Comparing tree structures derived among airborne, terrestrial and mobile LiDAR systems in urban parks

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ABSTRACT
Measuring tree structure using three-dimensional (3D) mapping tools such as light detection and ranging (LiDAR) remote sensing is needed to provide well-managed and designed green spaces. The metrics used to estimate tree structure could be different depending on which LiDAR systems are used. This may lead to confusion and reduce confidence when evaluating tree structures and their derived products, such as plant area index (PAI). Therefore, studies that can determine similarities among measurements derived from different LiDAR systems are needed. In this study, structural canopy metrics in airborne laser scanning (ALS), terrestrial laser scanning (TLS), and mobile laser scanning (MLS) were compared to seek consistencies among the three LiDAR systems. The specific objectives were to test whether the estimates made by the metrics differed depending on single or clustered trees and to test whether LiDAR-derived errors in the metrics are related to tree structures. Tree point clouds were manually classified into single and clustered trees. Heights-related metrics, Rumpel Index, area, and PAI were calculated for comparison analysis. Root-mean-square error (RMSE), bias, and Pearson’s correlation coefficient (r) were calculated to evaluate the consistencies in each metric among the LiDAR systems. The results showed that the maximum height of the point clouds (ZMAX) and max and mean heights derived from the canopy height models (minCHM and maxCHM) demonstrated good consistency (RMSE% < 10%, Bias% < 10%, and r > 0.900). Moreover, the biases from the ZMAX- and CHM-derived metrics comparisons among the LiDAR systems did not show strong linear relationships with the tree heights and canopy complexities (i.e. Pearson’s correlation coefficient r < 0.291). On the contrary, the 95th percentile (Zq95) height and mean z height (ZMEAN) differed depending on the tree classes and showed significant linear relations with canopy heights and complexity. The configurations of LiDAR systems, such as point density and sensing locations, seem to affect the Zq95, ZMEAN metrics, and PAI. Our results suggest that assessing for consistencies among the different LiDAR systems is required before using multiple LiDAR systems interchangeably to estimate the structure of urban park areas.

1. Introduction
A detailed dataset of cityscape tree structures is needed to provide well-managed and designed green spaces. Estimates of both horizontal (i.e. canopy cover) and vertical (i.e. vertical canopy distribution) tree structures are essential to manage and monitor green areas because these parameters identify tree vigor and relate to ecosystem functions and urban biodiversity (Omasa et al. 2007; Nadrowski, Wirth, and Scherer-Lorenzen 2010; Song et al. 2016; Smith, Dearborn, and Hutrya 2019). Owing to the importance of estimating tree structures and the limitations imposed by using two-dimensional spatial datasets (e.g. airborne imagery and satellite imagery) to describe the vertical information of tree structures, there is an urgent need for more elaborate spatial datasets created using high resolution remote sensing systems and data processing such as light detection and ranging (LiDAR) remote sensing (Lefsky et al. 2002; Eitel et al. 2016; Lepczyk et al. 2021).

Many studies have used LiDAR sensors to assess horizontal and vertical tree structures (Song et al. 2016; Choi, Song, and Jang 2019). LiDAR is one of the most accurate active remote sensing tools. A laser scanner collects object imagery in a three-dimensional (3D) perspective (i.e. a point cloud dataset) by calculating the time intervals between emitting laser pulses and receiving their reflections from target objects. There are three LiDAR platforms or systems, depending on where the sensors are
TBM and which systems are used; airborne laser scanning (ALS), terrestrial laser scanning (TLS), and mobile laser scanning (MLS or handheld laser scanning) (Hyppä et al. 2020). Although ALS can cover large areas (local to region levels), there are concerns that ALS collect sparse sub-canopy data for forests due to the specifications of the LiDAR sensors, such as the laser footprint, pulse repetition rate, and flight altitude; The footprint of a laser is not small enough to penetrate the gaps in tree canopies or is blocked by high canopies (Goodwin, Coops, and Culvenor 2006; Bater et al. 2011; White et al. 2016; Wang et al. 2019). TLS can generate a highly dense point cloud, but tree heights may be underestimated because of the occlusion effects of the lower canopy (Hilker et al. 2012; Krooks et al. 2014; Wang et al. 2019), whereas ALS estimates of tree heights < 10 m show good agreement regardless of stand complexity (Wang et al. 2019; Wu et al. 2020). Although TLS can collect accurate data from tree structures, it has disadvantages in collecting top-canopy data and in surveying regional areas with limited access. Recently, the use of MLS in canopy studies has increased. MLS has been developed in the field of robotics and has adopted simultaneous localization and mapping (SLAM) robotics systems. MLS is more convenient than TLS for collecting 3D datasets of extensive areas (Liang et al. 2016; Heo et al. 2019; Schneider et al. 2019; Hyppä et al. 2020). Moreover, forest inventory results using MLS have shown good agreement compared to TLS-derived results (Su et al. 2020; Wang and Fang 2020).

ALS datasets may be useful for city planners to plan and manage their urban areas; however, the economic cost of ALS makes it difficult to collect consistent multi-temporal ALS datasets that correspond to urban land-use changes (White et al. 2016). TLS and MLS may solve the acquisition problems for these temporal data (Bauwens et al. 2016; Bienert et al. 2018). However, to the best of our knowledge, there are few studies of which LiDAR-derived structural variables of green areas can be used in common among the different LiDAR systems. Most studies have been conducted using single LiDAR systems with field surveys for validation. Hilker et al. (2012) concluded that tree-level (i.e., collecting individual tree data) measurements are more accurate using TLS than using ALS, whereas height estimation is more accurate using ALS. Pyörälä et al. (2019) and LaRue et al. (2020) compared ALS-derived canopy metrics with TLS-derived wood properties and found that several wood properties are predictable using the ALS datasets. Ojoatre et al. (2019) and Bazezew, Hussin, and Kloosterman (2018) estimated forest biomass by integrating ALS and TLS datasets.

Each LiDAR system has its pros and cons in terms of its purpose of use. Stand-alone LiDAR systems can successfully estimate tree structures (Heo et al. 2019; Wu et al. 2020; Su et al. 2020). However, the estimated tree structure measurements could be different depending on which LiDAR system is used (Hilker et al. 2012; LaRue et al. 2020). This may lead to confusion and reduce confidence when evaluating tree structures and their derived products, such as the plant area index (PAI), biomass, and carbon stocks (Almeida et al. 2019; Wang and Fang 2020; Duncanson et al. 2021). A standalone LiDAR system does not capture entire spaces both vertically and horizontally; ALS is weak at sensing understory canopy structures, and TLS and MLS are unfavorable in sensing top canopies and covering broad areas (Hilker et al. 2012; LaRue et al. 2020). Therefore, assessing consistencies among the different LiDAR systems should be conducted in advance. Although a few studies have integrated different LiDAR systems (Hilker et al. 2012; Pyörälä et al. 2019; LaRue et al. 2020), a greater depth of understanding regarding the similarities, variations, or consistencies among measurements resulting from LiDAR metrics is required. By comparing canopy metrics indifferent LiDAR systems, it would be possible to determine a methodology for combining metrics to substitute for and complement each other. Besides, recently various LiDAR systems, such as the unmanned aerial vehicle laser scanning system (e.g., Brede et al. 2017) and mobile laser scanning system (e.g., Hyppä et al. 2020), have been developed, and there is a great opportunity to combine various LiDAR datasets to monitor tree structures.

Therefore, this study compares tree structure variables such as height metrics, complexity index, and plant area index among ALS, TLS, and MLS datasets and seeks alternative structural variables that could be applied when an ALS dataset is not available. Specifically, this work aims to determine whether the
estimates of different metrics differ depending on whether trees are single or clustered and whether the errors in LiDAR-derived metrics are related to tree structures. The clustered trees were defined as the trees whose canopies were overlapped by or with other near tree canopies, including multi-layered canopies, while single trees were defined as stand-alone trees in this study. These complex structures meant that the lasers could not detect entire canopy structures due to occlusion effects (Bauwens et al. 2016; Schneider et al. 2019). For seeking alternative structural variables among the LiDAR platforms in the urban forest, the differences in metrics between the single and clustered trees acquired from the different LiDAR platforms should be explained.

2. Methods and materials

2.1 Study site and tree classification

Small, isolated urban parks categorized as children’s parks in Cheonan City, South Korea were selected as study sites. Nine small parks were surveyed using TLS and MLS to acquire LiDAR data (Figure 1). These small, isolated urban parks typically consist of trees lower than 22 m in height, a playground facility, and pergolas. In this study, different types of single and clustered trees were considered the general vegetation structure in typical of parks in South Korea.

The surveyed vegetation in the parks consisted of general tree species found commonly in South Korea. Generally, sub-canopies (e.g. Acer palmatum and Chaenomeles sinensis), and high canopies (e.g. Zelkova

![Figure 1](image-url). Study site (a, red boundary: parks surveyed using ALS, TLS, and MLS) and vegetation height information on numbered parks in this study (b).
serrata, Sophora japonica, and Ulmus davidiana var. japonica) form the canopy structures in the parks. The surveyed trees and their shapes are shown in Figure 2.

2.2 LiDAR survey and processing

Table 1 lists the sensor specifications. The TLS dataset was acquired from May 10–11, 2017 during a foliated season. The TLS instrument was placed at several positions in each park to reduce the occlusion effects of trunks, twigs, branches, or other objects. Furthermore, the sphere-shaped targets were located for the registration process; the sphere-shaped targets were used as the control points in each collected scene. After scanning the parks, the separate scenes were merged from each position into one complete scene using FARO SCENE software (FARO, Lake Mary, FL, US). The TLS dataset was georeferenced to the ALS dataset by manually picking more than 30 points of the building vertices in both the ALS and TLS datasets and using the iterative closest point (ICP) algorithm in the CloudCompare program (https://www.danielgm.net/cc/) (Figure 3). The positional errors (i.e. the root-mean-square error [RMSE]) between the terrestrial-based LiDAR systems (i.e. TLS and MLS) and ALS were between 0.15–0.5 m (Figure 4).

The MLS dataset was acquired from April 21–25, 2020 mostly during the same season as when the TLS dataset was acquired. Because the MLS was acquired three years after the ALS and TLS acquisition, coexisting trees in between years were selected for comparisons. Since the MLS system incorporated simultaneous localization and mapping (SLAM) (Pandey, McBride, and Eustice 2011; Zhang et al. 2016; Maddern et al. 2017), occlusion effects could be avoidable and complete 3D scenes of the parks were obtained almost by walking.
inside and outside the parks. Moreover, we made a closed loop route for the sensing trajectories to improve the quality of the MLS dataset (Zhang et al. 2016).

The ALS datasets were acquired on 14 May 2017 using an IGI LiteMapper 6800 sensor (Samah Aerial Survey Co.). The study sites were surveyed following eight flight lines at an altitude of 1,000 m with a 50% width overlap of the scanned areas. The beam divergence was 0.3 mrad, and the field of view was 60°. The point density was > 5 points/m². The dataset was preprocessed and classified using algorithms built into TerraScan software (Terrasolid, Helsinki, Finland) on a MicroStation (Bentley Systems, PA, USA) platform. Non-tree objects were manually deleted, including benches, fences, playground facilities, and building structures.

Table 1. Configuration of the LiDAR sensors used in this study.

| Specification               | ALS                  | TLS                  | MLS                  |
|----------------------------|----------------------|----------------------|----------------------|
| Equipment                  | IGI LiteMapper 6800  | FARO Focus 350 laser scanner | Kaarta Stencil (Velodyme16 sensor) |
| System                     | Mounted on an aircraft | Mounted on a tripod | Mounted on a hand-held computer (SLAM system, 1. 5 m height above ground level) |
| Range                      | 38,000 m (width: 1,155 m) | 0.6 m to 350 m | 1 m to 30 m |
| Accuracy                   | <±10 cm              | <±0.5 cm            | <±3 cm |
| Point density              | 2–8 point/m²         | > 1,000 point/m²    | > 1,000 point/m² |
| Field of view              | 60°                  | Verticality: 0 ~ 300° | Verticality: 30 ~ 330° |
| Sensing method and locations | ALS system, flying at an altitude of 1000 m | Positioned several locations at a height of 1.5 m above ground level | SLAM system. Moving while sensing and following loop trajectories |
| Projection                 | WGS 1984 52 N | Local (Georeferenced using ALS) | Local (Georeferenced using ALS) |
| Data acquisition           | 14 MAY 2017          | 10–11 MAY 2017      | 21–25 April 2020     |

Figure 3. LiDAR data processing and tree classification.
Table 2. Tree classification.

| Classification  | NO. | Average of canopy area (m²) | Maximum canopy area (m²) | Minimum canopy area (m²) | Average of canopy height (m) | Maximum canopy height (m) |
|-----------------|-----|----------------------------|--------------------------|--------------------------|-----------------------------|--------------------------|
| Clustered trees | 35  | 214.63                     | 762.07                   | 16.94                    | 7.29                        | 21.26                    |
| Single tree     | 28  | 44.29                      | 142.97                   | 5.74                     | 6.55                        | 14.69                    |

Figure 4. Examples of registered and normalized point clouds (a, b, and c are a park point cloud from the airborne laser scanning, terrestrial laser scanning, and mobile laser scanning, respectively).

Figure 5. Examples of single trees (a) and clustered trees (b) (purple: airborne laser scanning; white: terrestrial laser scanning; sky blue: mobile laser scanning); Classification was conducted manually using CloudCompare software after overlaying the georeferenced airborne laser scanning, terrestrial laser scanning, and mobile laser scanning datasets.
Table 3. Summary of the variables derived from airborne, terrestrial and mobile LiDAR scans.

| Variable | Description | Unit | Reference |
|----------|-------------|------|-----------|
| ZMAX     | Maximum value of z (height, m) of a point cloud | m    | Roussel et al. 2020 |
| ZMEAN    | Mean value of z (height, m) of a point | m    | |
| Zq95     | 95th percentile heights of a point cloud above | m    | |
| ZSD      | The standard deviation of a point cloud above | m    | |
| maxCHM   | Maximum canopy height derived from the canopy height model (CHM) (1-m resolution) | m    | Calculated in CloudCompare software(https://www.danielgm.net/cc/) and ArcGIS pro (ESRI, Redlands, CA, USA) |
| meanCHM  | Mean height derived from the CHM (1-m resolution) | m    | |
| Std. of CHM | The standard deviation of the CHM (1-m resolution) | m    | |
| Rumple index | Canopy complexity is calculated by dividing the 3D surface area by the 2D surface area (CHM/ortho area) of the parks | m²/m² | Roussel et al. 2020; Parker et al. 2004 |
| Area     | Green area based on the point cloud | m²   | Roussel et al. 2020; Hosozi and Omasa 2009 |
| Plant area index | One-sided area of vegetation, including both woody and leaf parts, per unit ground area. The voxel size was set as 1 m × 1 m × 1 m, vertical distance, dz, was set to 2.5 m, and the constant k was set as 0.5 | m²/m² | Roussel et al. 2020; Hosozi and Omasa 2009 |

Figure 5) to test for errors in the LiDAR-derived metrics based on the vegetation type. All classifications were conducted manually, and the point cloud of any vegetation that had an irregular shape due to occlusion effects were excluded.

2.3 Deriving the structural variables of trees in urban parks

The structural variables, as shown in Table 3, were calculated using the liDr (Roussel et al. 2020) and TreeLS (de Conto 2020) packages of R software (R Core Team 2021). Height-related metrics, such as the maximum value of height (ZMAX), mean value of height (ZMEAN), 95th percentile height (Zq95), and standard deviation of height (ZSD), are generally used to estimate tree biomass (Goodwin, Coops, and Culvenor 2006; Hilker et al. 2010; LaRue et al. 2020). Moreover, these metrics describe the vegetation structures; ZMAX is the highest point in the trees and ZMEAN is the average value of the heights of the points (z). Zq95 is the 95th percentile heights of the point clouds. Canopy height model (CHM)-related metrics, such as maxCHM, meanCHM, and Std. of CHM are associated with the forest biomass. These CHM-related metrics were used to describe the canopy surfaces, because ALS was able to detect the canopy surfaces, which were then described by the CHM. The CHMs were calculated by subtracting the digital surface model (DSM) from the digital elevation model (DEM) using CloudCompare and ArcGIS pro softwares (ESRI, Redlands, CA, USA) to describe the absolute heights of the canopies at the study sites. The resolution of the CHM was 0.5 m. The CHM-derived metrics from the LiDAR sensors were calculated and they were ascertained whether the TLS and MLS values were similar to those of ALS.

The Rumple Index is calculated by dividing the 3D surface area by the 2D surface area, which generally represents the complexity of the canopy (Parker et al. 2004). A high Rumple Index value implies a highly complex canopy structure (Parker et al. 2004; Kane et al. 2010).

Finally, PAI was derived from the voxelized point clouds. PAI is defined as the one-sided area of vegetation, including both woody and leaf parts, per unit ground area (Hosozi and Omasa 2009; Zhu et al. 2020). The classified point clouds were voxelized as 1 m³ (1 m × 1 m × 1 m) units to alleviate the effects of differences in the point density of each LiDAR system (Table 1). The PAI was calculated by summing up the plant area density (m²/m³) of the classified point clouds.

2.4 Assessing the accuracy of the LiDAR-derived indices

The Pearson’s correlation coefficient (r), root mean square error (RMSE), relative RMSE (%), bias and relative bias (%) were calculated in three pairs (Wang et al. 2019) for the tree-structure metrics. Comparisons
were made between ALS-based vs TLS-based metrics (ALS-TLS), ALS-based vs MLS-based metrics (ALS-MLS), and TLS-based vs MLS-based metrics (TLS-MLS).

The RMSE was derived from the linear regression from each pair (i.e., ALS-TLS, ALS-MLS, and TLS-MLS). The ALS dataset metrics were set as references for relative comparisons among other instruments because 1) underestimation of the TLS and MLS in canopy height was assumed (Hilker et al. 2012), and 2) since the study sites were urban parks, high and dense tree species were planted, which are reliably detectable using ALS, and understory canopies or trees were sometimes pruned for the citizens’ safety. The TLS data served as the reference values for the TLS-MLS metrics pair. The relative RMSE (%) was calculated by dividing the mean values of the reference data from the RMSE. Bias was calculated by subtracting the mean values of the reference data from the mean of the compared values, and relative bias (%) was derived after dividing the mean values of the reference data from the bias.

Furthermore, a t-test was conducted to determine whether the calculated tree measurements showed significant differences depending on whether they were derived from single or clustered trees. Pearson’s correlation test was conducted to determine whether the calculated measurements have a linear relationship with the canopy structures. The Pearson’s correlation coefficient (r) has a value between −1 to 1. If the r value is close to 1, then it indicates that the two compared datasets show a strongly positive linear relationship and vice versa. All calculations were conducted using R software (R Core Team 2021).

3. Results

3.1 Comparing height metrics among the three LiDAR systems

Table 4 and Figure 6 show comparisons of the height-related metrics among the three datasets. ZMAX was the most consistent variable among the three LiDAR systems, although evaluation of ZMAX indicated that ZMAX was sometimes underestimated by ALS, considering the biases (Table 4). The ALS dataset had a low-density point cloud (5 points/m² to 8 points/ m²), meaning that points representing tree apices could be missing (Zhao et al. 2018). On the other hand, MLS’s ZMAX values were higher than those derived from TLS and ALS. Since the MLS dataset was acquired 3 years after the ALS and TLS datasets, it was assumed that canopy growth had occurred, and this canopy growth was shown by the higher positive biases compared to ALS and TLS. Figure 6a demonstrates the higher ZMAX values of MLS. In Figure 6a of the MLS pairs, the dots and linear regression graphs are generally located below the 1:1 line, indicating higher ZMAX values than for the other two LiDAR platforms.

Since ZMEAN and Zq95 values can easily be affected by the location of the LiDAR, resulting in discrepancies in the point cloud density, differences were more considerable than in ZMAX. A comparison of ZMEAN and Zq95 showed that the dots in the ZMEAN plots were more scattered than those in the Zq95 plots (Figure 6b and Figure 6c), indicating that Zq95 was more stable and provided an alternative LiDAR metric to that of ZMEAN. A comparison of ZMEAN and Zq95 values revealed that ALS values were higher than those derived by the other two LiDAR systems. Notably, in the case of ZMEAN and Zq95, there were closer linear relationships for the ALS-TLS pairs than for the ALS-MLS and TLS-MLS pairs (Table 4 and Figure 6b and Figure 6c).

ZSD values revealed a linear relationship among the LiDAR systems (the Pearson’s coefficient r values were higher than 0.7), but the values were not very precise (RMSE (%) was almost 20% and with low biases). In particular, ZSD derived from TLS showed relatively low consistencies with the ZSD from ALS and MLS (Pearson’s r for ALS-TLS and TLS-MLS were lower than the TLS-MLS pair).

By comparing single and clustered trees, the coefficients of determination (R² values) of the height-related metrics of clustered trees, except for ZMAX, were lower than those derived for single trees (see R² in Figure 6).

3.2 Comparing CHM-derived canopy height metrics from each LiDAR systems

Table 5 and Figure 7 show comparisons of CHM-derived height metrics among the LiDAR platforms. The maxCHM describes the same results as the ZMAX in the evaluations and the scatterplots. A comparison of the meanCHM results showed low RMSEs and biases (≤ 0.39 m and ≤ 0.66 m, respectively) compared to those of the maxCHM. ALS also produced lower meanCHM values than the other two LiDAR systems. The ALS and
TLS datasets, which were acquired on almost the same dates, had higher agreements in the maxCHM and meanCHM values. The Std. of CHM showed overall agreement in the pairs (RMSEs (%)) were slightly higher than the other evaluations, but the biases (%) were lower than others. Because the mean CHM and Std. of CHM were calculated based on the surface heights of the canopies, the values showed greater agreement than did those of the ZMEAN and the ZSD (as the CHM showed only the height of the surfaces).

Likewise, in comparing single and clustered trees, the R square values of the single trees were higher than those of the clustered trees except for the MaxCHM (see R² in Figure 7).

### 3.3 Comparing the area, the Rumple index, and plant area index determined using the LiDAR systems

Table 6 and Figure 8a compare areas, Rumple Index, and plant area index values among the pairs. The area data were relatively consistent among the LiDAR systems. Table 6 and Figure 8a describes the higher area values in the MLS than ALS and TLS; biases in Table 6 and dots on the plots in Figure 8a show that the highest area values were in the MLS dataset. Moreover, the ALS-TLS pair showed nearly a 1:1 relation in the area comparison (Figure 8a). The all pairs derived higher R² values in area comparisons for clustered trees than single trees.

The Rumple Index values showed relatively low agreement among the LiDAR systems (Table 6 and Figure 8b). The ALS-TLS pair showed the highest consistency (RMSE (%)) = 9.34 and bias (%) = 1.50), while the TLS-MLS pair had lower values. By comparing single and clustered trees, the rumple index for the single trees showed a greater R² value than that for clustered trees among the LiDAR datasets (Figure 8b).

Point clouds with low density were excluded to calculate the PAI; 25 clustered trees and five single trees were used to derive the PAI. Table 6 and Figure 8c compare the PAI values among the pairs. All pairs showed low linear relations with
each other (Pearson’s r > 0.4). In particular, the TLS-MLS pair showed a greater consistency (i.e. low RMSE and bias and high Pearson’s coefficient r) rather than other two pairs.

4. Discussion

4.1 LiDAR configurations

In this study, ten tree structure metrics (Table 3) were investigated. Most of the metrics derived from each LiDAR system showed linear relationships (values of Pearson’s correlation coefficient r was higher than 0.4, and most were strongly correlated, except for the ZMAX, Rumple Index, and PAI) (Tables 4, 5, and 6).

4.1.1 Consistencies of height metrics

The ZMAX, maxCHM, and meanCHM, which informed the tree-height values, showed substantial similarity among the LiDAR systems (Tables 4 and 5). Although these metrics were highly consistent, differences remained for the bias values. Our TLS and MLS data estimated the canopy heights to be higher than estimates by the ALS data at the study sites (Tables 4 and 5); the biases in the height comparisons in the ALS-TLS and ALS-MLS pairs showed positive values, although the TLS and MLS data generally tended to underestimate the canopy height compared to ALS data in the previous studies (Hilker et al. 2012; Wang et al. 2019). Since our research sites consisted of small urban parks, with relatively short trees and a sparse canopy density, it was not difficult to set the TLS and MLS locations, which enabled the tops of the canopies to be detected more easily than would be the case in dense forest. Moreover, due to the sparse point density (< 8 points/m²) provided by ALS, it was speculated that ALS missed some tree apices (e.g. Song et al. 2016; Zhao et al. 2018), resulting in lower height values (e.g. ZMAX and maxCHM) compared to TLS and MLS (see biases in Tables 4 and 5).

More considerable differences in the ZMAX and Zq95 values may have resulted from the specifications of each LiDAR system (Table 1). Because ALS observed its targets from above, the points were concentrated in the higher canopies (skewed toward the top, Figure 9) (Hilker et al. 2012). In contrast, the TLS- and MLS-acquired points were concentrated lower in the canopies (skewed toward the bottom, Figure 9) (Hilker et al. 2012). These differences in height point densities could have resulted in the large discrepancies observed in the ZMAX and Zq95 values. Figure 10 appropriately represents the distribution of point clouds and their height metrics. Since the ALS dataset was concentrated on the upper canopies, the ZMAX and Zq95 were greater than those of TLS and MLS (Figure 6b and 6c).

4.1.2 Consistencies of tree structural metrics

The ZSD, Std. of CHM, area, Rumple Index, and PAI describe the structural diversity of canopies. The Rumple Index, in particular, indicates the vertical complexity of a canopy (Parker et al. 2004; Kane et al. 2010). A comparison of the Rumple Index results derived from each LiDAR system showed relatively low agreement (RMSE (%) = 9.34–13.50% and bias (%) = –4.13–1.50%). However, the ALS-MLS and TLS-MLS showed lower consistency than the ALS-TLS pair.

| Table 5. Assessment and comparison of the tree-structure indices determined using the LiDAR systems. |
|----------------------------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Evaluation                      | RMSE (m)       | RMSE (%)       | Bias (m)       | Bias (%)       | RMSE (m)       | RMSE (%)       | Bias (m)       | Bias (%)       | RMSE (m)       | RMSE (%)       | Bias (m)       | Bias (%)       | RMSE (m)       | RMSE (%)       | Bias (m)       | Bias (%)       |
| ALS vs. TLSa                    | 0.43           | 4.46           | 0.27           | 2.81           | 0.99           | 0.27           | 3.88           | 0.15           | 2.11           | 0.99           | 0.20           | 13.30          | 0.01           | 0.48           | 0.95           |
| Total                           | 0.27           | 2.53           | 0.24           | 2.27           | 1.00           | 0.26           | 3.57           | 0.15           | 2.10           | 0.98           | 0.15           | 8.56           | 0.02           | 1.04           | 0.95           |
| Clustered                       | 0.55           | 6.59           | 0.31           | 3.67           | 0.98           | 0.28           | 4.27           | 0.14           | 2.13           | 0.99           | 0.20           | 16.74          | –0.01          | –0.56          | 0.96           |
| Single                          | 0.43           | 5.15           | 0.60           | 7.21           | 0.99           | 0.36           | 5.49           | 0.63           | 9.62           | 0.98           | 0.25           | 20.93          | –0.03          | –2.48          | 0.94           |
| ALS vs. MLSa                    | 0.44           | 4.57           | 0.78           | 8.11           | 0.99           | 0.36           | 5.17           | 0.66           | 9.46           | 0.98           | 0.25           | 16.62          | 0.02           | 1.10           | 0.92           |
| Total                           | 0.40           | 3.75           | 0.92           | 8.68           | 0.99           | 0.35           | 4.80           | 0.68           | 9.35           | 0.97           | 0.22           | 12.56          | 0.05           | 3.06           | 0.90           |
| Clustered                       | 0.43           | 5.15           | 0.60           | 7.21           | 0.99           | 0.36           | 5.49           | 0.63           | 9.62           | 0.98           | 0.25           | 20.93          | –0.03          | –2.48          | 0.94           |
| Single                          | 0.52           | 5.25           | 0.51           | 5.16           | 0.98           | 0.39           | 5.49           | 0.51           | 7.20           | 0.97           | 0.20           | 13.23          | 0.01           | 0.63           | 0.95           |
| TLS vs. MLSb                     | 0.42           | 3.85           | 0.68           | 6.26           | 0.99           | 0.41           | 5.51           | 0.53           | 7.10           | 0.95           | 0.24           | 13.56          | 0.04           | 2.00           | 0.90           |
| Total                           | 0.56           | 6.47           | 0.30           | 3.41           | 0.98           | 0.37           | 5.53           | 0.49           | 7.34           | 0.98           | 0.14           | 11.79          | –0.02          | –1.93          | 0.97           |

*Biases were calculated by subtracting the ALS values from the TLS and MLS values.*

**Biases were calculated by subtracting the TLS values from the MLS values.**

Light gray indicates significant differences after t-test between biases of single and clustered trees derived from the LiDAR comparisons (p < 0.05)
Since the Rumple Index was calculated by dividing the areas derived from the CHM surface areas (Parker et al. 2004), the large variances of ZSD, Std. of CHM (Tables 4, 5, 6) owing to differences in point distribution (Figure 9) could have influenced the results. In particular, the area values derived from the MLS being greater than those from the ALS and TLS might have lowered the Rumple Index values derived from the MLS relative to those from the ALS and TLS (Table 6 and Figure 8). Besides, MLS was able to survey entire targets, and this reduced occlusion effects due to the adoption of the SLAM system. The use of SLAM enabled MLS to obtain an almost complete view of the targets, while TLS missed some points due to issues with sensing locations and shadow effects.

Figure 6. Comparison of height related metrics among the LiDAR systems (The dashed line is the 1:1 line; gray band is the 95% confidence interval).
Figure 7. Comparison of the CHM-derived heights metrics among the LiDAR systems (Dashed line is the 1:1 line; gray band is the 95% confidence interval).

Table 6. Assessment and comparison of the tree-structure indices determined using the LiDAR systems.

| Metrics          | Area (m²) | Rumble index (m²/m²) | Plant area index (m²/m²) |
|------------------|-----------|----------------------|--------------------------|
| Evaluation       | RMSE (m²) | RMSE (%)             | Bias (%)                 | RMSE (m²/m²) | RMSE (%) | Bias (%) | RMSE (m²/m²) | RMSE (%) | Bias (%) |
| ALS VS. TLSa     | Total     | 8.19                 | 5.90                     | 8.74         | 6.29     | 1.00     | 0.15     | 9.34       | 0.02     | 1.50     | 0.89     | 0.77     | 24.75   | −0.69   | −22.27 | 0.60       |
|                  | Clustered | 8.85                 | 4.12                     | 9.89         | 4.61     | 1.00     | 0.10     | 6.13       | 0.04     | 2.44     | 0.83     | 0.72     | 23.12   | −0.83   | −26.68 | 0.66       |
|                  | Single    | 4.91                 | 11.09                    | 7.30         | 16.49    | 0.99     | 0.16     | 10.17      | 0.00     | 0.29     | 0.94     | 0.42     | 13.59   | 0.03    | 0.82    | 0.89       |
| ALS VS. MLSa     | Total     | 15.81                | 11.38                    | 16.67        | 12.00    | 0.99     | 0.17     | 10.59      | −0.04    | −2.69    | 0.85     | 0.85     | 27.33   | −0.63   | −20.16 | 0.46       |
|                  | Clustered | 18.92                | 8.82                     | 21.81        | 10.16    | 0.99     | 0.11     | 6.74       | 0.00     | −0.12    | 0.80     | 0.79     | 25.37   | −0.80   | −25.75 | 0.58       |
|                  | Single    | 9.26                 | 20.91                    | 10.26        | 23.16    | 0.97     | 0.21     | 13.35      | −0.09    | −6.02    | 0.88     | 0.70     | 22.65   | 0.28    | 9.12    | 0.67       |
| TLS VS. MLSb     | Total     | 15.00                | 10.16                    | 7.93         | 5.37     | 0.99     | 0.22     | 13.50      | −0.07    | −4.13    | 0.76     | 0.29     | 11.99   | 0.07    | 2.72    | 0.88       |
|                  | Clustered | 18.58                | 8.28                     | 11.91        | 5.31     | 0.99     | 0.21     | 12.56      | −0.04    | −2.50    | 0.61     | 0.19     | 8.32    | 0.03    | 1.27    | 0.92       |
|                  | Single    | 8.64                 | 16.75                    | 2.95         | 5.72     | 0.98     | 0.22     | 13.94      | −0.10    | −6.30    | 0.83     | 0.54     | 17.33   | 0.26    | 8.24    | 0.50       |

*Biases were calculated by subtracting the ALS values from the TLS and MLS values.
**Biases were calculated by subtracting the TLS values from the MLS values.
Light gray indicates significant differences after t-test between biases of single and clustered trees derived from the LiDAR comparisons (p < 0.05)
In this study, the setting of the parameters (i.e. Voxel size = 1 m × 1 m × 1 m, dz = 2.5 m, k = 0.5) to derive the PAI (Table 3) was applied same to all LiDAR datasets. The PAI comparison of the TLS-MLS pair showed relatively good consistency (Table 6 and Figure 8c). However, the ALS-MLS and ALS-TLS pairs showed low consistencies (Table 6). In particular, as shown in Figures 9 and 10, the point density of each LiDAR system was different. These differences in point densities among the LiDAR systems could result in poor agreements in PAI comparisons of ALS-TLS and ALS-MLS pairs. Furthermore, to accurately estimate LAI using LiDAR systems, various factors, such as optimal voxel size, occlusion effect, clumping effect, and others, should be considered with field survey data for calibration (Almeida et al. 2019; Wang and Fang 2020).

### 4.2 Time difference of data acquisition

Since the MLS data were acquired three years after acquiring the ALS and TLS data, ZMAX, maxCHM, and meanCHM metrics derived from the MLS data, which indicated higher values than those derived by other LiDAR systems (Tables 4 and 5), would reflect vertical tree growth in urban parks (e.g. Song et al. 2016; Choi, Song, and Jang 2019).

![Figure 8. Comparison of areas, Rumble Index, and plant area index values among the LiDAR systems (Dashed line is the 1:1 line; gray band is the 95% confidence interval).](image-url)
Moreover, the lateral growth of the trees (Song et al. 2016; Choi, Song, and Jang 2019) might have affected the greater biases in the area values of the ALS-MLS and TLS-MLS comparisons.

4.3 Uncertainty of the structural indices derived from the three LiDAR systems

4.3.1 Evaluation of the degree of differences between the references and observations for the single and clustered trees

It was assumed that biases (differences between the references: the ALS and the observations: the TLS and the MLS) would be distinct depending on the single and clustered trees because of occlusion effect and different point cloud distributions. The t-tests of the mean distances between clustered and single trees were conducted (i.e. testing the mean values of the differences between the references and the observations for single and clustered trees) (Light gray colors in Table 4, 5, and 6).

As shown in Table 4 and Figure 6, the ZMAX and the area showed great consistencies among the LiDAR systems. However, the biases in the ZMAX and area were not significantly different in the ALS-TLS pair, while the ZMAX and area biases by tree class showed significant differences in the ALS-MLS and TLS-MLS pairs (p < 0.05). In the ALS-MLS and TLS-MLS pairs, clustered trees showed greater mean distances (0.92 m and 0.68 m, respectively) than single trees (0.60 m and 0.30 m, respectively) in ZMAX comparisons. Moreover, in the ALS-MLS and TLS-MLS pairs, clustered trees showed greater mean distances (21.81 m² and 11.91 m², respectively) than single trees (10.26 m² and 2.95 m², respectively) in area comparisons. It is considered that additional unknown reasons, such as soil conditions,
tree species composition, and stand complexity, may have impacted tree growth and contributed to the higher ZMAX and area estimates in clustered trees as derived by MLS. Oldfield et al. (2015) found that stand complexity and the existence of the shrubs in stands could enhance tree growth. This study showed more complex structures in the case of clustered trees (rumple index values = 1.63 ± 0.18 m²/m²) than single trees (1.57 ± 0.46 m²/m²), and clustered trees included shrubs (Figure 5). Therefore, the differences in biases between clustered and single trees might have resulted from the stand complexity (Figure 11) and other environmental factors (Oldfield et al. 2015).

ZMEAN and Zq95 values showed significant bias differences for the ALS-TLS and ALS-MLS pairs (Table 4). These metrics showed that point densities for heights were skewed (Figure 9) as a result of the sensor locations. Clustered trees had more data acquisition points at the low heights than did single trees, so both TLS and MLS collected more data for lower heights. This tendency resulted in lower ZMEAN and Zq95 values, especially for clustered trees when the data were derived from TLS and MLS rather than from ALS (Table 4). In this study, ZMEAN and Zq95 values showed no significant differences by tree class between TLS and MLS.

In terms of the CHM-related metrics, maxCHM produced exactly the same results as ZMAX, and differences in the biases were for the same reasons as identified for ZMAX (i.e. tree growth rates might be different depending on soil conditions, stand complexity, and the existence of shrubs). The meanCHM and Std. of CHM showed no significant differences for all the pairs. CHMs (1-m resolution) derived from the LiDAR platforms could be used interactively.

### 4.3.2 Evaluating the degree of the biases by the tree height, area, and complexity

In this study, we considered the ALS-derived canopy metrics as a reference for comparing the sensors, because underestimation of the TLS and MLS in top of canopies was assumed (Figure 9)(Hilker et al. 2012). Therefore, the biases were calculated by subtracting the ALS values from the TLS and MLS. Between TLS and MLS, the biases were calculated by subtracting the TLS values from the MLS values.

These biases showed strong correlations with the ALS-derived rumple index (|r| > 0.33) and canopy height metrics (|r| > 0.41) (Figure 11). The strong correlations imply that more complicated canopy structures might introduce errors in measuring trees by using TLS and MLS instruments.

### 5. Conclusions

In this study, we assessed the consistencies in tree structural variables among the ALS, TLS, and MLS datasets to find alternative structural variables that can be derived from MLS and TLS and applied when ALS datasets are not accessible in urban parks.

Our results reveal that ZMAX, CHM-derived structural metrics and area values showed good agreement among the ALS, TLS, and MLS platforms. These metrics could, therefore, be interchangeable among the three LiDAR systems. We speculate that differences in the data acquisition dates impacted the agreements of ZMAX, CHM-derived, and area metrics more considerably compared to sensing locations and point density in this study.

This study also emphasized the configuration of LiDAR systems for estimating tree measurements. Depending on the point density and sensing location, the tree measurements could be differently calculated (e.g. ZMEAN and Zq95) and result in different derived outcomes, such as PAI. ZMEAN and Zq95 showed preliminary agreement among the LiDAR systems used in this study. Moreover, in estimating PAI, more factors should be considered in the estimation, and different parameter settings should be required among the ALS and other terrestrial-based systems. Therefore, further studies would be necessary to find methods to alleviate differences in point density and its distribution by different LiDAR configurations. Although most metrics showed good agreement, differences among the sensors had linear relationships with canopy height metrics (ZMAX and meanCHM) and canopy complexity (Rumple index) (Figure 11).

Given the increasing interest in using multiple LiDAR systems (e.g. Bazezew, Hussin, and Kloosterman 2018; Pyörälä et al. 2019; Wu et al. 2020) to measure tree structure and its derivation such as biomass, our results suggest the importance of assessing consistencies among different LiDAR systems before using multiple LiDAR systems for tree measurements. Scheduling tree measurement periods should be considered carefully because urban canopy structures or shapes could be easily changed owing to growth and various
disturbance events. Finally, as there is an increasing demand for LiDAR technology in urban planning and design and particularly for managing urban green spaces, our results could help when there is a need to fill gaps in datasets.

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