UTILIZING SINGLE PHOTON LASER SCANNING DATA FOR ESTIMATING INDIVIDUAL TREE ATTRIBUTES

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ABSTRACT:

Mapping and monitoring forest resources require collection of spatially explicit and timely remote sensing (RS) data. Although field measurements are still important, the RS-based forest inventory helps mapping large areas to be cheaper, faster, less labor intensive, and spatially more explicit. The single-photon laser (SPL) scanning data has been exploited for different forestry applications but lacks deep examination in mapping individual trees as well as being compared with ordinary laser scanning (Linear-mode, LML) data and different individual tree detection (ITD) methods. Hence, this research focuses on applying and comparing two datasets (SPL and LML) for extracting attributes of individual trees by applying two tree crown segmentation methods (local maxima and watershed segmentation) on both datasets. The results were validated over 49 field measured plots of different species, located in southern boreal forest.

The SPL yielded more accurate results for both tree density and height estimation. Watershed segmentation method yielded more accurate results for tree density and height estimation in both LML and SPL datasets. Tree density was underestimated by 4.7% (rRMSE: 32.3%) for all species. Comparing tree density estimation of different species, it was most accurate in deciduous plots (rBias: -9.5, rRMSE: 17.0%). Tree height estimation with SPL explained the variations of field-measured height very well (R^2= 0.93), and was reliably accurate, underestimated by 3.4% (rRMSE: 7.0%). The mean tree height estimation was most accurate in pine plots (rBias: 4.9%, rRMSE: 1.1%). In this research, SPL represented reliable and usable point cloud data for estimating tree height and density.

1. INTRODUCTION:

Sustainable management of forest resources is an important aspect of combating climate change. This management requires timely and spatially detailed information from the forest resources. Remote Sensing (RS) technologies mapping and monitoring large forest areas. For example, airborne laser scanning (ALS) is an active RS method that provides three-dimensional data remotely from a desired object by sending laser pulses to the target and records the back-reflected pulses. Laser scanner sends high-power and high-frequency short pulses (Holopainen et al., 2013). ALS has been exploited and proved for forest mapping (Hyyppä et al., 2012) (White et al., 2016). However, the emergence of the SPL system enforces the question of whether it is capable of improving state-of-the-art accuracy for forestry applications.

The single-photon laser (SPL) scanning system detects reflected photons more accurately, faster and energy efficiently than conventional LiDAR systems (Swatantran et al., 2016). SPL's short channel recovery time (only 1.6 nanoseconds) allows it to store multiple range measurements for each laser pulse, while in other conventional systems the channel recovery times are longer (Degnan, 2016). The method with SPL allows for very dense point clouds and up to 30 times the speed of operation compared to other conventional systems. It is suitable for fast forest structure and 3D-scanning for terrains for example, digital elevation models (DEM) (Brown et al., 2020) (Swatantran et al., 2016). The SPL system has been used in a few studies internationally, and few in Finland. The earlier studies have documented that SPL can be a promising technology for forestry applications (White et al., 2021) (Raty et al., 2021), (Yu et al., 2020); (Wästlund et al., 2018). For example, Wästlund et al., (2018) studied SPL with area-based-approach (ABA) method in a hemi-boreal forest area of 1300 ha where forest management is active. They concluded that the SPL has great potential for efficient mapping of detailed information, similarly in White et al. 2021. However, exploiting the feasibility of SPL with two individual tree detection (ITD) methods left unstudied, as well as comparing them with conventional linear mode laser (LML) systems.

The SPL requires less flight strips for the same area compared to conventional systems due to the high flight altitude and wider swath width on the ground (Mandlburger et al., 2019). SPL has been shown to have moderate vegetation penetration in leaf-on situations (Mandlburger et al., 2019; Brown et al., 2020). However, the LML system provided better ground coverage under tree canopies, outperformed the SPL for providing a sharper and more concise mapping of both topography and buildings (Mandlburger et al. 2019).

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Individual tree detection (ITD) (Hyyppä et al., 1999) method is one of the major approaches when using ALS data for forestry. It requires higher point density (> 2 pulses/m^2) point cloud data (Holopainen et al., 2013). ITD is often based on searching for local maxima (LM) from rater-based canopy height models (CHM) (Holopainen et al., 2013). LM-method determines the location of the treetop based on the highest points on a specific area. Another commonly used ITD method is watershed segmentation (WS) which is based on geometric structure in CHM or point clouds data and can be seen as water is poured on trees and the method then delineates these edges and generates tree crown boundaries (Wang et al., 2004). Comparing the two methods and especially with the two datasets (SPL and LML) is rarely addressed, which is one of the main aims of this study.

Objectives:
Hence, this study aims to examine the capability of SPL for large-area forest mapping and compares it with LML in retrieving tree density and height in mature boreal forests using two ITD methods (WS and LM). This study presents the results for all trees, pine, spruces, and deciduous plots. Therefore, this research aims to answer the following research questions:

1. How accurately SPL can estimate tree density and height?
2. Which ALS data (SPL or LML) could be more reliable for tree attribute estimation?
3. Which segmentation method (WS or LM) could yield more accurate tree attributes?

2. MATERIALS AND METHODS

2.1. Field data

The study area is located in the southern boreal forest zone in Akaa (61°10′00″N, 23°52′05″E) Finland (Figure 1). Forests in the area are mainly managed forests where Norway spruce and Scots pine constitute as the dominant tree species.

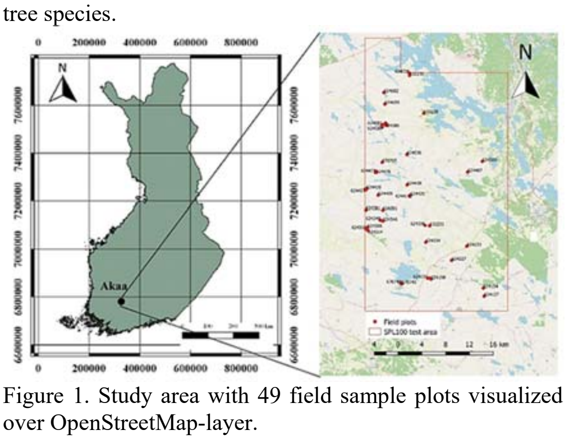

Figure 1. Study area with 49 field sample plots visualized over OpenStreetMap-layer.

Field measurements were carried out during May and June 2017. A total of 49 fixed radius plots are located in the area. During field visit, tree height, diameter at breast height (DBH) and tree density (unit: trees per hectare (TPH) were measured among other forest variables such as age, growing stage and tree species class. The location of plot centers was recorded using GPS and, in the center, a GNSS device (sensing rod) was installed. Tree height measurements were carried out using Vertex which was calibrated daily and every time when weather changed during measurements. Finally, the attributes describing the structure at plot level were calculated using tree attribute sum averages. A summary of plots is given in Table 1.

Table 1. The variation of different tree attributes measured in field plots (n = 49) per species class and total. Max, Min, Stdev, and TPH refer to maximum, minimum, standard deviation, and trees per hectare, respectively.

	Species	Max.	Min	Mean	Stdev
Tree density (TPH)	Pine	1140	240	647	279
	Spruce	1533	240	700	315
	Deciduous	904	550	753	110
	Total	1533	240	687	286
Tree height (m)	Pine	29.4	14.3	21.9	3.4
	Spruce	31.0	15.8	22.3	3.7
	Deciduous	23.7	13.2	16.6	3.6
	Total	31.0	13.2	21.5	4.3

Two types of plots have been used in field measurements. Smaller plot with a 9-meter fixed radius and a bigger plot with 12.62-meter fixed radius. The radius was chosen based on the number of trees inside the plot. Should tree density be less than 20 trees at 9-meter radius then the plot radius was grown to 12.62-meter. Otherwise, the 9-meter radius was used. In this study, we focused on forest stands in the development class of mature and regeneration-ready stands with an average DBH > 16 cm and age > 25 years (Tapio. (2006) with only single species at each plot. Thus, species classification is not needed by assuming all segments are from trees. We have 25 plots as spruce, 18 pine and 6 deciduous.

2.2. Remote sensing data

Remotely sensed data consist of SPL data from SPL100 sensor, and LML data from Riegl vq1560i sensor that is used as conventional systems (Table 2).

Table 2. Features for SPL (Leica's SPL100) and Riegl linear-mode laser (LML) scanning data with the achieved point density (points/m^2) overall, and among plots with specific species class.

	SPL	LML
Date of flight	31.5.2018	21.-24.5.2018
Flight altitude (m)	3750	1450
Scan angle	30º	40º
Bandwidth on ground (m)	2010	1000
Pulse density (pulses/m^2)	27.0 (28.1*, 26.0**, 26.3***)	22.8 (22.6*, 21.1**, 24.5***)

*Spruce, **Pine, ***Birch

2.2.1. Pre-processing LiDAR data

Data pre-processing and noise filtering from the SPL data was carried out by SigmaSpace using Leica HxMap software's default settings. Filtering of SPL raw point cloud data takes advantage of the relative randomness of noise data versus the relatively orderly data from the targeted surfaces. Next, the National Land Survey of Finland (NLS), the data ordered, conducted geoid fix for the data to transform it into the national N2000-height system. This is crucial for SPL as it generates false echoes when photons hit dust, aerosol, clouds or even birds in mid-air. Next, both data were height normalized using Lastools (Lastools, 2014) using software's tool *lasheight.*

2.2.2. Creating canopy height models (CHM)

The canopy height models (CHM) were created by interpolating all first returns with a triangulated irregular network and then rasterizing it onto a grid of 20 cm to create the CHM. Splatting - means using option "subcircle" in lasgrid - replaces each return by a circle with a specific radius (we used 10 cm). In order to avoid omission of edgetrees from tree detection, an extra 2-meter buffer was added to all plots. Trees with treetops inside plot, were located and counted

2.2.3. Tree crowns segmentation with Local Maxima

The tree crowns were delineated using LM, implemented in the ForestTools package that implements the variable window filter (vwf) algorithm (Popescu and Wynne, 2004) to detect treetops from a CHM automatically. The vwf technique assumes that there are multiple tree crown sizes, and that the moving LM filter should be adjusted to an appropriate size that corresponds to the spatial structure found on the CHM and on the ground. Next, to create segment boundaries from the defined treetops, marker-controlled watershed function in that package was used.

The parameters were tested and optimized using 5 plots, then the same settings applied for all plots. The height limit was set to 6 m using the minHeight argument. In the CHM smoothing stage, a gaussian smooth was used with window size of 3 and sigma value of 0.7 (used when filter parameter is equal to Gaussian, default).

2.2.4. Tree crown segmentation with Watershed method

Similar to the LM method, we smoothed the CHMs in QGIS Gaussian simple filter (QGIS.org 2020). The WS tool then generates seed points and segments depicting the crowns (Figure 2).

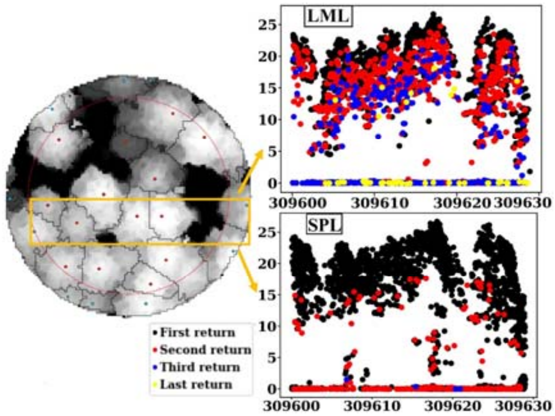

Figure 2. Delineated tree crowns with treetops with canopy height model (CHM) derived from linear mode laser (LML) data in the background (left) together with 2D (X and Z) plot of point clouds from LML and single-photon laser (SPL) data inside the orange rectangle shape in the middle of plot (right). Number of points inside this orange intersecting rectangle was 3,180 (54.3%, 32.5%, 11.5%, 1.6%) and 3,167 (90.6%, 9.3%, 0.1%, 0.0%) in LML and SPL (proportion of first, second, third, and last return), respectively. This plot contains spruce trees.

All steps and workflow were identical for both SPL and LML data. Finally, the height and xy-location of each segment were extracted. The number of detected trees inside plots were extracted and converted to TPH, as well as calculating plot-level mean height.

2.2.5. Accuracy evaluation

To evaluate the reliability of remotely sensed tree height, estimates were compared to the plot-level mean tree height and density from field measurements. Absolute and relative RMSE (rRMSE) were calculated for each attribute. Also, the absolute bias (Bias) produced by the models, and the relative bias (rBias) derived from it were used to evaluate accuracy of the remote sensing.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \ddot{y}_i)^2}{n}},$$

$$\mathrm{rRMSE} = 100 \times \frac{\mathrm{RMSE}}{\bar{y}},$$

$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(\mathrm{yi} - \ddot{\mathrm{y}})}{\mathrm{n}},$$

$$\mathrm{rBIAS} = 100 \times \frac{\mathrm{BIAS}}{\bar{y}},$$

where n = the number of plots
y_i = value from the field data for plot i
$\ddot{y}_i$ = remotely sensed (estimated) value for plot i
$\bar{y}$ = mean of the variable in the field data.

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3. RESULTS

3.1. Tree density estimation using SPL

Using the LM method, tree density was underestimated by 7.4% (rRMSE: 35.9%) for all species (Figure 3). The rRMSE of tree density was 29.6%, 41.2% and 19.2% for pine, spruce, and deciduous plots, respectively. It was also underestimated for spruces and deciduous plots by 27.5% and 1.8%, respectively; however, overestimated for pine by -19.9% (Figure 3). The tree density estimation was most accurate in deciduous plots with underestimation of <2%.

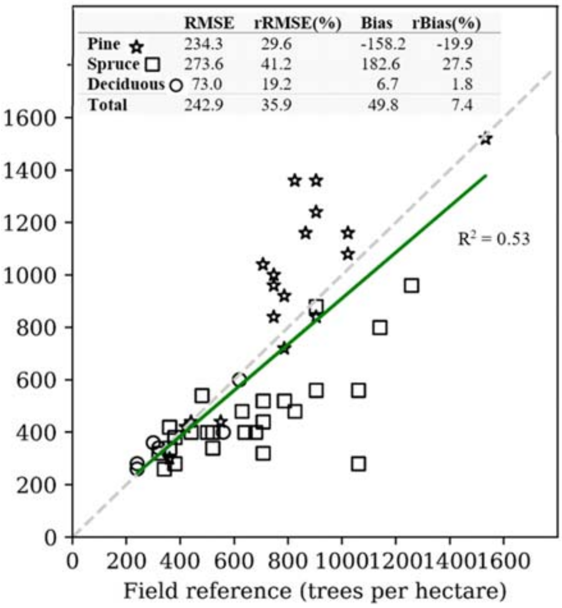

Figure 3. Tree density estimation (trees per hectare, TPH) using local maxima method with SPL data per each and all species classes.

Using the WS method, tree density was underestimated by 4.7% (rRMSE: 32.3%) for all species (Figure 4). The rRMSE of tree density was 28.4%, 35.6% and 17.0% for pine, spruce, and deciduous plots, respectively. It was also underestimated for spruce plots by 23.9%; nevertheless, overestimated for pine and deciduous plots by -19.9% and -9.5%, respectively (Figure 4). It was most accurate in deciduous plots, overestimated by <10%.

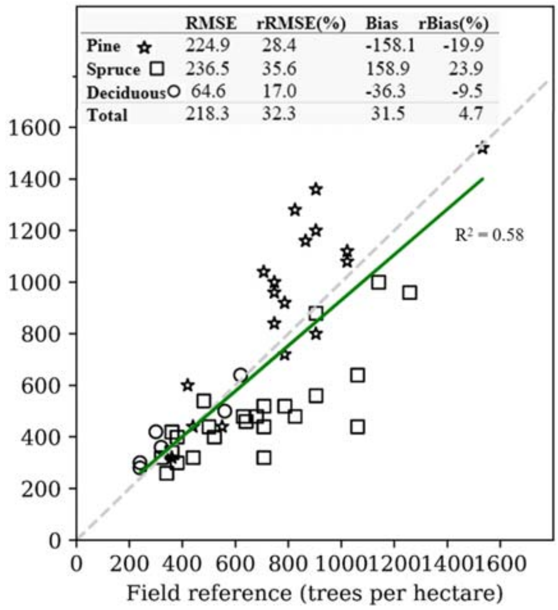

Figure 4. Tree density estimation (trees per hectare, TPH) using watershed segmentation method with SPL data per each and all species classes.

3.2. Tree density estimation using LML

Using the LM method, tree density was underestimated by 15.1% (rRMSE: 30.6%) for all species (Figure 5). The rRMSE of tree density was 18.4%, 39.3% and 13.6% for pine, spruce, and deciduous tree plots, respectively. All species were underestimated. The tree density estimation was most accurate in deciduous plots with 3.5% underestimation (rRMSE: 13.6%).

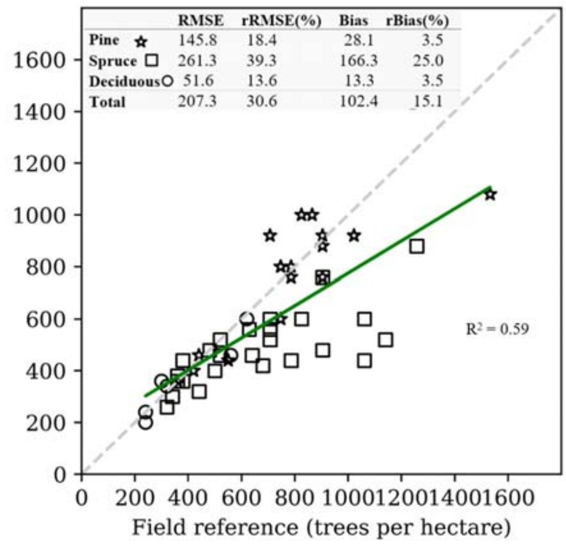

Figure 5. Tree density estimation (trees per hectare, TPH) using local maxima method with LML data per each and all species classes.

Using the WS method, tree density was underestimated by 10.0% (rRMSE: 25.4%) for all species (Figure 6). The rRMSE of tree density was 14.0%, 31.4% and 40.4% for pine, spruce, and deciduous plots, respectively. It was also underestimated for spruce plots by 18.3% and pine plots by 5.1%; nevertheless, overestimated for deciduous plots by -28.1% (Figure 6). Comparing the tree density estimation between each species, the estimation was most accurate between pine plots with underestimation of 5.1% (rRMSE: 14.0%).

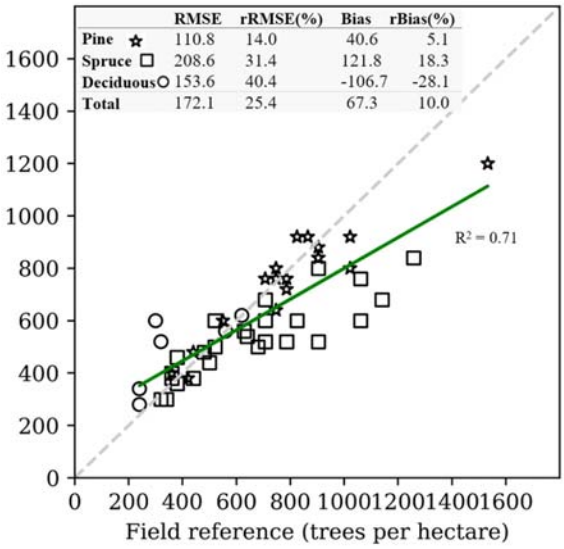

Figure 6. Tree density estimation (trees per hectare, TPH) using watershed segmentation method with LML data per each and all species classes.

3.3. Tree height estimation using SPL

Using the LM method, the mean tree height was underestimated by 3.7% (rRMSE: 7.3%) for all species (Figure 7). The rRMSE of tree height was 9.4%, 6.0% and 9.0% for pine, spruce, and deciduous plots, respectively. It was also underestimated for all species; pines, spruces, and deciduous plots by 6.8%, 1.6% and 6.4%, respectively (Figure 7). The mean tree height estimation was most accurate between spruce plots with 1.6% underestimation (rRMSE: 6.0%).

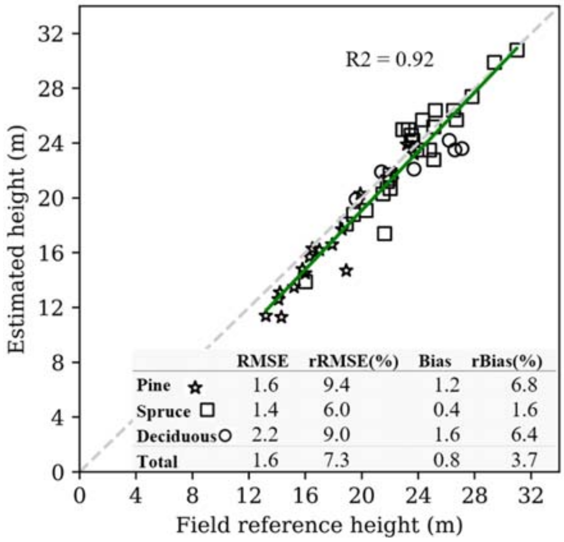

Figure 7. Mean tree height estimation (meter) using local maxima method with SPL data per each and all species classes.

Using the WS method, the mean tree height was underestimated by 3.4% (rRMSE: 7.0%) for all species (Figure 8). The rRMSE of tree density was 6.5%, 6.5% and 9.0% for pine, spruce, and deciduous plots, respectively. It was underestimated by 4.9%, 2.1% and 6.0% for pine, spruce and deciduous, respectively. The tree height estimation was most accurate in pine plots with underestimation of 4.9% (rRMSE: 1.1%).

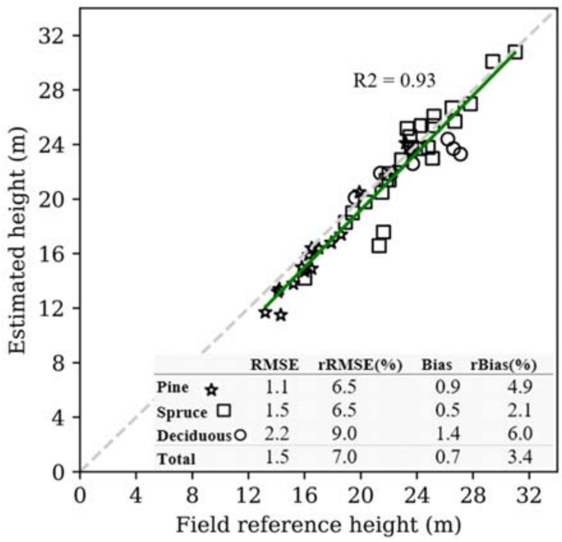

Figure 8. Mean tree height estimation (meter) using watershed segmentation method with SPL data per each and all species classes.

3.4. Tree height estimation using LML

Using LML data with the LM method, the mean tree heights were underestimated by 4.0% (rRMSE: 6.4%) for all species (Figure 9). The rRMSE of tree height was 9.0%, 5.4% and 6.0% for pine, spruce, and deciduous plots, respectively. It was underestimated for all species of pines, spruces, and deciduous plots by 7.0%, 2.6% and 4.0%, respectively (Figure 9). The mean tree height estimation was most accurate in spruce plots, underestimated by 2.6% (rRMSE: 5.4%). The coefficient of determination (R^2) was 0.95 for all species. It was 0.94, 0.92 and 0.96 for pine, spruce and deciduous, respectively.

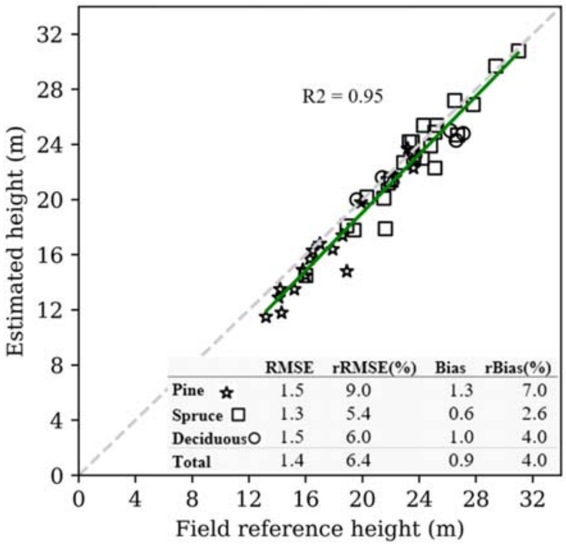

Figure 9. Mean tree height estimation (meter) using local maxima method with LML data per each and all species classes.

Using the WS method, the mean tree height was underestimated by 2.4% (rRMSE: 8.0%) for all species (Figure 10). The rRMSE of tree heights was 7.1%, 4.8% and 15.6% for pine, spruce, and deciduous plots, respectively. The mean tree height estimation was most accurate between spruces, underestimated by 1.9% (rRMSE: 4.8%). The R^2 of all plots was 0.87, and it was 0.87, 0.74, and 0.50 for pine, spruce, and deciduous, respectively.

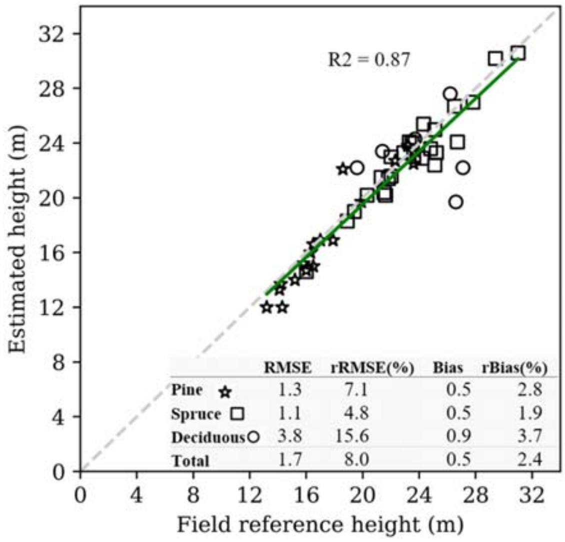

Figure 10. Mean tree height estimation (meter) using watershed segmentation method with LML data per each and all species classes.

4. DISCUSSION:

This research aimed to investigate the applicability of SPL data for estimating tree density and height in boreal forests, compare it with LML data, and test the two datasets with two methods (LM and WS). Comparing the two methods used in this study, WS outperformed LM method for tree density estimation. Tree density of deciduous plots was more accurately estimated compared to coniferous plots in both methods and overestimated in pine plots. Comparing mean tree height estimation using the two datasets of this study, the results of SPL were more accurate than LML.

The tree density estimation with SPL was overall more accurate than LML (rRMSE: 30.6% and 35.9%, respective). In pine plots, the decrease was from rRMSE of 29.6% to as low as 18.4%. Plots with spruce were still the most challenging tree to locate as LML generated rRMSE of 39.3%. As results showed, watershed was not as susceptible to misinterpretations of the tree density as LM. However, it should be mentioned that the most significant weakness of LM is the parameter used in it in the search window and its effect by tree species. It works best for trees with a single well-defined apex, such as coniferous species (Popescu and Wynne, 2004). Should the tree be abnormal with crown figures, identifying it as a single tree might be problematic. For example, we observed that with SPL data using LM method, the number of trees was overestimated where the average height of the stand in the plot was low. Otherwise, the method underestimated the tree density of stands. Hence, further studies could tailor the parameters settings per species strata to improve the results of the LM method, however this is not favorable for operational forestry.

To the best of the author's knowledge, there was no investigation for the application of SPL for tree density estimation using the ITD method. Hence, we compare our results with other studies using ordinary ALS data. For example, Packalén et al. (2008) achieved an rRMSE of 49.1% using ordinary ALS data (0.7 points/m^2) in 472 plots using ITD method in a managed coniferous-dominated boreal forest in eastern Finland. Comparing the two methods, the WS method yielded more accurate tree density estimations (rRMSE: 32.3%) compared to LM method (35.9%) using SPL data.

Comparing tree density prediction among species classes, deciduous trees were most accurately predicted in both WS and LM methods. Pine plots, on the other hand, were overestimated in both methods (WS and LM). The overestimation of pine density may be due to branching tops, which the method considers to be a separate tree crown. In the case of spruce, the data SPL underestimated the tree density. Spruce had the biggest deviation, which at its worst differed by 781 TPH from the field-measured 1,061 TPH. Notably, the large differences in the tree density of the plots may be due to possible errors in the field measurements and GPS accuracy for defining the centers of the plots.

The mean tree height estimation was overall more accurately predicted using SPL (rRMSE: 7.0%) than LML (8.0%) using WS method, although the underestimation was smaller in LML (2.4%) than SPL (3.4%). Coniferous plots were more accurately predicted, for example pine with underestimation of 4.9%.

The tree height estimation obtained in this study using SPL data (rRMSE of 7.0%) were in line with Wästlund et al. (2018) with SPL data (point density of 25.4 points/m^2), achieved rRMSE of 6.1% in semi-boreal forest in southern Sweden. Note that the R^2 with tree heights in this study was lower (0.93) than theirs (0.96). The possible reason for differences can be due to the ABA method they used compared to our ITD method. Similarly, our results were in line with Yu et al. 2021 that achieved an rRMSE of 6.73% (rBias: -0.22%, R^2: 0.95) for predicting mean tree height in southern Finland. Yet, the results obtained in this study with ITD method were more accurate than White et al. (2021) with ABA modeled with randomForest regression. They achieved an rRMSE of 7.24% in estimating the tree height using SPL data (32.4 point/m^2) in 269 field plots of mixed wood forests of Canada.

To compare our results with other studies using ordinary ALS data for forest inventory attributes, the results of this research improved the state-of-the-art accuracy of other ALS-related studies. For example, Vastaranta et al. (2012) used ITD method to train ABA in southern boreal forest in Evo, Finland, and achieved tree height rRMSE of 8.2% in with 254 plots. They also tested visually corrected ITD methods which gained rRMSE of 10.0%. Lower accuracy may be due to CHM pixel size of 0.5m (compared to this study's 0.2 m) or lower point density (10 points/m^2). Also, Packalén et al. (2008) achieved an rRMSE 8.4% using ordinary ALS data (0.7 points/m^2) in 472 plots using ITD method in typical managed boreal forest in eastern Finland with coniferous tree species dominating the site. Moreover, Yu et al. (2011) used LML data over 1476 trees in boreal forest area in southern Finland using a point density of 2.6 points/m^2. They achieved the tree height rRMSE of 10.0% with ITD together with randomForest estimation method.

Further studies could consider collecting both ALS and field measurements at the same growing season. Because our ALS data were captured in late May 2018 (before growth starts) and field measurements were gathered mainly after growth of 2017, except a few (n = 11) plots in later May, so no computational growth was applied in this study. Thus, the time-lag between collecting RS and field data is only a half-growing season and these plots were mature forests (mostly over 50 years old), their height growth is negligible within the time-lag. Moreover, in this study, all segments were considered as trees and plots contained single species class and thus species classification was skipped. Admittedly, the species classification using proper aerial imagery should be considered for application of SPL in large-area forest mapping with mixed species classes. Moreover, the results of forest step (tree density estimation) could affect the results of the following step (tree height estimation), because in this study we used plot-level field data, which could be improved by tree-level measurements in further studies.

Overall, the tree density and height estimations using SPL data were overall as accurate as LML data, although it was collected from higher altitude (3,750 m) than LML (1,450m) in this study.

5. CONCLUSIONS:

The two ALS data (SPL and LML) were tested with two segmentation methods (WS and LM) for characterizing individual trees in mature southern boreal forests of Finland.

According to the results obtained in this study, the WS method was more robust for tree density estimation compared to the LM method, in both SPL and LML data. The tree density of deciduous trees was more accurately estimated than coniferous trees in all conditions (in both data and both methods). The tree density of pine was overestimated in all conditions. Our results also demonstrated that LML data yielded more accurate tree density estimates than SPL in both methods.

Regarding tree height estimation, SPL data predicted mean tree heights more accurately than LML data. The WS method with SPL data yielded the most accurate mean tree heights. Surprisingly, both methods (LM and WS) yielded very similar results for SPL. In LML data, the results demonstrated that the LM method was more accurate than the WS method. Tree heights of spruce were most accurately estimated in all conditions except watersheds with SPL where pine was the most accurately estimated species. The tree height of deciduous trees was constantly less accurately estimated compared coniferous trees except LM with LML whereas deciduous overrun pine with accuracy.

Findings obtained in this study showed that SPL could be as reliable as LML and could further enhance and fasten acquisition of forest resources data.

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REFERENCES:

Brown, R., Hartzell, P., Glennie, C., 2020. Evaluation of SPL100 single photon lidar data. Remote Sens. 12, 1–16. https://doi.org/10.3390/rs12040722

Degnan, J.J., 2016. Scanning, multibeam, single photon lidars for rapid, large scale, high resolution, topographic and bathymetric mapping. Remote Sens. 8. https://doi.org/10.3390/rs8110958

Holopainen, M., Hyyppä, J., Vastaranta, M., 2013. Laserkeilaus metsävarojen hallinnassa (In English: Laser scanning in forest resource management). Department of Forest Sciences, University of Helsinki (In Finnish: Helsingin yliopiston metsätieteiden laitoksen julkaisuja).

Hyyppä, J., Yu, X., Hyyppä, H., Vastaranta, M., Holopainen, M., Kukko, A., Kaartinen, H., Jaakkola, A., Vaaja, M., Koskinen, J., Alho, P., 2012. Advances in forest inventory using airborne laser scanning. Remote Sens. 4, 1190–1207. https://doi.org/10.3390/rs4051190

Hyyppä, J.M., Hyyppä, H., Samberg, A., 1999. Assessing forest stand attributes by laser scanner, in: Proc.SPIE. https://doi.org/10.1117/12.351373

LAStools, 2014, "Efficient LiDAR Processing Software" (academic), obtained from http://rapidlasso.com/LAStools, accessed 2020

Mandlburger, G., Lehner, H., Pfeifer, N., 2019. A COMPARISON of SINGLE PHOTON and FULL WAVEFORM LIDAR. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 4, 397–404. https://doi.org/10.5194/isprs-annals-IV-2-W5-397-2019

Packalén, P., Pitkänen, J., Maltamo, M., 2008. Comparison of individual tree detection and canopy height distribution approaches: a case study in Finland. SilviLaser 2008 1,22–29.

Popescu, S.C., Wynne, R.H., 2004. Seeing the Trees in the Forest : Using Lidar and Multispectral Data Fusion with Local Filtering and Variable Window Size for Estimating Tree Height. Photogramm. Eng. Remote Sens. 70, 589–604. https://doi.org/10.14358/PERS.70.5.589

QGIS.org, 2020. QGIS Geographic Information System. QGIS Association. http://www.qgis.org

Raty, J., Varvia, P., Korhonen, L., Savolainen, P., Maltamo, M., Packalen, P., 2021. A Comparison of Linear-Mode and Single-Photon Airborne LiDAR in Species-Specific Forest Inventories. IEEE Trans. Geosci. Remote Sens. 1–14. https://doi.org/10.1109/TGRS.2021.3060670

Swatantran, A., Tang, H., Barrett, T., Decola, P., Dubayah, R., 2016. Rapid, high-resolution forest structure and terrain mapping over large areas using single photon lidar. Sci. Rep. 6, 1–12. https://doi.org/10.1038/srep28277

Tapio. (2006). Hyvän metsänhoidon suositukset. [Recommendations for forest management in Finland]. Forest Development Centre Tapio. Metsäkustannus oy. 100 p. [In Finnish].

Vastaranta, M., Kankare, V., Holopainen, M., Yu, X., Hyyppä, J., Hyyppä, H., 2012. Combination of individual tree detection and area-based approach in imputation of forest variables using airborne laser data. ISPRS J. Photogramm. Remote Sens. 67, 73–79. https://doi.org/10.1016/j.isprsjprs.2011.10.006

Wang, L., Gong, P., Biging, G.S., 2004. Individual tree-crown delineation and treetop detection in high-spatial-resolution aerial imagery. Photogramm. Eng. Remote Sensing 70, 351–357. https://doi.org/10.14358/PERS.70.3.351

Wästlund, A., Holmgren, J., Lindberg, E., Olsson, H., 2018. Forest variable estimation using a high altitude single photon lidar system. Remote Sens. 10. https://doi.org/10.3390/rs10091422

White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T., Tompalski, P., 2016. Remote Sensing Technologies for Enhancing Forest Inventories: A Review. Can. J. Remote Sens. 42, 619–641. https://doi.org/10.1080/07038992.2016.1207484

White, J.C., Penner, M., Woods, M., 2021. Assessing single photon LiDAR for operational implementation of an enhanced forest inventory in diverse mixedwood forests. For. Chron. 97, 78–96. https://doi.org/10.5558/tfc2021-009

Yu, X., Hyyppä, J., Vastaranta, M., Holopainen, M., Viitala, R., 2011. Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. ISPRS J. Photogramm. Remote Sens. 66, 28–37. https://doi.org/10.1016/j.isprsjprs.2010.08.003

Yu, X., Kukko, A., Kaartinen, H., Wang, Y., Liang, X., Matikainen, L., Hyyppä, J., 2020. Comparing features of single and multi-photon lidar in boreal forests. ISPRS J. Photogramm. Remote Sens. 168, 268–276. https://doi.org/10.1016/j.isprsjprs.2020.08.013