Research Article

Application of handheld laser scanning technology for forest inventory purposes in the NE Turkey

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Abstract: Forest inventory (FI) is the most challenging stage of forest management and planning process. Therefore, in situ surveys are often reinforced by modern remote sensing (RS) methods for collecting forestry-related data more efficiently. This study tests a state-of-the-art data collection method for practical use in the Turkish FI system for the first time. To this end, forest sampling plots were conventionally measured to collect dendrometric data from 437 trees in Artvin and Saçınka Forest Enterprises. Then, each plot was scanned using a handheld mobile laser scanning (HMLS) instrument. Finally, HMLS data were compared against ground measurements via basic FI measures. Based on statistical tests, no apparent differences were found between the two datasets at the plot level (P < 0.05). There were also robust correlations for diameter breast height at individual tree level (r > 0.97; P < 0.01). Residual analysis showed that both positive and negative errors had a homogeneous distribution, except for plot 8 where tree stems were in irregular shapes due to anthropogenic pressures. When all plots' data were aggregated, average values for the number of trees, basal area, and timber volume were estimated as 535 trees/ha^{-1}, 49.6 m^2/ha^{-1}, and 499.7 m^3/ha^{-1}, respectively. Furthermore, secondary measures such as the number of saplings and slope were successfully retrieved using HMLS method. The highest overestimation was in timber volume with less than 10% difference at the landscape level. The differences were attributed to poor data quality of conventional measurements, as well as marginal site conditions in some plots. We concluded that the HMLS method met the accuracy standards for most FI measures, except for stand height. Thus, the Turkish FI system could benefit from this novel technology, which in turn supports the implementation of sound forest management and planning.

Key words: Artvin Province, forest inventory, forest management, GeoSLAM Zeb Revo, LiDAR, mobile laser scanning

1. Introduction

Management planning is often referred to as a decision-making process, and all decision-makers need accurate information (Penman et al., 2003; Ganivet and Bloomberg, 2019). Forest planners, specifically, need up-to-date and spatially explicit information that characterizes the current states of forest ecosystems not only for sustainable management of these limited resources but also for the international reporting systems (Temerit et al., 2005; Asan, 2017; Ozkan and Demirel, 2018). Forest inventories (FIs) are the main data resources for these information flows. The primary objective of an FI is to estimate wood availability through mean and total measures for timber supply in a specific area (Kangas et al., 2006). To this end, many developed countries have been implementing periodic inventory surveys based on ground sampling for more than a century (Vidal et al., 2016). In Turkey, for example, FI surveys have regularly been implemented at the forest enterprise level at either 10- or 20-year intervals since 1963

(Kayacan et al., 2016), although the first attempts can be dated back to more than 100 years (Başkent et al., 2005; Kırış, 2013).

The most common measures for FI are diameter breast height (DBH), timber volume, basal area, and number of stems, which are used in forest management plans (Kangas and Maltamo, 2006; Bettinger et al., 2009; Bulut et al., 2016). These measures are critical because they are directly related to revenue; thus, a forest owner can quickly assess the financial status of his/her forest enterprise. More importantly, they allow forest planners to calculate the sustained yield of timber production, as well as to envision the future states of the forest when combined with growth and yield models. Briefly, the success of a forest management plan strictly depends on the accuracy of this information gained from FI data. However, data collection by conventional ground measurements is the most expensive, time-consuming, and labor-intensive stage in the forest planning process (Trotter et al., 1997; Eler, 2001;

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Teremit et al., 2005; Demirel and Özkan, 2018; Kanja et al., 2019). Therefore, terrestrial photogrammetry and optic remote sensing (RS) products such as multicameras, aerial photos, and satellite images have been widely utilized for estimations of forests' structural characteristics in combination with ground measurements both in Turkey (Demirel and Özkan, 2018; Günlü and Kadıoğulları, 2018; Çil et al., 2015; Bulut et al., 2016; Kanja et al., 2019; Sakici and Günlü, 2018; Yilmaz and Güngör, 2019) and in the world (Ozdemir and Karnieli, 2011; Holopainen and Kalliovirta, 2006; Forsman et al., 2016; Surovy et al., 2016; Ucar et al., 2018). Nevertheless, the estimations based on optic RS hardly meet the requirements for accuracy in FI studies compared with conventional ground measurements (Holopainen and Kalliovirta, 2006; Sefercik and Atesoglu, 2017). Terrestrial photogrammetry techniques, on the other hand, generally suffer from unfavorable lightning conditions beneath the forest canopy. Thus, the image quality decreases and noises occur in point cloud data (Forsman et al., 2016). Thereby, further studies using new techniques are still needed for collecting more accurate and cost-effective data at required standards, as concluded recently by Ozkan and Demirel (2018), and Demirel and Özkan (2018).

In the 21st century, the introduction of laser scanning (LiDAR – Light Detection and Ranging) technology has opened a new era in many fields, including forestry (Leeuwen and Nieuwenhuis, 2010). One of the distinctive features of this technology is that the biophysical structure of trees can be measured directly through 3D point clouds with high accuracy (Hyyppä and Inkinen, 1999; Oveland et al., 2018; Akay et al., 2009). Owing to this feature, LiDAR has allowed foresters to collect more accurate data on forests' structural characteristics even at the individual tree level (Hyyppä et al., 2008; Akay et al., 2009). LiDAR instruments are grouped based on their platforms as: (i) spaceborne-, (ii) airborne- (ALS), and (iii) terrestrial-laser scanning (TLS). However, there are not many LiDAR missions sent into space, therefore spaceborne LiDAR systems are still unfamiliar, at least in the field of forestry (Leeuwen and Nieuwenhuis, 2010). In contrast, ALS is widely used for large-scale forestry purposes all over the world (Cabo et al., 2018; Oveland et al., 2018). Similarly, TLS became popular in the field of forestry, although it was developed mainly for engineering purposes. However, TLS has many limitations for practical forestry use. First, scanning from a fixed position limits usage due to obstructed areas behind large trunks and branches (Leeuwen and Nieuwenhuis, 2010; Bauwens et al., 2016). This so-called occlusion effect may be overcome by scanning from multiple points as Yurtseven et al. (2019) did on a forest plot – but it is almost impossible in an FI survey (Oveland et al., 2018), as hundreds of plots are

sampled for only one forest enterprise. Other limitations embedded within TLS are its weight as well as equipment acquisition cost. Therefore, it is neither a practical nor a cost-effective tool for FI purposes, as already reported by some researchers (Wulder et al., 2008; Ryding et al., 2015; Apostol et al., 2018). Nevertheless, recent studies have suggested that such difficulties could be overcome by using lightweight mobile laser scanning (MLS), an emerging technology in the world (Bauwens et al., 2016; Oveland et al., 2018). Unlike TLS, MLS continuously collects data in the forest while an operator easily carries the handheld instrument through sampling plots. Using handheld MLS (HMLS) technology, which significantly reduces the operation time (Ryding et al., 2015), forest stands can be digitized and single-tree parameters can be effectively calculated via 3D point clouds. Some researchers have successfully used this system for modeling purposes in the forests of the UK, Spain, and Italy (Ryding et al., 2015; Cabo et al., 2018; Giannetti et al., 2018; Del Perugia et al., 2019).

As for Turkey, several Turkish researchers used LiDAR technology abroad in the previous decade (Akay, 2004; Ozdemir and Donoghue, 2013; Genç et al., 2004) and introduced its potential applications in forestry to the national foresters (Genç et al., 2004; Akay et al., 2009; Özdemir, 2013a, 2013b). However, no forestry studies have been conducted using this technology in Turkey until the last few years, mainly due to the limitations of traditional LiDAR instruments described above. Finally, such studies have progressively emerged in Turkey (see Yurtseven et al., 2019; Arslan et al., 2016; Büyüksalih et al., 2017, among others), like in many other developed countries. Akgül et al. (2016), for instance, estimated DBH, tree height, and crown base height using TLS on the campus of Istanbul University. They found that there were no statistically significant differences between TLS data and ground measurements. Şahin et al. (2018), on the other hand, successfully detected tree locations on a small afforestation site by using ALS data in İzmir. All these studies, except for Kanja (2016) and Özkal (2017), were conducted in relatively small and uniformly structured "artificial landscapes" (e.g., park, campus, plantation area, urban greenings, etc.), where trees are located individually in certain patterns. In contrast, Kanja (2016) studied natural Calabrian pine forests in Bergama State Forest Enterprise. He estimated timber volume, number of trees, and mean height using ALS data. Özkal (2017), in another study, estimated the number of trees with the help of ALS for Oak-Maritime pine mixed forests in Bentler State Forest Enterprise. The studies pointed out that estimating FI measures for "natural landscapes" was challenging work, as they presented complex structures in terms of topography and species composition (see also Gadow et

al., 2012). To the best of our knowledge, there is no other LiDAR study for practical FI use in Turkey so far.

Therefore, the objective of this study was to evaluate state-of-the-art HMLS technology for FI purposes with its first practical application in Turkey. Our approach is to compare basic FI measures that were conventionally calculated by ground measurements with the same measures derived from HMLS data. To this end, nine sampling plots showing different stand structures were set up in Artvin and Saçınka State Forest Enterprises. The results are expected to support management planners by providing them more accurate and timely information on forest resources. It can be useful for the Turkish FI system, especially in terms of reducing costs and workforce.

2. Materials and methods

2.1. Study area and sampling design
The study areas consisted of nine sampling plots located at Artvin and Saçınka Forest Enterprises, NE Turkey (Figure

1). Because the area is in the Caucasus Biodiversity Hotspot (CEPF, 2013), thus consisting of highly diverse and mixed temperate forests that are one of 200 priority ecoregions in the world (Manvelidze et al., 2009), it has enormous ecological importance. The topography of the region is very mountainous with altitudes as high as 3000 m. The climate is characterized by cold winters and hot summers with average annual precipitation of 753 mm between 1987 and 2017 (SMS, 2018). Dominant tree species are the Caucasian spruce (*Picea orientalis* L.), Scots pine (*Pinus sylvestris* L.), Caucasus fir (*Abies nordmanniana* Stev. Matt.), oriental beech (*Fagus orientalis*), sweet chestnut (*Castanea sativa* Mill.), and Çoruh oak (*Quercus dschorochensis*) in either pure or mixed forest stands. Moreover, stone pine (*Pinus pinea*)—a typical Mediterranean tree species—exists locally, especially on the bottom of V-shaped valleys in Hatila National Park. Regarding soil types, shallow sandy loam soils are common, showing distinct A- and C-horizons with almost no B-horizon in their profiles (Sariyildiz, 2008).
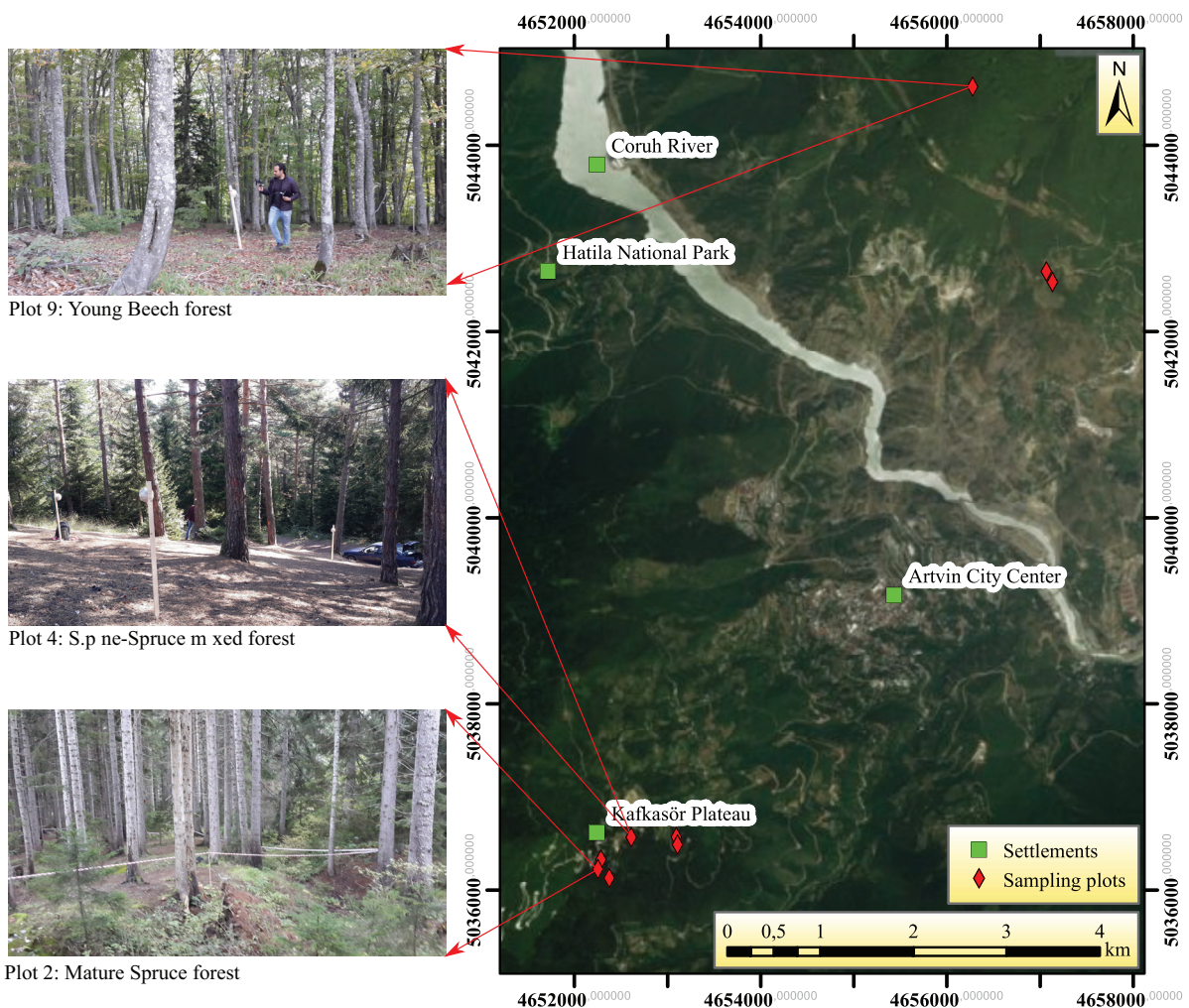

Figure 1. Location of the study area with sampling plots.

Nine sampling plots differing in size were specifically designed based on stand types identified by tree species, canopy closure, and developmental stage, as in the Turkish FI system (GDF, 2017). Figure 2 shows the Scots pine plot on a poor and rocky site. Notable irregularities of tree stems can be easily seen both on the photograph and in point cloud data (Figures 2a and 2b). Further information about other sampling plots is given in Table 1.

2.2. Instrumentation and operational principles of HMLS

In this study, Zeb-Revo, which was commercialized by GeoSLAM Ltd. company (Geoslam, 2018), is used as an HMLS instrument. The main components of the instrument are a laser scanner and a low-cost Inertial Measurement Unit (IMU) on a rotary engine (Figure 3a). The ability to operate independently of Global Navigation Satellite System (GNSS), as well as its Simultaneous Localization and Mapping (SLAM) algorithm, make HMLS ideal for detail extraction studies, particularly in areas where it is difficult to receive a signal from GPS satellites (e.g., forest, tunnel, mine, etc.). Moreover, 1-kg weight makes it more functional, especially in the woods (Figure 3b). Owing to these attributes, instant point cloud data are generated by calculation of 3D laser distance and IMU-based angles. As it moves, the data is continuously combined from the previous moment to the next using SLAM technology. This technology enables scanning the same objects at different points through a moving user or platform. The only requirement for SLAM is that the objects have to be stationary during scanning, which is usually the case for tree stems in a forest. Finally, the alignment process is performed by the Iterative Closest Point algorithm (Besl and McKay, 1992) used for registering point clouds. According to the manufacturer (Geoslam, 2018), Zeb-Revo has a horizontal resolution of 0.625° with a relative error of a maximum of 2–3 cm. Nevertheless, these error rates meet the required standards for large-scale forestry projects. The scanning range of the instrument is a maximum of 30 m at 90% reflectance rate. It has a measuring ratio of 43,200 per second with a scanning speed of 100 MHz.

2.3. Methods

The methodology is mainly based on the approach that is comparing HMLS data against conventional ground measurements via basic FI measures, such as average DBH and timber volume. Based on that approach, we drew a flow chart of this study in Figure 4. More detailed information on workflow steps is given in the following subsections.

2.3.1. Data acquisition and processing

As a first step, point cloud data were acquired by walking with Zeb-Revo instrument at hand. Walking routes were planned as a closed loop. Free walking from the reference target (i.e., the marked stake for plot center) towards the
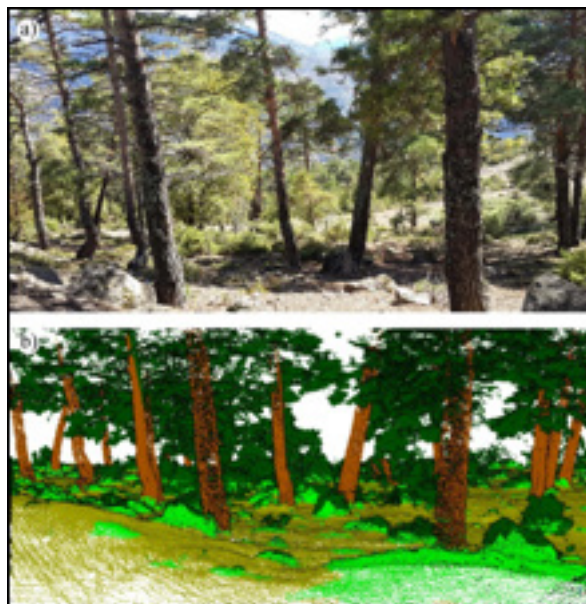

Figure 2. (a) General view of plot 8 located on a rocky site; (b) 3D visualization of the same plot on HMLS data.

plot border was performed on each sampling plot. Then, the loop was closed by returning to the plot center (Figure 5a). The data acquisition step lasted between 3 and 9 min, depending on plot size and topography.

In the next step, raw point cloud data were processed using GeoSLAM Desktop software at the office. It lasted about 20 min for all plots' data. Then, processed data were converted to the *.las* file format for efficient handling in GIS software. Though tree coordinates were unnecessary for most FI studies at the (forest) landscape level, no geo-referencing was performed to point cloud data. The data were directly clipped based on sampling size, taking the reference target as plot center (Figure 5b). Since the reference target was visible on the point cloud, the clipping process was rather straightforward. As such, 3D visualization of stand structures was performed with a modest laptop computer with an i5 processor. These processes were iteratively repeated for each plot.

As for single-tree extraction, point cloud data were first classified using cloth simulation filtering algorithm (Zhang et al., 2016) based on ground and aboveground points. In this way, tree height measurements were made easier on data and data density was reduced for faster processing on the laptop computer. Then, distances from aboveground locations (i.e., tree heights) were calculated based on the Euclidean algorithm. This algorithm refers to the ordinary straight distance in Z-axis between the point of interest and ground level in a Euclidean space, and is referred to as normalization (Anton and Rorres, 2010). In the next step, the height interval for DBH measurements was determined between 1.28 and

Table 1. Main characteristics of the sampling plots.

Plot no.	XY coordinates	Forest entpr.	Elev. (m)	Aspect	Plot size (m²)	Plot shape*	Stand type**	Stand density
1	41°09′40″ – 41°47′34″	Artvin	1271	NE	1000	R	Lde3	1.14
2	41°09′39″ – 41°47′37″	Artvin	1253	NE	1000	R	Lcd3	1.35
3	41°09′47″ – 41°47′28″	Artvin	1260	NE	2000	R	Lde3	1.26
4	41°09′50″ – 41°47′42″	Artvin	1269	E	400	C	Çscd2	1.06
5	41°09′49″ – 41°47′58″	Artvin	1205	Flat	800	C	Lcd3	1.16
6	41°09′50″ – 41°47′55″	Artvin	1200	Flat	1600	R	Lcd3	1.17
7	41°12′16″ – 41°50′01″	Saçınka	940	S	600	C	Çscd2	0.90
8	41°12′15″ – 41°50′04″	Saçınka	917	SE	800	C	Çsd1	0.76
9	41°13′06″ – 41°49′40″	Saçınka	1364	SE	400	C	Knbc3	1.39

*R: rectangular; C: circle.
**Stand types were given in their original codes, as in Turkish forestry system. Accordingly, the first uppercases refer to tree species: L for spruce, Çs for Scots pine, and Kn for beech; the lowercases refer to developmental stage: b for poles (8–20 cm), c for thin trees (20–36 cm), d for medium trees (36–52 cm), and e for large trees (≥ 52 cm); the digits refer to canopy closure: 1 for sparsely-closed, 2 for medium-closed, and 3 for fully-closed stands (GDF, 2017).

Figure 3. (a) General view of the Zeb-Revo instrument; (b) View of the instrument during data acquisition on plot 4 (Çscd2 stand).

Figure 4. The general workflow of the present study.

1.33 m above ground points as tree DBH was measured at 1.30 m above ground level as in the Turkish FI system (GDF, 2017). The 5-cm-thick disks were then extracted from the entire point cloud data (Figure 5c), and circles were fitted to them using the Least Square Estimation algorithm (Chernov and Lesort, 2005) in Polyworks software. In this step, the number of circles was considered as the number of trees for each plot. Finally, the diameters of those circles were calculated and recorded as DBH for each tree (Figure 5d).
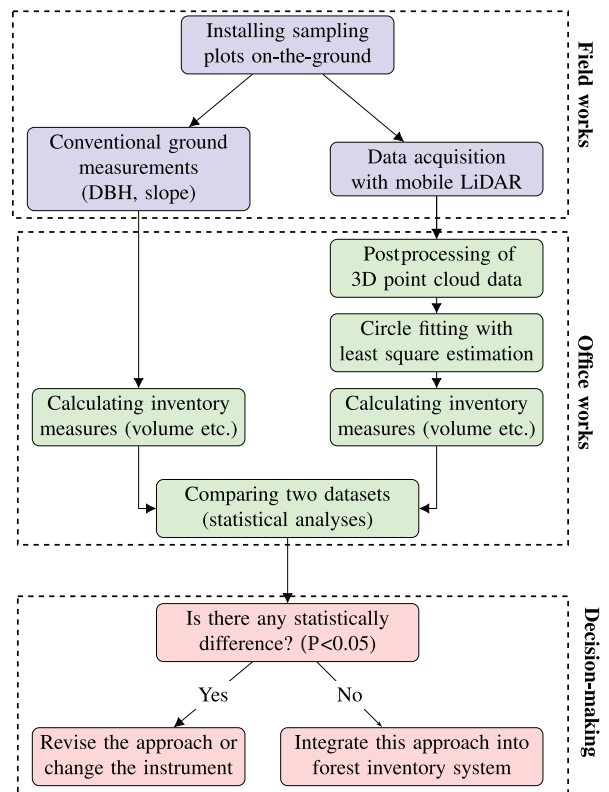
2.3.2. Ground measurements
In the present study, ground measurements were conventionally performed based on the "timber stock inventory method" documented in the Turkish forest

management regulation (GDF, 2008) and its detailed guideline (GDF, 2017). First, a Garmin GPS receiver was used for recording the coordinates of sampling plots in the field. Then, plot borders were determined by a Vertex hypsometer based on the sampling size. Owing to transponder adapter and monopod of the hypsometer, no cord was needed to range finding for suspicious trees near the plot borders. In a sampling plot, all trees with DBH more than 7.9 cm were marked, enumerated, and measured at breast height using Haglöf caliper by species (Figure 6a). Concurrently, their stem qualities were visually assessed according to the forest management guideline (GDF, 2017). Then, tree heights were measured using the hypsometer for 4, 6, or 8 representative trees on a plot (i.e., 100 trees per hectare). In the next step, the surface slope rate was determined with the help of a clinometer in percent unit. Finally, we assessed other forestry parameters such as stand type and sapling recruitment and recorded all data into inventory sheets (Figure 6b). No measurement was performed for diameter increment or tree age since they have been rarely assessed during the current Turkish FI surveys in practice. Instead, the number of saplings and the number of stumps were counted, if any. The minimum DBH threshold was 4 cm for the stumps.

2.3.3. Calculation of inventory measures

Data from each plot measured by both conventional and HMLS methods was used to calculate the basic FI measures, including timber volume, basal area, number of trees, number of saplings, and number of stumps. Respective yield models (Ercanlı and Yavuz, 2006) and local volume tables (GDF, 2006a; 2006b) were utilized to calculate individual stem volumes on each plot. Then, Equation 1 and Equation 2 were used for calculating basic FI measures at the plot level (Asan, 2017). Finally, all FI measures were standardized to per unit area (i.e., 1 ha) using Equation 3 for making a consistent comparison amongst the plots differing in size (Asan, 2017).

$$TV = \Sigma\, V \tag{1}$$
$$G = (\pi\,/\,4) \times \Sigma\, d_{1,30}{}^2 \tag{2}$$
$$CCH = 10000\,/\,SPS \tag{3}$$

Where TV is the total timber volume of a sampling plot (m^3), V is the commercial stem volume for each standing tree in a sampling plot (m^3), G is the basal area of a sampling plot (m^2), $d_{1,30}$ is the DBH of each tree on a sampling plot, CCH is the coefficient of conversion to hectare (unitless), and SPS is the sampling plot size (m^2).
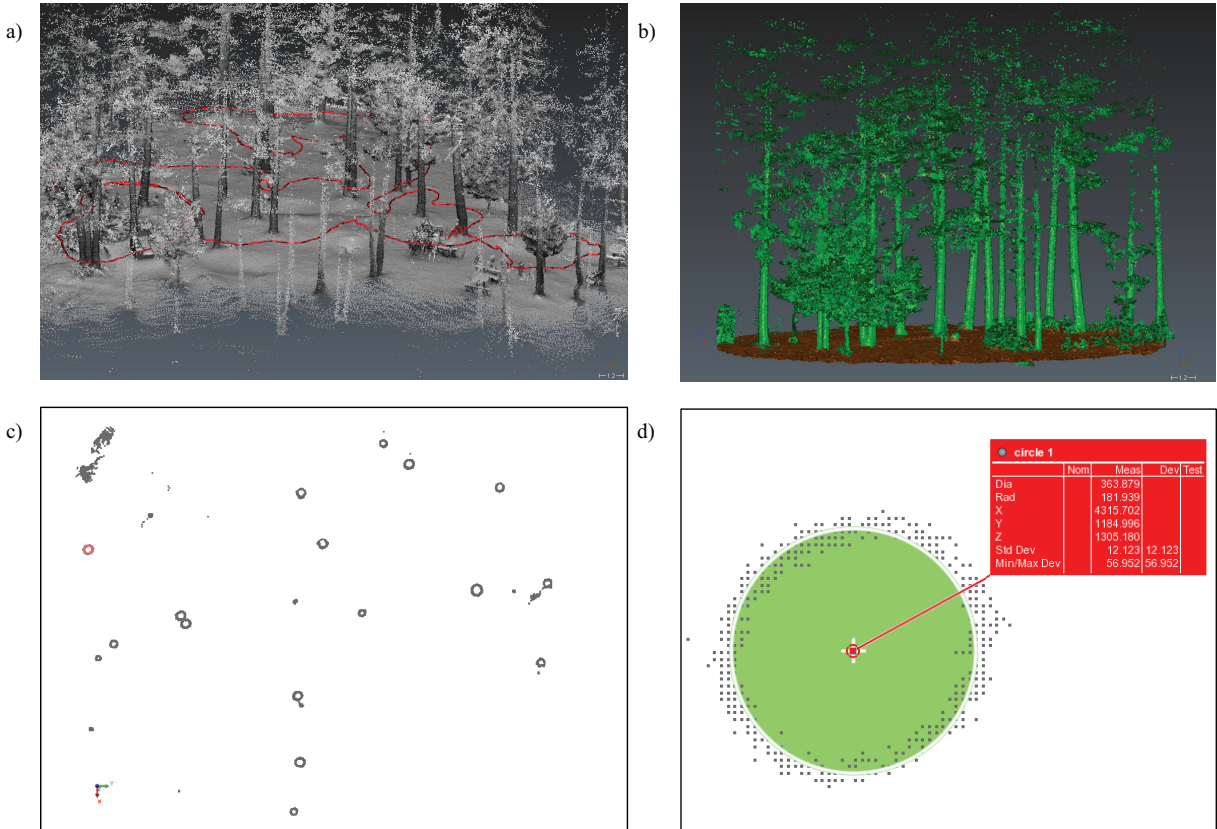

Figure 5. (a) Trajectory for LiDAR survey in plot 4 (Çscd2 stand); (b) 3D visualization of plot 9 (Knbc3 stand); (c) extracted tree disks at 1.30 m above ground level; (d) DBH calculation on a fitted circle.

2.3.4. Statistical analyses

After controlling whether ground- and HMLS-derived datasets are normally distributed, DBH of individual trees were sorted by ascending and then subjected to Pearson's correlation analysis. If data were not showing a normal distribution, Spearman's correlation analysis was preferred. Paired samples t-test was used to see if there are any statistically significant differences between the two datasets at the plot level in terms of DBH. Finally, a residual analysis was performed to evaluate the distribution of errors. All analyses were performed in R software (R Core Team, 2018) at minimum 95% confidence level.

3. Results

3.1. DBH estimations

Except for plot 8, all sampling plots showed a normal distribution (P > 0.05), as expected under natural forest conditions (Table 2). The tree forms on plot 8, on the other hand, had some irregularities and human-induced defects, as shown in Figure 2. The average DBH of 437 trees was 34.2 cm, as seen in the box-plot graphic (Figure 7). HMLS method yielded slightly higher DBH values than conventional ground measurements. Statistical analyses found robust and positive correlations between ground measurements and HMLS data for DBH (P < 0.01). Accordingly, correlation coefficients ranged between 0.978 and 0.998. Paired samples t-test, moreover, indicated there were no significant differences between two datasets in any sampling plots at 95% confidence level (Table 2). Thus, the HMLS method was found to be reliable for DBH estimations in Turkish FI system both at the individual tree and at plot levels.

Figure 6. (a) A marked tree located on the plot center; (b) recording tree data into an inventory sheet.

Residual analysis showed that both positive and negative errors had a homogeneous distribution along the zero lines, except for plot 8. The residuals of plot 8 had a nonhomogeneous distribution pattern, as seen in Figure 8. It was the only plot that was not showing a normal distribution. Overall, no significant bias was found in the residuals for 437 trees at the plot level.

3.2. Basic inventory measures

Necessary FI measures, including the number of trees, basal area, and timber volume were calculated based on the DBH data reported in the previous subsection. The bar charts related to these measures were given in Figure 9 by sampling plots at the landscape level (i.e., forest enterprise). Regarding the number of trees, two datasets showed considerable similarity, as no additional calculation was conducted for tree counting. The average positive difference for the number of trees was only 0.6% at the landscape level. Such overestimations by the HMLS method yielded slightly higher results in basal area and timber volume too (Figure 9). Nevertheless, the differences were less than 10% on average – 8.9% for basal area and 9.8% for timber volume. When all sampling plots were aggregated, HMLS estimated the average values for the number of trees, basal area, and timber volume as 535 trees/ha^{-1}, 49.6 m^2/ha^{-1}, and 499.7 m^3/ha^{-1}, respectively. Overall, the HMLS method was found to be suitable for deriving necessary FI measures in the Turkish FI system at the landscape level (i.e., for per unit area, 1 ha).

3.3. Additional measures

Apart from basic measures, additional FI parameters, including the number of saplings, number of stumps, tree heights, and surface slope were estimated using HMLS data. Amongst them, the best fit was provided on the number of saplings. Both over- and under-estimations were observed for this measure, as seen in Figure 10. As for the number of stumps – plot 4, plot 8, and plot 9 were estimated entirely, too. Exceptionally, tree height estimations were very poor, with negative differences more than 50%, and thus they were not reported in this paper. In general, estimations on additional measures were more accurate than those of basic FI measures', as they owed their accurate estimates to be directly counted one by one – except for surface slope. Contrastingly, basal area and timber volume required extra equations (i.e., Equation 2, Ercanlı and Yavuz, 2006) or volume tables (GDF, 2006a; 2006b) for the final calculation. Slope data, on the other hand, generally showed bias in a positive direction compared to ground truth measured by a clinometer. They were underestimated by the HMLS method on almost every plot (Figure 10). When all plots were taken together, however, average slope rates were somehow consistent despite ca. 15% difference between the two datasets. It was

Table 2. Statiscal test results by sampling plots.

Plot no.	n*	Distribution	Correlation test	r coefficient	P-values (for t-test)
1	36	Normal	Pearson	0.996	0.22
2	71	Normal	Pearson	0.997	0.36
3	105	Normal	Pearson	0.998	0.16
4	18	Normal	Pearson	0.992	0.52
5	37	Normal	Pearson	0.996	0.67
6	82	Normal	Pearson	0.994	0.36
7	23	Normal	Pearson	0.978	0.50
8	16	Not normal	Spearman	0.998	0.70
9	49	Normal	Pearson	0.993	0.76

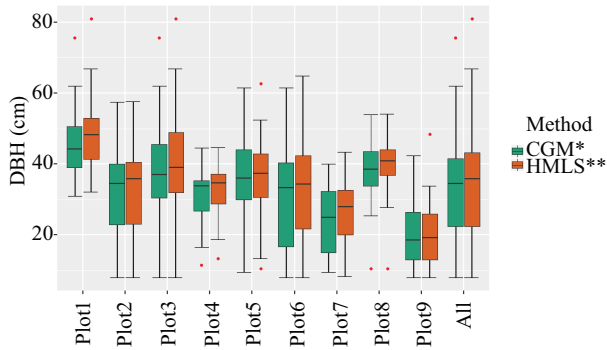*n: Sample size (number of trees on a sampling plot).

Figure 7. Box-plots for DBH datasets (*CGM: conventional ground measurements; **HMLS: handheld mobile laser scanning).

attributed to different slope directions considered by the two methods.

4. Discussion
In general, the HMLS method overestimated tree DBH in all sampling plots. One reason for this may be the quality of ground measurements in Turkish FI system, as recently pointed out by Büyüksalih et al. (2017). During FI surveys in Turkey, DBH is measured by a caliper on the uphill side of the tree (GDF, 2017). For noncircular stems, two measurements—at 90° angles to each other—are performed, and their arithmetic means are recorded into inventory sheets. However, many error sources are embedded in this approach. These likely stem from the measuring position of the operator (e.g., determining the breast height, slope direction, right angles, etc.), trees with noncircular cross-sections, and/or the variation in bark thickness, especially for pine species. For breast height,

1.37 m above ground level is used in the USA, while 1.20 m is used in Japan (Laar and Akça, 2007). We measured DBH at 1.30 m above ground level, as is done in Turkey and most other parts of the world. Since a tree stem is not fully cylindrical, the diameter tends to decrease as it moves upward along the stem. Therefore, DBH may vary depending on the measurement height. In order to perform more accurate and reproducible results, collar diameter may be measured at a fixed distance from the base of the tree using a diameter tape. The diameter tape can measure tree DBH almost error-free from the circumference of the stem by dividing it with pi. Because it is less affected by the shape of the stem, diameter tape provides more accurate results compared with caliper measurements (Laar and Akça, 2007). That is why collar diameter is preferred in nursery and regeneration studies, in which precise DBH measurements are needed. Eventually, it was evaluated that—like in Akay et al. (2012) and Büyüksalih et al. (2017)—the low quality of the ground data is likely to be responsible for the overestimations by HMLS method.

This study has revealed that as stem quality gets higher, estimation accuracy increases as well. Relatively poor estimates were generally obtained from plot 7 and plot 8, which were located on poor sites with anthropogenic pressures such as illegal cutting and grazing in forested lands. On these plots, tree stems were in irregular shapes due to defects or poor technical quality. There were also many crooked and protruding stems on these sites. As such, stand structures were far from naturalness in terms of size class distribution. Although the forest enterprise was managed by the even-aged system (GDF, 2006b), both small- and large-sized trees coexisted on the plots. In another LiDAR study, Apostol et al. (2018) obtained similar findings in the Southern Carpathians forests. They observed higher error rates in DBH within the stands that
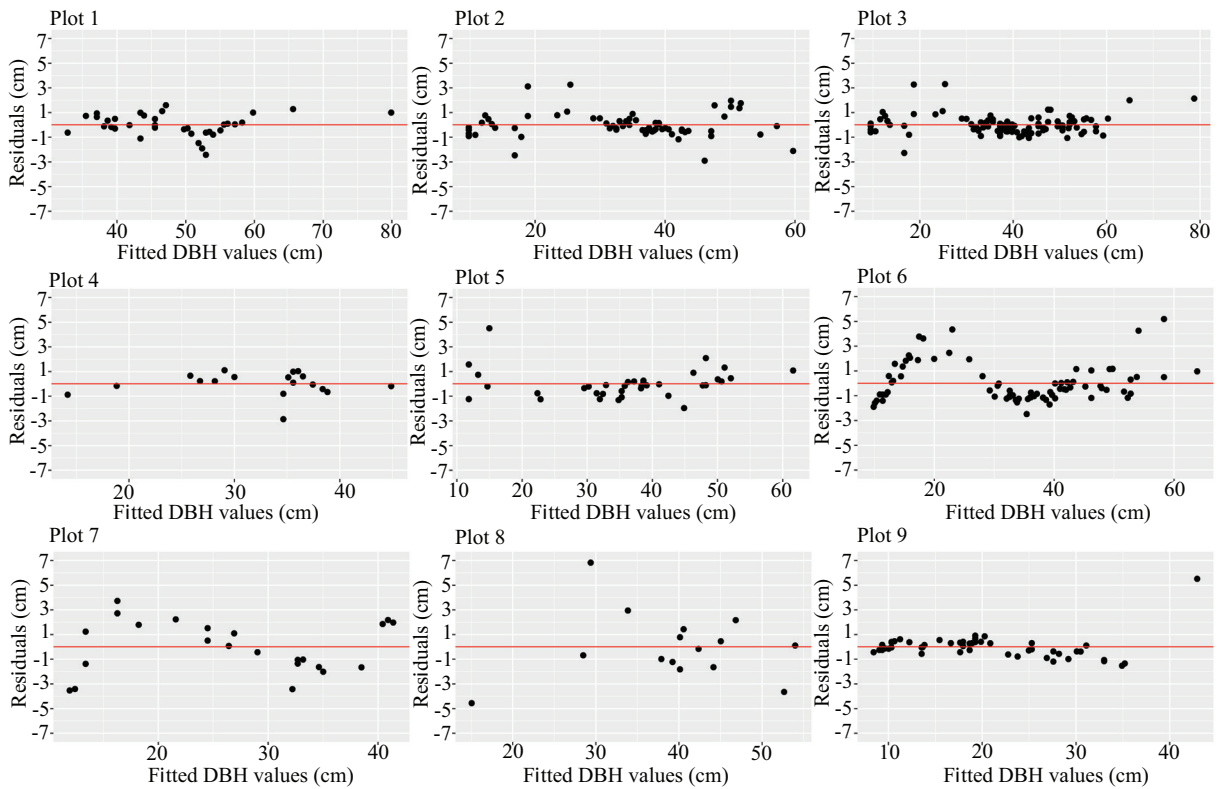
Figure 8. Distribution of the residuals by sampling plots.

had higher coefficients of variation. Contrastingly, the errors were relatively low in the case of DBH variation coefficient of less than 40%. The high level of error rates was attributed to the inappropriate interventions in the forest. Nonetheless, the Turkish FI system focuses more on managed forests, showing a somehow homogeneous structure and generally located on good sites. Unlike managed forests, sampling density is reduced by a quarter on unmanaged forests that are set aside for conservation or nonprovisional ecosystem services (GDF, 2017; Demirel and Özkan, 2018). Since stem quality is higher in managed forests, no problem seems to arise in our approach, as we were able to estimate DBH much better for plots 1, 2, 3, 5, and 9. These plots had good site conditions with elite trees. Aside from site conditions, the dominant tree species (Scots pine) may be another reason leading to overestimations in DBH. It is well known that this species may make thick and fissured bark on the lower trunk, especially in its maturity period. As a matter of fact, the developmental stage of plot 7 and plot 8 was d (i.e., 36–52 cm in DBH), indicating older ages in Scots pine's lifespan. Therefore, the bark roughness of this species might explain the errors encountered by both conventional and HMLS methods in low-quality stems.

The correlation analyses showed that our results were in good agreement with other LiDAR studies in the literature.

In the present study, tree DBH estimates by HMLS method were strongly and positively correlated with conventional ground measurements. Using HMLS we found that all correlation coefficients were higher than 0.97 in all plots at the individual tree level. Using TLS, Pazhouhan et al. (2017) saw a strong relationship between the two methods with an R^2 value of 0.98 for DBH in the Hyrcanian forest. Similarly, Yurtseven et al. (2019) found an R^2 value of 0.99 for DBH in Istanbul, Turkey. In another study, Akgül et al. (2016) reached an R^2 value of 0.97 for the same measure in Istanbul too. Unlike ours, their LiDAR-derived DBH estimates were lower than ground measurements. Comparing ALS and ground measurements, Akay et al. (2012) also found a strong relationship between two datasets with an R^2 value of 0.92 in Oregon, USA; however, they measured crown widths instead of DBH. As for Germany, Heurich (2008) estimated timber volume using ALS with 85.2% accuracy level in a Spruce-Beech mixed forest. Many other studies using different LiDAR data reported similar findings on the topic (Moskal and Zheng, 2012; Srinivasan et al., 2015, among others). Thus, our experimental findings are generally consistent with the relevant literature.

The overall results indicate that there appears to be no shortcoming in DBH estimations with HMLS technology in terms of accuracy. Estimating tree heights and canopy
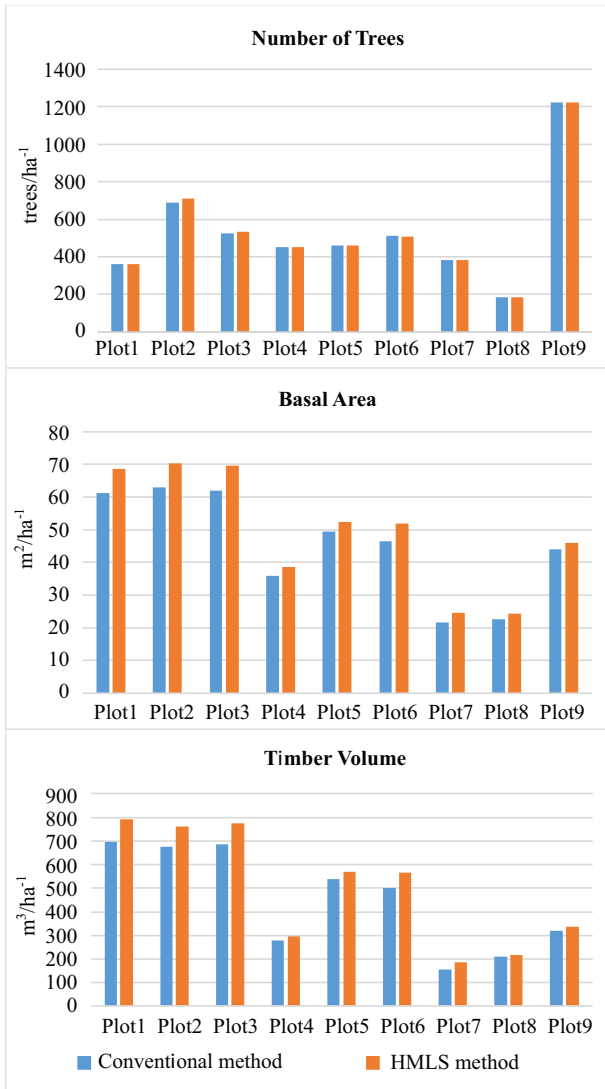
Figure 9. Forest inventory measures derived by two different methods.

Figure 10. Additional forestry measures derived by two different methods.

cover, on the other hand, was indeed a significant challenge using Zeb-Revo instrument in our case. In particular, the tops of the tall trees were invisible to the instrument from the forest floor due to its limited scanning range (ca. 16–17 m in practice). Although most recent mobile instruments can reach up to 100 m (e.g., Velodyne VLP-16), both lower branches and dense crowns in natural forests limit the visibility of the tree tops, especially in deciduous forest plots. Therefore, no reliable estimates were achieved on tree height nor canopy cover during the present study. Other researchers experienced this shortcoming in their studies as well. Cabo et al. (2018), for instance, underestimated the heights of tally trees using the HMLS method on urban green space in NE Spain. Indeed, this is likely the most significant problem of HMLS for the field of forestry.
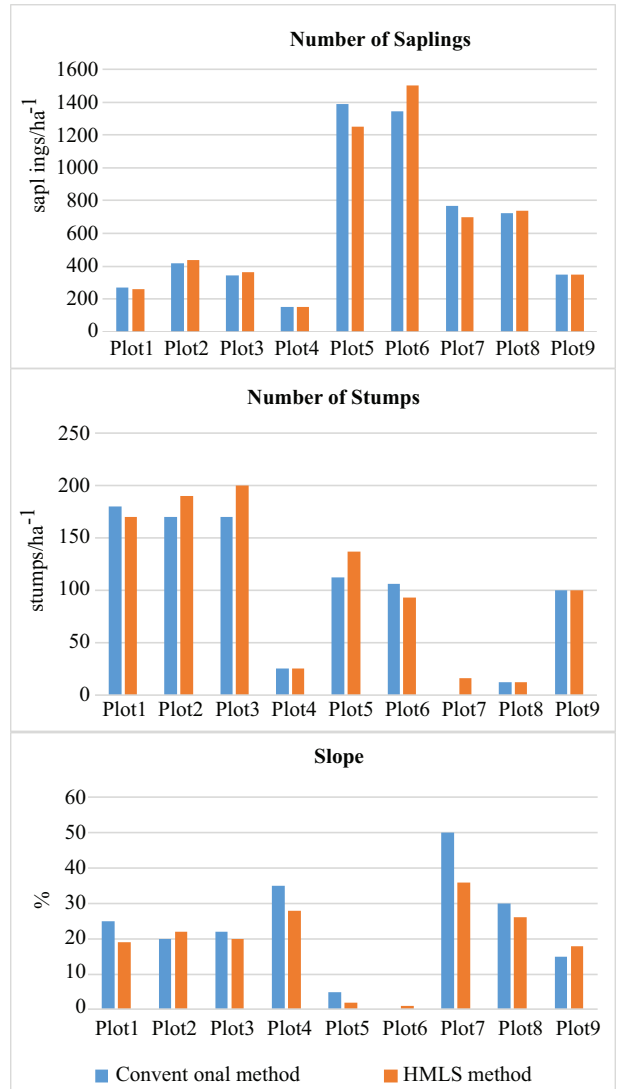
Combining HMLS data with the point clouds produced by Unmanned Aerial Vehicles (UAV) or ALS may be the right solution for this, as proven by Giannetti et al. (2018) in Italy. Fortunately, no quantitative information is required for either height or canopy in the current Turkish FI surveys (GDF, 2017). Since they are secondary measures for timber inventories, no measurement is performed for tree height; on the other hand, canopy cover is determined by a field engineer as three broad closure classes based on observation, as described in the footnotes of Table 1. Thus, foresters can quickly identify the closure class while walking through a forest plot with an MLS at hand. To date, DBH value with reasonable accuracy is still the key measure of FI surveys, as it is nearly sufficient for assessing wood availability within forest enterprises (Kangas et al., 2006).

Unlike ground measurements, HMLS-derived raw data needs postprocessing efforts in order to derive meaningful information on FI measures. However, we processed it using a modest laptop computer in a relatively short time (ca. 20 min for nine plots). Therefore, easy data processing may be considered another advantage of HMLS compared to other LiDAR instruments. Many studies using TLS instruments, for instance, required high-tech workstations (Yurtseven et al., 2019, among others) or a long time period of up to 10 h (Apostol et al. 2018). Considered with the necessary working time in the field—reaching more than one hour per plot in some cases— its operational use in an FI study is minimal, at least for now (Ryding et al., 2015; Oveland et al., 2018; Cabo et al., 2018). These limitations embedded in TLS mainly result from very dense point cloud data, as well as its geo-referencing processes, whereas both of them are actually unnecessary for most of the FI studies. Despite the higher precision of point clouds recorded with TLS, Cabo et al. (2018) showed that there was no significant difference in DBH estimations by both HMLS and TLS at individual tree level (P < 0.05). As a matter of fact, the key object in FI is the general structure of the forest at the landscape level (i.e., for forest enterprise) from a forest management point of view. It seems, however, that most recent TLS-based forestry research became so involved in details that "they cannot see the forest for the trees." For this reason, the right balance between efficiency and effectiveness should always be struck in the course of compelling forestry research.

In this study, HMLS technology was tested using a mobile LiDAR instrument, particularly for FI purposes, through the lens of forest management and planning. Data validation was done by comparison with conventional ground measurements via some FI measures such as average DBH and timber volume. Statistically, no significant difference was found between the two datasets (P < 0.05). There were powerful correlations for DBH at individual tree level (r > 0.97; P < 0.01). At the landscape level, the slight differences in estimating the average DBH, number of trees, basal area, and timber volume were 5%, 0.6%, 8.9%, and 9.8%, respectively. Moreover, additional forestry parameters, including the number of saplings, number of stumps, and surface slopes were successfully estimated on point cloud data. However, we could not do reliable estimations on tree heights using HMLS data.

In conclusion, HMLS is evaluated as the most suitable method among other LiDAR approaches for FI purposes in Turkey. It can be used in timber surveys as easily as walking through forest sampling plots, and thus FI data are collected at required standards. In this way, the Turkish FI system can gain time and cost efficiency in practice. For these reasons, it is likely that HMLS will soon start attracting more attention in the field of forestry. Therefore, future efforts should focus on developing automatic height extraction algorithms for the vertical structure of forest ecosystems. It is of equal importance to integrate low-cost sensors into HMLS instruments through speeding up research and development processes, as equipment acquisition costs are still a significant constraint for low- and middle-income countries.

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