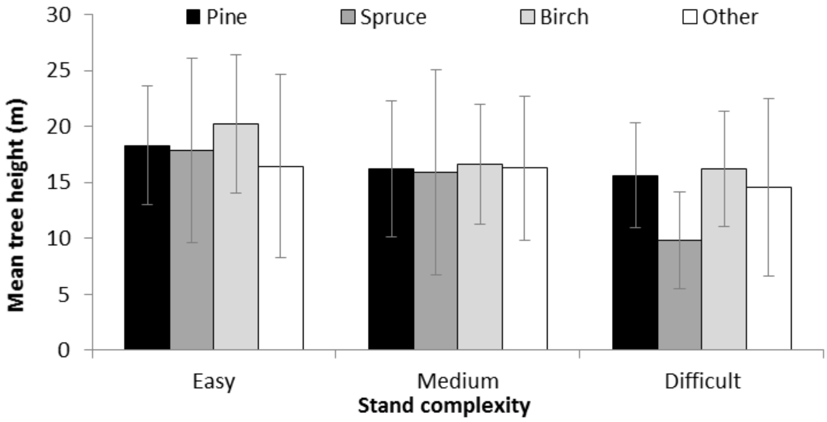


Figure 3: DBH distribution in three complexity categories as number of stems in DBH classes in 2 cm interval

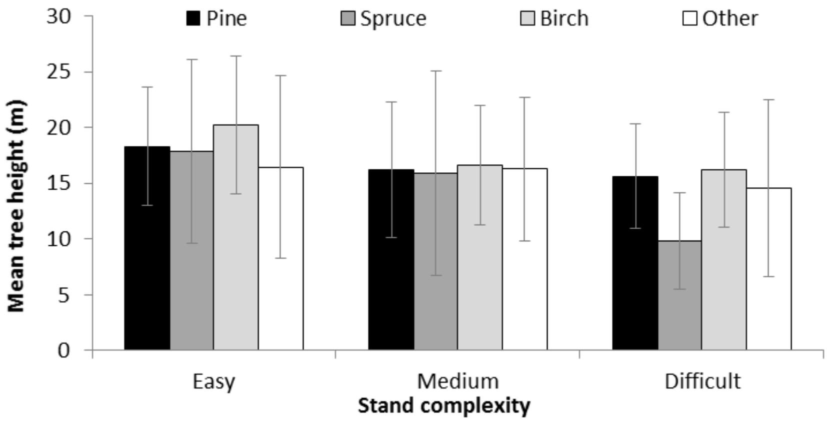
The species composition in each complexity categories is described using the tree-species-specific plot statistics, i.e., the mean and standard deviation values of DBH and tree height and the mean basal area of the main species, as presented in Figure 4. Figures 4 (a) and (b) indicate that DBH and tree height decreases for all species as the complexity category increases. The figure (c) shows that the plots in the categories “easy” and “medium” are pine and spruce dominated, respectively. The category “difficult” shows the heterogeneity of the species distribution in the plots, while the basal areas of pine, spruce and birch are close to each other.



(a) Mean diameter at the breast height and standard deviation per tree species in the complexity categories



(b) Mean tree height and standard deviation per tree species in the complexity categories



(c) Mean basal area per tree species in the complexity categories

Figure 4: Statistics of the test plot per tree species in the complexity categories. (a) Mean diameter at breast height and standard deviation. (b) Mean tree height and standard deviation. (c) Mean basal area.

3.2 *The TLS Data of the Sample Plots*

The sample plots were scanned in summer 2014, using a Leica HDS6100 (Leica Geosystems AG, Heerbrugg, Switzerland) terrestrial laser scanner. The scanner measure distances with a continuous wave of 650–690 nm. The field of view is 360° × 310° and the distance measurement accuracy is ±2 mm at 25 m from the scanner. Data acquisition used a "High Density" mode. The increment is 0.036° in both horizontal and vertical directions, which gives a point spacing of 15.7 mm at 25 m from the scanning location in both horizontal and vertical directions. A full-field-of-view scan takes approximately 3 minutes.

The data acquisition speed is highly relevant to the forest structure. Per day, 3-7 sample plots were measured including scanning setup, 5 scans per plot and transportation between plots. In general, the field TLS measurement is pretty fast in the foresters' opinion.

The sample plots were scanned as is, i.e., without any pre-scan preparation, such as the removal of lower tree branches or the clearance of undergrowth. Five scans were made in each plot: one scan at the plot center and four scans at the four quadrant directions, as shown in Figure 5. The theoretical position of the middle scan is at the plot's center and the distance between four quadrant scans to the center scan was 11.3 m. The exact scanning positions may be moved around the theoretical locations according to the forest structure, to find a suitable place for the scanner setup, e.g., away from tree stem next to the scanning position.

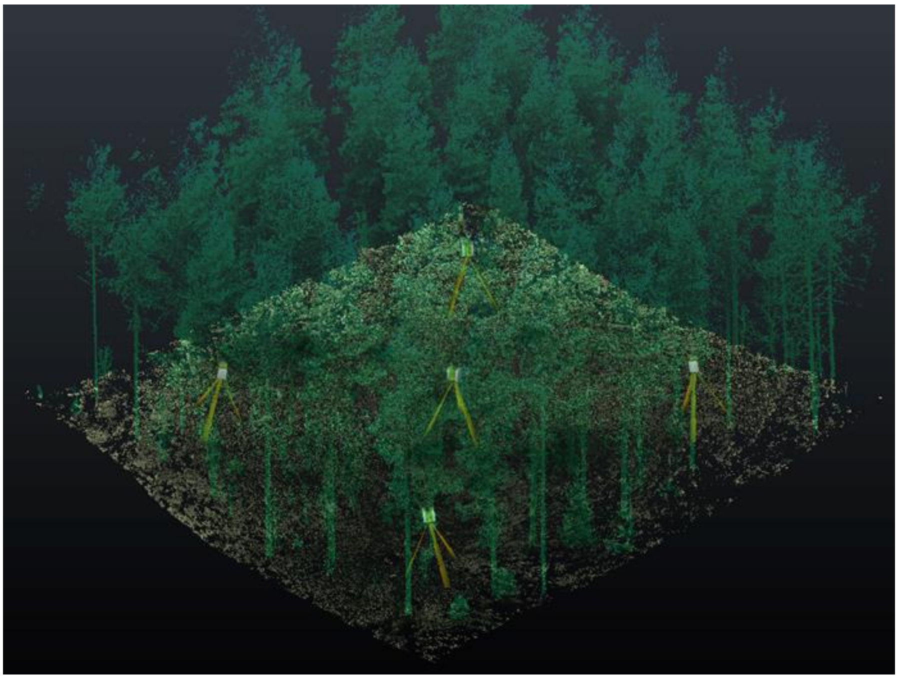


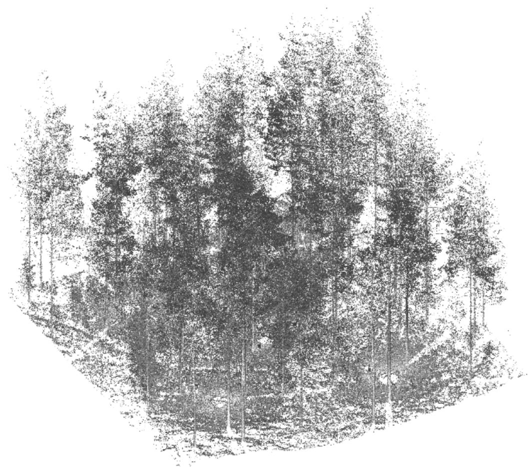
Figure 5: The scanning positions in the sample plots

The influences of the scanning pattern on the tree attribute extraction of a sample plot are among the main targets of the benchmarking project. Therefore, TLS data are acquired using multi-scan approaches, and the project's partners have the option to process the registered multi-scan data and the single-scan data from the plot center. According to practical experience, the number of TLS-acquisition positions is a trade-off between the cost of field work (e.g., time and expense) and the data quality. In this project, five scanning positions, which is a typical setup in the multi-scan approach, is employed, because it normally leads to a merged TLS point cloud covering all trees within a forest plot and optimally balances the completeness of tree information with cost and labor intensity.

Artificial spheres with a constant radius of 198 mm were set up as reference targets throughout the plot for data registration. For each sample plot, all five scans were registered using targets and merged as multi-scan TLS data with an average registration accuracy of 2.1 mm; the center scan was employed as single-scan TLS data. Examples of test data in the single- and multi-scan TLS in the three complexity categories were presented in Figure 6. In the TLS point cloud, the complexity category 'Easy' typically has good visibility for both single- and multi-scan TLS data. The visibility or completeness of trees in the point cloud of the complexity category 'Difficult' can be low, even in multi-scan TLS, due to the heavy occlusion effects created by the dense stands.

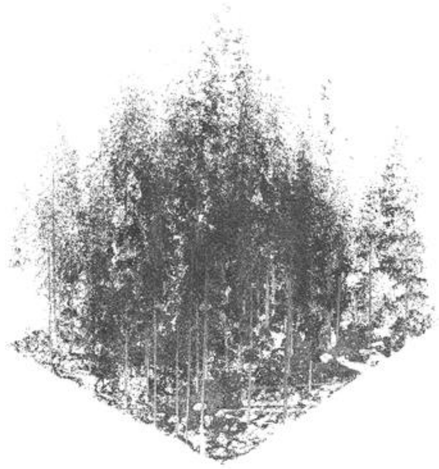
TLS and reference data from six test plots, i.e., two from each complexity categories in both single- and multi-scan, are open for non-profit research purposes. (The link to the data will be published soon.)

(a) single-scan TLS data in the category "Easy"

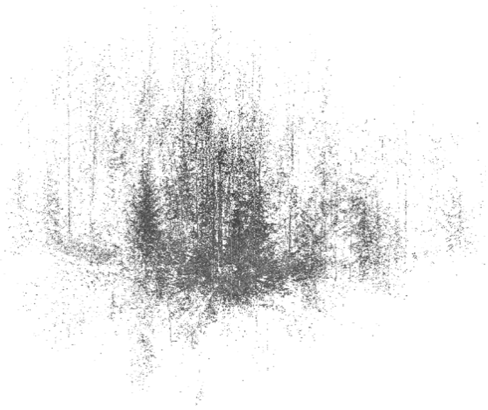


(b) multi-scan TLS data in the category "Easy"

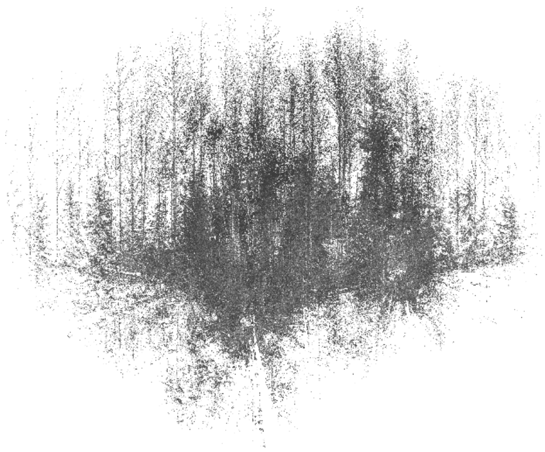
(c) single-scan TLS data in the category "Medium"



(d) multi-scan TLS data in the category "Medium"



(e) single-scan TLS data in the category "Difficult"



(f) multi-scan TLS data in the category "Difficult"

Figure 6: Examples of forest sample plots in the single- and multi-scan terrestrial laser scanning data in the three complexity categories.

3.3 Acquisition of Reference Datasets

Reference information is collected through a design integrating field inventories and manual measurements from TLS data to evaluate it credibly; thus, the ground truth of the sample plots can be presented as accurately as possible in the reference datasets. This section details the reference data collection.

3.3.1 Tree map and basic tree-level attributes

A detailed map of trees whose DBHs are greater than 5 cm for each sample plot is generated by integrating manual measurements from the multi-scan TLS data and in the field. A preliminary tree map is manually measured from multi-scan TLS data for trees having high-quality 3D points in TLS data. The tree location was defined as the stem's center point at the breast height. This preliminary map is verified in situ during a revisit to the field, and the location of omitted trees in the preliminary tree map is determined by the distances and directions of the omitted tree to its four neighbouring known trees on the preliminary tree map. A full tree map is created after the field verification, and the full tree map is double-checked again with reference to multi-scan TLS data, ensuring that the locations of field-measured trees were consistent with the TLS-recorded tree locations.

Tree-level attributes such as tree height and DBH are measured for each tree using conventional field measurement methods. For DBH, stem diameter is measured at the breast height from two perpendicular directions utilizing steel calipers to the nearest millimeter, the average value of these two diameters is recorded as DBH of a tree. Tree height was measured with Vertex 3.0 (Haglöfs, Sweden) to a resolution of 0.1 m. Vertex 3.0 utilizes a tangent method to calculate tree height. The manufacturer promises 1% accuracy in distance measurement and 0.1 degree accuracy in angle measurement. The expected accuracy of tree-height measurement was 0.5 m. Tree-height was measured from a location where the whole tree was clearly visible, normally from a distance equal to the tree length.

3.3.2 Digital Terrain Model

The digital terrain model can be retrieved through either point cloud data or field mensuration. In general, the point cloud from the multi-scan TLS records the terrain information in great detail. However, both terrain and dense ground vegetation may block the laser pulses, consequently creating large shadows on the terrain surface where no 3D points are recorded. Accurate ground-point classification from the point cloud is another challenge, which is hard to accomplish with fully automated algorithms. Alternatively, the DTM can be measured in field inventories, e.g., using total station. The field inventory has the potential to be the most accurate measurement since the operator can find the best observational perspectives, measure the true ground surface and have full coverage of the whole plot. But the associated cost is high since the manual measurement takes a long time.

To balance the requirement for the high accuracy with the time and labor costs, the multi-scan TLS point cloud is selected as the data source, and the reference DTMs of the sample plots are retrieved through a semi-automated approach that combines the automated data processing and manual editing. The ground points are first identified utilizing the ground classification algorithm in TerraScan software (Terrasolid, Finland). The algorithm is based on a triangulated irregular network (TIN) densification algorithm that uses local low points as initial points and starts to densify the TIN by adding more ground points according to the given parameters (Axelsson, 2000), which accurately generates DTM generation in many applications. In the automated phase, the same parameter setting is applied for all sample plots. Remaining non-ground objects, such as stones and stumps whose diameters are larger than a predefined threshold, are visually checked and manually removed. The threshold was defined as 63 cm according to a manual estimation of the average stones and stumps size in the sample plots.

The reference DTMs are generated through rasterizations of the classified ground points. The resolution of the reference DTMs is 20 cm, considering the plot size, the details in final DTMs and the amount of interpolations required at the shadowed areas on the terrain surfaces. In the rasterization approach, a grid of 20 cm resolution is overlaid on the ground points. For a cell where multiple ground points exist, an average of the z values of the points is calculated and taken as the cell's z value. For a cell in the shadowed area where no ground point exists, the z value is interpolated as an average of its neighboring cells. Figure 7 illustrates an example of the ground points and the DTM reference of a sample plot.

Figure 7: An example of the ground points classified by a semi-automated approach and the rasterized DTM. Holes in the ground points are created by shadows from big rocks and stumps or the low point density towards the plot borders.

3.3.3 Stem curve

Each tree stem was manually digitized through multi-scan TLS point cloud to measure the stem curves. The stem curve of an individual tree consists of stem diameters starting at the height of 0.65 m above the ground, followed by diameters at the DBH height and at every meter above the DBH height, i.e., 0.65 m, 1.3 m, 2 m and 3 m, till the maximum measurable heights from the point cloud data.

For each sample plot, the multi-scan TLS point cloud is first cut for each individual tree. The points of each tree are then sliced on specific heights above local ground-height level. Points in each cross-section were inspected from a top view, and a circle was manually fitted on the stem points using the TerraScan software. In many cases, the stems do not present exact circular shapes on the cross-sections. Each circle was thus fitted to minimize the least square error between the stem points and the arc of the circle. Stem curves started from the lowest height and continued up the stem so long as a sufficient amount of points could be recognized as a stem cross section. At each measurement position, the central coordinates and diameter of the fitted circle are recorded. An example of the stem-curve measurement is presented in Figure 8.

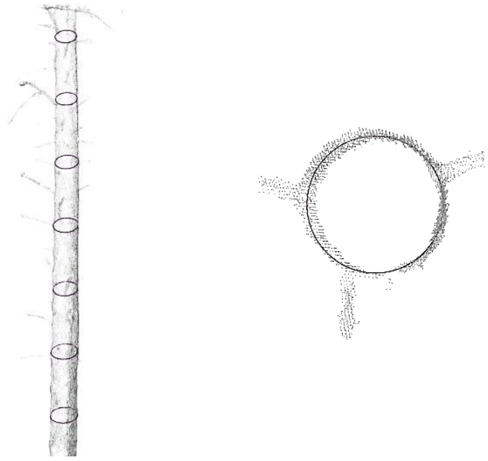
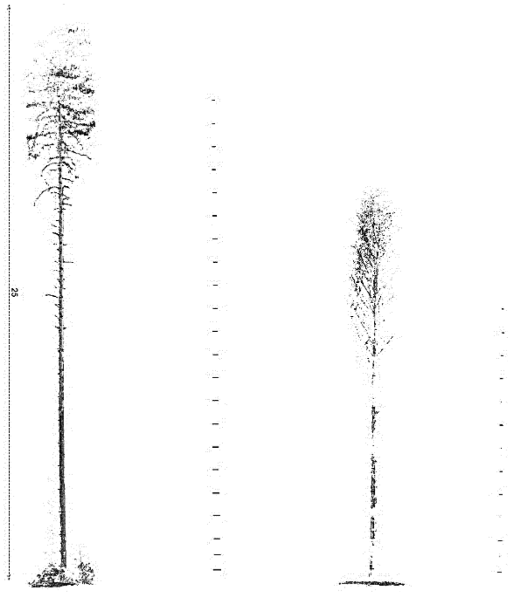


Figure 8: An example of a set of stem diameter measurements on a Scots pine tree (left) and of a single measurement circle fitted on stem points (right).

Even though the multi-scan TLS data provides a large amount of details in forests, in most cases, regardless of the stand conditions in the sample plots, the stems are blurred close to the treetops, due to occlusion effects and the distances to the scanning positions. The severity of the occlusion effect varies from plot to plot and from tree to tree, depending on the stand density, species and the tree’s position in the plot. If insufficient points are found at a particular height, the diameter of the previous measurement at a lower height is used to estimate the diameter at that height. In some very special cases, the tree stems are divided into smaller sub-stems from the root and no clear main stem can be identified. In such cases, multiple stems are recorded for a single tree if the separation of the main stem occurs below the breast height and if the divided sub-stems satisfy the 5 cm DBH threshold. Examples of the reference stem curve measurement were shown in Figure 9, which compares the stem curve measurements in the sample plots of “Easy” and “Difficult” complexity categories, where the stem curve is measured for visible parts in the point clouds.



(a) (b)

Figure 9: Examples of the reference stem-curve measurement. (a) A Scots pine tree on an easy plot. Stem curve was measured to the tree top but not to the apex, since most of the tree trunk is visible in the TLS data and the top part the tree stem is occluded by the tree crown. (b) A birch tree on a plot in the complexity category difficult. The stem curve is measurable only for the visible parts. The dashed line on the left is 25 meters and gives the scale for both sub-figures.

3.3.4 Stem volume and total aboveground biomass

Stem volume was estimated based on the stem curve. The stem was divided into sections based on the retrieved diameters. In addition, the total stem volume was calculated as the sum of the sections. The stem section between two adjacent diameters was modelled as a cylinder whose radius was the mean of the radii of the top and bottom of the block. The upper most tree stem was modelled as a cone using the highest stem diameter and tree height. The base of the tree, i.e., between the ground and the lowest diameter was estimated using a cylinder whose height was 65 cm and diameter equalled to the lowest retrieved diameter.

The total aboveground biomass of a tree was estimated using the multivariate statistical models presented in (Repola, 2008, 2009). The models use DBH and tree height as explanatory variables to predict the biomass. Repola's models were developed for birch, Scots pine and Norway spruce trees in Finland. For other tree species, the birch model was applied.

4 METHODS OF EVALUATION

The partners of the benchmarking project are required to deliver their extraction results for the criterion, i.e., the DTM, tree locations, tree height, DBH, and stem curve of each sample plot utilizing the TLS datasets of the 24 sample plots. Partners' results are evaluated respecting the relevant reference data described in section 3.3 and utilizing standardized evaluation procedures defined in this section.

4.1 The accuracy of the DTM

Partner DTMs were evaluated using the 'Output control report' tool of the TerraScan software, which is designed for elevation comparison between laser ground points and the known ground control points. For each sample plot, the reference DTM is employed as the ground control data, and the DTM from partners is compared against the reference DTM.

For each given (x, y) location of the reference DTM, three nearest points from the DTM to be evaluated are selected, and a small 3D triangulate plane is created using the selected points. An elevation value z_e derived from the triangulate plane is compared with the reference z value at the location (x, y). The root mean square error (RMSE) of the built DTM is calculated based on the elevation difference between z and z_e.

In addition to the RMSE, the percentage of the reference DTM covered by partners' results was taken into the evaluation, since the combination of the RMSE and the area covered gives a more comprehensive evaluation than the single factor. For example, a small RMSE can be achieved by limiting the extracted DTM to areas where TLS data coverage is good, because errors in the DTM estimation tend to increase in areas where TLS data coverage is inadequate.

4.2 Tree matching

The first step in evaluating the tree-level attributes is to verify the correctness of the detected individual trees using various algorithms. An automated tree-matching approach is developed to evaluate whether a tree in a plot is correctly detected or not.

The detected and reference trees were matched according to both tree locations (x, y) and DBHs. For each detected tree, all reference trees within a neighbourhood of 50 cm radius are retrieved. The detected tree was linked to the neighbouring reference tree whose DBH is closest to that of the detected tree to form a preliminary match.

In this preliminary matching, more than one detected tree may correspond to the same reference tree. To remove such duplicate matches, the following four steps were repeated until unique links between the detected and reference trees are found: 1) a non-unique match was sought; 2) a match was established if the DBH of a detected tree was closest to the reference's DBH; 3) other links to the reference are removed, and the reference tree is also removed from reference map; and 4) a new matching iteration starts from step 1 using the remained detected and reference trees. The iteration continues until all reference or detected trees found a match in the other list, if possible. If no reference tree can be found for a detected tree, the detected tree is considered a commission error. If no detected tree can be found for a reference tree, an omission error is counted.

With the matching approach, tree detection, location, DBH, and the tree height are all evaluated simultaneously.

4.2.1 Tree detection accuracy

Tree detection accuracy was evaluated using three measures, i.e., the completeness, the correctness and the mean accuracy.

Completeness measures how large a part of the reference tree is found using an algorithm. Correctness measures how a large part of the trees extracted using an algorithm is correct. They are defined as

$$\text{Completeness} = \frac{n_{\text{match}}}{n_{\text{ref}}} \tag{1}$$

$$\text{Correctness} = \frac{n_{\text{match}}}{n_{\text{extr}}} \tag{2}$$

where n_{match} is the number of correct detections , n_{ref} is the number of reference trees and n_{extr} is the number of trees detected.

The mean accuracy of detection was defined as the joint probability that a detected tree randomly chosen was a correct detection and that a reference tree randomly chosen is detected by an algorithm. It is defined as

$$\text{Mean accuracy of detection} = \frac{2n_{\text{match}}}{(n_{\text{ref}} + n_{\text{extr}})} \tag{3}$$

4.2.2 The accuracy of tree location, DBH, and height

The accuracy of the extracted tree location, tree height and DBH is evaluated using the RMSE and bias, except for the tree location where only RMSE is calculated. In addition, relative RMSE and relative bias were calculated for DBH and tree height. The accuracy measures were calculated by comparing the extracted values $\hat{y}_i$ to the reference values y_i, i.e., tree parameter such as tree location, height or DBH, where i is the index of the match. RMSE is defined with the equation

$$\text{RMSE} = \sqrt{\frac{1}{n_{\text{match}}} \sum_{i=1}^{n_{\text{match}}} (\hat{y}_i - y_i)^2} \tag{4}$$

Bias is defined with the equation

$$\text{Bias} = \frac{1}{n_{\text{match}}} \sum_{i=1}^{n_{\text{match}}} (\hat{y}_i - y_i) \tag{5}$$

The relative RMSE and bias, in percentages, were calculated by comparing the RMSE and bias to the mean reference value $\bar{y}$ defined as

$$\bar{y} = \frac{1}{n_{\text{match}}} \sum_{i=1}^{n_{\text{match}}} y_i \tag{6}$$

The relative RMSE was calculated with the equation

$$\mathrm{RMSE_{rel}} = \frac{\mathrm{RMSE}}{\bar{y}} \times 100\% \tag{7}$$

and the relative bias with the equation

$$\mathrm{Bias_{rel}} = \frac{\mathrm{Bias}}{\bar{y}} \times 100\% \tag{8}$$

4.3 The stem-curve accuracy

At an individual tree level, the accuracy of the stem-curve estimates was evaluated using RMSE and bias of the extracted stem curve which were calculated using equations (9) and (10), respectively.

The extracted stem curves consisted of diameters $\hat{d}_i(\hat{z}_{i,j})$ at heights $\hat{z}_{i,j}$, where i is the index of the match and j is the index of the extracted diameter. The corresponding reference measurements are denoted by $d_i(z_{i,k})$, where k is the index of the measured diameter. Since the heights $\hat{z}_{i,j}$ at which the extracted diameters may vary between participants, i.e., not equal to the defined reference heights $z_{i,k}$, the accuracy of the extracted curve was evaluated by comparing the diameters $\hat{d}_i(\hat{z}_{i,j})$ to the linear interpolated reference values at the same heights $d_i^{\mathrm{interp}}(\hat{z}_{i,j})$.

$$\mathrm{RMSE}_i = \sqrt{\frac{1}{m_i}\sum_{j=1}^{m_i}\left(\hat{d}_i(\hat{z}_{i,j}) - d_i^{\mathrm{interp}}(\hat{z}_{i,j})\right)^2} \tag{9}$$

$$\mathrm{Bias}_i = \frac{1}{m_i}\sum_{j=1}^{m_i}\left(\hat{d}_i(\hat{z}_{i,j}) - d_i^{\mathrm{interp}}(\hat{z}_{i,j})\right), \tag{10}$$

where i is the index of the match and m_i the number of extracted diameters in the ith match. The extracted diameters outside the range of the reference diameters were ignored in the accuracy evaluation.

At a plot level, the accuracy of the extracted stem curves is evaluated using averages of the tree-wise RMSEs and biases using equations

$$\overline{RMSE} = \frac{1}{n_{\mathrm{match}}}\sum_{i=1}^{n_{\mathrm{match}}} \mathrm{RMSE}_i, \tag{11}$$

$$\overline{Bias} = \frac{1}{n_{\mathrm{match}}}\sum_{i=1}^{n_{\mathrm{match}}} \mathrm{Bias}_i \tag{12}$$

In addition to the measurement accuracy, the efficiency of each algorithm is evaluated by the proportion of the stem covered by the extracted diameters. For this purpose two measures are defined, i.e., curve length ratio (CLR) and the percentage of the tree height covered (PHC). Both measures are calculated using histograms whose bins correspond to height intervals along the stem. The bin edges are designed such that the default heights of the retrieved diameters (see *section 3.4.2.*) are in the middle of the bins. The bin was occupied if at least one diameter is retrieved between the bin edges; otherwise, it is empty. The lengths of the occupied bins were summed to determine the stem length that is covered by the retrieved stem curve. CLR is the ratio of the stem length covered by the extracted curve to the stem length covered by the reference curve in percentage. PHC is otherwise the same as CLR, but the denominator is replaced by the measured reference tree height.

CLR measures how large a part of the manually measured reference stem curve is retrieved with an algorithm-extracted curve, which also reveals how well the (semi-) automatic stem-curve extraction methods perform compared to manual measurements by laser scanning experts, i.e., the best a human being can achieve. CLR may have a value larger than 100%, meaning the method extracts more curve than the manually measured reference data, or the computer over-performs human beings if the method is fully automated. PHC reveals the degree of the whole tree retrieved by the extraction methods, 100% being the ultimate goal where an algorithm fully depicts the object. PHC indicates the capacity of the TLS point cloud and an algorithm to depict the object in the field.

The average CLR and PHC over all matched trees in a plot were also calculated in the same way as the average of tree-wise RMSEs and biases of stem curves as mentioned above, to gain an overall measure of how large a part of the trees were covered by the extracted curves using different algorithms.

Since some extracted matches do not contain an extracted stem curve, a modified completeness is used in the curve-related evaluations, which considers only those matches with an extracted stem curve. It is defined as

$$\mathrm{Completeness}_{\mathrm{RMNSC}} = \frac{(n_{\mathrm{match}} - n_{\mathrm{match,\ no\ stem\ curve}})}{n_{\mathrm{ref}}} \tag{13}$$

where $n_{\mathrm{match,\ no\ stem\ curve}}$ is the number of matches that do not have an extracted stem curve. $\mathrm{Completeness}_{\mathrm{RMNSC}}$ is the modified completeness, where the subscript 'RMNSC' comes from the words 'removed matches with no stem curve'.

4.4 The accuracy of stem volume and total biomass

Although same mathematical models are applied to all participants for stem volume and biomass estimation, the evaluation actually reveals the combined impacts of extracted tree height, DBH and stem curves to the volume and biomass estimates. Because each algorithm has its own strength and weakness with respect to different tree attributes, e.g., improving estimate accuracy by scarifying completeness, the volume and biomass evaluation provides an overview of the overall performance of all the extracted tree attributes of an algorithm.

The absolute and relative RMSE and bias of volume and biomass over the trees in each plot are calculated using equations 4-8. Two volume ratios and one biomass ratio are also used to evaluate the volume estimation. Volume ratio 1 is ratio of the total stem volume of the matched extracted trees to the total volume of the reference trees in the plot. It evaluates the correct volume extractions at the plot level. Volume ratio 2 is the ratio of the total volume of all extracted trees to all reference trees in the plot. It evaluates the overall volume estimations. Biomass ratio is the ratio of the total biomass of the matched extracted trees to the total biomass of all reference trees in the plot. It compares the biomass of the correct tree detections to the reference biomass at a plot level.

5 CONCLUSION

Accurate forest inventories with high time and cost efficiencies have been long awaited by multiple applications and users. Terrestrial Laser Scanning technology was anticipated to hold the potential to provide optimal plot-level forest measurements with high quality and a high level of automation, which outpaces the outcomes from conventional field measurements. However, even though a great leap forward in the hardware evolution can be witnessed in the past 20 years, brought about by the enormously decreased size and weight of the equipment, the continuously advanced data quality, and the considerably dropped hardware costs, the data-processing sophistication has not kept pace with the hardware surge, leading to a very limited application of TLS in practical operations.

Nevertheless, awareness of TLS potential of in forest applications in both public and commercial sectors is increasing, seeing that tremendous efforts have been invested in the relevant studies. It is now time to inspect the achievements and the remaining barriers of the TLS-based forest investigations, so further research and applications receive a clear orientation on their path toward practical TLS operations in forest inventories.

In such a context, the international TLS benchmarking project was launched in 2014. The project aims to evaluate the performance of recent TLS data-processing algorithms for extracting forest attributes, thereby clarifying TLS's strengths and weaknesses as a measure of forest digitization, and recent algorithms' capacity to extract tree attributes from the TLS data. The outcomes of this benchmarking are expected to provide comprehensive guidance for future research and application works in this field.

This paper focuses on the fundamental components of the benchmarking project, i.e., the selection of sample plots, the collection of TLS data, the acquisition of reference datasets, the definition of evaluation criteria, and the development of evaluation procedures, thus pave the way for a understanding the evaluation results reported in another separated paper. All components are designed to safeguard the main project objectives, namely, to inspect the TLS performance from the perspectives of the quality of TLS data and the capability of the data processing algorithms, and to discover the advantages and difficulties of TLS applications in forest measurements.

The 24 sample plots are selected by foresters considering the different growth stage, stem density, species composition, and richness of sub canopy growth in the stands. Three complexity categories, i.e., "easy", "medium", and "difficult" are defined for the sample plots by foresters, which also reflects the level of complexity of the TLS data processing. The TLS data was collected in each sample plot utilizing both single-scan and multi-scan approaches. The reference information is generated with an integration of field measurements and manual measurements from multi-scan TLS point clouds. The partners process the TLS datasets and deliver extracted attributes of a given set of standardized criteria, namely, the DTM of each sample plot, the tree location, height, DBH, stem curve of each tree in the sample plot. The results from all the partners are automatically evaluated using procedures specifically developed for this project, including a couple of evaluation criteria proposed first in this benchmarking project. Therefore, algorithms of all the partners are projected to a same reference frame by processing identical datasets, extracting same attributes, and being evaluated by reliable reference information with common automated procedures. The impacts from the complexity of forest stands and the pattern of TLS data acquisition to the quality of TLS point cloud, and consequently, to the attribute extract results of different algorithms can therefore be investigated through the comparison of result from the three sample plot difficulty categories and the single- and multi-scan TLS datasets.

To promote the understanding and the credibility of the evaluation results of this benchmarking project, the conceptual and technical details are described in this paper. More information about the algorithms of the 18 partners, the evaluation results, and findings derived from the benchmarking project are presented in the subsequent paper.

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