Article

Under-Canopy UAV Laser Scanning Providing Canopy Height and Stem Volume Accurately

Juha Hyyppä[1,3,*], Xiaowei Yu[1], Teemu Hakala[1], Harri Kaartinen[1,2], Antero Kukko[1,3], Heikki Hyyti[1], Jesse Muhojoki[1] and Eric Hyyppä[1]

1 Department of Remote Sensing and Photogrammetry, Finnish Geospatial Research Institute, 02430 Masala, Finland; juha.hyyppa@nls.fi (J.H.); xiaowei.yu@nls.fi (X.Y.); harri.kaartinen@nls.fi (H.K.); teemu.hakala@nls.fi (T.H.); antero.kukko@nls.fi (A.K.); heikki.hyyti@nls.fi; jesse.muhojoki@nls.fi; eric.hyyppa@nls.fi
2 Department of Geography and Geology, University of Turku, 20014 Turku, Finland
3 Department of Built Environment, School of Engineering, Aalto University, P.O. Box 11000, 00076 Aalto, Finland
* Correspondence: juha.hyyppa@nls.fi, juha.coelasr@gmail.com

Abstract: Automation of forest field reference data collection has been an intensive research objective for laser scanning scientists ever since the invention of terrestrial laser scanning more than two decades ago. Recently, it has been proposed that such automated data collection providing both the tree heights and stem curves would require a combination of above-canopy UAV point clouds and terrestrial point clouds. In this study, we demonstrate that an under-canopy UAV laser scanning system utilizing a rotating laser scanner can alone provide accurate estimates of the canopy height and the stem volume for the majority of the trees in a boreal forest. To this end, we mounted a rotating laser scanner based on a Velodyne VLP-16 sensor onboard a manually piloted UAV. The UAV was commanded with the help of a live video feed from the onboard camera of the UAV. Since the system was based on a rotating laser scanner providing varying view angles, all important elements such as treetops, branches, trunks, and ground could be recorded with laser hits. In an experiment including two different forest structures, namely sparse and obstructed canopy, we showed that our system can measure the heights of individual trees with a bias of -20 cm and a standard error of 40 cm in the sparse forest and with a bias of -65 cm and a standard error of 1 m in the obstructed forest. The accuracy of the obtained tree height estimates was equivalent to airborne above-canopy UAV surveys conducted in similar forest conditions. The higher underestimation and higher inaccuracy in the obstructed site can be attributed to three trees with a height exceeding 25 m and the applied laser scanning system VLP-16 that had a limited height measurement capacity when it comes to trees taller than 25 m. Additionally, we used our system to estimate the stem volumes of individual trees with a standard error at the level of 10%. This level of error is equivalent to the error obtained when merging above-canopy UAV laser scanner data with terrestrial point cloud data. Future research is needed for testing new sensors, for implementing autonomous operation inside canopies through collision avoidance and navigation through canopies, and for developing robust methods that work also with more complex forest structure. The results show that we do not necessarily need a combination of terrestrial point clouds and point clouds collected using above-canopy UAV systems in order to accurately estimate the heights and the volumes of individual trees.

Keywords: under-canopy surveys; UAV laser scanning; tree height; stem curve; stem volume; field reference; forest plot

1. Introduction

Since the adaptation of airborne laser scanning for operative forest inventories, especially in the boreal zone, research in remote sensing of forests has moved towards automating forest field reference data collection at plot level with the goal of using this reference data for the calibration of airborne lidar surveys. Conventional plot-level field inventories are mainly based on calipers, measuring tapes and hypsometers, the consistency and accuracy of such measurements has been reported to be variable [1]. For example, tree heights can be obtained with 2-3% errors using conventional instruments (clinometer, hypsometer, rangefinder) when well-trained staff is applied. The biometric (e.g. density of the forest) and topographic factors explain most of the remaining errors [1-2]. In Luoma et al. [1], the largest difference within repeated conventional measurements of the same tree was less than 1.5 m for 73.3% of the trees.

The need for forest information varies. But increasingly, there are multiple uses that require optimization of forest resources. In field reference data collection, a selective sampling of trees is needed and the most important forest parameters to measure include, e.g., tree position, diameter at breast height (DBH), tree height, stem form, and other physical traits. When it comes to the amount of wood, species-specific stem volume is the most important parameter to be measured. The most accurate way to estimate the stem volume is based on an accurate definition of stem curve/form as a function of the height from ground.

Airborne laser scanning (ALS) has been known to provide the height of trees with a good accuracy for more than 20 years [3]. In many studies and reviews, the quality of the field reference data used to judge ALS-based tree heights has been questioned [3-5]. Since the advent of unmanned aerial vehicle (UAV)-based laser scanning systems, most enabling a high point density (Jaakkola et al. [6]), tree height estimates with a high accuracy have been reported. In Jaakkola et al. [6], tree heights were obtained with 40 cm accuracy using mini-UAV laser scanning.

With terrestrial laser scanning (TLS), the capacity to provide tree heights has been significantly limited. In [7], tree height estimation accuracies were broadly reported using TLS during 2004-2014. Using single scan and 16 plots of varying density, root-mean-square error (RMSE) of 4.9 m was reported for tree height estimation in Olofsson et al. [8]. Recently, Wang et al. [9] concluded that TLS has a limited capacity to measure tree height for trees taller than 15 m in dense stands, mainly due to the occlusion of the upper crowns. According to them, the TLS point clouds captured completely most of the suppressed trees, for which the TLS-measured tree heights were highly accurate. Furthermore, they reported that the root-mean-square deviation between TLS-measured tree heights and field measured tree heights was 1.4 m for trees with a height of 15-20 m and 2.4 m for trees with a height exceeding 20 m. Multi-scan approaches increase the height estimation accuracy. As a summary, the density of the canopies and scans determine the obtained accuracy for tree height when using a TLS system for the measurement.

Despite the need for accurate tree height estimates, the accuracy of tree height estimation has been discussed only in few previous studies utilizing a mobile laser scanning (MLS) system. In [10], a phase-based mobile laser scanner operated from an all-terrain vehicle and backpack was used to assess tree heights. RMSE of 20%, 33% and 40 %were reported for tree height in easy, medium and difficult forests. Cabo et al. [11] and Gianneti et al. [12] reported that tree height estimation of tall trees is considerably hindered by the limited scanning range of the hand-held laser scanner. [13-15] reported that MLS (backpack/hand-held laser scanner with SLAM (Simultaneous Localization and Mapping)) can provide tree heights with an accuracy of 1 m.

Even though the stem volume is one of the most important tree attributes to be derived in a forest inventory, only a few published mobile laser scanning studies have reported accurate stem volume estimates until recently [10, 16-17]. These studies have reported relative RMSE ranging from 20% to 50% in easy and medium difficult boreal forests, which is not yet sufficient for operational field reference data collection. Operational work requires a relative RMSE of approximately 10%. In our recent paper using under-canopy UAV laser scanning [14], we were able to obtain high-quality stem volume estimates by combining stem curves estimated from the under-canopy UAV data with tree heights estimated from above-canopy UAV data.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 1 April 2021 doi:10.20944/preprints202104.0003.v1

An under-canopy flying UAV for forest measurements was first proposed by Vandapel et al. [18]. Vian and Przylbylko [19] visioned a remote sensing sensor system to generate measurement information using under-canopy flights. Chisholm et al. [20] prototyped a UAV lidar flying along the forest road and they showed that the UAV lidar system was capable of measuring diameters of trees along this road. The first forest informatics study using under-canopy UAV laser scanning was conducted by Hyyppä et al. [14]. In the paper, we were able to compute stem volume estimates for the detected trees with a relative RMSE of 10% in both sparse and obstructed forest sites by combining stem curves extracted from the under-canopy UAV laser scanner data with tree heights obtained from separate high-density above-canopy UAV laser scanning data. Wang et al. (2021) tested single-flight integration of above- and under-canopy UAV laser scanning for forest investigation in order to overcome, e.g., the tree height measurement problem [21].

In this study, we show that under-canopy UAV laser scanning surveys using a rotating laser scanner can provide both the canopy height and the stem volume for mature trees in boreal forest conditions with an accuracy sufficient for operational field reference data collection. Additionally, we discuss whether single-sensor under-canopy UAV laser scanning will remove the need to combine above-canopy UAV point clouds with terrestrial point clouds.

2. Materials and Methods

2.1. Study area and reference data

A boreal forest in Evo, Finland (61.19∘N, 25.11∘E) was used as the study area. The measurements were conducted on two test sites of size 32 m × 32 m representing sparse and obstructed forests. The classification of forest type was based on stem density, visibility of the tree stems and the amount of understory vegetation. The sparse site consisted mainly of pines that had a visible and straight stem. The obstructed site represented a mixed stand consisting of pines, spruces and birches and the stem density varied inside the plot but was at the same level as in the sparse site (slightly over 400 trees per hectare). Small spruces occluded the visibility of near-by tree stems and the stems of such spruces were only hardly visible in nature and from the point clouds. Descriptive statistics of the test sites are provided in Table 1.

Table 1. Descriptive statistics of the test sites.

Test Site	Trees	Stem density	DBH (cm)				Height (m)				Volume (m^3)			
		(stems/ha)	Mean	Std	Min	Max	Mean	Std	Min	Max	Mean	Std	Min	Max
Sparse	42	410	25.9	5.2	10.9	33.2	21.4	2.8	12	24.5	0.58	0.23	0.076	0.99
Obstructed	43	420	27.1	10.1	5.3	57.5	22.2	6.0	7.4	27.6	0.73	0.56	0.008	3.27

The field reference data was collected with multi-scan TLS in 2014 and updated in 2019. Trees having a diameter at breast height (DBH) exceeding 5 cm were included. Individual tree point cloud clusters were detected from the point cloud, and semi-manual circle fitting was performed at various heights to obtain a reference stem curve. The accuracy of the reference stem curve was at the level of 0.5 cm. The reference tree heights were measured with a hypsometer. Using stem curve information and tree heights, we were able to calculate reference stem volumes with the help of a fitted parabolic function according to [14].

2.2. Under-canopy UAV laser scanner system

The under-canopy flights were performed with a 960-mm (motor to motor) sized hexacopter, which was equipped with a first-person-view (FPV) camera. The video transmitted from the camera was viewed by the pilot wearing FPV goggles. The flights were piloted manually using this video feed, with stability assistance from the autopilot of the drone. The GeoSLAM Zeb Horizon laser scanner was mounted to the bottom of the drone in a way to minimize the occlusion caused by the frame of the drone as shown in Figure 1. We developed this configuration especially for this study. Two flights were then performed at the chosen test sites. Since the flights were manual, the flight plan was just to cover the test area as well as possible without getting too close to obstacles. The flying height was about 1-3 meters above ground, with some higher spots when the canopy had a gap. Flying speed was mostly very slow, i.e., 1-2 m/s. The flight trajectory of the sparse test site is shown in Figure 2.

GeoSLAM Zeb-Horizon scanner is officially a handheld laser scanning system which has a rotating arm. We chose to mount the Zeb-Horizon scanner onto the drone since we wanted to have a rotating laser scanner that provides adequate coverage of the canopy. In a previous study, we applied a Kaarta Stencil-1 laser scanner (Kaarta, Pittsburgh, Pennsylvania, USA). Such a system based on the Velodyne VLP-16 sensor (Velodyne Lidar, San Jose, California, USA) had a 360◦ horizontal field of view and 16 laser profiles corresponding to ±15◦ vertical field of view, which enabled us to extract the stem curve for pines approximately up to the height of 8m with a good precision while flying at a few meters height. Due to the rotating scanner, the laser scanner provided a point cloud extending from the ground to the treetops. The Zeb Horizon scanner also applies the Velodyne VLP-16 sensor operating at 905 nm. Horizontal and vertical beam divergences are 3 and 1.5 mrads. At the 10 m range, the laser spot sizes are then 40.1 and 24.5 mm, respectively. As an alternative to the rotating arm, one could also use laser scanners with a wider Field of View (FoV) in order to capture the upper canopy. For example, an Ouster OSO scanner with a 90-degrees FoV would provide complementary data to our approach. VLP-16 has officially an operating range of 100 m, whereas Ouster OSO scanners have a range of 50 m. The range capacity is discussed in more detail in the results and discussion.

The raw data collected with the ZEB Horizon scanner was processed using GeoSLAM Hub (version 6.0.0.) software and the default processing parameters (Convergence threshold: 0, Window size: 0, Voxel density: 1, Rigidity: 0, Maximum range: 100 m, Closed Loop) and afterwards exported into las-format for further processing.

Figure 1. Drone equipped with a rotating laser scanner developed for the study.

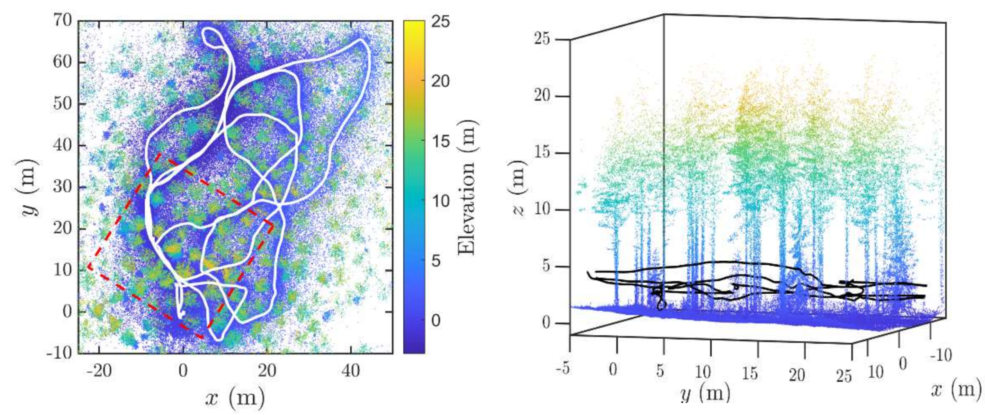


Figure 2. Flight trajectory for the under-canopy drone flight (white line) in the sparse test site. The original point cloud has been down sampled for good visualization. Left: top view of the flight. The red rectangle shows the location of the sparse plot. Right: side view of the flight trajectory (dark line).

2.3. Processing of under-canopy UAV laser scanner data

Point cloud processing after GeoSLAM Hub included the following steps in Matlab: 1) digital terrain model (DTM) generation, 2) segmentation and 3) stem detection and stem curve estimation, 4) tree height and stem volume estimation.

DTM was calculated using a voxel-based algorithm. Within each xy-pixel, the ground elevation was obtained by computing the average z coordinate of the lowest height interval containing at least 1% of the total number of the points. The final DTM was obtained by applying Gaussian smoothing for the preliminary DTM. The canopy height model was obtained by subtracting ground elevation from the highest laser hits within each xy-pixel.

In order to speed up the stem detection in step 3, the point cloud data was then segmented by applying the watershed algorithm for the canopy height model. Each of the resulting watershed segments included up to a few trees. Note that the segmentation process resembled that used to detect individual trees in the processing of above-canopy UAV point clouds. Importantly, we do not use the segmentation step to detect individual trees but to divide the point cloud into many smaller regions, which reduces the total time taken by the clustering algorithm used for the stem detection in step 3. Our implementation of the clustering algorithm used in the step 3 has an approximate time complexity of $O(n^{1.6})$, and therefore, it is significantly faster to process the point cloud in many small parts than as a single large point cloud.

In the stem detection algorithm of step 3, we aimed to find tree trunk hits from the point cloud data that was analyzed segment-wise as explained above. Despite the integrated SLAM (Simultaneous Localization and Mapping) in the GeoSLAM system, the positioning error of the scanner was approximately at the 10 cm level. Thus, we applied an arc-based stem detection algorithm detailed in [13, 14] to obtain accurate estimates of the stem curves. To this end, we first grouped the points in the point cloud based on their time stamp and z-coordinate by using a time interval of 1 s and a height interval of 0.4 m, respectively. Then, we applied the arc extraction algorithm described in [14] for each of the point groups. The arc extraction algorithm consisted of four steps that were 1) density-based clustering (DBSCAN) [22], 2) robust circle fitting using random sample consensus (RANSAC) [23], 3) removal of remaining noise points using an arc division algorithm [14],

 doi:10.20944/preprints202104.0003.v1

and 4) a quality check for each of the arcs using pre-determined quality criteria that included, e.g., the largest acceptable standard deviation of the radial residuals, and a minimum acceptable central angle. Having extracted arcs for all the time and height intervals, we clustered the extracted arc centers using the DBSCAN algorithm in the XY plane in order to group the arcs into trees. After that, we estimated the growth direction of the trees using principal component analysis (PCA). Final stem curves were obtained using a smoothing cubic spline.

Tree heights were obtained from the same point cloud data by exploiting the locations of the detected stems. To determine the height of a tree, we first found all the points that were located within 1m from the 3D stem line obtained from PCA. Subsequently, we divided the found points into groups based on their z-coordinate and the tree height was estimated by comparing the number of points within each interval against a point number threshold similarly to [14]. Finally, stem volumes were estimated with the help of the extracted stem curve and tree height by using the fitting method described in [13].

We did not optimize the used parameters. The selection of the parameter values was based on heuristics and logic. Same parameter settings have been used successfully in totally different forests (different tree species, different density of stems) in other parts of Finland.

2.4. Error analysis

To evaluate the success rate of stem detection, we calculated the completeness and the correctness of the detected trees. The completeness is defined as the number of reference trees found divided by the total number of reference trees, whereas the correctness is defined as the number of reference trees found divided by the total number of trees found.

The bias describes the systematic errors in the estimation and root-mean-square error (RMSE), i.e., standard error, includes both bias and random errors, and they were obtained as

$$\text{bias} = \frac{\sum_{i=1}^{n} x_i - x_{i,\text{ref}}}{N} \quad \text{and} \quad \text{RMSE} = \left(\frac{\sum_{i=1}^{n} (x_i - x_{i,\text{ref}})^2}{N}\right)^{1/2}, \tag{1-2}$$

where N is the number of found trees, x_i refer to the obtained estimates and $x_{i,\text{ref}}$ denote the corresponding reference values. The relative bias (%) and RMSE (%) were calculated against the sample mean of the variable in question.

3. Results and Discussion

3.1. Completeness and correctness of stem detection

We concentrated on detecting trees with a visible stem since the volume of such trees can be estimated accurately. Therefore, the parameters of our algorithm were far from optimal for detecting small, occluded spruces present on the test sites. The completeness and correctness of stem detection are reported in Table 2.

In the sparse site, we found 38 out of the 39 pines, and we missed three small spruces. We missed one tree near the southwest corner of the sparse plot due to a low point density caused by being distant from the flight trajectory (See Figure 2). There were no falsely detected stems and, thus, the correctness of stem detection was 100%.

In the obstructed site, we found 29 out of the 30 pine stems, one out of the 8 small spruces, and four out of the five birches. The correctness was again 100%.

Let us then compare our stem detection results against those reported in previous studies using under-canopy UAVs for forest field reference measurements [14, 21]. The studies in [14] were conducted on the same test sites as the current study. Here, we found one tree less in the sparse site, and two trees less in the obstructed site than in [14]. The slightly lower completeness in the current study as compared with the results of [14] is

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 1 April 2021 doi:10.20944/preprints202104.0003.v1

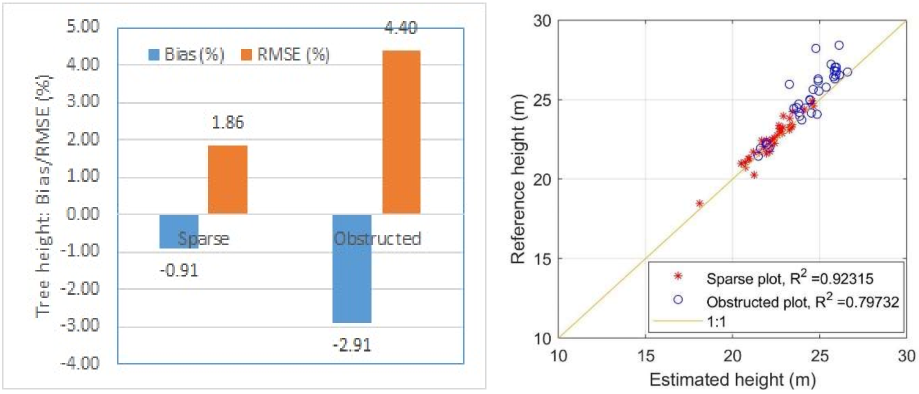
most likely due to a lower point density. In [14], the VLP-16 scanner was looking forward and did not see the treetops, whereas in this study, the return hits were more equally distributed also to treetops. In [21], the completeness of automated tree detection in a very sparse site (1/3 of stem density versus Table 1) was 96%.

Table 2. Completeness and correctness of stem detection. The number of detected trees is reported in the parentheses.

	Completeness (%)				Correctness (%)
	All	Pine	Spruce	Birch	
Sparse	90.5 (38/42)	97.4 (38/39)	0 (0/3)	-	100 (38/38)
Obstructed	79.1 (34/43)	96.7 (29/30)	12.5 (1/8)	80.0 (4/5)	100 (34/34)

3.3. Tree Height estimation

Results for tree height determination can be seen in Figure 3. For the sparse site, we obtained a bias of -20 cm (-0.91%) and a standard error of 40 cm (1.86%), and for the obstructed site, we obtained a bias of -65 cm (-2.91%) and a standard error of 1 m (4.4%). In general, such accuracies are comparable to the best previous studies. Hyyppä et al. [24] reported a standard error of 1.5-2.5% for tree height determination using hand-held laser scanning (1.5-2%) and high-density above-canopy UAV laser scanning (2-2.5%) in sparse forest sites. The bias is also comparable to the results obtained with a hand-held laser scanner in [24]. The results are also better than those obtained with the current implementation of the backpack laser scanner [24]. When comparing the results of the obstructed site to previous studies, the standard error obtained in this paper was lower than in any of the previous studies from the same site [24]. Previous standard errors obtained in the same site [24] have ranged from 5-6% (for backpack and hand-held laser scanning) up to 6-8% (for high-density above-canopy UAV laser scanning data). In Wang et al. [21], the standard error of tree heights estimated from UAV data was 6.1% for trees with a DBH exceeding 15 cm, which is similar to the results reported in [24]. Our results imply that under-canopy UAV laser scanning may provide tree height estimates with a slightly better accuracy than conventional high-density above-canopy UAV laser scanning. It should be noticed that previous results [24] have been obtained with above-canopy UAV data that employs point densities from 320 to 4800 pts/m².



Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 1 April 2021 doi:10.20944/preprints202104.0003.v1

Figure 3. Left: Bias and relative root-mean-square error (RMSE) of the tree height estimates in the sparse plot and in the obstructed plot. Right: Scatter plot of the UAV-derived tree height vs the reference height for the sparse plot and the obstructed plot.

When looking at the scatterplot of tree heights, presented in Figure 3 (right), there are three trees, the heights of which are strongly underestimated. Figure 4 illustrates a point cloud for one of these trees. The height underestimation by more than 2.5 m is caused by the low number of tree top hits. As a result, the used threshold value for the tree height estimation was obviously far too high. As explained previously, we did not optimize the threshold values and a better selection of the parameter values would have resulted in extremely high-quality tree height estimates. As can be read from reference [14], the threshold number of hits indicating treetops was higher for mature trees than for smaller trees. Since the point cloud of Figure 4 clearly shows that the tree height measurement capacity of VLP-16 is limited for tall trees, this logic should be modified.

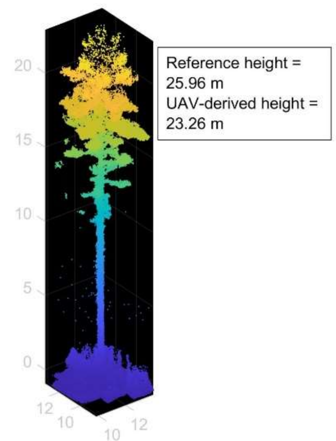


Figure 4. An example of three trees higher than 25 m that we underestimated by the under-canopy UAV laser scanning system.

3.3. Derivation of Stem Volumes

Results for stem volume estimation are depicted in Figure 5. For the sparse site, we obtained a bias of -3.1% and a standard error of 12.5% and for the obstructed site, we obtained a bias of -2.2% and a standard error of 8.6%. Hyyppä et al. [24] reported corresponding accuracies that had been obtained using systems based on backpack laser scanning, handheld laser scanning and a combination of under-canopy UAV laser scanning and above-canopy UAV laser scanning. The obtained accuracies in this study are, however, better than those obtained using conventional field measurements (RMSE 12% for sparse and 23% for obstructed site) and those obtained using above-canopy UAV laser scanning (18-20% for sparse and about 50% for obstructed site).

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 1 April 2021 doi:10.20944/preprints202104.0003.v1

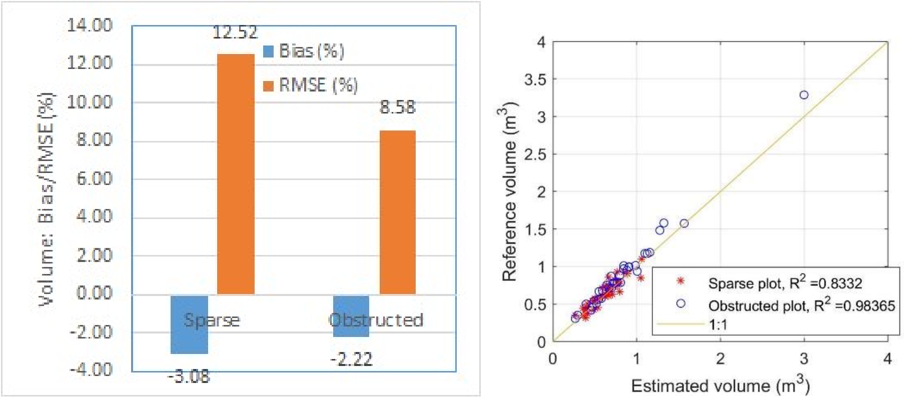


Figure 5. Left: Bias and relative root-mean-square error (RMSE) of the volume estimates in the sparse plot and in the obstructed plot. Right: Scatter plot of the estimated volume vs the reference volume for the sparse plot and the obstructed plot.

3.4. Further Discussion

There are multiple needs in forest informatics, and therefore, different kind of sensors and mapping systems can provide added value. In this section, we discuss whether a combination of above-canopy UAV and terrestrial point cloud data is really needed in the light of our results. It is obvious that the above-canopy UAV systems provides a detailed description of the canopy top including information of tree heights, crown areas, and crown volume. The above-canopy UAV systems provide high-density point clouds of high positional accuracy since GNSS-positioning provides high absolute accuracy above the canopy. On the other hand, locally collected terrestrial point clouds, which have a high local accuracy, a high density, and a low point–cloud-to-point–cloud variation, are another optimal element for characterizing lower parts of the forest canopies. Together such point clouds can provide an optimal characterization of a canopy and the highest quality derivatives can be extracted from such data. The added value of the data includes mm level accuracy of the terrestrial point cloud, dm level accuracy of the canopy height components, and possibility for more accurate change detection. On the other hand, such data is also highly expensive and laborious to collect. Laborious steps include the collection of the TLS scans, matching of the TLS scans to each other and to the above-canopy point cloud. In reality, a single forest plot requires multiple TLS scans, and therefore only few TLS plots can be collected in a single workday. The collection of the UAV-data does not necessarily require a significant amount of time, but it multiplies the costs of the needed sensor technologies and it also multiplies the collected data.

In order to provide both the terrestrial and canopy top point cloud with a reasonable accuracy, there exist also two other technological solutions. The first one is a rotating laser scanner with a high-quality SLAM system complemented with state-of-the-art point cloud extraction methods. The second one uses a large FoV laser scanner capable of seeing both the treetops and the ground. Similarly to the first system, the second scanner should also be integrated with a SLAM system. When using either of these solutions, the resulting point cloud is of lower accuracy as compared with a combination of TLS and above-canopy UAV point clouds due to the need to use multi-beam laser scanners that typically have 2-3 cm ranging errors. In theory, tree trunk data can be obtained at cm-level, and treetops can be obtained with an accuracy ranging from the decimeter level to 1 m, since range accuracy, point density, visibility of the treetops and SLAM accuracy deteriorate the quality. From such data, it is presumably more difficult to extract quality related features from tree stems, branches and foliage. The added value is a more straightforward use of the technology. Only a single-sensor system and processing flow are needed. It is expected that the collection speed of field reference data with such a system is about 10 times higher in terms of the number of trees collected in a single day as compared with

 doi:10.20944/preprints202104.0003.v1

data collection methods needed for the combination of TLS and above-canopy UAV point clouds.

This study was arranged on the same sites as the previous studies [14,24] so that we could compare the developed approach against various other approaches for field reference acquisition including various mobile laser scanning techniques, under-canopy UAV laser scanning combined with above-canopy UAV laser scanning, various above-canopy UAV laser scanning techniques, and conventional field reference data collection. Surprisingly, the results of this paper indicate that the under-canopy UAV system equipped with a rotating scanner provides tree height information with an equal or slightly better accuracy than above-canopy UAV systems providing high-density (320-4800 pts/m^2) point clouds. Our under-canopy UAV system equipped with a rotating scanner also provides stem volume estimates with an accuracy equivalent to the previous best mobile laser scanning techniques even if the previous best techniques are complemented with additional above-canopy UAV laser scanning data. Our assumption is that the technology depicted in this paper is more ready and more feasible to be applied on economically exploited, more sparse boreal forest canopies, whereas the previously proposed approach based on a combination of UAV and TLS is more feasible for ecological studies of forests and for use in complex deciduous and temperate forests.

When it comes to applying an under-canopy UAV system as the data collection platform, future research is needed to implement autonomous operation inside canopies through collision avoidance and navigation inside the forest canopies. Operating the under-canopy UAV system in more complex forest structures provides an additional challenge. An alternative technological solution is an above-canopy flying UAV that can measure the arcs of a tree stem from the above, as proposed in [25] and recently also tested in [26,27]. This requires a small laser beam, a low enough point spacing distance (a high pulse repetition rate) and a low mirror scan speed. Such a system may be feasible for dense, spruce-dominated forests, where an UAV cannot be flown under the forest canopy due to the large number of obstacles. Such a single-sensor system may also provide adequately accurate estimates for tree height and stem volume.

4. Conclusions

Automation of forest field reference has been an intensive research objective for laser scanning scientists for two decades similarly to Holy Grail in Arthurian literature. Since the advent of the first UAV (Unmanned Aircraft Vehicle) flights under the canopy, collection of the forest field reference with such a technique has attracted the attention of scientists. The first study on using an under-canopy UAV laser scanning system for collecting forest informatics resulted in stem volume estimates with a relative RMSE (root-mean-square error) of 10% at an individual tree level. However, this first approach relied on tree heights estimated from another point cloud collected with an above-canopy flying UAV. In order to overcome the tree height collection problem, the first two papers [14, 21] proposed the seamless integration of above- and under-canopy UAV laser scanning for forest field reference data collection.

Therefore, in this paper, we wanted to show that such integration is not necessarily needed. We mounted a rotating laser scanner based on a Velodyne VLP-16 sensor onboard a manually piloted UAV, and the UAV was commanded with the help of a live video feed from the onboard camera of the UAV. Point cloud processing steps after a SLAM correction included DTM generation, segmentation, stem detection, stem curve estimation, and estimation of tree height and stem volume. We compared the individual stem volumes obtained using the proposed method against highly accurate field reference data acquired semi-manually with multi-scan TLS. We showed that the under-canopy UAV system equipped with a rotating scanner provides estimates of tree height and stem volume with an accuracy equaling the previous best mobile laser scanning techniques even if the previous best techniques were complemented with additional above-canopy laser scanning data. Surprisingly, the system developed for this study enabled us to obtain tree height estimates with an equal or slightly better accuracy than has been previously obtained from high-density (320-4800 pts/m^2) point clouds collected with above-canopy UAV laser scanning measurements on the same test sites [24].

Author Contributions: J.H. made the experimental plan, provided basic concepts for data processing, secured funding and wrote the majority of the paper. E.H. provided, and created all the algorithms, and participated in writing the article. T.H. developed hardware and made the measurements. H.K. preprocessed the data. X.Y. processed the data into forest informatics. A.K., T.H., H.K, H.H., J.M. and X.Y. participated in writing the paper. X.Y. and E.H. acted as senior authors. All authors have read and agreed to the published version of the manuscript.

Funding: : We gratefully acknowledge Academy of Finland, Strategic Research Council and ministry of Agriculture and Forestry that funded this research through grants (Decisions 334830, 334002, 337811, 337656, and VN/3482/2021 (PI J.H.), 334829 (PI A.K.), 314312 (PI H.K)). Publication is also part of Finnish Research Flagships Forest-Human-Machine Interplay (UNITE)

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Not applicable

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Luoma, V., Saarinen, N., Wulder, M.A., White, J.C., Vastaranta, M., Holopainen, M.,Hyyppä, J. Assessing precision in conventional field measurements of individual tree attributes. Forests **2017**, 8(2), p.38.
2. Stereńczak, K., Mielcarek, M., Modzelewska, A., Kraszewski, B., Fassnacht, F.E., Hilszczański, J. Intra-annual Ips typographus outbreak monitoring using a multi-temporal GIS analysis based on hyperspectral and ALS data in the Białowieża Forests. Forest ecology and management **2019**, 442, pp. 105-116.
3. Hyyppä, J., Inkinen, M. Detecting and Estimating Atributes for Single Trees Using Laser Scanner. Photogrammetric Journal of Finland **1999**. 16(2), pp. 27-42.
4. Persson, A., Holmgren, J., Soderman, U. Detecting and measuring individual trees using an airborne laser scanner. Photogrammetric Engineering and Remote Sensing **2002**, 68(9), pp.925-932.
5. Hopkinson, C., Chasmer, L., Hall, R.J. The uncertainty in conifer plantation growth prediction from multi-temporal lidar datasets. Remote Sensing of Environment **2008**, 112(3), pp.1168-1180.
6. Jaakkola, A., Hyyppä, J., Kukko, A., Yu, X., Kaartinen, H., Lehtomäki, M., Lin, Y. A low-cost multi-sensoral mobile mapping system and its feasibility for tree measurements. ISPRS journal of Photogrammetry and Remote Sensing 2010, 65(6), pp.514-522.
7. Liang, X., Kankare, V., Hyyppä, J., Wang, Y., Kukko, A., Haggrén, H., Yu, X., Kaartinen, H., Jaakkola, A., Guan, F., Holopainen, M., 2016. Terrestrial laser scanning in forest inventories. ISPRS Journal of Photogrammetry and Remote Sensing **2016**, 115, pp.63-77.
8. Olofsson, K., Holmgren, J., Olsson, H. Tree stem and height measurements using terrestrial laser scanning and the RANSAC algorithm. Remote sensing **2014**, 6(5), pp.4323-4344.
9. Wang, Y., Pyörälä, J., Liang, X., Lehtomäki, M., Kukko, A., Yu, X., Kaartinen, H., Hyyppä, J. In situ biomass estimation at tree and plot levels: What did data record and what did algorithms derive from terrestrial and aerial point clouds in boreal forest. Remote Sensing of Environment **2019**, 232, p.111309.
10. Liang, X., Wang, Y., Pyörälä, J., Lehtomäki, M., Yu, X., Kaartinen, H., Kukko, A., Honkavaara, E., Issaoui, A.E., Nevalainen, O., Vaaja, M. Forest in situ observations using unmanned aerial vehicle as an alternative of terrestrial measurements. Forest Ecosystems **2019**, 6(1), pp.1-16.
11. Cabo, C., Del Pozo, S., Rodríguez-Gonzálvez, P., Ordóñez, C., Gonzalez-Aguilera, D. Comparing terrestrial laser scanning (TLS) and wearable laser scanning (WLS) for individual tree modeling at plot level. Remote Sensing **2018**, 10(4), p.540.
12. Giannetti, F., Puletti, N., Quatrini, V., Travaglini, D., Bottalico, F., Corona, P., Chirici, G. Integrating terrestrial and airborne laser scanning for the assessment of single-tree attributes in Mediterranean forest stands. European Journal of Remote Sensing **2018**, 51(1), pp.795-807.
13. Hyyppä, E.; Kukko, A.; Kaijaluoto, R.; White, J.C.; Wulder, M.A.; Pyörälä, J.; Liang, X.; Yu, X.; Wang, Y.; Kaartinen, H.; et al. Accurate derivation of stem curve and volume using backpack mobile laser scanning. ISPRS J. Photogr. Remote Sens. **2020**, 161, 246–262.
14. Hyyppä, E.; Hyyppä, J.; Hakala, T.; Kukko, A.; Wulder, M.A.; White, J.C.; Pyörälä, J.; Yu, X.; Wang, Y.; Virtanen, J.P.; et al. Under-canopy UAV laser scanning for accurate forest field measurements. ISPRS J. Photogr. Remote Sens. **2020**, 164, 41–60.
15. Balenović, I., Liang, X., Jurjević, L., Hyyppä, J., Seletković, A.,Kukko, A. Hand-Held Personal Laser Scanning–Current Status and Perspectives for Forest Inventory Application. Croat. J. Forest Eng. **2020**.

16. Liang, X.; Kukko, A.; Hyyppä, J.; Lehtomäki, M.; Pyörälä, J.; Yu, X.; Kaartinen, H.; Jaakkola, A.; Wang, Y. In-situ measurements from mobile platforms: An emerging approach to address the old challenges associated with forest inventories. ISPRS J. Photogr. Remote Sens. **2018**, 143, 97–107.
17. Bienert, A.; Georgi, L.; Kunz, M.; Maas, H.G.; von Oheimb, G. Comparison and combination of mobile and terrestrial laser scanning for natural forest inventories. Forests **2018**, 9, 395.
18. Vandapel, N., Kuffner, J., Amidi, O. Planning 3-D path networks in unstructured environments, in: Proceedings of the 2005 IEEE International Conference on Robotics and Automation, IEEE **2005**. pp. 4624–4629.
19. Vian, J.L., Przybylko, J. Tree metrology system. US Patent **2012**, 9,198,363.
20. Chisholm, R.A., Cui, J., Lum, S.K. Chen, B.M. UAV lidar for below-canopy forest surveys. J. Unmanned Veh. Syst. **2013**, 1 (1), pp. 61-68
21. Wang, Y., Kukko, A., Hyyppä, E., Hakala, T., Pyörälä, J., Lehtomäki, M., El Issaoui, A., Yu, X., Kaartinen, H., Liang, X., Hyyppä, J. Seamless integration of above-and under-canopy unmanned aerial vehicle laser scanning for forest investigation. Forest Ecosystems **2021**, 8(1), pp.1-15.
22. Ester, M., Kriegel, H.P., Sander, J., Xu, X. A density-based algorithm for discovering clusters in large spatial databases with noise. In Kdd **1996**, Vol. 96, No. 34, pp. 226-231.
23. Fischler, M.A., Bolles, R.C. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM **1981**, 24(6), pp.381-395.
24. Hyyppä, E., Yu, X., Kaartinen, H., Hakala, T., Kukko, A., Vastaranta, M., Hyyppä, J. Comparison of Backpack, Handheld, Under-Canopy UAV, and Above-Canopy UAV Laser Scanning for Field Reference Data Collection in Boreal Forests. Remote Sensing **2020**, 12(20), p.3327.
25. Jaakkola, A., Hyyppä, J., Yu, X., Kukko, A., Kaartinen, H., Liang, X., Hyyppä, H., Wang, Y. Autonomous collection of forest field reference—The outlook and a first step with UAV laser scanning. Remote sensing **2017**, 9(8), p.785.
26. Neuville, R., Bates, J.S., Jonard, F. Estimating forest structure from UAV-mounted LiDAR point cloud using machine learning. Remote Sensing **2021**, 13(3), p.352.
27. Puliti, S., Breidenbach, J., Astrup, R. Estimation of forest growing stock volume with UAV laser scanning data: can it be done without field data? Remote Sensing **2020**, 12(8), p.1245.