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Is field-measured tree height as reliable as believed – A comparison study of tree height estimates from field measurement, airborne laser scanning and terrestrial laser scanning in a boreal forest

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ABSTRACT

Quantitative comparisons of tree height observations from different sources are scarce due to the difficulties in effective sampling. In this study, the reliability and robustness of tree height observations obtained via a conventional field inventory, airborne laser scanning (ALS) and terrestrial laser scanning (TLS) were investigated. A carefully designed non-destructive experiment was conducted that included 1174 individual trees in 18 sample plots (32 m × 32 m) in a Scandinavian boreal forest. The point density of the ALS data was approximately 450 points/m^2. The TLS data were acquired with multi-scans from the center and the four quadrant directions of the sample plots. Both the ALS and TLS data represented the cutting edge point cloud products. Tree heights were manually measured from the ALS and TLS point clouds with the aid of existing tree maps. Therefore, the evaluation results revealed the capacities of the applied laser scanning (LS) data while excluding the influence of data processing approach such as the individual tree detection. The reliability and robustness of different tree height sources were evaluated through a cross-comparison of the ALS-, TLS-, and field- based tree heights. Compared to ALS and TLS, field measurements were more sensitive to stand complexity, crown classes, and species. Overall, field measurements tend to overestimate height of tall trees, especially tall trees in codominant crown class. In dense stands, high uncertainties also exist in the field measured heights for small trees in intermediate and suppressed crown class. The ALS-based tree height estimates were robust across all stand conditions. The taller the tree, the more reliable was the ALS-based tree height. The highest uncertainty in ALS-based tree heights came from trees in intermediate crown class, due to the difficulty of identifying treetops. When using TLS, reliable tree heights can be expected for trees lower than 15–20 m in height, depending on the complexity of forest stands. The advantage of LS systems was the robustness of the geometric accuracy of the data. The greatest challenges of the LS techniques in measuring individual tree heights lie in the occlusion effects, which lead to omissions of trees in intermediate and suppressed crown classes in ALS data and incomplete crowns of tall trees in TLS data.

1. Introduction

Tree height is one of the most important tree attributes in forest resource investigations. Together with other fundamental attributes, such as diameter at the breast height (DBH) and tree species, tree height is widely used in predicting other important tree attributes that are not directly measurable in a non-destructive manner, such as age, wood volume, biomass, and carbon stock. The accuracy of the tree height measurements is crucial since the estimation of most tree attributes requires tree height as an input parameter. For example, Tompalski

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et al. (2014) found that errors in tree height estimates can impact individual-tree volume estimates more significantly than errors in species classification. Feldpausch et al. (2012) and Kearsley et al. (2013) found that the bias in their carbon stock and biomass estimates was mainly caused by the uncertainties in the tree height measurements. However, measuring the tree heights in the field is not an easy task. The error in the field-measured tree heights can be higher than that in other field acquired tree attributes, such as the DBH (Luoma et al., 2017). Errors in tree height propagate to forest management decisions; therefore, the accuracy of tree height measurements has always been an important topic in forest science.

The most common method to non-destructively measure the tree height is to use clinometers that are based on trigonometric relationships between the planimetric distance from the instrument to a tree and the angle between the displacements from the instrument to the base and the top of the tree. The angle mensuration requires clear visibility to both the tree base and the treetop. The distance mensuration requires a clear view to the tree base when using devices such as handheld laser rangefinders. However, the visibility of the tops and the bases of trees is limited in natural forest conditions, because of various reasons such as the restricted observation positions, the complex shape of large and wide tree crowns, the occlusion by other neighboring crowns, the rugged terrain and the neighboring undergrowth. Consequently, errors are present in field tree height measurements.

Omule (1980) reported that the crew–measured tree heights using the tangent method included a significant positive bias. Päivinen (1992) noted that the field measurements slightly overestimated (approximately 30 cm) the tree heights for all tree species considered in the study. Educated and experienced mensurationists are generally acknowledged to provide more precise results than beginners with only basic knowledge. Kitahara et al. (2010) confirmed the importance of training and operator experience in the quality of field tree height measurements. Silva et al. (2012) stated that simple visual estimations of tree heights by trained operators were more accurate than measurements made using the Haglöf Vertex instrument in a natural semi-deciduous seasonal forest in Brazil. The same study also pointed out that the accuracy of field tree height measurements degrades with increasing tree heights. Larjavaara and Muller-Landau (2013) noted that under typical forest conditions with rough terrain, leaning trees and limited visibility, the performance of the tree height measurement instruments cannot attain the manufacturer-reported accuracies, which were derived under ideal conditions. Some researchers have even questioned the possibility of accurate tree height measurement in the field (Saatchi, 2012). Nevertheless, up to now, field measurements are widely understood to be the most reliable source of tree height information. The rigorous evaluation of the accuracy of field-measured tree heights based on large sample sizes has yet to be performed because of the prohibitively high costs.

In recent decades, the most significant progress in remote sensing-based forest resource investigations is due to the development of laser scanning (LS). LS, also referred to as topographical light detection and ranging (LiDAR) is an active sensing technology, which provides a practical way to measure the tree height. The major advantages of LS include (1) the direct acquisition of 3D positions of objects at the centimeter scale or even higher levels of geometrical accuracy; (2) the capability of canopy penetration, which reveals the terrain, the bases and the treetops blocked by the canopy; and (3) a high level of automation in data processing, which facilitates efficient measurements over large areas. Given the advantages, LS systems, especially airborne laser scanning (ALS), have achieved great popularity in the studies of forested ecosystems (Hyyppä et al., 2008; Nelson, 2013; Wulder et al., 2013; White et al., 2016). LS techniques have also been operationally used in national forest inventories, for example, in Nordic countries, Austria and Switzerland.

Two most commonly applied approaches to ALS-based forest inventory are the area-based approach (ABA) and the individual tree-based approach (ITD). The ABA retrieves the forest structure at a stand level, and the ITD extracts tree parameters by individual tree detecting and modeling. Concerning the tree height measurement, the ITD can be considered as an alternative to the conventional field measurement method. The main challenge is the quality of the ALS data, that is, the completeness and the geometric accuracy of tree digitization in the data, which affects and the ability of the ITD algorithms to detect and to model individual trees (Wang et al., 2016).

From the point of view of the point cloud data, the ALS-based tree height measurement is influenced by many factors. Næsset (2009a, 2009b) investigated the impacts of the terrain models, the sensors, and the fight and sensor configurations on ALS-derived canopy metrics. Yu et al. (2004) investigated the effects of flight altitude and laser footprint size on tree height estimation in a boreal forest and found that the underestimation of tree height (and standard deviation) increased with higher flight altitudes. The degree of underestimation did depend on species; however, birch was less affected than spruce or pine. In addition, it is possible that the quality of the digital terrain model (DTM) is reduced in the local area directly beneath a tree crown, which further influences the tree height measurements. Leckie et al. (2003) reported that errors in the ALS-derived measurement of tree base elevation due to ground vegetation and terrain micro relief could easily introduce up to 0.5 m of variability in height measurements.

Another highly relevant factor affecting the tree height estimation is the ALS point density, which depends on the sensor characteristics and flight settings. Maltamo et al. (2004) compared ALS-derived tree height measurements with accurate field measurements for 29 Scots pine trees. The field measurements were acquired with a fiberglass rod or, in the case of taller trees, using a tacheometer and theodolite with a distometer. They reported that ALS (10 pts/m^2) underestimated the tree heights by 0.65 m, with a standard error of 0.49 m. Wilkes et al. (2015) proposed a point density of 0.5 pts/m^2 to be the threshold of obtaining useable canopy height estimates from ALS. Roussel et al. (2017) stated that approximately 10 pulses/m^2 (i.e., at least 10 pts/m^2, taking multiple returns into account) are required to estimate the canopy height with a reasonable accuracy (mean bias less than 10 cm). Zhao et al. (2018) proposed an empirical model, which takes the point density as a variable for estimating the tree heights from the ALS data.

ALS systems are generally thought to underestimate tree heights due to the chances of missing treetops for various reasons. This conclusion is also based on the hypothesis that the field-measured tree height from clinometers is accurate, since most studies have relied on the field–-measured tree heights to evaluate the accuracy of the estimates from LS data (e.g., Kaartinen et al., 2012) or to construct regression models of canopy structures (e.g., Bouvier et al., 2015).

Nevertheless, the disturbance from the errors in the field measurements in evaluating ALS-based tree heights has been a common concern in previous studies. Persson et al. (2002) noted that a significant portion of the RMSE of ALS-based tree height estimates in their study could be caused by errors in the field height measurements. Hyyppä et al. (2004) recognized that the accuracy of conventional field inventory techniques may not be sufficient for detailed evaluations of the errors in ALS tree height measurements. Hunter et al. (2013) reported that under tropical forest conditions, the field-measured heights are consistently higher than the ALS-based heights for dominant trees, yet the potential underestimation bias in ALS-derived tree height is smaller than the uncertainties in the field estimates.

Rigorous comparison between LS- and field-based tree height measurements is rare due to the difficulty and cost of collecting ground truth data, and contradictory conclusions have been reached in recent discussions. For example, Andersen et al. (2006) claimed that the tree heights acquired with an impulse handheld laser rangefinder are significantly more accurate than those acquired via ALS (6 pts/m^2) based on a total station survey of 30 ponderosa pine and 29 Douglas fir trees. In contrast, Sibona et al. (2016) reported that based on destructively measured tree heights of 100 felled trees (including *Larix decidua*, *Picea* *abies* and *Pinus sylvestris*) in an alpine forest, the ALS (10 pts/m^2) estimates of tree heights were closer to the ground truth than the non-destructive field-measured heights.

The hypothesis that the field-measured tree heights are accurate enough to evaluate other measurement methods has not been seriously challenged up to now. An essential question remains unclarified: Which of the non-destructive measurement instrument/technologies is the most reliable and robust one?

To provide convincing answers to this question requires a large number of samples from forests with different types of stand conditions. However, existing accuracy comparisons between LS- and field-based tree height observations in forests are hampered by the small amount of sample data (i.e., less than a hundred individual trees) and by the fact that the forest stand conditions have been insufficiently investigated. Therefore, the conclusions derived may lack representativeness. For example, according to the pictures of the test sites provided in Andersen et al. (2006), the stands had low stem densities and flat terrain, which represent simple forest conditions favorable for rangefinder measurements. In addition, the applied LS data in existing reports are no longer representing the state of the art. Recently developed, reasonably priced LS systems produce much denser point clouds (e.g., above 100 pts/m^2 in Amiri et al. (2017)) than what was used in 10–20 years ago (e.g., approx. 10 pts/m^2 in Wang et al., 2008).

In this paper, we would like to start this discussion through a comparison study of tree heights derived from conventional field measurements, ALS and terrestrial laser scanning (TLS) in typical Nordic boreal forests. The ALS dataset used in this study is a high-density point cloud acquired from a very low flight altitude and represents a state-of-the-art scenario that is balanced between the point density and the cost. The TLS data were collected via a multi-scan approach, which represents the state-of-the-art terrestrial data in an operational scenario from various platforms (e.g., static, mobile and personal platforms (Liang et al., 2014)) and different point-cloud sources (e.g., laser scanning, image and structure light (Hyyppä et al., 2017; Liang et al., 2015)). The data were chosen to benchmark the best efforts of state-of-the-art point cloud technologies.

The analysis included 1174 individual trees in 18 sample plots. The tree heights were manually measured from the ALS and TLS datasets, and in the field using conventional non-destructive measurements techniques. The test sites, the acquisition of the LS datasets and the measurement of tree heights utilizing ALS, TLS, and field measurements are introduced in Section 2. Sections 3 and 4 carry out thorough investigations on the accuracy of the tree heights from different sources in different stand conditions. In addition, the influences of the crown class, the tree height and the species are discussed. Important findings of this study are summarized in Section 5. To the best of our knowledge, such a large dataset has not been used in evaluating tree height measurements so far. In addition, up until now, this is the most detailed study on the reliability of individual tree height measurement using LS and conventional field techniques.

2. Materials and methods

2.1. Test site and sample plots

The study area was located in a southern boreal forest in Evo, Finland (61.19°N, 25.11°E) as shown in Fig. 1. The main species in the area included Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* H. Karst L.), silver birch (*Betula pendula* Roth) and downy birch (*Betula pubescens* Ehrh). Eighteen sample plots comprising various forest stand conditions were selected for the test. The sample plots had a fixed size of 32 m × 32 m.

The sample plots were classified by professional foresters into three stand complexity categories, namely, 'easy', 'medium', and 'difficult'. The 'easy' category featured a low stem density (ca. 700 stems/ha), minimal understory growth, and mostly mature trees. The 'medium' category featured a moderate stem density (ca. 1000 stems/ha), moderate understory vegetation, and trees in diverse growing stages. The "difficult" category, featured a high stem density (ca. 2000 stems/ha), abundant understory growth, and mostly young trees. Detailed statistics for all trees (with DBH greater than 5 cm) in the three stand categories are listed in Table 1.

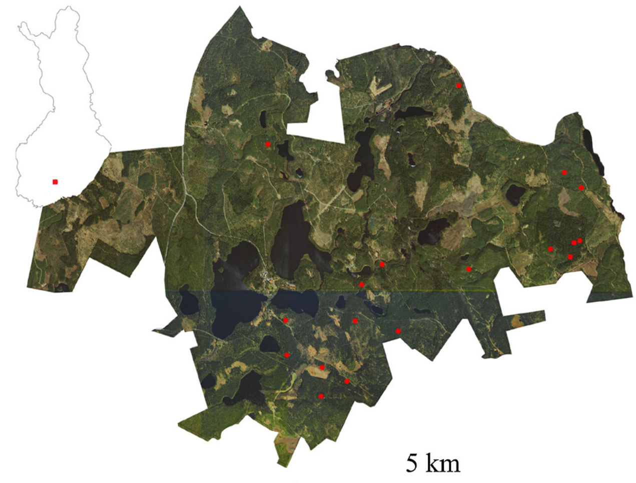


Fig. 1. Map of the test site and sample plots in Evo, Finland.

2.2. Experiment design

The aim of the experiment was to evaluate the accuracy of ALS, TLS and conventional field measurements in non-destructive tree height measurements. Thus, the following conditions must be satisfied; First, the locations of individual trees are accurately measured in the field and the LS point clouds in order to recognize corresponding trees from the three data sources; Second, tree height measurements using different technologies are independent from each other; Third, tree height measurements using each technique are independent from impact factors other than the systematic setups of the applied technologies.

Therefore, the whole process of the field measurement and the LS data processing was guided by tree maps of sample plots that were produced by a combination of interpretation of multi-scan TLS data and in-situ inspections. To guarantee the independency of the tree height measurements from different data sources and to minimize the influences of LS data processing methods, individual tree detections and tree height measurements were manually carried out in ALS and TLS point clouds separately. Therefore, no automatic point cloud processing methods, such as automatic tree detection and modeling, were applied in this study.

To solve the problem of lacking absolute ground truth of tree heights, the tree height observations from the three sources, i.e., ALS-point cloud, TLS-point clouds, and field measurements, were cross-compared to each other. The conclusions were drawn based on comparative statistical analyses and logical deductions. Furthermore, the evaluation was carried out with respect to different stand complexity conditions (i.e., easy, medium and difficult plots), crown classes (i.e., dominant, co-dominant, intermediate and suppressed trees), height groups (in 5 m interval), and species (i.e., spruce, pine and birch).

2.3. Datasets

In-situ manual measurements, in-situ multi-scan TLS data acquisitions, and low-altitude ALS data acquisitions were carried out for all sample plots.

Table 1
The statistics of the stand complexity categories.

Complexity categories	Stem density (stems/ha)		DBH (cm)		Tree height (m)		Basal area (m^2/ha)		Number of sample plots
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	
Easy	660	174	19,9	7.5	18.0	6.4	22.9	6.7	5
Medium	898	343	17.1	11.7	15.3	7.4	29.6	9.9	6
Difficult	2130	502	12.2	6.4	13.2	5.8	30.9	6.8	7

2.3.1. Multi-scan terrestrial laser scanning data

The multi-scan TLS data were collected in the sample plots as the first step in the whole data acquisition campaign. The sample plots were scanned in summer 2014, using a Leica HDS6100 TLS scanner (Leica Geosystems AG, Heerbrugg, Switzerland). The wavelength of the scanner was 650–690 nm, the field of view was 360° × 310°, and the range measurement accuracy was ± 2 mm at 25 m distance to the scanner. The data acquisition used a “high density” mode where the angle increment was 0.036° in both horizontal and vertical directions, which gives a point spacing of 15.7 mm at 25 m distance to the scanning location in both horizontal and vertical directions. A full field-of-view scan takes approximately 3 min. The raw point cloud of each scan was de-noised using the software provided by the manufacture of the scanner and with default parameter settings.

The plots were not touched during the data collection except when placing the TLS scanner and reference spheres that were used to register the individual scans. To minimize the impact of occlusion within a plot, each plot was scanned from the center and the four corners. The theoretical position of the middle scan was at the plot center and the distance between the four scans in four quadrant directions to the center scan was 11.3 m. Six spheres were placed such that they were visible to the center scan and at least three spheres could be seen in each corner scan. The average registration accuracy for all sample plots was approximately 2 mm, which corresponds to the discrepancy between the 3D sphere locations in the registered scans.

The multi-scan TLS point cloud was then registered to the world coordinate system (EUREF-FIN) based on the locations of the reference spheres measured with a Trimble R8 GNSS receiver (Trimble Inc., CA, USA) with a real-time kinematic correction and a Trimble 5602 DR200+ total station. The GNSS receiver was used to define at least two reliable reference points in an open area either inside or outside each plot to guarantee the visibility of the satellites. A survey point was established near the plot center by measuring the distance and angles from the survey point and two reference points. The locations of the reference spheres (ATS Scan Reference System, ATS Ab, Goethenburg, Sweden) were then measured using the total station. The goal of this setup was to achieve a registration precision that was as high as possible for the multi-scan TLS datasets, so that the alignment between the TLS and the ALS point clouds could be realized.

2.3.2. In situ field measurements

Based on the multi-scan TLS data, a preliminary tree map was generated for each sample plot by manually labeling trees with high stem visibility in the point cloud, which guided the following field measurements in each sample plot.

In the field, the preliminary tree map was verified and updated by double-checking the locations of labeled trees and adding the omitted trees (due to occlusions in the data) to the map. For each sample plot, all the standing trees with a DBH value greater than 5 cm were marked on the finalized tree map. The locations of the trees were then revisited again in the multi-scan TLS point cloud to inspect the consistency between the on-site modifications and the point cloud.

During the on-site plot visiting, the heights of all mapped trees were measured with a Vertex 3.0 instrument (Haglöfs, Sweden) at a resolution of 0.1 m. For each mapped tree, three independent measurements were made from the same location where the visibility of the treetop was guaranteed, and the average was used as the tree height. The species and the DBH of the mapped trees were also recorded.

In addition, all the trees on the tree map were classified into four different crown classes, i.e., dominant (Dom), codominant (CoD), intermediate (Int) and suppressed (Sup), following the quantificational definitions applied in Kaartinen et al. (2012) and Wang et al. (2016):

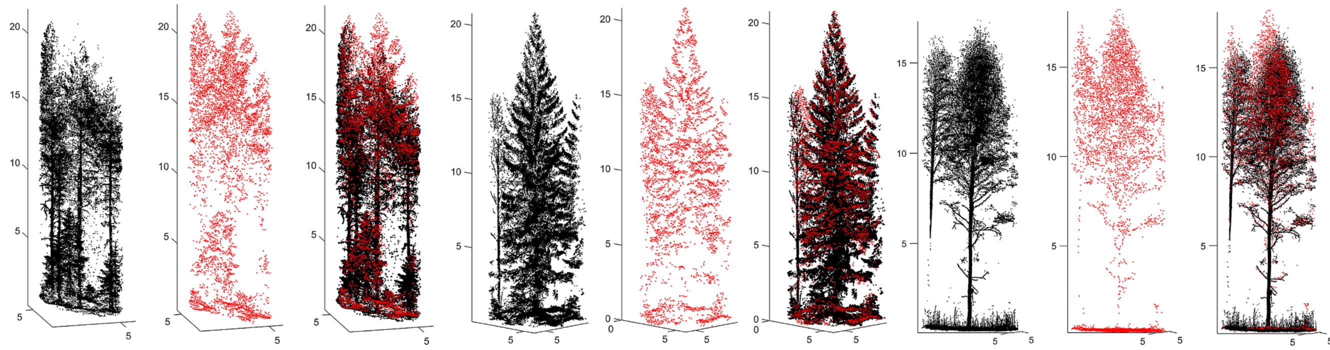
Dominant:	Tallest trees in the neighborhood or isolated trees that have a 2D distance to the closest neighboring tree that exceeds 3 m;
Codominant:	Trees in a group of similar trees, where the 2D distance between these trees and the closest neighbor is less than 3 m;
Intermediate:	Trees located next to a larger tree and whose crowns are partly covered;
Suppressed:	Trees located under a larger tree and whose crowns are totally covered by neighboring crowns.

2.3.3. High-density airborne laser scanning data

The ALS data were acquired in the winter 2014 from a helicopter using a Riegl VQ-480-U scanner (RIEGL Laser Measurement Systems GmbH, Austria). The Riegl VQ-480-U is a light-weight (7.5 kg) pulsed scanner with a 60° field of view. The laser beam wavelength is 1550 nm, and the beam divergence is 0.3 mrad. The scanner was operated with a scan speed of 150 Hz and a pulse repetition rate of 550 kHz. The flight altitude was 75 m above the ground level, which is a similar to the altitude of a drone (i.e., UAV) platform; thus, the ALS data can be considered analogous to UAV-based LS data. The target flight speed was 50 km/h; therefore, a very dense point cloud was produced with a ground footprint size, on-ground pulse spacing along the scan line, and on-ground pulse spacing between scan lines of approximately 2.3 cm, 4.7 cm, and 9.3 cm, respectively. The error points, that is, isolated points in the sky or below the ground level were manually removed. The point density of the ALS data was approximately 450 points/m^2.

The ALS data was geo-referenced into a world coordinate system (EUREF-FIN). To further align the aerial and terrestrial point clouds, the ALS point clouds of the sample plots were manually co-registered to the multi-scan TLS point clouds by determining whether the tree crowns in both point clouds overlapped from the top-view and two side-views. Manual fine-tuning was implemented when an offset between the point clouds remained observable in the horizontal plane. Based on an on-screen estimation, the remaining discrepancy between the ALS and TLS point clouds was less than 10 cm in the horizontal plane.

Fig. 2 illustrates three examples of trees recorded in the multi-scan TLS and ALS point clouds. The examples were selected after the representative species on site, that is, a group of pine trees, a spruce tree, and a birch tree. Fig. 2(a–c) presents the occlusion effects in the TLS data, especially on the upper part of crowns. The crown of the tree in the middle is occluded by the tree to its left. In Fig. 2(d–f), an ideal situation is presented in both TLS and ALS data. Fig. 2(g–i) show the occlusion on the upper crown of a tree brought by its own lower crown in the TLS data. The figures also show that the influence of the leaf-off situation on the height of birch trees is minor, for example, referring to the lower branches of the birch tree recorded in the ALS data. Furthermore, considering the shape of the crowns in the ALS data, there is no evidence of canopy deformation brought by downwash of the helicopter.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Fig. 2. Examples of trees in the LS data. LS point clouds are in local coordinate system and the axes unites are in meters; (a) a group of pine trees in multi-scan TLS data; (b) the corresponding trees of (a) recorded in ALS data; (c) multi-scan TLS and ALS data of the pine trees in the same scene; (d) a spruce tree in multi-scan TLS data; (e) the corresponding spruce tree of (d) recorded in ALS data; (e) multi-scan TLS and ALS data of the spruce tree in a same scene; (g) a birch tree in multi-scan TLS data; (h) the birch tree in (e) recorded in ALS data; (i) multi-scan TLS and ALS data of the birch tree in the same scene.

2.4. Tree height measurement from aerial and terrestrial point clouds

DTMs were generated from the multi-scan TLS data and the ALS data independently. Regardless the source of the point cloud, the generation of DTMs followed an identical procedure. First, points belonging to the ground were classified utilizing the classification algorithm in TerraScan software (TerraSolid oy, Helsinki, Finland). The algorithm is based on the method introduced in Axelsson (2000). Second, a DTM of 20 cm × 20 cm resolution was fitted to the ground points by applying linear interpolation to fill in the shadowed (no data) space. In a final step, the DTMs were visually inspected and any abnormal peaks were manually removed. The altitude differences between the ALS- and multi-scan TLS- based DTMs are given in Fig. 3. In the easy and medium plots, the RMSDs (Root-Mean-Square-Deviations) between the DTMs are below 10 cm. In difficult plots, due to the shadows on ground in both ALS and TLS point clouds, the difference between the DTMs significantly increased (e.g., doubled compared to the easy and medium plots), but the RMSD was below 20 cm and the per *XY* location bias was below 6 cm. The altitudes of the TLS-based DTMs tend to be higher than that of the ALS-based DTMs (i.e., Fig. 3(b)).

Both multi-scan TLS data and ALS data were normalized with respect to the corresponding DTM extracted from each LS data separately. The tree heights were manually measured from the normalized point clouds under the guidance of the tree maps. For each tree on the tree maps, the existence of its treetop was interactively inspected in the TLS or ALS point clouds. The ALS- and TLS-based treetop identification of all individual trees was carried out by an experienced operator, and the treetops were defined as the highest visible TLS or ALS point inside the crown area of an individual tree. The normalized height of the TLS or ALS treetop point was then taken as the tree height from the corresponding data source. Among 2417 individual trees present in the 18 sample plots, 1174 trees satisfied the condition stipulating that their treetops were identifiable by the human eye in both the multi-scan TLS and the high-density ALS point clouds, indicating that both ALS-based and TLS-based tree heights were available. The following analysis of the tree heights is based on these 1174 trees.

2.5. Evaluation

The comparison was carried out in pairs. The Pearson's correlation coefficient (***r***), the RMSD, RMSD%, bias and bias% were calculated in three pairs: the ALS-based versus the field-based tree heights, the TLS-based versus the field-based tree heights, and the TLS-based versus the ALS-based tree heights. The RMSD% and bias% were the relative versions of the RMSD and bias, respectively, and they equaled $\text{RMSD\%} = 100\% \times \text{RMSD}/\bar{H}$ and $\text{bias\%} = 100\% \times \text{bias}/\bar{H}$, where $\bar{H}$ is the mean tree height. In addition, the influence of the stand condition (easy, medium, and difficult) and the four crown class on each of the three measurement techniques was investigated. The detailed results of the analysis are given in Section 3.

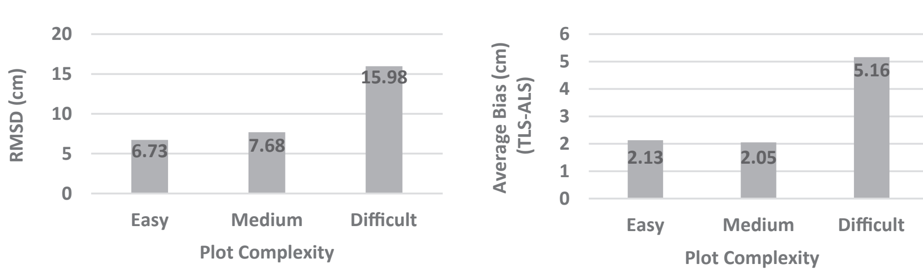
In addition, the analysis identified a group of outliers, in which clear differences exists among the three tree height measurements, indicating that at least one of the measurements likely contains coarse error. The outliers are defined as follows: for each tree t^i, $i = 1, \cdots, n$, where i is the index of the tree and n is the number of trees, the relative residual $\Delta^i_{(a,\text{field})}$ between the measurement method a, $a \in \{\text{'ALS'}, \text{'TLS'}\}$ and field measurement were calculated using the equation

$$\Delta^i_{(a,\text{field})} = |H^i_a - H^i_{\text{field}}|/H^i_{\text{field}} \tag{1}$$

where H^i_a is height observation of the tree t^i from the measurement source a. H^i_{field} is the height observation of the tree t^i from the field. Using the relative difference $\Delta^i_{(a,\text{field})}$, we define the outlier S (also called a 'suspicious case' below) as

$$S = \{t^i | \ \Delta^i_{(\text{TLS,field})} \geq 0.2 \bigvee \Delta^i_{(\text{ALS,field})} \geq 0.2\} \tag{2}$$

The outliers are considered as errors, therefore, excluded from the



(a) (b)

Fig. 3. Comparison between the ALS-based and Multi-scan TLS-based DTMs; (a) RMSD between TLS-based and ALS-based DTMS; (b) Per *XY* location bias between TLS-based and ALS-based DTMs.

Table 2
Statistical evaluations of the comparisons of tree heights derived from ALS, TLS and field measurements in easy plots.

Crown Class	ALSv.Field			TLSv.Field			TLSv.ALS		
	RMSD (RMSD%)	Bias (Bias%)	r	RMSD (RMSD%)	Bias (Bias%)	r	RMSD (RMSD%)	Bias (Bias%)	r
Dom	0.61 m (3.2%)	0.06 m (0.3%)	0.99	1.60 m (8.2%)	−0.96 (−4.9%)	0.95	1.51 m (7.7%)	−1.02 m (−5.2%)	0.97
CoD	0.56 m (2.7%)	−0.06 m (−0.3%)	0.99	2.05 m (9.9%)	−1.44 (−7.0%)	0.95	1.87 m (9.1%)	−1.38 m (−6.7%)	0.95
Int	1.17 m (6.9%)	0.22 m (1.3%)	0.98	1.15 m (6.8%)	−0.70 (−4.2%)	0.98	1.42 m (8.3%)	−0.92 m (−5.4%)	0.98
Sup	0.38 m (5.4%)	−0.11 m (−1.6%)	0.98	0.35 m (5.0%)	−0.23 (−3.3%)	0.99	0.27 m (3.9%)	−0.11 m (−1.7%)	0.99
All	0.69 m (3.6%)	0.04 m (0.2%)	0.99	1.68 m (8.8%)	−1.04 (−5.5%)	0.97	1.59 m (8.3%)	−1.08 m (−5.7%)	0.97

analyses in Sections 4.2–4.4. They are separately discussed in Section 4.5.

3. Results

The evaluations of the ALS-based and TLS-based tree heights with respect to the field-based tree height are denoted as ALSv.Field and TLSv.Field, respectively. The evaluation of the TLS-based tree height with respect to the ALS observations is denoted as TLSv.ALS. All 1174 trees were included in the analyses in this section. It should be noted that for the RMSE% and bias%, the divisor $\bar{H}$ of the ALSv.Field and TLSv.Field comparison was the average of the field- measured tree heights, while the divisor of the TLSv.ALS comparison was the average of the ALS-based tree heights.

3.1. Tree height observations in the easy plots

In the easy stands, a high correlation was observed among the tree heights from all three data sources, that is, the values of correlation coefficients ($\boldsymbol{r}$) are close to 1.0. The detailed statistics are listed in Table 2. Overall, the RMSD and bias values of the ALSv.Field indicate a high consistency between ALS- and field-derived tree height measurements in the easy plots. The intermediate crown class has the lowest consistency between the ALS- and field-based tree height estimates, suggesting a higher uncertainty in the tree height measurements of intermediate trees. The distribution of the tree height estimates in Fig. 4(a) reveals that ALS generally does not underestimate the tree height with respect to the field-measured tree height as the overall bias is 0.04 m and hence close to zero.

The RMSD and bias values of TLSv.Field and TLSv.ALS clearly showed that TLS underestimates the tree heights. This agreed the general understanding on TLS-based tree height measurements (e.g., Liang et al. (2018)) A more detailed investigation indicates that a turning point exist at a tree height of approximately 15 m. For trees taller than 15 m, the residuals between the TLS-based tree height and the other two tree heights are markedly higher, as shown in Fig. 4(b) and (c). When the tree heights are above 20 m, such residuals increase even more remarkably. Thus, a threshold for reliable TLS-based tree height measurements is suggested to be below 15–20 m.

3.2. Tree height observations in medium plots

The correlation in medium plots remains strong among the tree heights derived from all three different sources, as shown in Table 3 and Fig. 5. However, the residuals between tree height measurements from different sources become larger than those in the easy plots. The results, as illustrated in Fig. 5(a), indicate that the intermediate crown class has the highest uncertainty in the ALS vs. field comparison. According to the bias values in Table 3, the ALS-based tree heights are obviously lower than those from the field (−0.52 m bias) for co-dominant trees, which was, however, not observed in other crown classes.

For TLS-based tree heights, the turning point at approximately 15 m remains observable in the medium complexity stands, as shown in Fig. 5(b) and (c). The TLS-based tree heights of trees lower than 15 m are consistent with the ALS-based and the field-based tree heights. However, significant underestimations present in the TLS-based tree heights with respect to both ALS- and field-based tree heights for trees taller than 15 m.

When the tree height is below 15 m, the majority of the outliers in the medium plots of all three pair comparisons come from the intermediate trees (Fig. 5). This is similar to is the situation in the easy plots (Fig. 4).The largest disagreements of this tree-crown class among different sources suggest that the heights of intermediate trees are difficult to measure. Fig. 5 also shows that, when the tree height is below 15 m,

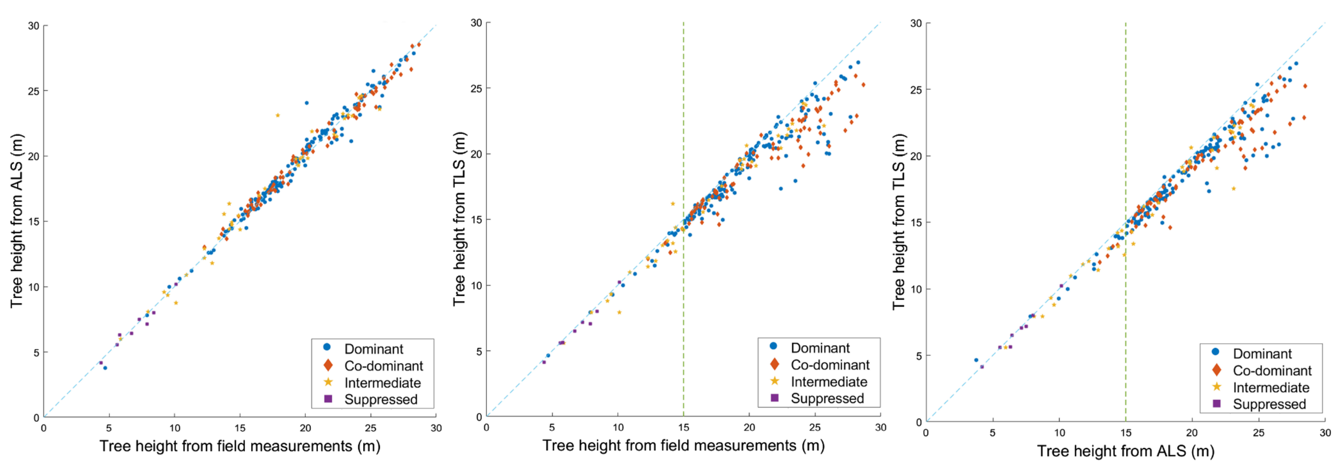


Fig. 4. Correlation of tree height observations from ALS, TLS and field measurements in easy forest stands: (a) ALS vs. field; (b) TLS vs. field; (c) TLS vs. ALS. The dashed light blue line represents the identity function $y = x$. The vertical lines in (b) and (c) indicate the turning point at 15 m beyond which TLS tends to underestimate the heights of trees. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3
Statistical evaluations of the comparisons of tree heights derived from ALS, TLS and field measurements in medium plots.

Crown Class	ALSv.Field			TLSv.Field			TLSv.ALS		
	RMSD (RMSD%)	Bias (Bias%)	*r*	RMSD (RMSD%)	Bias (Bias%)	*r*	RMSD (RMSD%)	Bias (Bias%)	*r*
Dom	0.98 m (4.7%)	−0.03 m (−0.2%)	0.99	2.48 m (11.8%)	−1.72 (−8.2%)	0.97	2.34 m (11.1%)	−1.69 m (−8.1%)	0.98
CoD	0.98 m (5.6%)	−0.52 m (−3.0%)	0.99	1.88 m (10.9%)	−1.48 (−8.6%)	0.98	1.41 m (8.4%)	−0.96 m (−5.7%)	0.99
Int	1.41 m (11.7%)	0.28 m (2.3%)	0.94	1.08 m (8.9%)	−0.33 (−2.7%)	0.96	1.43 m (11.5%)	−0.60 m (−4.9%)	0.94
Sup	0.31 m (4.3%)	−0.01 m (−0.2%)	1.00	0.26 m (3.6%)	−0.02 (−0.3%)	1.00	0.21 m (2.9%)	−0.01 m (−0.1%)	1.00
All	1.11 m (6.6%)	−0.12 m (−0.7%)	0.99	1.92 m (11.4%)	−1.21 (−7.2%)	0.98	1.77 m (10.6%)	−1.09 m (−6.5%)	0.98

more co-dominant and intermediate trees are located closer to the identity function in (c) than in (a) and (b). This indicates a higher agreement between the ALS- and TLS-based tree height measurements compared to the agreement between ALS and field and agreement between TLS and field. For suppressed trees, all three tree height measurement techniques maintain a very high consistency, with r equal to 1.0 and bias close to zero (Table 3).

3.3. Tree height observations in difficult plots

In contrast to the easy and medium plots, large disagreements were observed among the tree height measurements in the difficult forest stands. The overall correlation coefficients of the ALSv.Field and the TLSv.Field decreased to below 0.95, and the correlation coefficients of the intermediate and the suppressed trees in the ALSv.Field and TLSv.Field comparisons dropped by approximately 50%, as shown in Table 4.

On the other hand, the correlation coefficient of the TLSv.ALS tree heights in difficult stands remained at a robust level similar to that in the easy and medium plots. These results indicate that, in the difficult stands, a good agreement existed between the ALS- and TLS-based tree heights, while the field-based tree heights deviated from both the ALS- and TLS-based tree heights. This pattern can also be observed by comparing the sub-figures of Fig. 6, in which the number of the outliers in (a) and (b) is clearly higher than that in (c).

With respect to the crown classes, the tree heights of dominant and codominant trees from both the ALS and TLS data tended to be lower than those from the field measurements (with above 0.5 m negative bias). For intermediate and suppressed trees, the height estimates from ALS and TLS clearly deviated from the field measurements, thereby producing the majority of the outliers. Compared with the field measurements, the disagreements between ALS- and TLS-based tree heights, especially for intermediate and suppressed trees, were clearly lower, as illustrated in Fig. 6(c). The 15-m turning point for the underestimation of TLS-based tree height in the TLSv.Field comparisons was less significant in difficult plots than in the easy and medium plots (Fig. 6(b)). However, it was still present in the TLSv.ALS comparison, as shown in Fig. 6(c).

4. Discussion

The findings from the cross-comparisons of tree heights derived from ALS, TLS and field regarding the plot complexity are summarized in Section 4.1. To further clarify the causes for the disagreements between the three height measurement techniques, we need to study the trees that clearly deviate from the identity functions if Figs. 1–3 (i.e., outliers/suspicious cases). Three sets of outlier cases, that is, $S_{(als,field)}$, $S_{(tls,field)}$ and $S_{(als,tls)}$, were identified according to Eq. (2) in Section 2.4. Out of the 1174 trees, a subset of 103 trees, or 9%, were identified as outliers, and was excluded from discussion in Sections 4.2–4.4, then specifically studied in Section 4.5.

4.1. The tree height observations in different stand categories and crown classes

According to the comparison results in Section 3, in general, disagreements between the ALS-, TLS- and the field-based tree height measurements increase with an increasing complexity of the forest stand. The following three interesting observations were achieved. First, the correlation between the TLS- and ALS- based tree height measurements are robust with respect to the stand conditions. The values of r in TLSv.ALS comparisons remained at a same level in three stand complexity categories as shown in Tables 2–4. On the contrary, the correlations in the ALSv.Field and TLSv.Field comparisons

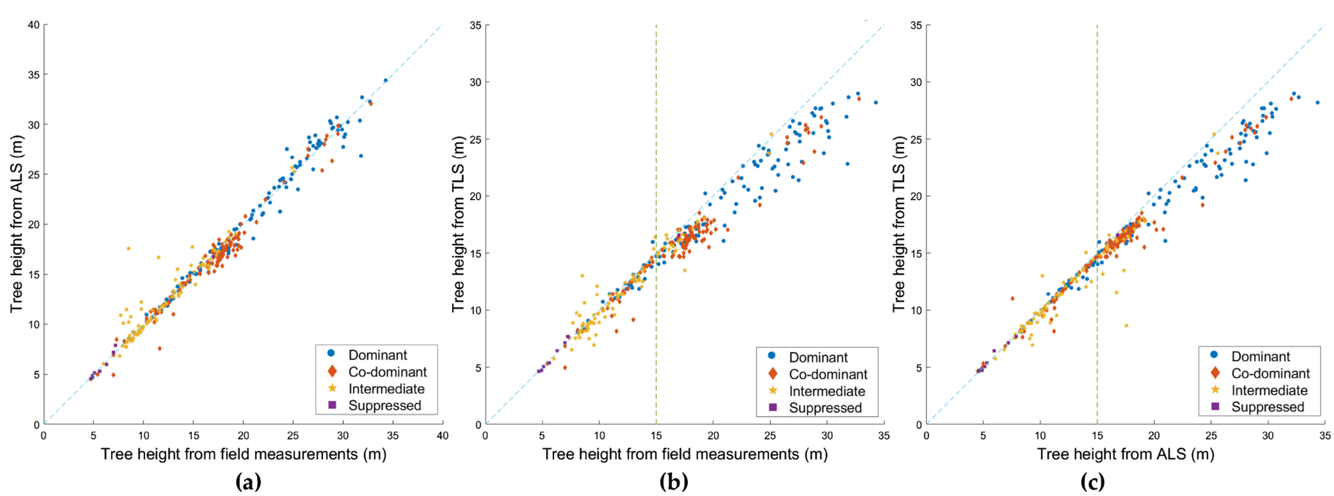


Fig. 5. Correlation analyses for tree height observations from ALS, TLS and field measurements in medium forest stands: (a) ALS vs. field; (b) TLS vs. field; (c) TLS vs. ALS. The dashed light blue line represents the identity function $y = x$. The vertical lines in (b) and (c) indicate the turning point at 15 m beyond which TLS tends to underestimate the heights of trees. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Statistical evaluations of the comparisons of tree heights derived from ALS, TLS and field in difficult plots.

Crown Class	ALSv.Field			TLSv.Field			TLSv.ALS		
	RMSD (RMSD%)	Bias (Bias%)	*r*	RMSD (RMSD%)	Bias (Bias%)	*r*	RMSD (RMSD%)	Bias (Bias%)	*r*
Dom	1.16 m (6.2%)	−0.52 m (−2.8%)	0.98	2.50 m (13.4%)	−1.79 (−9.6%)	0.94	1.80 m (9.9%)	−1.27 m (−7.0%)	0.96
CoD	1.14 m (6.1%)	−0.65 m (−3.4%)	0.95	2.08 m (11.1%)	−1.69 (−9.0%)	0.92	1.43 m (7.9%)	−1.04 m (−5.8%)	0.94
Int	2.01 m (15.4%)	0.28 m (2.2%)	0.86	1.96 m (15.0%)	−0.45 (−3.4%)	0.86	1.61 m (12.0%)	−0.73 m (−5.5%)	0.92
Sup	2.66 m (41.4%)	0.99 m (15.4%)	0.51	2.18 m (33.9%)	0.76 (11.9%)	0.55	0.81 m (11.0%)	−0.22 m (−3.0%)	0.97
All	1.69 m (10.8%)	−0.12 m (−0.8%)	0.94	2.11 m (13.6%)	−1.02 (−6.6%)	0.94	1.56 m (10.1%)	−0.90 m (−5.8%)	0.96

significantly vary with the changing stand conditions, especially for intermediate and suppressed trees. Taking the suppressed tree as an example, the values of ***r*** in easy, medium and difficult plots were 0.99, 1.00, and 0.55, respectively, in the TLSv.Field comparison; In the ALSv.Field comparison, the corresponding values of ***r*** were 0.98, 1.00, and 0.51, respectively, and in the ALSv.TLS comparison 0.99, 1.00, and 0.97, respectively. Considering the totally different terrestrial and aerial viewing geometries of the TLS and the ALS, the high correlation between TLS and ALS suggests that both TLS and ALS data record the top part of tree crowns. Specifically in the difficult plots, the RMSD of TLS and ALS tree height measurements was 0.81 m, which also supports the assumption that both TLS and ALS data approximately reached the top part of crowns. Meanwhile, in difficult plots, the ***r*** of suppressed trees in ALSv.field was 0.55 and in TLSv.field 0.51, which dropped approximately 50% in comparison with the easy and medium plots. The 2.66 m RMSD in ALSv.field and 2.18 m RMSD in TLSv.field revealed large disagreements between ALS- and field-, as well as between TLS- and field- measured tree heights for suppressed trees in difficult plots. It is therefore reasonable to question the reliability of the field-measured suppressed tree heights in difficult plots. The possible reasons for the unreliable field-based suppressed tree height can be the difficulties of identifying treetops or measuring instrument-stem distances due to the dense undergrowth. Thus, it can be concluded that the field-measured tree height was more sensitive to the stand conditions than the LS systems. The more complex the stand, the more unstable was the performance of the field measurements.

Second, from the point of view of the crown classes, the highest uncertainty is associated with the intermediate trees, regardless of the stand conditions or the applied measurement methods (Tables 2–4). In easy and medium plots, all three techniques provide creditable tree height measurements for suppressed trees, with less than 0.40 m RMSD and correlation ***r*** close to one in all comparisons. In difficult plots, the uncertainties in the height of suppressed trees significantly raised, and as discussed above, such uncertainties can be associated with the instability of the field measurements. Thus, it can be concluded that ALS performance was stable in height measurements of suppressed trees, regardless of the stand conditions.

Third, the ALS-based tree heights can be either higher or lower than those of the field measurements, except for the co-dominant trees whose height estimates tend to be lower than the field measurements in all stand conditions. The underestimations in TLS-based tree heights were easy to recognize, especially when the trees were taller than 15 m.

4.2. The agreement and disagreement in the tree heights observations from different sources

By excluding the outliers, the absolute values of the tree heights acquired from the ALS-, TLS- and field-based measurements in all 18 sample plots are plotted in Fig. 7 in ascending order sorted by the field-based tree height. The four sub-figures represent the different crown classes.

According to Fig. 7(a)–(d), the residuals between the ALS-, TLS- and field-based tree heights of trees lower than 15 m are smaller than those of the trees taller than 15 m, indicating a common reliability of the tree height measurements for small trees from all three techniques. It is again recalled in Fig. 7(a)–(c) that underestimation of tree heights from TLS become more obvious for trees taller than 15 m. In the ALS-based tree height observations for trees taller than 15 m, no significant trend of over- or underestimation can be observed in dominant and intermediate trees, as shown in Fig. 7(a) and (c). However, for the co-dominant trees in Fig. 7(b), the ALS-based tree heights tended to be lower than the field-based tree heights, specifically when trees are taller than 15 m.

For trees taller than 15 m (outliers excluded), the RMSD and bias values of the ALSv.field comparison are (RMSE and bias, respectively) 0.84 m and −0.04 m for dominant trees, 1.02 m and −0.54 m for co-

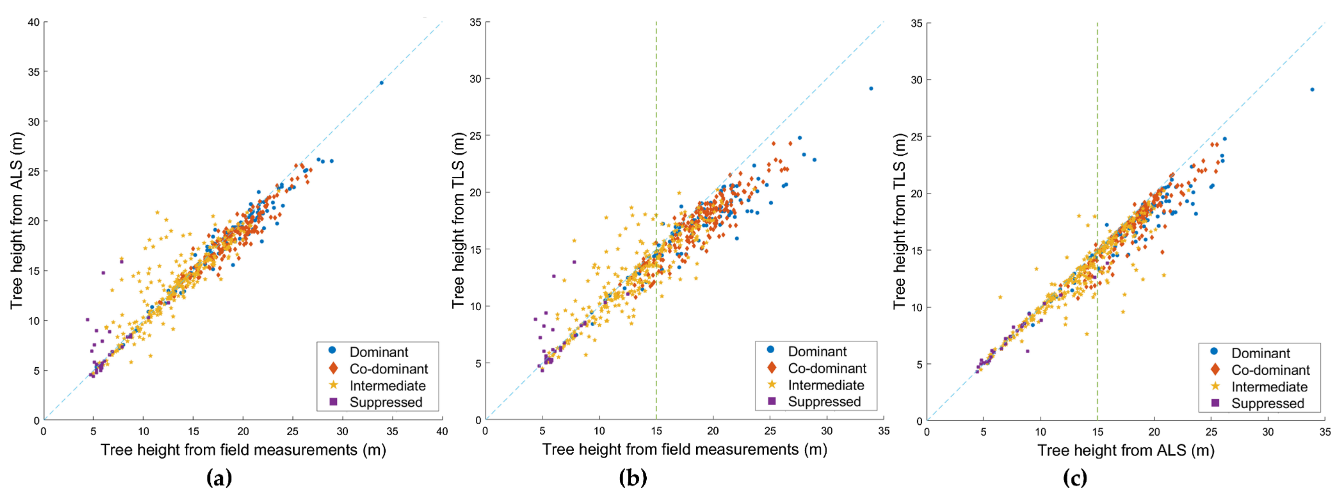


Fig. 6. Correlation analyses for tree height observations from ALS, TLS and field measurements in difficult forest stands: (a) ALS vs. field; (b) TLS vs. field; (c) TLS vs. ALS. The vertical lines in (b) and (c) indicate the turning point at 15 m beyond which TLS tends to underestimate the heights of trees.

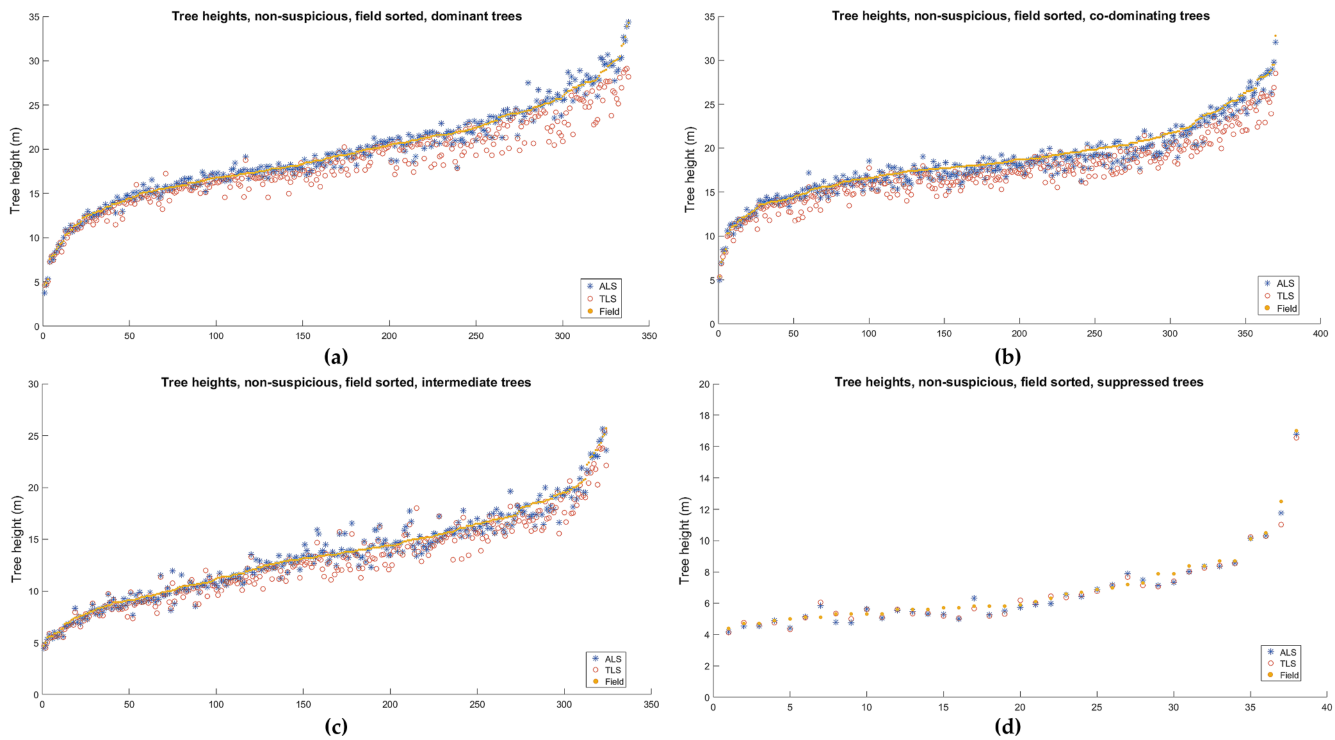


Fig. 7. Tree height observations from ALS (in blue), TLS (in red) and field measurements (in yellow) for dominant (a), co-dominant (b), intermediate (c) and suppressed (d) trees. The x-axis represents the number of trees; the y-axis represents the absolute tree height value. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

dominant trees, and 1.06 m and 0.00 m for intermediate trees. Suppose that ALS underestimates tree heights as understood in previous studies. Then, the underestimation should at least appear on all trees in the uppermost canopy layer, which is not the case in this study. Therefore, it is safe to suggest that, in this study, the field-measured heights for tall trees in codominant canopy class tended to be higher than the real tree height.

As was reported in Larjavaara and Muller-Landau (2013), due to the difficulty in determining the exact locations of the base and the top of a tree from a distance, operators tend to shoot high up when using tangent tree height instruments, leading to overestimations of the tree height. The abnormality of the field-based tree height for co-dominant trees also suggests that it was more difficult for the field operators to define the treetops of co-dominant trees even when they were located in the uppermost canopy layer. Thus, at least in this study, the overestimation of the height of the co-dominant trees in the field-based technique can be considered as a systematical phenomenon.

4.3. The impact of tree height on tree height measurements

The RMSD% of the ALSv.Field comparison generally decreases with an increasing tree height, as shown in Fig. 8(a). However, such a trend reaches an inflection point at tree heights greater than 20 m, and the RMSD% starts to rise. This pattern is unreasonable for ALS data since tall trees should have a better observation geometry and suffer less from occlusion effects than small trees. Thus, tall trees should be observed with higher certainty than small trees. Hence, the increased ALSv.Field RMSD% for trees above 20 m height can most likely be attributed to the decreased accuracy in the field-based tree heights. In this case, the field-based tree height observations were higher than the true heights, in agreement with the findings based on the crown classes in the previous section.

The increasing trend in TLSv.Field RMSD% in Fig. 8(b) agrees with the general understanding of the TLS-based tree height observations, namely, the taller the tree, the higher are chances for tree height underestimation.

On the other hand, the ALS- and TLS-based tree height observations have a stronger agreement. The RMSD value is below 0.4 m for trees under 10 m, and below 1 m for trees between 10 and 20 m, as shown in Fig. 8(c). This observation is similar to the findings presented in Section 3 demonstrating that the threshold for reliable TLS-based tree height observation is between 15 and 20 m. Notably the TLSv.ALS RMSD% of

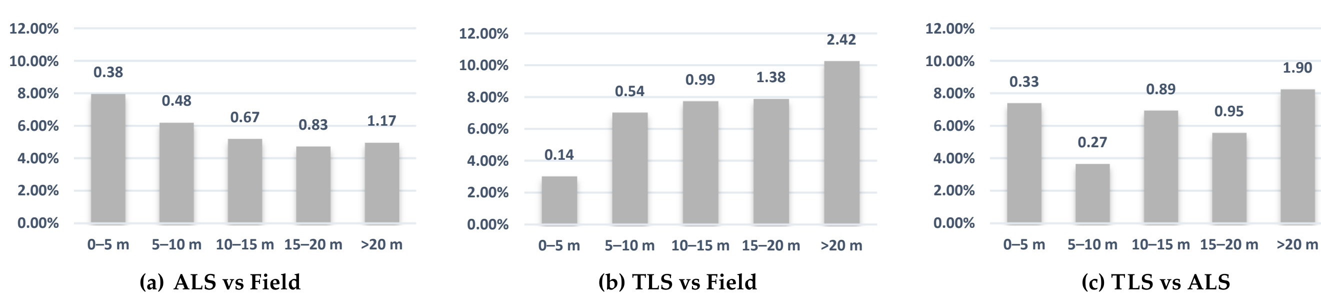


Fig. 8. RMSDs of tree height observation pairs in different height categories. x-axis is the tree height category; y-axis represents RMSD% of the compared tree height observations; labels above the bars represents the RMSD values in each tree height category, the units are in meters.

the tree height group 0–5 m included a single large error, which did not belong to the outlier case defined by Eq. (2). The larger error significantly influenced the RMSD% calculation in the group of small trees. Should this case have been excluded, the TLSv.ALS RMSD would have been 0.15 m (3.4%), which was more than 50% less than the value given in Fig. 8(c). Consistency exists between the ALS- and TLS-based tree height observations of small trees (i.e., below 10 m), where TLS has a favorable viewing geometry of small trees and a high probability of recording their tree tops. This consistency reveals that once sufficient visibility was provided, high-density ALS is capable of recording the treetops of small trees.

In summary, for tree height measurement, the influence from the geometric accuracy inside the TLS and ALS point clouds was not crucial. However, the different observation perspectives, that is, terrestrial vs. aerial, did have significant impacts on the visibility inside the canopies and consequently influenced the performance of the LS systems in digitizing the trees. Given the robustness of systematic geometric accuracy of the LS point clouds, the actual accuracy of the height estimate of a tree was determined by the completeness of the tree digitization in the point clouds. For example, TLS has a limited capacity to measure tree height for trees taller than 15 m in complex stands, mainly caused by the dropped completeness of the upper crowns due to the strong occlusion effects. When the trees were completely captured, for example, for most of the suppressed trees, TLS-measured tree heights were highly accurate.

4.4. The impact of species on tree height measurement

The total number of trees in each species class was 398, 324, 323 and 29 for pine, spruce, birch and others, respectively. The distribution of each species in different crown classes is illustrated in Fig. 9. The dominant trees in the test plots were mainly comprised by pines and spruces, and the co-dominant trees were mainly pines and birches. The amount of the three tree species in intermediate trees were similar, and the suppressed trees were mainly spruces. Considering the sizes of the samples, the following discussion is concentrated on the pines, spruces and birches.

As illustrated in Fig. 10(a)–(c), the largest residuals existed in the TLS- and the field-based tree height measurements regardless of the species. A general trend was that the tree height observations of ALS lay between those of field and TLS. Usually, the field-measured tree height is the highest among the three methods, and TLS-based tree height is the lowest, with the distance between ALS- and TLS-based tree heights larger than that between ALS and field. Such a trend was less relevant to the species classes.

Given the robustness of the geometric accuracy in LS point clouds (Section 4.3), the accuracy of the LS-based height estimation of a tree was determined by the visibility of the tree in the point cloud, that is, how completely the tree was recorded in the data. In Fig. 10(c), it is shown that the largest residuals between ALS and TLS tree height observations came from spruce, followed by birch. From the aerial perspective of the ALS, it was unlikely that the crown completeness could be seriously impacted for a large population of spruce and birch; therefore, it should be the TLS-based tree height observations that were influenced due to the occlusions brought by the branches of spruce and birch at the lower part of the stem. Thus, the influence of the species to the LS-based tree height measurements was actually due to the occlusion effects brought by the crown and branch shapes of certain species.

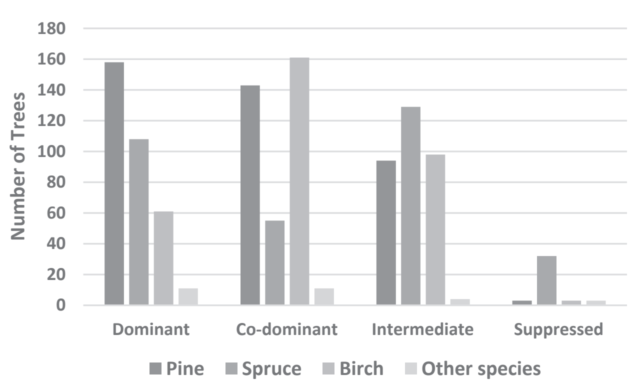


Fig. 9. Distribution of species in crown classes.

What comes to the comparison between ALS- and field-based tree heights, it was clear that the residuals for pine and spruce kept at a similar level, which was approximately 0.6 m. For birch, the residuals between the two observations almost doubled (Fig. 10(a)). Considering the point density of the applied ALS data, as previously mentioned, the ALS-based tree heights were relatively robust against different species classes. Therefore, it can be suggested that the higher residual of birch in the ALS- and field-based tree height comparisons was mainly brought by the uncertainties in the field-measured tree heights. Namely, uncertainties in field-measured tree heights of birch were higher than those of pine and spruce, which agreed with the understanding that the in-situ identification of the treetop of birch was much more difficult than that of pine and spruce.

4.5. Analysis of the outliers

In the 103 cases of outliers, 38 cases (36.9%) were associated with uncertainty in the field-based measurements, 17 cases (16.5%) were associated with uncertainty in the ALS-based measurements, and 48 cases (46.6%) were associated with uncertainty in the TLS-based measurements. The outliers represent errors in the measurements, thus, the appearance of the outliers in each measurement methods reveals the weaknesses of the corresponding method.

4.5.1. Cases in which the field-based tree heights were more uncertain than the other measurements

In total, 38 trees fell into the intersection of $S_{(\mathrm{ALS,field})} \cap S_{(\mathrm{TLS,field})}$. As illustrated in Fig. 11, for all trees in this group, relative residuals between ALS and TLS based tree heights were below 30%, which is a much lower value than that of ALSv.Field and TLSv.Field. This indicates that the large residuals are likely caused by errors in the field-based tree heights.

As discussed in previous sections, compared to the LS systems, the field measurements are more sensitive to the stand conditions, the crown classes of trees, and the species of trees. The distribution of the outlier cases in Table 5 indicates that the field measurements are hampered by the difficult forest stands, where there are high risks of errors in the tree height measurements of intermediate and suppressed trees.

4.5.2. Cases in which the ALS-based tree heights were more uncertain than the other measurements

In total, 17 trees have large residuals associated only with ALSv.Field, that is, the trees are in set $S_{(\mathrm{ALS,field})}$ but not in the set $S_{(\mathrm{TLS,field})}$. The relative residuals of the ALSv.Field, TLSv.Field and TLSv.ALS comparisons of these 17 trees are illustrated in Fig. 12. Because the ALS-based tree height observations deviated from those of the other two datasets, the uncertainty is clearly much higher in the ALS-based observations.

Fifteen of the 17 trees, were intermediate trees (Table 6). The number of intermediate trees increases with an increasing forest stand complexity. The remaining two of the 17 included one co-dominant tree in a medium plot and one suppressed tree in a difficult plot. Therefore, the intermediate trees are the most challenging cases for ALS-based tree height measurement, associated with difficulty of identifying the exact treetop location of such trees in the ALS point cloud.

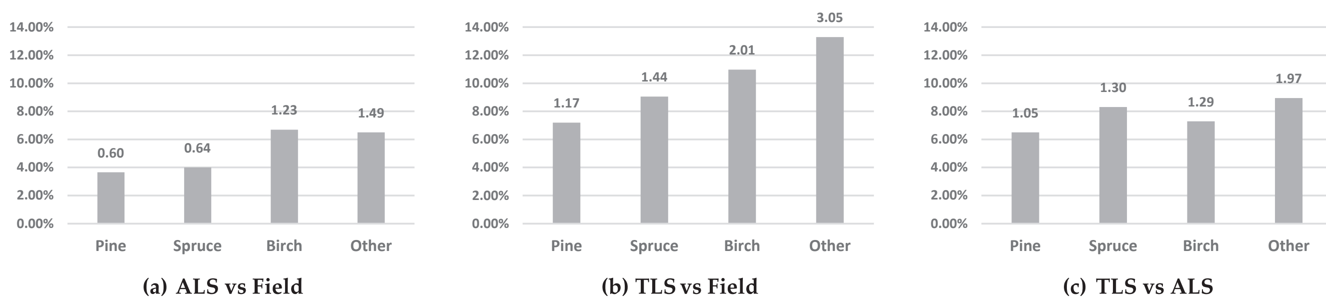


Fig. 10. RMSDs of tree height observation pairs for different species classes. The x-axis represents the tree height category, and the y-axis represents the relative RMSD of the compared tree height observations. The labels above the bars represent the absolute RMSD values in each tree height categories, the units are in meters.

4.5.3. Cases in which the TLS-based tree heights were more uncertain than the other measurements

There were 48 trees in the set $S_{(\mathrm{TLS,field})}$ and not in the set $S_{(\mathrm{ALS,field})}$ (Fig. 13). Three random errors (Nos. 25, 28, and 29) in which the TLS-based tree heights were overestimated were found in this set, and all three were intermediate trees. These three trees were actually from a same dense difficult plot with four layers. Most of the co-dominant and intermediate trees in this plot were situated in small groups with intermingled crowns. These conditions could be the reason for the misidentification of the treetops in the TLS data. Otherwise, a general trend of underestimation in the TLS-based tree height was obvious for the remaining 45 trees in the group (Fig. 13). Therefore, systematic errors, i.e., underestimations, are likely present in the TLS-based tree height observations in this group.

Analysis of the stand conditions and crown classes of the trees in this group revealed that most of the problematic TLS-based tree height observations were associated with dominant and codominant trees (Table 7). The results in this study agree with the common understanding that TLS is limited by its terrestrial perspective in recording the upper parts of the crowns of high trees, leading to a systematic underestimation of tree heights, especially for tall trees.

5. Conclusions

The results reveal a high agreement among all three tree height observation methods for small trees with tree heights of less than 10 m in easy and medium stands. Also, the consistency between the ALS- and TLS-based tree height observations of small trees (i.e., below 10 m) is high in all three stand difficulty categories. Considering the ability of TLS to digitize small trees with height completeness, such consistency reveals that ALS is also capable of recording the treetops of the sub-canopy and small trees with high reliability, given a good visibility and a high point density.

Table 5
Distribution of the trees with suspicious field-based tree heights.

	Dominant	Co-dominant	Intermediate	Suppressed
Easy plots	0	0	0	0
Medium plots	0	1	4	0
Difficult plots	1	0	25	7

The statistics presented in this study show that the applied type of TLS, e.g., 5 scans per plot, is reliable in measuring tree heights for trees up to 15 and 20 m in height. The easier the stand, the taller the tree can be accurately measured with TLS. The underestimation of height for trees taller than 15–20 m is systematic in TLS due to the limited visibility of the upper part of the tree crowns. In general, the taller the trees, the less accurate are the TLS-based tree height measurements. Considering that multi-scan TLS captures a terrestrial point cloud with the highest data quality, this finding also applies to, for example, image-based point clouds (Liang et al., 2015).

Results in this study reflect the robustness of the LS systems in recording the height of trees, regardless the complexity of the forest stand, the crown class, the height and the species of the trees. The most important factor affecting the LS-based tree height accuracy is the visibility of a tree, that is, the completeness of tree digitization in the

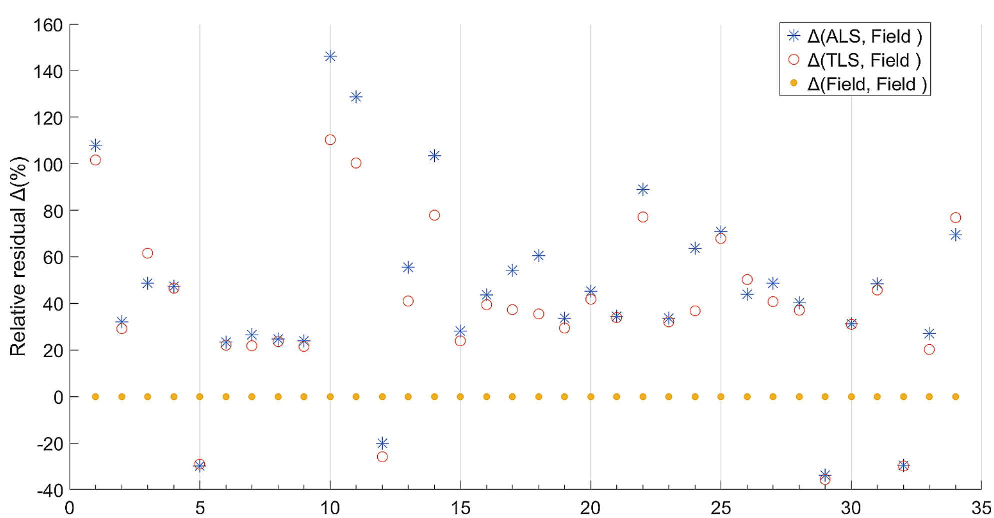


Fig. 11. Relative tree height residuals with respect to the field-measured tree heights for cases in which the field-measured tree heights are suspicious. The x-axis represents the ID of trees, and the y-axis represents the relative residuals. The blue line marks the ALSv.Field relative residual; the orange line marks the TLSv.Field relative residual; the yellow line marks the residual value of zero. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

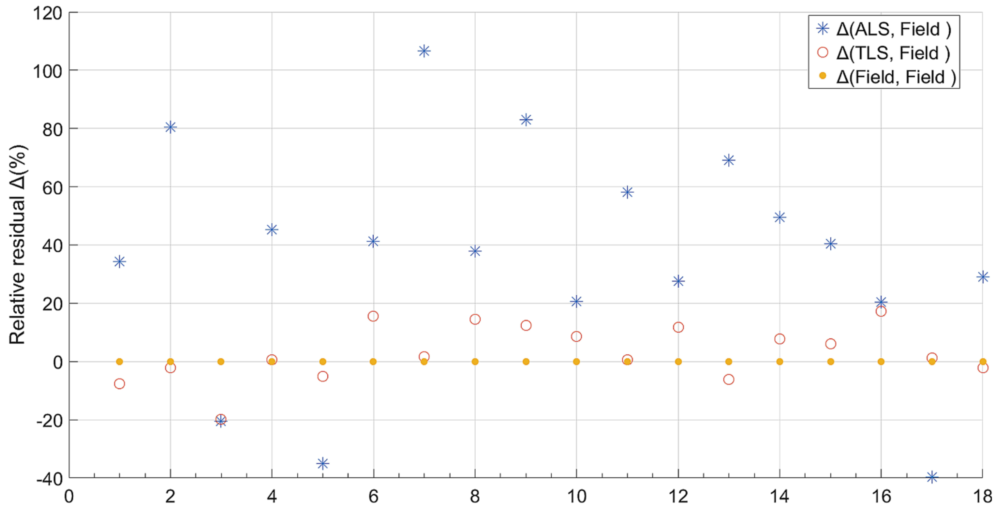


Fig. 12. Relative tree height residuals with respect to the field-measured tree heights for the cases in which the ALS-based tree heights are suspicious. The *x*-axis represents the ID of trees, and the *y*-axis represents the value of relative residuals. The blue line marks the ALSv.Field relative residual; the orange line marks the TLSv.Field relative residual; the yellow line marks the residual value of zero. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Distribution of the cases with suspicious ALS-based tree heights.

	Dominant	Co-dominant	Intermediate	Suppressed
Easy plots	0	0	1	0
Medium plots	0	1	4	0
Difficult plots	0	0	10	1

Table 7
Distribution of the cases with suspicious TLS-based tree heights.

	Dominant	Co-dominant	Intermediate	Suppressed
Easy stand	5	3	1	0
Medium stand	3	5	2	0
Difficult stand	9	8	12	0

data. However, the completeness of the LS digitization of a tree suffers from the occlusion effects, which is dictated by the location of the tree with respect to other nearby trees (i.e., the crown class of the tree), the structure of its neighboring crowns (i.e., the stand structure), the structure of the tree itself (i.e., the tree species), the perspective of the observations (i.e., the geometry between the tree and the sensor) and the settings of the applied digitization system (e.g., the sensor and platform configurations). Given the absence of occlusion from the aerial perspective and the small risk of missing treetops in a dense point cloud, high-density ALS data should be a reliable technique to measure on tree height for upper-canopy trees, that is, for dominant and co-dominant trees.

Field-based tree height is more sensitive to the stand conditions, the crown class and the species of trees compared to LS systems. In this study, the field measurements overestimated the tree height for co-dominant trees. Analyses of the outliers also suggested that the suppressed and intermediate trees in complex stands are challenging for field measurements. Uncertainties in field-measured tree heights of birch were higher than those of pine and spruce. This agreed with the understanding that the in-situ treetop definition for birch was much

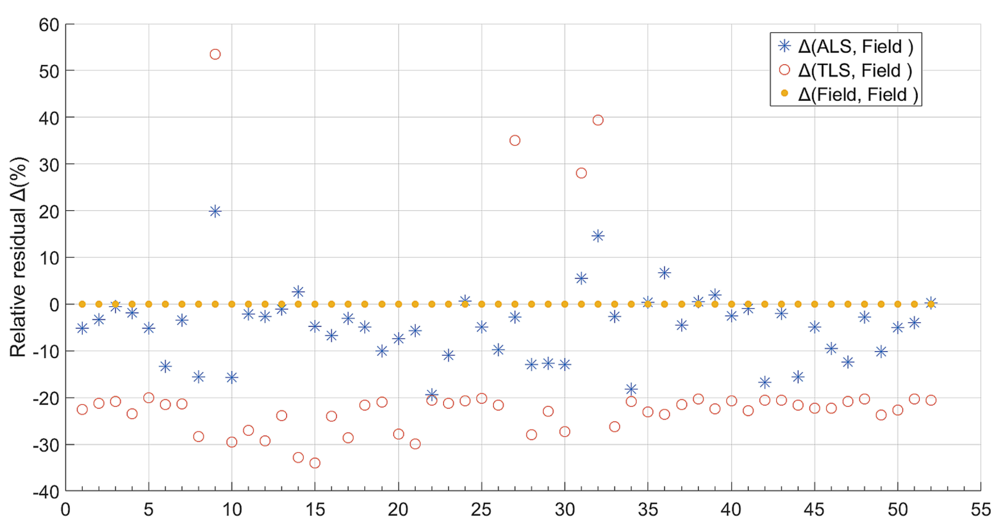


Fig. 13. Relative tree height residuals with respect to the field-measured tree heights for the cases in which the TLS-based tree heights are suspicious. The *x*-axis represents the ID of trees, and the *y*-axis represents the relative residual value. The blue line marks the ALSv.Field relative residual; the orange line marks the TLSv.Field relative residual; the yellow line marks the residual value of zero. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

more difficult than for pine and spruce. The accuracy of field-based tree heights generally degrades with increasing tree height. Therefore, more reliable height measurements for trees taller than 20 m should be expected from the ALS, with the precondition that the trees are correctly delineated from the point cloud.

The bottleneck of ALS-based approaches currently lies in the processing stage, that is, the automated detection and delineation of individual trees from the point cloud. Co-dominant and intermediate trees, as well as deciduous trees, in multilayered and/or dense forest stands remain especially challenging in terms of accurate crown detection and delineation. Thus, automated individual tree detection algorithms require further study and new innovations. Nevertheless, in certain applications, for example, in forest management decision making, one of the most often used forest inventory variables is the dominant tree height, that is, the mean height of the 100 largest trees per hectare. In this situation, ALS represents an optimal option since most of the recent individual tree detection algorithms are capable of achieving high accuracy with dominant trees in ALS point clouds.

Note that the ability of high-density ALS to record suppressed trees remains limited due to the occlusion effects. In addition, the identification of exact treetop locations from the point clouds can be challenging for intermediate and suppressed trees, even with human inspections. Among the total of 2417 trees in the 18 sample plots, manual treetop identification failed for 928 trees (38.4%) using the applied ALS data with a resolution of ~ 450 points/m^2. Therefore, the occlusion effects from the uppermost canopy layer remain the most important barrier for complete digitization of secondary layers from ALS.

This paper reveals the capability of cutting edge LS techniques in the measurement of tree height. Using high-end ALS configuration, it is possible to acquire tree height measurements more reliably than using conventional field measurements, and this applies especially for tall trees. Considering the constant technological progress, high density ALS data might be affordable for large scale survey in the coming years. On the other hand, and interesting future research topic would be to find out the minimum point density needed for accurate tree height measurement from ALS point clouds.

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Author Contributions

Yunsheng Wang, Xinlian Liang and Juha Hyppä designed the experiments; Yunsheng Wang performed the experiments and wrote the paper; Matti Lehtomäki, Jiri Pyörälä and Xinlian Liang participated the data processing and analyses; Antero Kukko and Anttoni Jaakkola developed laser scanning systems and carried out data collection and preprocessing; Ziyi Feng, Jingbin Liu and Ruizhi Chen contributed to the analyses.

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