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In-situ measurements from mobile platforms: An emerging approach to address the old challenges associated with forest inventories

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ABSTRACT

Accurate assessments of forest resources rely on ground truth data that are collected via in-situ measurements, which are fundamental for all other statistical- and/or remote-sensing-based deductions on quantified forest attributes. The major bottleneck of the current in-situ observation system is that the data collection is time consuming, and, thus, limited in extent, which potentially biases any further inferences made. Consequently, conventional field-data-collection approaches can hardly keep pace with the coverage, scale and frequency required for contemporary and future forest inventories. In-situ measurements from mobile platforms seem to be a promising technique to solve this problem and are estimated at least 10 times faster than static techniques (e.g., terrestrial laser scanning, TLS) at the plot level. However, the mobile platforms are still at the very early stages of development, and it is unclear which three-dimensional (3D) forest measurements the mobile systems can provide and at what accuracy. This study presents a quantitative evaluation of the performance of mobile platforms in a variety of forest conditions and through a comparison with state-of-the-art static in-situ observations. Two mobile platforms were used to collect field data, where the same laser-scanning system was both mounted on top of a vehicle and wore by an operator. The static in-situ observation from TLS is used as a baseline for the evaluation. All point clouds involved were processed through the same processing chain and compared to conventional manual measurement. The evaluation results indicate that the mobile platforms can assess homogeneous forests as well as static observations, but they cannot yet assess heterogeneous forest as required by practical applications. The major challenge is twofold: mobile-data coverage and accuracy. Future research should focus on the robust registration techniques between strips, especially in complex forest conditions, since errors of data registration results in significant impacts on tree attributes estimation accuracy. In cases that the spatial inconstancy cannot be eliminated, attributes estimation in single strips, i.e., the multi-single-scan approach, is an alternative. Meanwhile, operator training deserves attention since the data quality from mobile platforms is partly determined by the operators' selection of trajectory in the field.

1. Introduction

Forests is an essential provider of ecosystem services, such as carbon sequestration, which attracts increasing attention from policy makers and researchers specifically in the context of climate change, bioenergy and carbon sinks. To assess the amount and distribution of forest resources, forest information is gathered at various scales and at different user levels, e.g., from worldwide political decision making to operational forest management and from countrywide inventories to stand-level measurements. Accurate assessments of forest resources rely on the sampling of ground truth that is collected with in-situ measurements, which are fundamental for all statistical- and/or remote sensing-based deductions on quantified attributes of forests.

In-situ forest measurements are usually conducted in established sample plots, e.g., typically a small forest area with a radius approximately 10 m. To systematically represent the gradients of forest compositions and structures over a large area, the sample plots are usually widespread spatially throughout forested areas. Measuring trees precisely in sample plots, as well as re-measuring them with sufficient temporal resolutions, is crucial for correctly understanding the forest ecosystem, its dynamics and its functional traits. However, precise measurement is not straightforward since forests, especially natural

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forests, are characterized by high structural complexity and, consequently, in-situ measurements are difficult to implement. The number of sample plots that can be measured in practice are limited to a rather small number, which therefore accounts for less environmental heterogeneity and potentially biases any inferences made since errors affect the estimates calculated for a large area.

The lack of efficient inventory tools is an old and well-known challenge related to forest in-situ measurements. Unfortunately, it remains for its presence. Consequently, the forest structure beyond the sample plots and the tree structure at the individual-tree level are practically immeasurable and are therefore conventionally represented by the means and totals over the area of interest, despite the fact that forest structures vary in three-dimensional (3D) space and play an essential role in forest biophysical activities. For example, the stem curve (the function of stem diameters with respect to the height of the stem representing the stem shape) is the determining factor to estimate tree growth, stem quality and volume, but is rarely measured in-situ because it is too costly to acquire using conventional tools. Instead, it is estimated from regional or national allometric models, which are typically developed elsewhere with different climatic, geographic and silvicultural conditions and, therefore, not necessarily representative of individual trees. Even in a case when the stem curve is measured, its remeasurement is not guaranteed or it lacks the temporal resolution required for many applications. Another example is tree position, which is directly linked to the 3D forest structure and is the key parameter to match observations from different sources and from different points in time. However, measuring the tree position with centimeter-level accuracy is, in practice, extremely time-consuming due to the difficulty of collecting those measurements and the degradation of the Global Navigation Satellite System (GNSS) signals.

Lately, technologies such as the point clouds from terrestrial laser scanning (TLS) and images have presented feasible options for applying automated measurements to in-situ forest attributes, which have the capacity to provide 3D forest structure data accurately and automatically, e.g., the stem curves, and to improve the efficiency of field sampling. A main challenge lies in the speed of data acquisition. For example, a 1000 m^2 forest plot requires 20–60 min to measure using a stationary TLS.

The current question is whether in-situ 3D digitizing technologies can be promoted to the next level, in which tree- and plot-level attributes over large areas can be retrieved rapidly, accurately and cost-efficiently. Integrating 3D point cloud collection technologies with mobile platforms can provide a solution to the problem. A mobile system may consist of platforms with high mobility, e.g., car, all-terrain-vehicle, and human operator; one or several instrument, e.g., laser scanner(s) and/or camera(s); and positioning and orientation sensors, e.g., GNSS and/or inertial measurement units (IMU). The main advantages of such a system are its high mobility in various terrain conditions and its high flexibility for rapid data collection. It was shown in a previous study that the mobile system was 3 to 10 times faster than TLS and cameras (Liang et al., 2015). At this moment, mobile observations in forest environments are still in the very early stages of development. The limited studies were mainly on system demonstration in forests with simple structures, e.g., (Liang et al., 2014a, 2014b; Ryding et al., 2015; Bauwens et al., 2016; Forsman et al., 2016b; Marselis et al., 2016; Juraj et al., 2017; Oveland et al., 2017; Campos et al., 2018), but the usability of a mobile platform in varying forest stand conditions for forest in-situ observations has not been investigated. The quality of tree attribute data derived from contemporary mobile systems remains unclear.

This study evaluated the performance of mobile systems in various forest stand conditions, focusing on three critical factors, i.e., the 3D forest structure, the accuracy of the attribute estimates, including the stem tapering, volume and above-ground biomass (AGB), and the measurement efficiency. A comparison is also made between mobile systems and state-of-the-art of static observations from laser scanning. The findings in this paper are expected to provide orientations for exploring the new horizons of in-situ quantificational mapping of forests utilizing mobile platforms.

2. Materials and methods

The study in this work was based on 24 forest plots representing a variety of stand conditions with regard to species, growth stages and management activities. As references, the same plots were also measured using conventional in-situ measurements and state-of-the-art TLS. Point clouds were processed through the same processing chain and the results were evaluated using conventional measured references.

2.1. Test area

In 2014, 24 forest plots were selected by foresters in a southern boreal forest in Evo, Finland (61.19°N, 25.11°E) to be a test bed for various in-situ measurement techniques. The selected forest plots represent a variety of stand conditions with regard to species, growth stages and management activities, which were classified into three complexity categories from a forest inventory point of view, i.e., "easy", "medium" and "difficult". The complexity categories were defined based on stem visibility (the level of possible occlusion effects) at the ground level, the spatial stem density and the diameter at breast height (DBH) distribution of the sample plots. The category "easy" represents 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 the "difficult" category represents plots with high stem densities (~2000 trees/ha) and dense understory vegetation. Fig. 1 shows the plot-specific statistics of the mean DBH and the mean tree height to represent the variation in tree size for the sample plots.

Each plot has a fixed size of 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.

In this study, 23 of the 24 plots were measured from mobile platforms; data collection in one plot was unsuccessful because the field crew located the plot incorrectly during the operation. Therefore, the test results refer to 23 test plots and are also comparable to results from other tests based on the same test bed where all 24 plots are included.

2.2. Reference collection using TLS and conventional in-situ measurements

To accurately evaluate the performance of the mobile mapping systems, the same test plots were recorded with stationary TLS. The measurements were made in 2014 using Leica HDS6100 (Leica Geosystems AG, Heerbrugg, Switzerland) and the multi-scan approach. Five scans were made in each test plot: one scan at the plot center and four scans at the four quadrant directions, which represents the most accurate non-contact measurement in the field. Artificial spheres were set up as reference targets throughout the plot for the data registration. The registration accuracy is at a 2 mm level. The point spacing is 15.7 mm at 25 m from the scanning location in both horizontal and vertical directions. The forest was scanned as is, i.e., without any pre-scan preparation, such as removing lower tree branches or clearing undergrowth.

Conventional forest in-situ measurements were carried out in 2014. For each sample plot, a map of trees was measured by combining manual measurements from the multi-scan TLS data and the measurements taken in the field. Tree positions were preliminarily mapped from 3D TLS points and verified later in situ. All trees having a DBH larger than 5 cm were included in the plot tree maps.

Tree attributes, i.e., the tree height and the DBH, were measured for each tree using conventional field measurement methods, while the stem curves were manually digitized through multi-scan TLS point

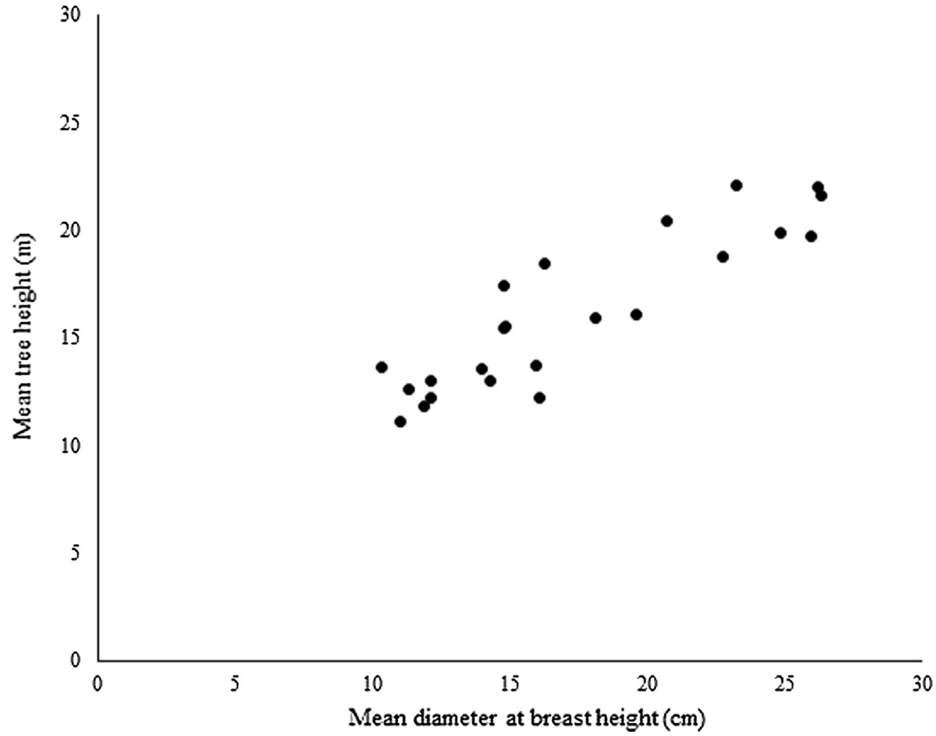


Fig. 1. Plot-specific statistics of the mean diameter at breast height and the mean tree height to represent the variation in tree size for the sample plots.

cloud. 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, 3 m and so on, until reaching the maximum measurable heights from the point cloud data.

2.3. Forest in-situ data acquisition from mobile platforms

The mobile data were collected in 2014. Two different mobile platforms were used for the kinematic in-situ measurements: one was an all-terrain-vehicle and the other was a backpack implementation. The two systems are also known as mobile laser scanning (MLS) and personal laser scanning (PLS), respectively. The measuring platforms are illustrated in Fig. 2. In this study, 7 plots were measured by MLS and 16 were measured utilizing PLS.

The core measuring system is the same for two platforms, which is an FGI in-house developed system, i.e., AkhkaR2 (Masala, Finland). The system is based on laser ranging and GNSS-IMU positioning, allowing free movement of the platform within the forests. The laser ranging is from a TLS (FARO Focus3D S120) that works in a profiling cross-track-scanning mode. The GNSS receiver was a NovAtel Flexpak6, and the IMU was a NovAtel UIMU-LCI.

The same scanning parameters were used in both platforms. The laser reached objects as far as approximately 100 m from the scanner, provided the visibility within the forest permits. The scanning frequency for the tree mapping was 95 Hz, which resulted in approximately 4 cm point spacing along the profile at a range of 35 m and 1.0–1.4 cm profile spacing on the ground at a typical moving pace (1.0–1.45 m/s).

In the field data acquisition, the operator walked or drove through and around the plots at a walking speed, aiming to minimize omission errors, i.e., to record trees in plots as completely as possible. The trajectory of the platform in the field depended on the actual accessibility of the forest stand, e.g., the ruggedness of the terrain, the density of

Fig. 2. Two mobile platforms applied for the in-situ measurements: (a) an all-terrain-vehicle, a.k.a. mobile laser scanning (MLS), and (b) a portable system on an operator's back, a.k.a. personal laser scanning (PLS).

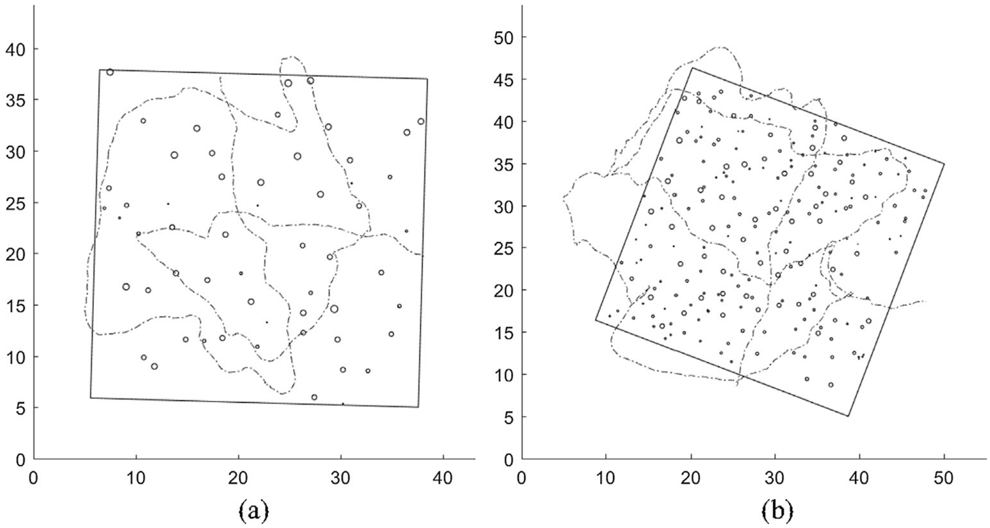


Fig. 3. Trajectory of the mobile platform (personal laser scanning) through two test plots: (a) plot category easy, and (b) plot category difficult. The square represents the boundary of each test plot. The circles/dots and their diameters show the tree locations and corresponding DBHs. The dashed lines indicate the trajectory of the platform.

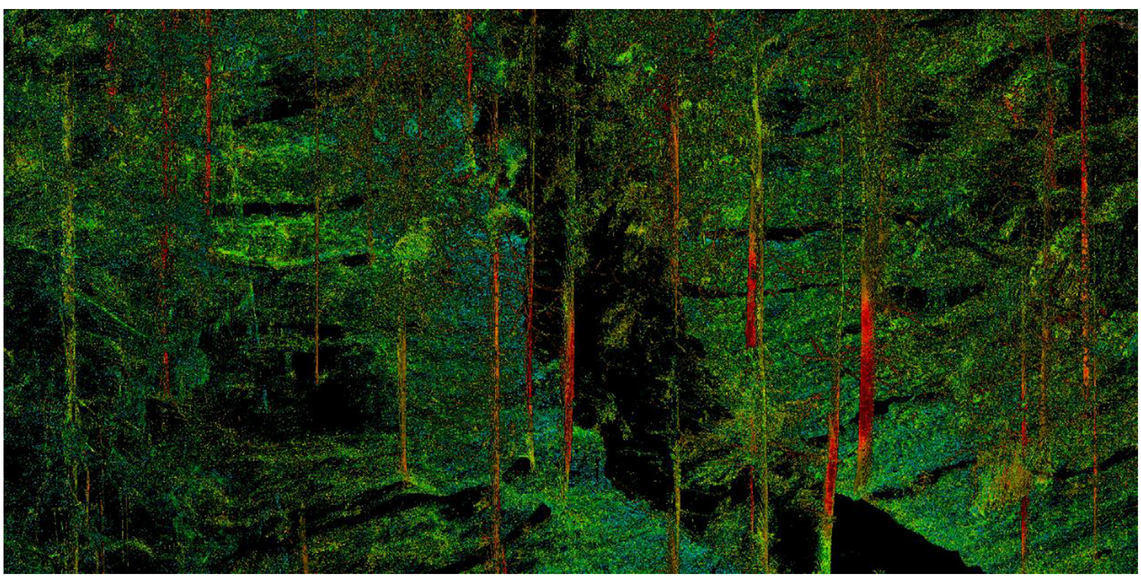


Fig. 4. A visualization scene of the 3D point cloud in a test plot collected with the AkhkaR2 PLS system. Points are colored based on point intensity. The data captures the tree geometry and terrain.

trees and the distribution of sub-canopy growth. The trajectory for each test plot was computed using Waypoint Inertial Explorer software and GNSS base station data from a Virtual Reference Station Network (Trimnet, Geotrim Oy, Finland). In post-processing, the trajectory was solved for instantaneous position (easting, northing, elevation) and altitude (roll, pitch, heading) data at a frequency of 200 Hz for geo-referencing the laser scanner data into registered 3D point clouds. The under-canopy trajectory data are expected to be solved at an accuracy at 0.2–0.8 m (Kaartinen et al., 2015; Kukko et al., 2017), which is directly propagated to the point cloud geometry. Fig. 3 demonstrates two trajectory cases in two test plots, presenting different tree coverage results in stands with different conditions but with similar efforts from the motions of the platform. Fig. 4 shows an example of the resulting point cloud data.

2.4. Retrieval of tree-level attributes from static observations

The TLS point cloud were processed using an improved tree-modelling method proposed in (Liang et al., 2012).

In the pre-processing, the original point cloud was sampled and de-noised. The original point cloud was first thinned through an equivalent sampling method, which samples the original point cloud data while preserves its spatial distribution. The 3D point data was digitized into a voxel space and the point closest to the center of gravity within each voxel (i.e., 1 cm cube) was selected as the representative point for the point distribution within the voxel. Isolated points and point clusters were then detected and deleted in the de-noising process.

A digital terrain model (DTM) was reconstructed using a morphological filter and linear interpolation. The 3D points were digitized into a 2D raster space. The lowest point in each pixel was selected as the seed point. In addition, the seed points were clustered based on 3D neighbor connectivity, and the largest connected group was interpreted to be part of the ground. Detached groups were accepted as ground if they were smoothly connected with the accepted ground, i.e., the slope between a detached group and the ground was gentle. The DTM was then built through the linear interpolation of the identified ground points

The stem detection and modeling follows the method proposed in (Liang et al., 2012). Points on vertical planar surfaces were first identified by analyzing the structure in their immediate neighborhood using principal components analysis. Tree stem models were built from the recognized stem points as a series of 3D cylinders representing the changes in growth direction of stems. The DBH and location of the stem were then estimated from the cylinder element at breast height (1.3 m above the ground), and the stem curve was estimated from the cylinder element at predefined heights, i.e., 0.65 m, 1.3 m, 2 m, 3 m and so on, until the maximum measurable heights was reached.

The tree height was estimated separately for big and small trees, where the tree groups were separated based on a DBH of 15 cm. Big trees were assumed mostly to be dominant or co-dominant trees that have direct access to the sunlight and have no trees above them (Wang et al., 2016). The elevation difference between the highest point within 20 cm distance from the stem and the DTM beneath was used as the estimate of tree height. Small trees are mostly intermediate and suppressed trees that are typically shadowed by other trees in the near vicinity. To find the treetop of a small tree, points around the stem were projected to the tree axis and the largest point group was assumed to belong to the tree. The elevation difference between the highest point in the group and the DTM beneath was used as an estimate of the tree height.

2.5. Retrieval of tree-level attributes from the mobile point clouds

Point cloud data collected from the mobile platforms were processed using a multi-single-scan type of method as in (Liang et al., 2014b). With mobile platforms, a tree may be observed several times from different locations on the trajectory. Spatial inconsistency in the point clouds from different observations prevails in mobile data because of the positioning errors. While automated registration is currently being developed and may in future largely improve the data accuracy, wind effects pose similar spatial-inconsistency problem that is difficult to completely remove, see examples from TLS point clouds in (Vaaja et al., 2016; Pyorala et al., 2018); therefore, it is worthy of noting that the spatial-inconsistency still exist after data-level registration.

Fig. 5 illustrates an example of the spatial inconsistency, i.e., the mobile point cloud of a 2-meter-long tree stem in 2D (a) and 3D (b). The same tree was observed from multiple positions and spatial inconsistency propagated from the positioning errors are clearly visible from the points on and surrounding the tree stem.

The multi-pass-corridor-mapping approach first models trees alongside the trajectory using the same method as that used for the stationary TLS. Since a tree may be observed several times on the trajectory, a single tree might be modeled multiple times. The tree models at the same location were identified as a single tree, and the stem model with the longest extracted stem was selected as the final tree stem model from which tree attributes were measured.

The method for tree modeling and attribute estimation were almost identical for both the stationary and mobile point clouds. The only difference was how the tree height was extracted. Since the stationary TLS is less likely to capture the treetops due to its limited perspectives and the occlusion effects of trees and branches, treetops were estimated from the original point cloud data to retrieve the treetops to ensure they were as high as possible. In contrast, the mobile platform observes the treetops from various perspectives and thus, has a greater probability of capturing the treetops multiple times with varied visibility. To reduce the risk of getting erroneous treetops, tree heights were estimated from the point cloud after the de-noising process.

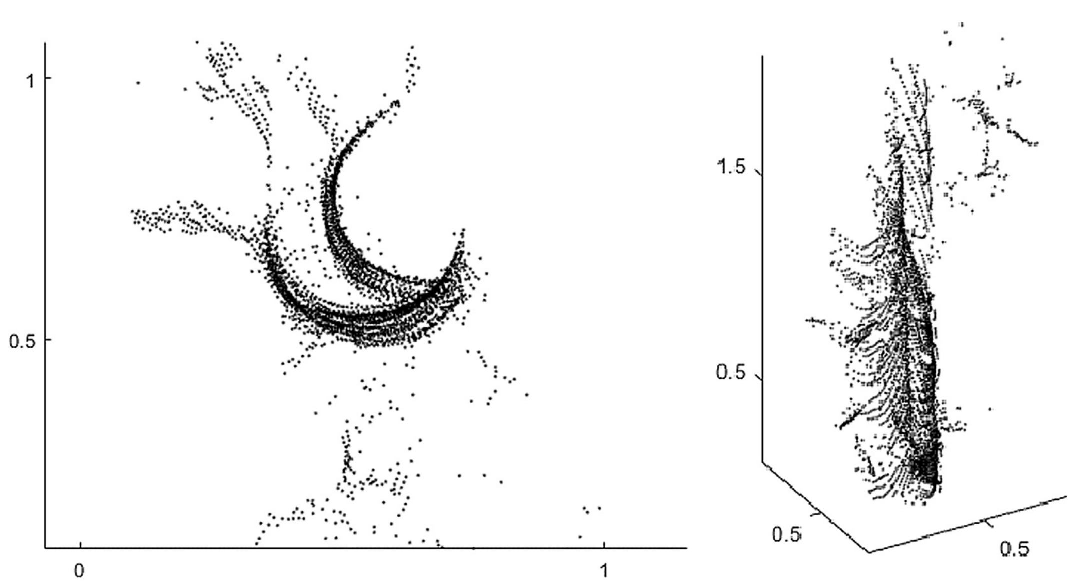
2.6. Evaluating individual tree attributes from the point clouds

The performance of the mobile platforms in in-situ measurements was evaluated by comparing the estimated tree-level attributes with the conventional manual in-situ measurements, as well as with the results from the stationary TLS, which represent the most accurate automated measurement technique currently available.

The detected and reference trees were first matched based on the horizontal locations and DBHs of the trees. For each detected tree, all of the reference trees within its neighborhood (150 cm radius, accounting for the positioning drift in the mobile data), were evaluated and the one with the most similar DBH was matched to the detection. The detection accuracy was evaluated using two measures, i.e., completeness and correctness, where the completeness shows the number of reference trees that are automatically detected and the correctness shows the number of the detected trees that corresponds to the reference trees.

The accuracy of the extracted tree location, tree height and DBH were all evaluated using the relative Root Mean Squared Error (RMSE) and bias, with the exception of the tree location, where only the absolute RMSE was calculated.

The stem curves consisted of the extracted stem diameters from specific heights. The accuracy of the extracted stem curve was evaluated by comparing the extracted diameters to the reference values of the stem curve at the same heights. For each matched tree, the accuracy of the stem curve was evaluated, and plot- and category-specific



(a) (b)

Fig. 5. An example mobile point cloud of a 2-meter-long stem section, in 2D (a) and 3D (b) scenes.

relative RMSE and bias were averaged.

The accuracy of the stem volume and total tree biomass were also evaluated using the relative RMSE and bias over the trees in each plot, providing an overall evaluation of the mobile platform performance since volume and biomass are dependent on multiple tree attributes. The volume is a function of the tree height and stem curve, and the biomass is from Finnish national allometric models as in (Repola, 2008, 2009). Volume ratio is the ratio of the sum of the stem volumes of the matched extracted trees to the sum of the stem volumes of the reference trees in one plot, which evaluates how much of the reference stem volume in one plot is extracted automatically from the point cloud.

3. Results

The performance of the mobile point cloud was evaluated through tree-attribute estimations in various forest conditions. The extracted tree attributes included those widely used in various forest applications, i.e., the DBH, the tree location, the tree height, the stem curve, the stem volume and total biomass. They were automatically derived from the mobile platforms and were evaluated against the commonly accepted conventional method and the best automated estimations achievable from state-of-the-art technology.

3.1. Stem detection and position

The results of stem mapping are reported in Fig. 6. A steady decline in the completeness of stem detection was observed as stand complexity increased, decreasing from approximately 90% in easy plots to 60% in difficult plots, similar to the stationary TLS. The correctness of stem detection from the mobile point cloud ranged between 50% and 80%, which is lower than the results from the TLS point cloud (i.e., approximately 90%). Such results indicate that the omission error of stem detection is at similar levels in the mobile and stationary data but the commission errors in mobile data were much higher than those in static data. The main source of commission errors in mobile data were the redundant/fake stem counts associated with positioning errors in the mobile point cloud. More discussion on this issue is in Section 4.

The stem-position accuracy, i.e., the distance between the estimated and the reference stem positions, is illustrated in Fig. 7. In general, the stem-position error from mobile platforms, which can be also propagated from the positioning errors under the forest canopy, is clearly bigger than the error from the static one. The easy plots have the smallest stem-position errors among the three stand difficulty categories because there is typically more open space and thus better GNSS-satellite visibility than in the medium and difficult plots. The result reveals that the positioning accuracy in current mobile systems, which relies on only GNSS-IMU positioning, is largely influenced by the forest stand conditions. In addition, Terrain conditions, e.g., roughness, influence on the smoothness of platform movement, and indirectly on positioning accuracy.

3.2. Diameter at breast height

The relative RMSE (RMSE %) and the relative bias (bias %) of the DBH estimates are reported in Fig. 8. In easy plots, the difference between the RMSE % of DBH estimates from the mobile and stationary platforms is insignificant (11.2% vs. 6.3%, respectively). In the medium and difficult forest stands, the RMSE % of the DBH estimate from the mobile data are much higher than that from the stationary data (23.4% vs. 8.4%, respectively, in medium plots, and 34.6% vs. 13.2%, respectively, in difficult plots). According to the bias % of the DBH estimates, it is much easier to derive exaggerated DBH from the mobile data, especially in the medium and difficult plots, which again resulted from positioning errors that were propagated to the point cloud data. More discussion on positioning errors and the accuracy of attribute estimations is provided in Section 4.

3.3. The stem curve

As shown in Fig. 9, the accuracy of the stem-curve estimation from the mobile point cloud is not yet comparable to what can be achieved from the stationary point cloud in all three difficulty categories of forest stands. The influence of the stand condition on the stem curve accuracy is much stronger with the mobile data than with the stationary data, emphasizing the influences of factors, such the positioning accuracy, the level of noise of the mobile point cloud and the stand complexity, on the overall data quality. As forest complexity increased, the quality of the mobile point cloud data decreased due to the reduced positioning accuracy, the decreased accessibility of the plot and the coverage of data, and the increased occlusion effects. The stem curve estimates from the mobile platforms are in general shorter than in the statistic measurement because of the spatial inconsistency.

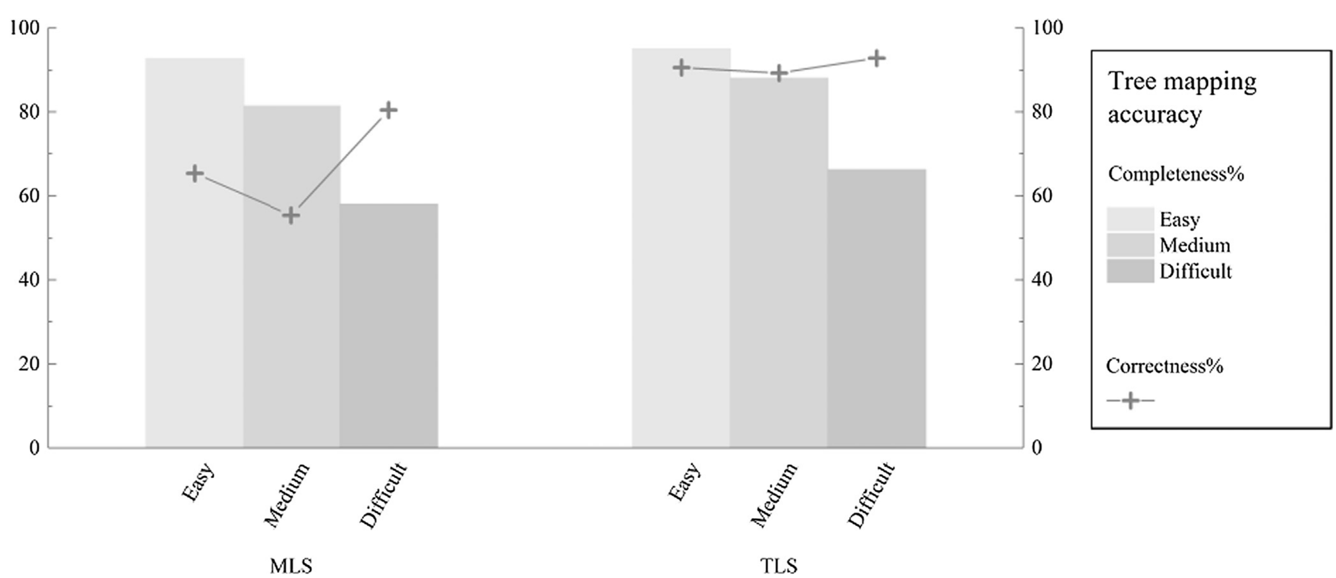


Fig. 6. Correctness and completeness of individual tree mapping from the mobile and static platforms. The left axis represents the completeness (%), and the right axis represents the correctness (%).

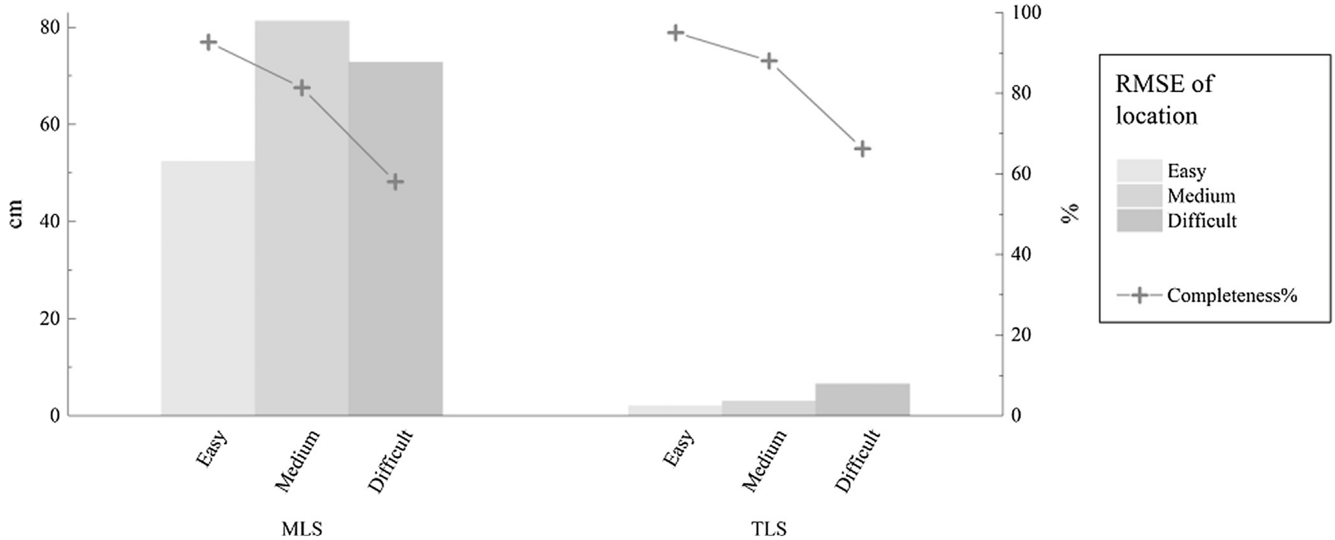


Fig. 7. RMSE of the stem location estimation from the mobile and static platforms. The left axis represents the distance values, and the right axis represents the completeness (%).

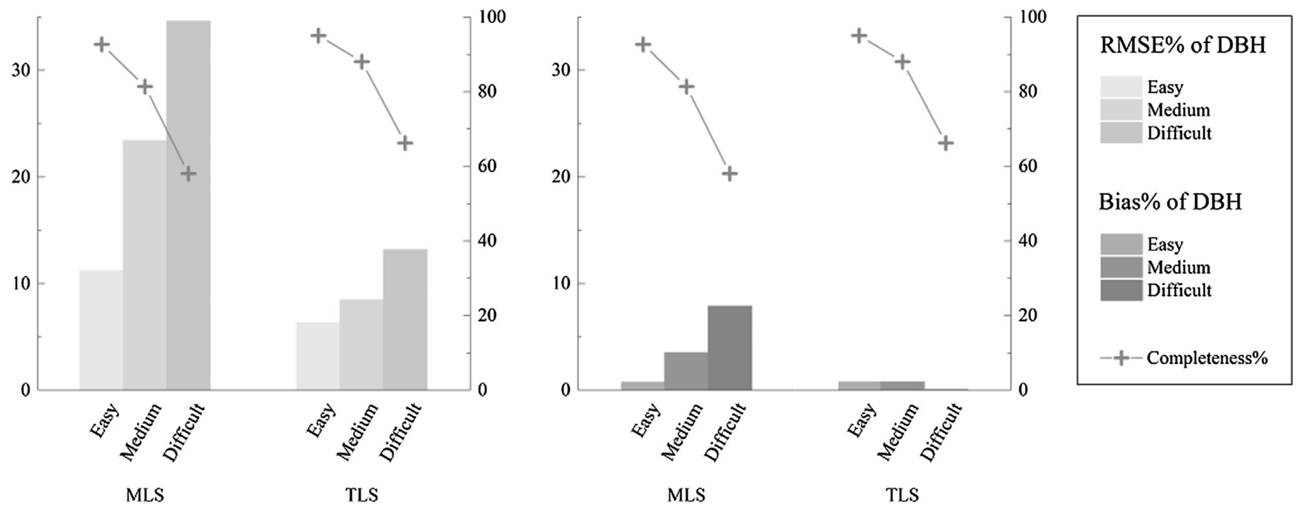


Fig. 8. Relative RMSE and bias of the DBH estimation from the mobile and static platforms. The left axis represents the RMSE % and Bias % values, and the right axis represents the completeness (%) value.

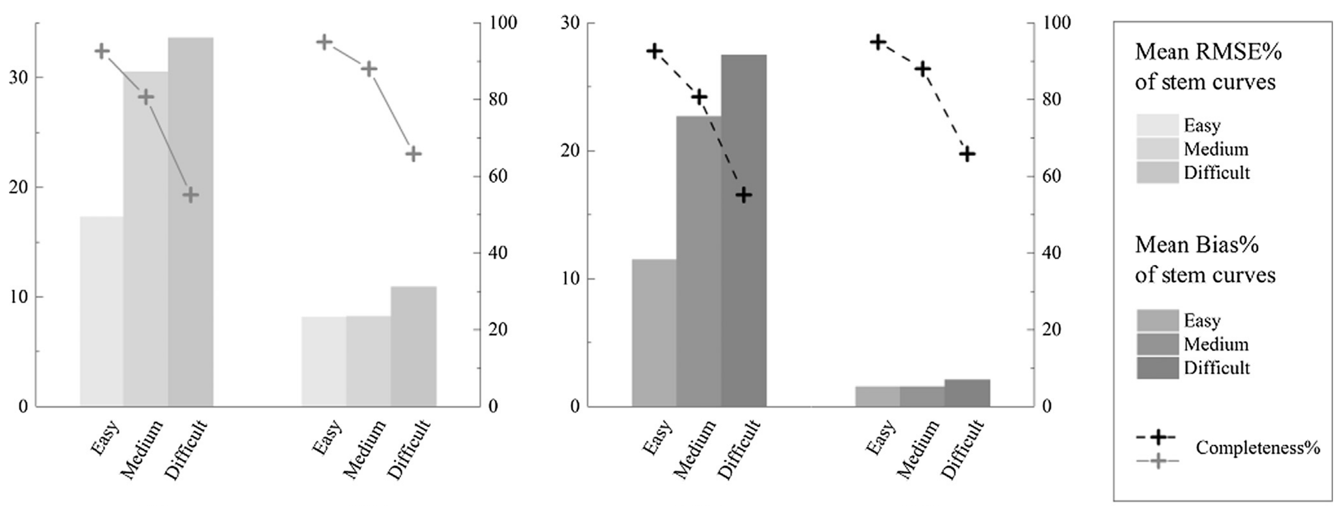


Fig. 9. Relative RMSE and bias of the stem curve estimation from the mobile and static platforms. The left axis represents the RMSE % and Bias % values, and the right axis represents the completeness (%) value.

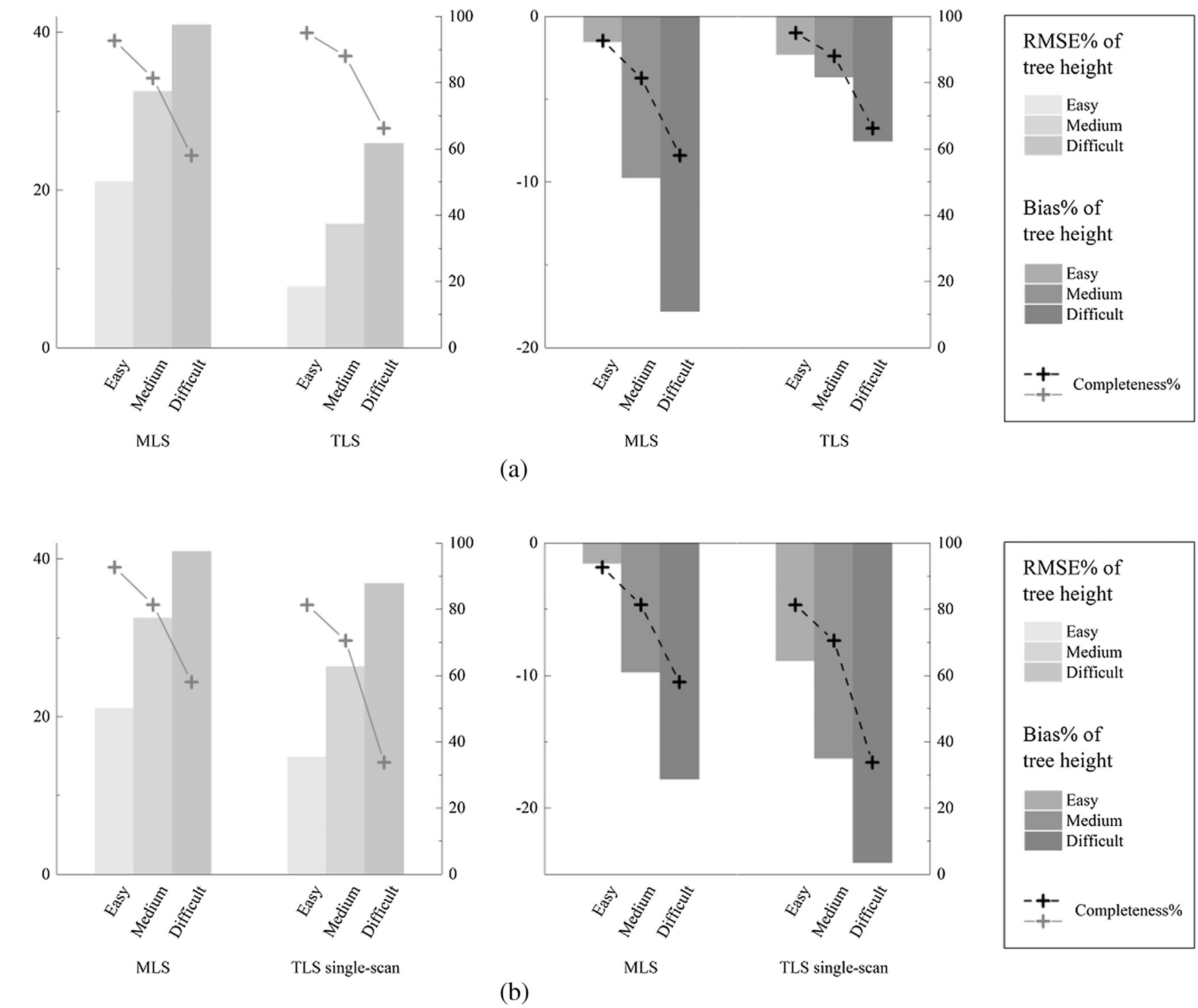


Fig. 10. Relative RMSE and bias of the tree height estimation from the mobile and multi-scan terrestrial laser scanning (a), and from mobile and single-scan terrestrial laser scanning (b). The left axis represents the RMSE % and bias % values, and the right axes represent the completeness (%) value.

3.4. The tree height

The RMSE % and bias % of the tree height estimates are reported in Fig. 10. In Fig. 10(a) and (b), the results from the mobile data were compared with multi- and single-scan TLS data, respectively. In principle, data collected through the multi-scan TLS represent the highest quality of available terrestrial point clouds, and mobile data are expected to be comparable to multi-scan TLS data. However, due to the positioning errors in forest environments, mobile data were processed in a multi-single-scan mode where the features were extracted from the path with the best visibility. This method processes mobile data in a similar way as the single-scan TLS. As shown in Fig. 10(b), mobile platforms and single-scan TLS provide tree height estimation with a similar accuracy; however, both are less accurate than the multi-scan data. These results indicate that the advantages of mobile platforms have not been fully exploited yet, because of the positioning challenges.

3.5. Stem volume

The relative RMSE and bias of the stem-volume estimates are reported in Fig. 11. The stem-volume estimation from mobile platforms is comparable to what is achieved from static TLS in easy forests. In the medium and difficult complexity categories, however, static observations provided smaller RMSE %, i.e., they were more accurate.

3.6. Total tree biomass

The results of the total tree biomass estimation are reported in Fig. 12. The mobile and static platforms provided similar RMSE % values in easy plots. The bias % value are similar to each other.

4. Discussion

The technological advantages and disadvantages of mobile systems both come from its mobility, which lends itself well to fast data acquisition but also triggers the possible degradation of data quality. The results in a variety of forest conditions in this study suggested that the mobile systems does not yet meet the practical requirements. The main challenges of applying them in forests are twofold: the accuracy of the point cloud registration, and the selection of the trajectories in the field. Currently, solutions for these two challenges are unavailable yet and should be investigated more closely before the mobile platforms can be

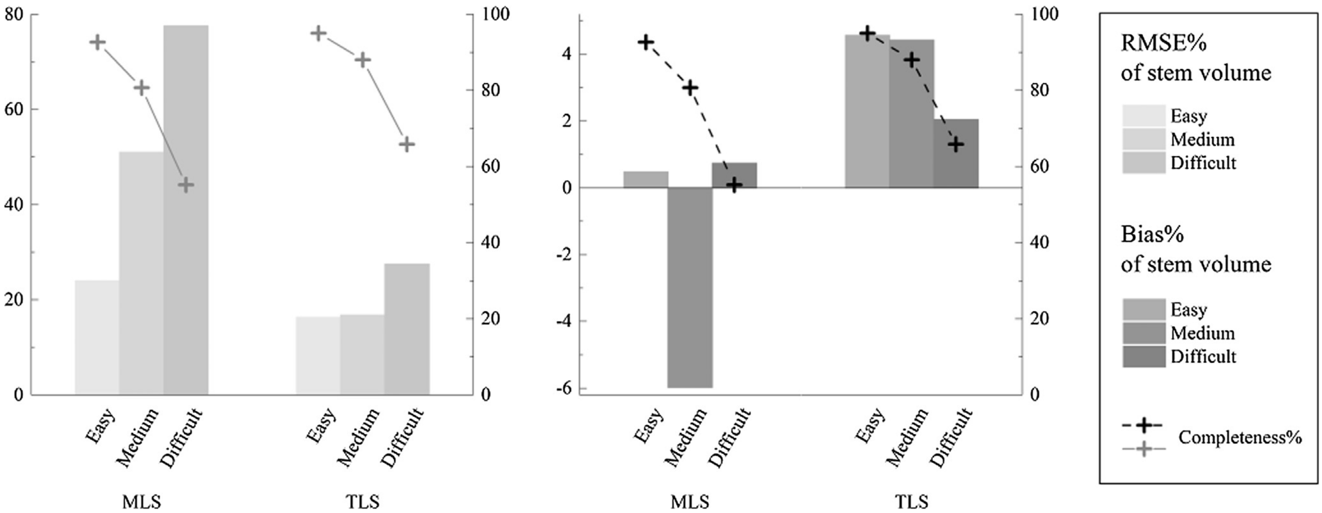


Fig. 11. Relative RMSE and bias of the stem-volume estimation from the mobile and static platforms. The left axis represents the RMSE % and bias % values, and the right axis represent the completeness (%) value.

used in practice.

4.1. Tree-attribute estimation from mobile platforms at a plot level

This study presents a quantitative evaluation of the performance of mobile platforms in a variety of forest conditions and through a comparison with state-of-the-art static in-situ observations. The results indicated that the tree detection of mobile and stationary laser scanning is approximately at the same level of accuracy. The results of the plot-level tree-attribute estimates diverse in different forest conditions. In homogeneous forests with simple structures, the current estimates from mobile platforms are less accurate but comparable with that from static platforms, such the DBH, volume and biomass, which demonstrates the potential of mobile mapping. In heterogeneous forest, tree attribute estimates of mobile systems are less accurate than multi-scan TLS, and not yet meet the requirement by practical applications.

It is worth to note that stationary multi-scan TLS represents the best quality terrestrial point cloud. The TLS results serve as a reference for further mobile systems development. In addition, the results of mobile laser scanning in this paper correspond to data without strip adjustment. When strip registration works automatically and reliably, the outcomes of this comparison may change.

4.2. Positioning accuracy of mobile point clouds

In dense forests, visibility is typically poor from fixed positions which imposes less probability of observing all trees in a plot. Mobile observation introduces a multi-view geometry, i.e., the viewing position and geometry are constantly changing and an object is observed from multiple positions, and significantly increases the probability of fully recording targets in the captured data by observing an object from various positions. Meanwhile, increased mobility under forest canopies introduces positioning errors. The positioning accuracy provided by the GNSS and/or IMU is typically inadequate to locate the platform positions with high accuracy. Consequently, the positioning errors propagate throughout the dataset, and mobile data are in general less accurate than static observations.

The positioning errors can be seen from the relative RMSE of the tree locations, which is clearly larger than that from the static TLS. The magnitude of the stem-position errors, i.e., 0.5–0.9 m, gives an indication of the GNSS-IMU errors under boreal forest canopies. This result is in line with what reported in the previous work (Kaartinen et al., 2015), where the positioning accuracy was 0.6–0.8 m from the combination of differential GNSS and IMU.

Some systematic shifts between the tree locations from the mobile

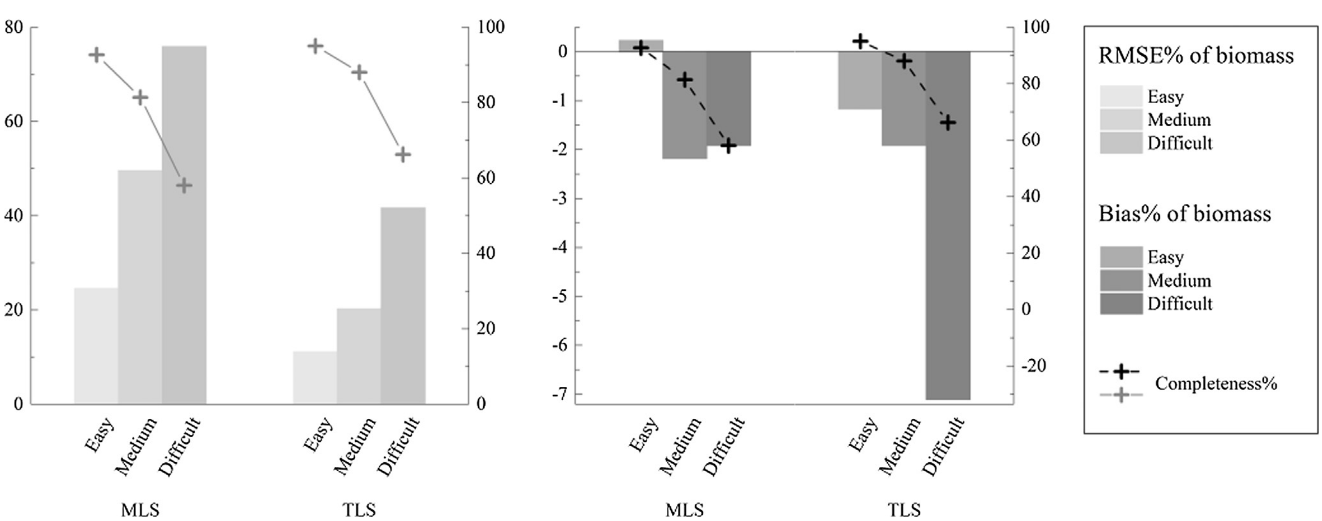


Fig. 12. Relative RMSE and bias of the tree biomass estimation from the mobile and static platforms. The left axis represents the RMSE % and bias % values, and the right axis represents the completeness (%) value.

platform and the reference were observed in this study, and the shift was more significant in the north-south direction than in the other directions. These shifts are likely related to the test-bed location, i.e., 60 degrees north of Earth's equator, where the visibility of the navigation constellations may not be ideal. Therefore, the matching distance between the detection and reference was set to 1.5 m in the evaluation to compensate for this shift, which is a relatively large value for matching. The number of matched trees was, however, decreased significantly if this criteria was reduced to 0.5 m, which also reflecting the positioning errors in the mobile platform trajectories.

4.3. Selection and realization of trajectory

Mobile systems give the operator flexibility in choosing the best route to move through forests to map the entire forest area, a task that may be too difficult to achieve from only a couple of static observation positions. In an ideal case, the operator went around the entire plot and all trees were close to at least one pass as shown in Fig. 3(a). However, this is not always possible in practical operations. The trajectory in a difficult forest plot was shown in Fig. 3(b), where many small trees are presented in the plot. The walked pass was quite nicely distributed in the plot. However, in the west part, some small trees were far away from any walked pass, and consequently, the data coverage was less favorable for successful tree mapping.

It is not always easy to find the ideal path to traverse a forest plot. In Fig. 3(b), the operator tried to go north at the south-west corner but gave up and instead moved towards the south, likely because of the difficulty imposed by small trees. Terrain may be another challenge. For example, ditches and steep slope may stop vehicle platforms. Operator's training and experience affect route selection and have direct effects on the data coverage and quality.

4.4. Selection of platforms and sensor systems

Two mobile platforms, i.e., human and all-terrain-vehicle, were employed in the study to collect terrestrial point cloud and both use the same sensor system. In general, two platforms are very similar. Both MLS and PLS have greater mobility in comparison with static TLS. Some differences may be noticed, since terrain, e.g., roughness, rocks and falling trees, and forest, e.g., structure, age and species, conditions influence the smoothness of platform movement and the measurement speed.

In MLS, a higher platform speed can be achieved if forest conditions allow and higher scanning frequencies are available. The first experience from this study showed that vehicle platforms are more suitable for flat terrain and forests with less complicated structures. In such contexts, the MLS can measure forests in a large area using a relatively short period of time. Meanwhile, given the same scanning frequency, higher moving speed leads to larger point spacing which negatively effects target-detection capabilities especially for objects far away from the trajectory.

The speed of PLS is limited and can be slightly raised by using smaller device. Human operators tend to have more abrupt heading changes to avoid obstacles or going to places where is hard to reach and vehicles mostly avoid to visit. Consequently, PLS tends to have less smooth trajectory, which indirectly influence positioning accuracies and may propagate to the point clouds and impact on tree detection and estimates. On the other hand, human operator has even greater mobility than the vehicles, since measurement can be made in areas forbidden for vehicles.

In addition to platforms, similar point clouds as in this study can also be obtained from image matching (Liang et al., 2015; Forsman et al., 2016a; Berveglieri et al., 2017; Mokroš et al., 2018) and structured light (Hyyppä et al., 2017; Tomaštík et al., 2017). The advantage of the image-based point cloud is that the data can be collected using low-cost, low-weight and small sized hardware that is affordable and easy to use for both professional and non-professional users. Laser sensors typically measures longer distances than image sensors and they can be in principle used in darkness. The fundamental challenge of mobile mapping systems is the data registration, whatever the source of the data. For example, spatial inconsistencies shown in mobile point clouds can also be found in both image- and structure-light-based point clouds, e.g., in (Liang et al., 2015; Hyyppä et al., 2017). The solutions to spatial inconsistencies are either point-level registration or feature/decision-level fusion.

4.5. Outlook

In future mobile platforms have the potential to reshape the landscape of the forest field inventories.

A straightforward benefit derived from mobile mapping is that the efficiency of field measurements can be significantly improved. The challenge is how to solve the spatial inconsistency problem. To improve the registration accuracy, there are two categories of solutions.

The first is object-level registration where the best observations (defined by applications) of the same object are recognized and used in estimating attributes, as shown in this study. The matching is performed at the feature level, whereas the tree attributes are estimated by decision-level fusion (Liang et al., 2014b). This solution requires the trajectory to be known, e.g., through GNSS. The challenge here is that the visibility of GNSS satellites could be poor in dense forests.

The second solution is data-level registration. A popular solution is to integrate observations with Simultaneous Localization and Mapping (SLAM). Currently, there are many efforts focusing on this, but there have not yet been reliable solutions applicable to forests. Improve the robustness of the solutions in different forest conditions requires time and more efforts. In (Bauwens et al., 2016), a mobile system based on IMU and SLAM successfully produced automatic co-registration in 8 out of 10 test plots. The system did not work in the remaining 2 plots. As noted in the paper, possible reasons for failed co-registration included a lack of objects for matching (in a sparse forest with a density 113 stems/ha) and a dense understory (a forest of 439 stems/ha). There might be more difficulties for automatic co-registration without GNSS in difficult plots, e.g., dense vegetation near the ground level. For mobile systems, forest is anyway a challenging environment to collect spatial consistent point cloud data, which differentiates forest applications from civil ones, e.g., (Guan et al., 2016).

To achieve the data-level registration, combining GNSS, IMU and SLAM is another solution, e.g., as seen in (Qian et al., 2016), where GNSS seems to provide a general position to solve the problems where SLAM failed. The GNSS receiver increases the system costs and complexity but also increases system stability in the circumstance that the navigation satellites are visible, and directly links the observations to the global coordinate system. A recent effort in solving for trajectory errors involves graph optimization of the GNSS-IMU solution of an MLS using only the scanning data and tree detections (Kukko et al., 2017). Another potential benefit of integration these observations is that GNSS signal may also provide another data source for estimating forest attributes, e.g., biomass, at a plot level (Liu et al., 2017).

In addition, mobile mapping introduces a new protocol to establish and measure forest sample plots, i.e., the visible area beside a single strip may serve as a forest plot rather than a conventional sample plot, as shown in (Liang et al., 2014b; Saarela et al., 2017). Such a field reference plot potentially accounts for more environmental heterogeneity and improves the inferences made based on the field reference. It further improves the measurement efficiency by transferring the unproductive time spent on transporting the equipment from site to site in stationary observations into productive inventories by continuous mensuration.

Until recently, these topics have been discussed insufficiently, which deserve further research.

5. Conclusion

In-situ observations are fundamental to forest resource management, which collects first-hand field data or data as field references to calibrate remote-sensing data. The major bottleneck of the current in-situ observation system is that the data collection is too slow. Consequently, conventional field-data collection approaches can hardly keep pace with the extent and frequency required for forest inventories. In-situ measurements from mobile platforms seem to be a promising technique to solve these problems.

Mobile systems have the potential to achieve a very fast measurement speed in various forest conditions, i.e., a couple of minutes and at least 10 times faster at the plot level or hundreds of times faster in a large area than that through static techniques (e.g., multi-scan terrestrial laser scanning). Over the long term, mobile systems are anticipated to become the standard platform for automatically measuring forests on the ground, if terrain and stand conditions enable its use. However, the mobile observations are still at the early stage of research, and adoption to practice will still take some time. Mobile systems are still very limited for end users and its technical readiness needs improvements. In addition, questions about what forest 3D measurements the mobile systems can record and at what accuracy have not been clarified. This study presented a quantitative evaluation of the performance of mobile platforms in a variety of forest conditions and in comparison with state-of-the-art static in-situ observations.

According to the results of this study, although tree-attribute estimates are slightly less accurate, the current forest 3D measurements from mobile platforms can measure forests of simple structure with an accuracy comparable with static observations. In heterogeneous forests, e.g., plots categorized as medium or difficult in this study, the results have not reached the same level of accuracy as the static observations, i.e., the multi-scan TLS, and as such, the mobile mapping does not fulfill practical requirements.

In general, the mobile and static data are equivalent, though the mobile data are distributed more homogeneously. Therefore, the technique that works fine for the static platforms is, in principle, also applicable to the data from mobile platforms. At this time, because of the shortcoming of the mobile system in terms of positional accuracy, where the registration in heterogeneous forest conditions is not yet adequately robust, mobile data are less accurate than data from the static platforms. Future research should focus on improving the in-situ registration technique, e.g., such as those based on SLAM. Meanwhile, operator training also deserves attention since the data quality derived from mobile platforms is partly determined by the operators' selection of trajectory in the field and can result in omission error.

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