Ecological Informatics 85 (2025) 102999

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Low-cost phone-based LiDAR scanning technology provides sub-centimeter accuracy when measuring the main dimensions of motor-manual tree felling cuts

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ARTICLE INFO

Keywords:
Remote sensing
Chainsaw
Wood
Volume
Loss
Forest operation

ABSTRACT

Motor-manual tree felling in one of the most important technical alternatives in timber harvesting. Commonly, it requires a sequence of cuts and may cause higher volume losses compared to mechanized tree felling. The wood lost depends also on the tree size, but accurate quantifications and their dependencies are difficult to establish since there is a limited ability to manually measure key dimensions and assimilate the tree bottom to parametric geometric features. Short-range LiDAR technology integrated in affordable mobile platforms has already been proved to produce reliable estimates on objects located in a limited space, and point cloud processing algorithms have been developed to compare two instances of the same object, potentially enabling the quantification of tree-level wood loss. However, volume loss estimates based on LiDAR scanning of tree bottoms are very sensitive to the accuracy of scans, while low-cost platforms may lack the capability to produce point clouds of an acceptable density at a reasonable distance. This study was setup to check to what extent proximal scanning by low-cost LiDAR platforms can provide accurate data to support the extraction and computation of volume loss by motor-manual tree felling. Eleven Norway spruce logs having a length of one meter and mid-diameters between 22 and 43 cm were used to make 63 notches by a chainsaw. The main dimensions of each notch were then measured manually to the nearest millimeter by a tape and used as reference data. These were the hinge width, depth of the bottom cut, depth of the top (inclined) cut and the notch height. Close-range (up to 50 cm) scans were taken on each notch by an iPhone 13 Pro Max platform using the freely available software 3D Scanner App. The resulted point clouds were imported to Cloud Compare software, where the same measurements were taken digitally and used as data for comparison. By the commonly used error metrics such as the bias (−0.73–0.10), mean absolute error (0.51–0.78) and root mean squared error (0.68–0.92), the differences between the two were in the sub-centimeter domain. Taken individually, all the measurements agreed well in a $\pm$ 2 cm range, with an obvious dominance in much lower ranges and no evident trends in variance related to the measurement size. These results are promising for the forest operations science and practice because they provide evidence on the fact that by low-cost close-range LiDAR scanning and point cloud processing one can get accurate estimations notch volume losses. In turn, this will provide the basis for leveraging the losses by considering the operational conditions, the used procedures and experience of the workers while supporting the attempts of quantifying and relating the losses to the mentioned factors.

1. Introduction

One of the important missions of forest operations engineering is to continuously improve the forest operations systems (Borz et al., 2024; Heinimann, 2007). Quality optimization has been recognized as one of the key performance areas under the concept of sustainable forest operations (Marchi et al., 2018), placing a great emphasis on improving the utilization rate of the harvested trees by using the best harvesting system in relation to local conditions. Under the growing concerns on the effects brought by the climate change, there is also an increasing policy interest

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https://doi.org/10.1016/j.ecoinf.2025.102999
Received 29 August 2024; Received in revised form 4 January 2025; Accepted 4 January 2025
Available online 8 January 2025

in storing the wood in long-term products and implementing the cascading economy principles in wood manufacturing and utilization industries (European Commission, 2021). These will likely have impacts on the local policies and the choice of harvesting systems, and will favor polarity in opinions, which in turn will require detailed data on how the various harvesting systems perform in terms of wood utilization rate.

Motor-manual tree felling holds an important share among the options used in timber harvesting around the world (Lundbäck et al., 2021; Moskalik et al., 2017). While it is supported by cheap equipment (Calvo et al., 2013; Oprea, 2008), it also comes with several important limitations such as poorer safety conditions and higher risks of accidents (Banciu et al., 2018; Melemez, 2015; Tsioras et al., 2014), poorer ergonomic conditions, and an intense use of manual labor (Cheţa et al., 2018; Papandrea et al., 2022; Potočnik and Poje, 2017). In addition, it requires highly skilled workers that should hold advanced knowledge and operational skills to prevent eventual wood losses and damaging of residual trees, while being able to enforce the safety requirements for themselves and for others (Marchi et al., 2018; Oprea, 2008), that is, people able to properly plan and carry on the operations (Neely and Wilhelmson, 2006). The knowledge and skills required to implement the operations are sourced largely from the established tacit experience gained from tree felling practices, as well as from the science and theory of tree felling (e.g. Knobloch et al., 2023;Lyons et al., 2012; Noll and Lyons, 2010; Oprea, 2008).

There are important variations in the procedures used to fell the trees motor-manually in terms of making the necessary cuts, which are usually being related to local factors such as the tree species, tree condition and tree size (Oprea, 2008). Many of them share the same common feature, namely the requirement to make a notch with the aim of guiding the tree during falling (Lyons et al., 2012; Noll and Lyons, 2010; Oprea, 2008). Notch dimensions, such as the depth, openness, and the height, are commonly related to the tree size (Oprea, 2008). Practice, however, has shown that the recommended dimensions are often disregarded (Borz et al., 2014; Koger, 1983), which may have implications for the work safety, degree of recovery and quality of the wood, and the resources involved in tree felling. For a visual reference on the main dimensions of a notch, the reader may check the papers of Đuka et al. (2020), Borz et al. (2014) and Koger (1983).

In terms of safety, it is assumed that there are other covariates that affect the incidence of unexpected events like the felling errors and accidents, such as the tree size, terrain slope, presence of rot on the stump, condition of the tree, and the type of harvesting (Nikooy et al., 2013; Poje et al., 2016); even when making the cuts correctly by experienced fellers, there is a degree of uncertainty on what might happen, since most of these events may occur after starting to fell a given tree (DeMille and Lyons, 2016). As a rule, the larger the tree the bigger the notch, which in turn will have implications on the amount of recovered wood. This comes in addition to the value loss due to the wood left in the stumps (Boston and Dysart, 2000; Oprea and Borz, 2007), as well as to the volume lost as sawdust when making the back cuts or when delimbing and debranching the trees (Oprea and Borz, 2007). Other contributors to value loss are tree breakage or splitting (Jourgholami and Abari, 2017; Oprea and Borz, 2007), some of which may be attributed to using an incorrect felling method (Oprea, 2008).

In terms of quantification, older studies (Kerbes and McIntosh, 1969) have found that one may lose as much as 47 % of the wood due to the conversion from standing trees into finished lumber. As the technology related to forest operations has progressed substantially, it is likely that the share of wood loses has considerably decreased. Often, however, such data may come from the local experience and it is not publicly available, or it may be constrained in terms of statistical power or generalizability given by the limited number of observations or conditions covered and used to make the estimations. In general, a world-wide standardization in definitions and quantification methods is currently lacking. In Romania, for instance, based on older statistics, it was estimated that the overall losses caused by partly-mechanized harvesting systems may account to 2–3 % of the standing volume of the harvested wood (Oprea and Borz, 2007).

The way of estimating the loses has its own limitations in accuracy, since it is likely to be often based on manual measurements (Borz et al., 2014; Đuka et al., 2020; Gerasimov and Seliverstov, 2010; Wang et al., 2004) followed by volume computations which are based on parametric geometrical assumptions (Borz et al., 2014; Đuka et al., 2020). Commonly, these limitations come from the highly irregular shape of the trees at the level at which the felling cuts are made, as well as from the variations in taper at the same levels, particularly in old forests, requiring new or improved methods of measurement. In addition to being reliable, these methods should be cost-effective, less intensive in terms of effort, and safe.

A potential solution lies in the use of affordable, mobile platforms such as the smartphones carrying various types of proximal sensing sensors; these can be used to collect and process tree (Gollob et al., 2021; Tomaštíc et al., 2017) or log (Niţă and Borz, 2023) related point clouds by freely available software while being competitive in terms of cycle time (Borz and Proto, 2022; Gollob et al., 2021) and ergonomics (Borz et al., 2022a). They were used lately for collecting tree related data with promising results in terms of accuracy. For instance, the study of Tomaštíc et al. (2017), which was based on Google Tango technology and close-range photogrammetry, found a RMSE (root mean squared error) for DBH (diameter at the breast height) of 1.61 to 2.10 cm, while the study of Gollob et al. (2021), which was based on LiDAR sensors, found a RMSE for DBH of 3.13 cm. However, their scans were likely taken from an average distance of more than 1 m, which probably affected the level of detail contained in the point clouds.

Although this level of accuracy may seem acceptable for practical applications such as inventories and volume estimation, it could be problematic for estimating the volume lost by making the felling cuts, or when one would like to relate the behavior of the tree during felling to the spatial layout and dimensions of the felling cuts. For a low-cost LiDAR based platform, a closer look to the tree by scanning is likely to enhance the level of detail contained in the point clouds since the distance between the LiDAR sensor and the scanned object controls the density of the points; for instance, Luetzenburg et al. (2021) have described for an iPhone 12 Pro Max a potential point density ranging from 7225 points m^{-2} at a scanning distance of 25 cm to 150 points m^{-2} at a scanning distance of 250 cm, which follows a linear trend on a logarithmic scale. This property may be applicable to accurately estimating the volume lost in notches since these features are rather small is size compared to their corresponding trees. In addition, limiting the movement during the scanning will also contribute to lowering the noise and drifts in the point clouds (Tomaštíc et al., 2017), making it possible to compare the scans taken before and after the felling cuts.

Lately, LiDAR-based applications have gained a lot of momentum in forestry. Using the data sourced by various platforms in conjunction with advanced machine learning techniques provided the tools required to better understand forest environments and their temporal changes (Yun et al., 2024). The latest applications include evaluations on forest status and disturbance severity (Iheaturu et al., 2024), structural diversity of the forests (Borges Gonçalves et al., 2024) and extraction of tree-level phenotypic characteristics (Gao et al., 2025). However, these have a limited applicability in extracting important features for forest engineering, which includes the estimates of volume losses due to felling cuts. On the one hand, such features may be too small to be accurately captured by conventional platforms such as remote airborne or terrestrial LiDAR scanning, while the accuracy and completeness of estimates may be affected by occlusion. On the other hand, their measurement is typically constrained by the way in which the tree felling operations progress, which requires the measurements to be taken right after making the felling cuts and before the tree is felled.

This study was designed as a proof of concept in terms of getting accurate readings by scanning the main dimensions of motor-manual tree felling cuts, while taking the advantage of using affordable technology. The first objective of the study was to check the agreement between the manually taken (reference) and digitally derived (compared) measurements taken on the hinge width, depth of the bottom cut, depth of the top (inclined) cut, and the notch height. The second objective was to estimate the deviation of digitally derived data, by the commonly used error metrics, and the third objective was to check if there are changes in the deviation variance caused by the dimensions of the felling cuts.

2. Materials and methods

2.1. Site of the study, data sourcing and processing

Field data collection was carried out in the spring of 2022, at the didactic facility of the Faculty of Silviculture and Forest Engineering, located near Brasov, Romania (Fig. 1a), where 11 Norway spruce logs having a length of about 1 m and mid-diameters of 22 to 43 cm were used as the study objects. An experienced feller was asked to cut evenly spaced notches on the same face of each log using his knowledge and skills to relate their dimensions to the log size at the level of making the cuts (Fig. 1c). In total, 63 notches were cut in the logs placed vertically in advance. On each notch, guiding marks were painted to enable manual measurement of their main dimensions (Fig. 2). The marks were placed with the main aim of pointing the middle of each notch on the top and bottom cuts, as well as on the hinge width line (Fig. 2a). Once the marking was done, manual measurements were taken on the hinge width (HW), depth of the bottom cut (BCD), depth of the top cut (TCD) and the notch height (NH), as described in Table 1 for both, reference and compared data.

Manual measurements were taken by a pocket tape to the nearest millimeter and the results were noted on paper sheets along with the log number and the order of the notch on the log from top to bottom. Following manual measurements, each notch was scanned by an iPhone 13 Pro Max (*iPhone 13 Pro Max - Technical Specifications*, 2023) running a freeware copy of the 3D Scanner App (3D Scanner App, 2023) software (Fig. 1b). Scans were run from up to 50 cm by using the LiDAR point cloud mode, and saved individually in chronological order on the internal memory. For each manual measurement recorded on paper sheets, the time of saving the scan was noted down, serving as a reference for identifying the files for digital measurements. The scans were exported into a. XYZ color, space delimited (CloudCompare, 2023) format, and saved as raw point clouds in individual notch-based folders created for each log. Among other features, the format contains information on three-dimensional local coordinates and colors stored in RGB format for each point (Fig. 3b). For each dimension (Table 1), manually taken reference data was transferred in a Microsoft Excel® sheet containing other identification attributes such as the log number, length, mid-diameter, notch number and file saving time. Then, the 2.12 alpha version of the CloudCompare freeware software (CloudCompare, 2023) developed for a Windows operating system was used to load, clean the point clouds, when necessary, by the use of Segment tool (CloudCompare User Manual, 2023), and to take the digital measurements on the same notch dimensions (Fig. 2b).

In the office phase of the study, it was observed that the last notch from log 1, first notch from log 2 and the last three notches from the log 7 had incomplete point clouds, therefore they were excluded from the study. As such, the sample size of the study contained 58 notches. Digital measurements were based on local geometry of each point cloud as seen on the computer's screen (Fig. 3c,d). Picking the starting and ending points was based on their conformance to the real closest starting and ending points (Fig. 2b, Fig. 3d). This was done by rotating and checking each point cloud storing the instant measurement in several viewing

Fig. 1. Study location and data collection: a) location of the study area at the national level, b) scanning notches by the mobile platform, c) logs prepared for scanning.

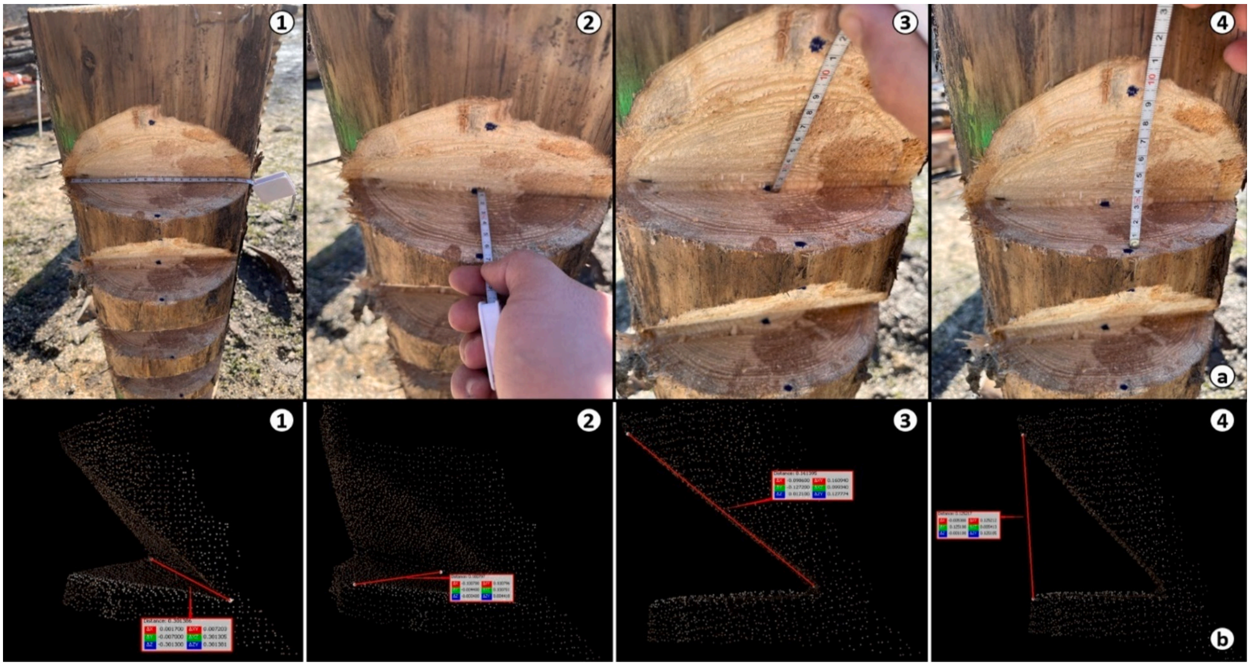

Fig. 2. Methods and tools used for manual (reference) and digital (compared) measurements: a) examples of manual measurements, b) examples of digital measurements, 1 – measurement of the hinge width, 2 – measurement of the bottom cut's depth, 3 – measurement of the top cut's depth, 4 – measurement of the notch's height.

Table 1
Description of notch dimensions taken into study.

Abbreviation	Description
HWC	Hinge width measured in CloudCompare
HWR	Hinge width measured manually by a tape
BCDC	Depth of the bottom cut measured in CloudCompare
BCDR	Depth of the bottom cut measured manually
TCDC	Depth of the top cut measured in CloudCompare
TCDR	Depth of the top cut measured manually by a tape
NHC	Notch height measured in CloudCompare
NHR	Notch height measured manually

perspectives. Once a measurement was considered to be accurate, the length of the corresponding dimension was paired with its reference data in the Microsoft Excel® sheet.

2.2. Statistical analysis

The agreement between the two measurement methods was checked by the Bland and Altman's method (Bland and Altman, 1995; Bland and Altman, 1999) which maps the differences between the reference and compared data (Eq. (1)) against the average of the measurements, in a space delimited by an upper (*ULOA*) and a lower (*LLOA*) limit of agreement. The limits of agreement (Eqs. (2–3)) are computed based on two statistical metrics namely the bias (Eq. (4)) and standard deviation of differences. The limits of agreement used in this study were assumed to be linear and they considered two standard deviations in differences (Bland and Altman, 1995; Bland and Altman, 1999; Giavarina, 2015). This assumption was complemented by heteroskedasticity tests (Breusch and Pagan, 1979; White, 1980) to check if the non-homogeneity of variance was present in data, as well as its type. In this regard, the main differences between the Breusch-Pagan and White tests for heteroskedasticity is that the former detects linear forms of heteroskedasticity, while the latter is able to detect other forms of heteroskedasticity when there is a limited number of regressors; also, the White's test does not assume normality in data (Obabiire et al., 2020; Williams, 2020).

$$\Delta RC_{ij} = R_{ij} – C_{ij} \tag{1}$$

$$ULOA_j = BIAS_j + 1.96 \times SD_j \tag{2}$$

$$LLOA_j = BIAS_j – 1.96 \times SD_j \tag{3}$$

$$BIAS_j = \frac{\sum_{i=1}^{n} Rij–Cij}{n} \tag{4}$$

$$MAE_j = \frac{\sum_{i=1}^{n} |Rij - C_{ij}|}{n} \tag{5}$$

$$RMSE_j = \sqrt{\frac{\sum_{i=1}^{n} (Rij - Cij)^2}{n}} \tag{6}$$

Where: ΔRC_{ij} is the difference between reference (R) and compared (C) data of the observation i ($i = 1$ to n) belonging to notch dimension j ($j = HW, BCD, TCD, NH$), $ULOA_j$ is the upper limit of agreement of the compared notch dimension j, $BIAS_j$ is the bias of compared notch dimension j, SD_j is the standard deviation of differences for compared notch dimension j, $LLOA_j$ is the lower limit of agreement of the compared notch dimension j, n is the sample size, MAE_j is the mean absolute error of the compared notch dimension j and $RMSE_j$ is the root mean squared error of the compared notch dimension j.

These statistical analyses were complemented by plotting the compared and reference data against the identity (equality) line, and by developing models of simple linear regression through origin (*RTO*). One of the mathematical mechanisms of simple linear regression through origin is that there is no intercept, therefore for null values of a reference variable the value of a compared variable should be also null (Eisenhauer, 2003). Under these circumstances, the models can be used as a visual surrogate to check how the compared data over- or underestimates the reference data. Coefficient of determination (R^2) can also be used to check how the compared data fits to the reference data. For each pair of compared dimensions, *RTO* models were developed and plotted against the identity line along with their corresponding lines of ordinary least square regressions. In addition, data distributions were

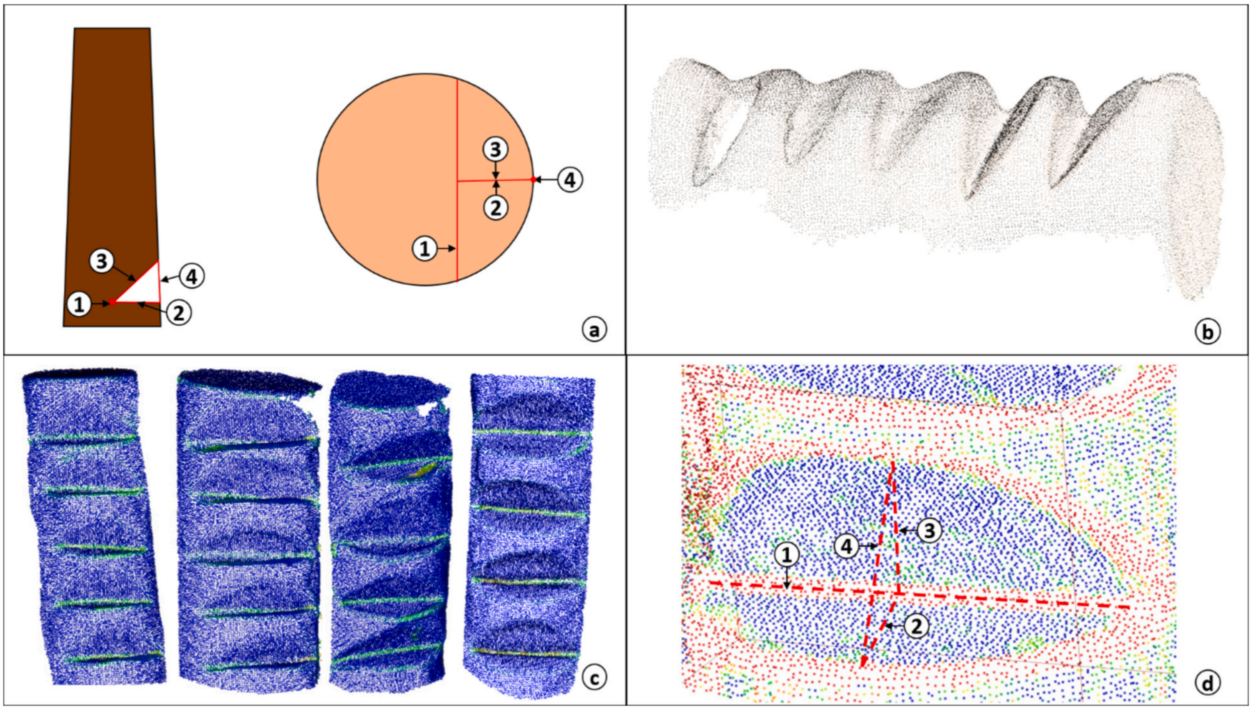

Fig. 3. Concept and methods used for manual (reference) and digital (compared) measurements: a) log sections showing the width of the hinge (1), depth of the bottom cut (2), depth of the top cut (3) and the height of the notch (4); b) an example of point cloud for a log shown in.XYZ CloudCompare format; c) a perspective over four logs showing the normal change rate and curvatures in the point clouds; d) the concept of digital measurements against the normal change rate and curvatures for a notch.

plotted as histograms and were accompanied by normality checks using the Shapiro-Wilk's (Shapiro and Wilk, 1965) and D'Agostino-Pearson's (D'Agostino and Pearson, 1973) tests. The main difference between the two tests is that, for inference, the former uses standard deviation data while the later uses the shape of the data distributions. A confidence level of 99 % was assumed for all statistical steps where relevant ($\alpha = 0.01$, $p < 0.01$).

Deviation of compared data was measured by the three commonly used metrics: bias (*BIAS*, Eq. (4)), mean absolute error (*MAE*, Eq. (5)) and root mean squared error (*RMSE*, Eq. (6)). The reason for using both *MAE* and *RMSE* are based on the arguments from Wilmott and Matsuura (2005) who indicate a better performance of *MAE* in describing deviance in data. However, *RMSE* was reported as well for comparison reasons and for providing data readily comparable to that from other studies. The bias, on the other hand, was used to generally indicate how the digital method over- or underestimates the reference data, since it also indicates the direction of differences.

2.3. Software used

The collected data were processed in Microsoft Excel® (Microsoft, 2023a) which was fitted with Real Statistics (Real Statistics Using Excel, 2023), a freeware tool for advanced statistical analysis. Functionalities of Microsoft Excel® were used for developing the Bland-Altman agreement plots, plotting the data against the identity line, developing the regression models, developing data distribution histograms, and computing the error metrics. Functionalities of Real Statistics were used for running the normality and heteroskedasticity tests. CloudCompare freeware software (CloudCompare, 2023) was used to import, clean, take digital measurements on point clouds, and to run normal change detection algorithms on some of the collected point clouds. Microsoft PowerPoint® (Microsoft, 2023b) was used to build composite figures, QGis version 3.28.4 (QGis, 2023) was used to build a study location map based on freely available data, and the 3D Scanner App (3D Scanner App, 2023) was used to collect the point clouds from the field.

3. Results

3.1. Summary of the data

The summary statistics (mean value and standard deviation) of the reference and compared notch dimensions are given in Table 2. As shown, in all the cases there was a close agreement in the average values between the reference (*R*) and compared (*C*) data.

The dimensions of the cuts, as made by the worker, were consistent with the recommended practices for motor-manual tree felling in Romania. For instance, it is common to use a depth accounting for about 33 % of the diameter when making the bottom cut (Borz et al., 2014; Oprea, 2008), which is reflected by the average depths (BCDR) in relation to the diameter of the used logs, as shown in Table 2. Also, the variability in the dimensions of the notch was fairly covered in the reference data by this study. For instance, the hinge line width (HWR) varied between about 20 and 40 cm; depth of the bottom (BCDR) and top (TCDR) cuts varied between 7 and 15 and 10–23 cm, respectively, while the notch height (NHR) varied between 8 and 18 cm.

3.2. Agreement of data

Fig. 4 shows the developed Bland-Altman plots of the four compared dimensions. There was a close agreement between the compared data in a range of ±2 cm, with an obvious agreement in lower data ranges for some of the variables (Fig. 4b,d). There were differences in a lower range for HW measurements when this dimension was of up to 25 cm and larger differences when it was between 25 and 40 cm (Fig. 4a). However, there were no evident trends in data variation as a function of the increment or decrement in dimensions' values, therefore the proportional bias (Ludbrook, 1997) was likely to be absent. There was, however, a systematic difference characterized by a constant bias in all cases. These trends are further supported by the data given in Sections 3.2 and 3.3. When comparing the hinge width (HW), the bias accounted for 0.10 cm, indicating a systematic underestimation of this dimension by the

Table 2
Main descriptive statistics of the compared data sets: HW, BCD, TCD and NH stand for hinge width, depth of the bottom cut, depth of the top cut and notch height, R stands for the reference (manual) data and C stands for the compared (digital) data.

Log no.	Mid diam. (cm)	No. of valid point clouds	HWR (cm)	BCDR (cm)	TCDR (cm)	NHR (cm)	HWC (cm)	BCDC (cm)	TCDC (cm)	NHC (cm)
1	22	6	21.12 ± 0.38	6.67 ± 0.14	11.13 ± 1.00	8.90 ± 1.16	21.27 ± 0.54	6.73 ± 0.26	10.95 ± 1.18	8.77 ± 1.39
2	22	6	19.88 ± 0.38	6.23 ± 0.59	9.80 ± 1.15	8.05 ± 1.15	19.58 ± 0.81	5.80 ± 0.33	9.45 ± 0.76	7.75 ± 0.87
3	24	8	21.50 ± 0.51	7.40 ± 0.86	10.73 ± 1.20	7.99 ± 1.12	21.71 ± 0.70	6.71 ± 0.83	9.93 ± 1.62	7.94 ± 1.23
4	23	6	22.05 ± 0.29	7.72 ± 0.64	12.53 ± 0.51	10.23 ± 0.64	22.18 ± 0.50	6.90 ± 0.75	11.65 ± 0.99	9.78 ± 0.81
5	24	7	22.20 ± 0.74	7.19 ± 0.64	11.61 ± 1.12	9.51 ± 1.10	22.67 ± 0.90	6.54 ± 0.62	10.63 ± 1.18	8.59 ± 0.94
6	34	5	31.84 ± 1.10	10.90 ± 0.45	16.58 ± 0.98	13.26 ± 1.24	32.10 ± 1.74	10.10 ± 0.50	15.76 ± 1.17	12.78 ± 1.45
7	43	2	39.40 ± 0.85	13.50 ± 1.41	20.10 ± 1.56	15.10 ± 1.56	38.70 ± 0.85	12.70 ± 1.13	19.85 ± 1.20	15.20 ± 2.12
8	43	4	39.98 ± 0.33	14.88 ± 0.30	22.68 ± 2.68	18.28 ± 3.46	39.95 ± 0.31	14.15 ± 0.95	22.03 ± 2.41	17.70 ± 2.66
9	40	5	37.12 ± 0.98	13.10 ± 1.64	19.18 ± 1.52	14.60 ± 1.13	37.36 ± 1.83	12.20 ± 2.08	18.58 ± 1.61	14.22 ± 1.18
10	41	4	38.03 ± 1.07	15.03 ± 1.04	21.90 ± 1.88	17.18 ± 1.85	38.23 ± 1.83	13.85 ± 1.07	21.88 ± 1.62	16.38 ± 1.35
11	41	5	38.56 ± 0.87	13.40 ± 1.48	18.98 ± 2.97	14.46 ± 2.11	38.34 ± 1.18	11.94 ± 1.40	17.90 ± 2.79	13.76 ± 2.07

digital data. For the rest of the compared variables, the bias had negative values, accounting for −0.73 cm in the case of the depth of bottom cut (BCD), −0.65 cm for the depth of the top cut (TCD) and for −0.44 cm for the height of the notch (NH). As a rule, there were observations that were found outside the computed limits of agreement, which accounted for a higher frequency in the comparisons run for the hinge width (HW) and notch height (NH). However, one can observe that a high share the data taken into analysis was found in a difference range of ±1 cm.

As such, for the hinge width (HW), about 88 % of the data was found in a difference range of ±1 cm, while for the depts of the top (TCD) and bottom (BCD) cuts about 71 and 74 % of the data was found in this range. For the notch height (NH) 84 % of the data has shown a difference located in the range of ±1 cm.

3.3. Deviation of data

On average, there was a sub-centimeter deviation in the data irrespective of the error metric used for such evaluations, as shown in Table 3. In this regard, the bias (see Section 3.1) is a score that indicates the magnitude of errors by considering their direction, as opposed to mean absolute error, which disregards the direction but weights equally the individual differences in the average, and to the root mean square error, which gives a larger weight to large errors by squaring the differences between the measurements (Wilmott and Matsuura, 2005). The absolute errors varied between 0 and 1.9 for HW, 0.1 to 1.8 for BCD, 0 to 2 for TCD and 0 to 1.8 cm for NH (data not shown herein). Overall, the MAE was lower for HW and NH, as opposed to BCD and TCD. The same trend was preserved in the case of RMSE (Table 3). From this perspective, LiDAR based data had a sub-centimeter accuracy when compared to manually taken measurements, and there were no errors large enough to bring high contrasts between the values of MAE and RMSE (Table 3). However, given the differences found between MAE and RMSE values, there was some difference in the magnitude of the absolute errors.

Fig. 5 is describing further the deviation in data. For instance, Fig. 5a shows the dependence relation between compared (HWC) and reference hinge width (HWR), mapped by an RTO model. The estimated RTO model closely follows the identity line in the whole data range, indicating that there were small differences between the compared datasets. This can be seen also in the equation of the model which indicates a slope of close to 1, while the coefficient of determination indicates a close dependence relation between the two. Panels b, c and d of Fig. 5 show the trends in BCD, TCD and NH data. In these cases, the models indicate that the digital method generally overestimates the measurement compared to the reference data. In all three cases, the coefficients of determination were close to 1, indicating that there was a strong dependence between the compared datasets. However, the slopes were less than 1 in all cases.

3.4. Homogeneity of variance

Occurrence of proportional bias is typically correlated with the presence of heteroskedasticity in data. As mentioned, Breusch-Pagan's test excels in detecting linear forms of heteroskedasticity, while the White's test can be used to detect other forms of heteroskedasticity. Table 4 shows the results of the normality and heteroskedasticity assumptions by the selected tests. By both tests used for normality checking, the data was found to follow a normal distribution. Similarly, by both tests used for heteroskedasticity checking, the data was found to be homoskedastic. All tests assumed a confidence level of $\alpha = 0.01$.

The findings of the tests validate further the validity of the statistical methods presented in the previous section of the results since most of these make assumptions on the normality of data and homogeneity of variance.

4. Discussion

This study was setup to check if the close-range mobile LiDAR scanning by affordable solutions may be of use in estimating the notch volume loses in motor-manual tree felling, by the main assumption that the accuracy of the collected point clouds can be described with a limited number of referenced linear measurements. The main findings are promising, indicating that this approach may provide sub-centimeter accuracy, and it might be useful to make assessments on volume loses. In addition, the findings clearly indicate the positive effect brought by a shorter scanning distance, which considerably improved the density of the collected point clouds. For instance, study of Borz et al. (2024) indicated an important accuracy increment when estimating the diameter of the trees based on digital LiDAR-based measurements taken very close to the trees. As such, by all the metrics used herein, the deviance of data was better as compared to similar studies which indicated deviances as high as RMSE of 1.6 (Tomaštíc et al., 2017) to 3.13 cm (Gollob et al., 2021) and comparable with that obtained when using an

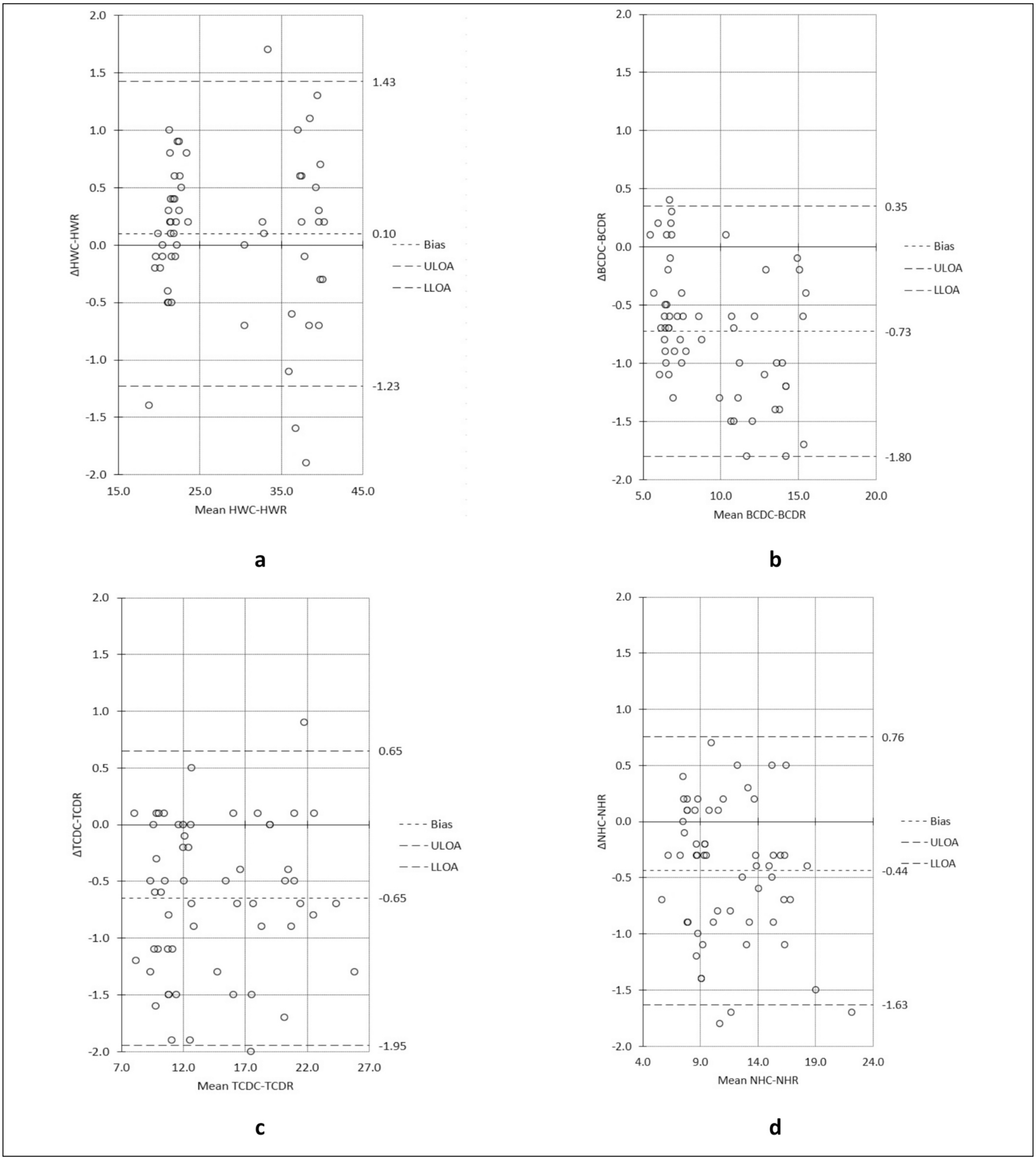

Fig. 4. Bland-Altman agreement plots of the four compared dimensions: a) HW, b) BCD, c) TCD, d) NH.

Table 3
Error metrics of the compared dimensions.

Compared parameters	Bias (cm)	MAE (cm)	RMSE (cm)
HWR-HWC	0.10	0.51	0.68
BCDR-BCDC	−0.73	0.78	0.91
TCDR-TCDC	−0.65	0.72	0.92
NHR-NHC	−0.44	0.59	0.74

augmented reality-based tree measurement app Wu et al. (2023).

The agreement in data was found to be acceptable in a range of ±2 cm, while most of the data on differences between the measurements were in a range of ±1 cm. However, the trends in differences were not consistent across all the notch dimensions considered in the study. For instance, the digital data seemed to slightly overestimate when the notch width was considered, while for the rest of dimensions an underestimating trend was found. Also, the average over- and

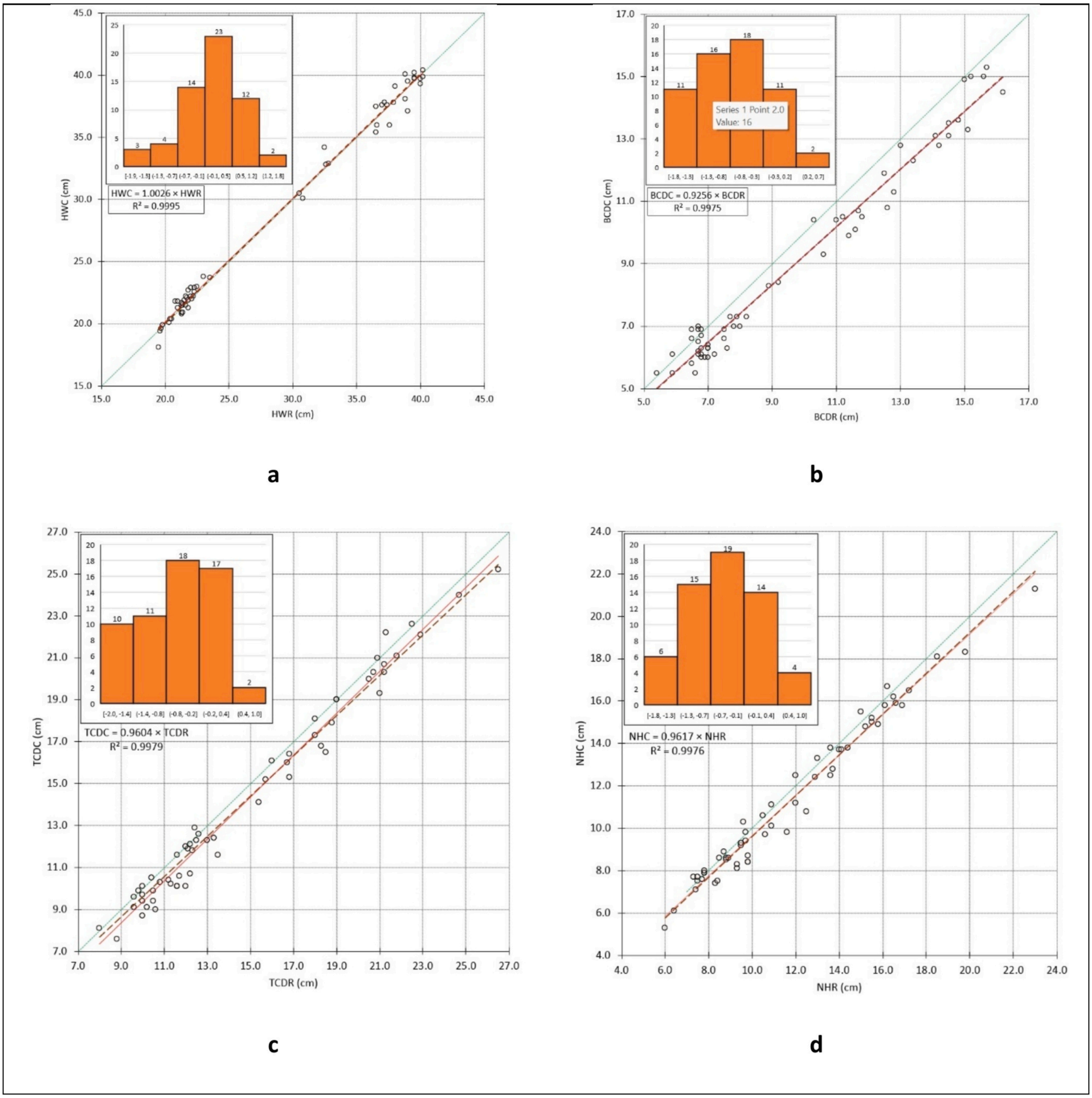

Fig. 5. RTO models and paired data plotted against the identity line for: a) hinge width (HW), b) depth of the bottom cut (BCD), c) depth of the top cut (TCD), and d) height of the notch (NH). Histograms show the distribution of differences, brown dashed lines stand for the RTO models and green continuous lines stand for the identity lines. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

underestimation, as measured by the bias metric, were quite different, with a value of 0.1 cm for the notch width, and with values of −0.44, −0.65 and − 0.73 cm for the notch height, depth of the top, and the depth of the bottom cut, respectively. These values, as well as their magnitudes can be largely explained by the way in which the data was digitally processed. In general, the linear measurements taken digitally had the highest observed certainty in actually hitting the starting and the ending points of the notch width. In CloudCompare, this is enabled by the sharp angles and edges made by the two faces of the cuts (see for instance Fig. 2), which provided very good references for the digital measurement. Although the point clouds were acceptable in terms of density, there were important difficulties to overcame when trying to identify those points characterizing the start and the end of the rest of the considered dimensions. This was because the number of points showing a black color was sometimes too low to enable an accurate detection of the marker's centers in the collected point clouds, which obviously resulted in hitting dominantly those points located at their outer extremes. In addition, making the top cut of the notch, generally resulted in a curved area at its intersection with the log, which came from the rather limited control over the blade when cutting in an

Table 4
Result of normality and heteroskedasticity tests (α = 0.01).

Compared parameters	Shapiro-Wilk's test	d'Agostino-Pearson's test	Breusch-Pagan's test	White's test
HWC-HWR	W = 0.964 $p = 0.088$ Normal	DA = 6.336 $p = 0.042$ Normal	LM = 5.937 $p = 0.015$ Homoskedastic	LM = 8.866 $p = 0.012$ Homoskedastic
BCDC-BCDR	W = 0.954 $p = 0.028$ Normal	DA = 4.324 $p = 0.115$ Normal	LM = 2.747 $p = 0.097$ Homoskedastic	LM = 3.393 $p = 0.139$ Homoskedastic
TCDC-TCDR	W = 0.967 $p = 0.116$ Normal	DA = 1.843 $p = 0.398$ Normal	LM = 0.111 $p = 0.739$ Homoskedastic	LM = 0.815 $p = 0.665$ Homoskedastic
NHC-NHR	W = 0.979 $p = 0.392$ Normal	DA = 0.960 $p = 0.619$ Normal	LM = 0.251 $p = 0.617$ Homoskedastic	LM = 1.302 $p = 0.522$ Homoskedastic

inclined plane. This had two consequences, namely the difficulty to actually locate and place the markers at the exact locations from which the depth of the top cut and the notch height started, as well as difficulties in locating those points in the digital data. The later held true also for the way in which the points were distributed near the hinge line; here, the limited point density has created curved shapes that increased the uncertainty of hitting the hinge line during the digital measurements. For that reason, this study used as supporting features for visualization the functions of CloudCompare designed to show by colors the normal change rate and curvature, although there was a higher uncertainty in actually hitting the centers of the markers. Considering the above-mentioned, it is likely that the measurements taken on the hinge width reflect better the accuracy of the digital data as opposed to the rest of the dimensions.

To be useful, a new method needs to provide accurate results in a wide range of data, as required by the practice, without obvious systematic deviations. The assumption on the occurrence of a proportional bias in digital measurements was infirmed based on the data and findings of this study. That is, the variation in the diameter of the log, as well as in the considered dimensions did not affect the variance of the digitally measured data. It seems, however, that the smartphones equipped with LiDAR sensors are sensitive to the size of the scanned objects (Borz et al., 2022b; Gollob et al., 2021), which is likely to produce a proportional bias in the data, particularly when scanning larger objects. In addition, the shape of the trees at their bottom may be highly irregular, particularly when working with very old trees, which exhibit well-developed buttresses (Jourgholami et al., 2013). Such operational cases require often the removal of buttresses before felling (Oprea, 2008) which complicates further the problem of estimating the volume loses, because there are no suitable manual methods to account for the volume displaced by removing them. From this point of view, scanning the trees before and after removing such features may provide a feasible solution for estimation by point cloud comparison.

In terms of tree variability in size and shape, further studies should be implemented for a more comprehensive analysis on how such features may affect the way in which the digital data deviates from the reference measurements. From this point of view, this study covers only a tree species, although the size of the logs in terms of diameter may fit very well with real case scenarios in which thinning or final felling is done. However, the diversity of forests and trees would require larger datasets to come at more precise estimates, a point that should be checked by future studies. Also, in our experimental conditions, occlusion was controlled by the way in which the logs were placed, which may not resemble the real conditions from forests. Nevertheless, LiDAR scanning by highly mobile platforms such as that tested herein may accommodate the occlusion problem since it can be done from a very close range.

When using machines such as the harvesters, there is a higher degree of control over a tree, therefore the incidence of breakage and splitting may be lower as compared to motor-manual felling. However, by many factors, such as the species and tree size, mechanized harvesting is a solution characterized by a limited coverage (Knobloch et al., 2023; Oprea, 2008). In both cases, the volume lost in bucking may be estimated by the number of cuts, diameters at which the cuts are done along the tree, and the width of the cuts. The most challenging to estimate are the volume loses caused by tree breakage and splitting, as well as those caused by making the felling cuts by motor-manual means, both of which typically apply to irregular shapes of the wood. Nevertheless, these may account for the highest share in the volume loses caused by the technology used in tree felling and processing (Boston and Dysart, 2000; Wang et al., 2004), proving the usefulness of digital solutions when such measurements can be taken from the ground.

Considering the above-mentioned, the results reported herein are encouraging, as they support the accurate estimation of volume loses by using digital LiDAR-based methods designed to compare point clouds. Such methods may be implemented by taking as a reference a point cloud captured before making the felling cuts, which can be compared to a point cloud taken after making the felling cuts. Besides the accurate estimations, this can provide other important benefits, such as providing readily available 3D data to better explain and relate the felling errors to the dimensions of the felling cuts, which otherwise is difficult to get, as well as to account for the volume of wood left in the stumps, and to relate it to the tree felling technology used, or to the skills of the workers. Indeed, the latest research did attempt to quantify the severity of anthropogenic disturbance in forests by including stums and other tree features as ground truth to characterize the disturbance (Iheaturu et al., 2024). However, it is still challenging to get reliable estimates on volume lost during harvesting from coarser and remotely-sensed data since, in addition to typical occlusion and precision, there is still the time-related scanning problem. In other words, to estimate the volume lost in motor-manual tree felling, the scanning process needs to keep the pace with tree felling operations, particularly when, for point cloud comparison, scans are required before and after making the felling cuts. Collected this way, the data will provide a reference for replicability and data validity assessments, while removing the labor-intensive, prone-to-error ways of collecting it (Borz et al., 2022a; Gollob et al., 2021; Niță and Borz, 2023). In addition, measurements taken by scanning provide an important benefit which is often overlooked, namely a better safety condition provided by excluding the direct contact measurements (Borz et al., 2022b; Borz and Proto, 2022).

5. Conclusion

Based on the findings of this study, the mobile LiDAR-based platforms stand for an accurate solution to estimate the volume loses in motor-manual tree felling when a close-range terrestrial scanning strategy is used. The findings support their use to collect, process and compare point cloud data, as a basis for the quality optimization in forest operations, and may also be of help in better understanding safety failures in motor-manual tree felling. Future studies should focus on how the variability in dimensional and tree shape data may affect the accuracy of estimates, as well as on capability limits of the solution taken into study.

CRediT authorship contribution statement

Stelian Alexandru Borz: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Andrea Rosario Proto:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and code supporting the findings of this study are publicly available to ensure transparency and reproducibility of the research. The data and code used in the analysis of this study are available for download from the link: https://drive.google.com/drive/folders/1LlHtrbaT8K7uveVq_95s_t17hEAe1in4?usp=drive_link

Should any further information be required, please email the corresponding author.

Acknowledgements

The authors would like to thank to the Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements, Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov for logistically supporting this study. Part of this work – the concept – was supported by a grant of the Romanian Ministry of Education and Research, CNCS – UEFISCDI, project number PN-III-P4-ID-PCE-2020-0401, within PNCDI III. Some activities in this study were funded by the inter-institutional agreement between *Transilvania* University of Braşov (Romania) and *Mediterranean* University of Reggio Calabria (Italy), and by two grants of the Romanian Ministry of Education and Research, CNCS – UEFISCDI, project number PN-IV-P8-8.1-PRE-HE-ORG-2023-0141 and project number PN-IV-P8-8.1-PRE-HE-ORG-2024-0186, within PNCDI IV.

References

3D Scanner App, 2023. Available at: https://3dscannerapp.com/. accessed on 3rd of November, 2023.
Banciu, T., Borz, S.A., Marcu, M.V., Iordache, E., Liampas, S.A.G., Drosos, V., 2018. An evaluation of risk-taking behavior in motor-manual tree felling and processing operations. Bull. Transilvania Univ. Brasov Ser. II For. Wood Industry Agric. Food Eng. 11, 1–20.
Bland, J.M., Altman, D.G., 1995. Comparing methods of measurement: Why plotting difference against standard method is misleading. Lancet 364, 1085–1087.
Bland, J.M., Altman, D.G., 1999. Measuring agreement in method comparison studies. Stat. Methods Med. Res. 8, 135–160.
Borges Gonçalves, N., Martins Rosa, D., Freitas Do Valle, D., Smith, M.N., Dalagnol, R., Alves de Almeida, D.R., Nelson, B.W., Stark, S.C., 2024. Revealing forest structural "fingerprints": an integration of LiDAR and deep learning uncovers topographical influences on Central Amazon forests. Eco. Inform. 81, 102628. https://doi.org/10.1016/j.ecoinf.2024.102628.
Borz, S.A., Proto, A.R., 2022. Application and accuracy of smart technologies for measurements of roundwood: evaluation of time consumption and efficiency. Comput. Electron. Agric. 197, 106990. https://doi.org/10.1016/j.compag.2022.106990.
Borz, S.A., Ignea, G., Vasilescu, M.M., 2014. Small gains in wood recovery rate when disobeying the recommended motor-manual tree felling procedures: another reason to use the proper technical prescriptions. Bioresources 9, 6938–6949.
Borz, S.A., Papandrea, S.F., Marcu, M.V., Bacenetti, J., Proto, A.R., 2022a. Postural assessment of three wood measurement options by the OWAS method: digital solutions seem to be better. Forests 13, 2007. https://doi.org/10.3390/f13122007.
Borz, S.A., Morocho Toaza, J.M., Forkuo, G.O., Marcu, M.V., 2022b. Potential of measure app in estimating log biometrics: a comparison with conventional log measurement. Forests 13, 1028. https://doi.org/10.3390/f13071028.
Borz, S.A., Morocho Toaza, J.M., Proto, A.R., 2024. Accuracy of two LIDAR-based augmented reality apps in breast height diameter measurement. Eco. Inform. 81. https://doi.org/10.1016/j.ecoinf.2024.102550.
Boston, K., Dysart, G., 2000. A comparison of felling techniques on stump height and log damage with economic interpretations. West. J. Appl. For. 15, 59–61.
Breusch, T.S., Pagan, A.R., 1979. A simple test for heteroscedasticity and random coefficient variation. Econometrica 47 (5), 1287–1294.
Calvo, A., Manzone, M., Spinelli, R., 2013. Long term repair and maintenance cost of some professional chainsaws. Croatian J. Forest Eng. 34, 265–272.
Cheţa, M., Marcu, M.V., Borz, S.A., 2018. Workload, exposure to noise, and risk of musculoskeletal disorders: a case study of motor-manual tree felling and processing in poplar clear cuts. Forests 9, 300. https://doi.org/10.3390/f9060300.
CloudCompare, 2023. 3D Point cloud and mesh processing software open-source project. Available at: https://www.danielgm.net/cc/. accessed on 3rd of November, 2023.
CloudCompare User Manual, 2023. Version 2.6.1. Available at: https://www.danielgm.net/cc/doc/qCC/CloudCompare%20v2.6.1%20-%20User%20manual.pdf. retrieved on 3rd of November, 2023.
D'Agostino, R.B., Pearson, E.S., 1973. Tests for departure from normality. Empirical results for the distribution of b2 and $\sqrt{b1}$. Biometrika 60, 613–622.
DeMille, G.J., Lyons, K., 2016. Unexpected events when manually falling trees in coastal British Columbia. For. Sci. 62, 433–439. https://doi.org/10.5849/forsci.15-164.
Đuka, A., Sertić, M., Pentek, T., Papa, I., Janeš, D., Poršinsky, T., 2020. Round wood waste and losses - is rationalisation in scaling possible? Croatian J. Forest Eng. 41, 287–298.
Eisenhauer, J.G., 2003. Regression through the origin. Teach. Stat. 25, 76–80.
European Commission, 2021. Communication from the European Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. New EU Forest Strategy for 2023. Available at https://eur-lex.europa.eu/resource.html?uri=cellar:0d918e07-e610-11eb-a1a501aa75ed71a1.0001.02/DOC_1&format=PDF. retrieved: 2nd of November, 2023.
Gao, J., Yuan, Y., Tang, L., Su, H., Chen, J., 2025. Extraction of tree branch skeletons from terrestrial LiDAR point clouds. Eco. Inform. 85, 102960. https://doi.org/10.1016/j.ecoinf.2024.102960.
Gerasimov, Y., Seliverstov, A., 2010. Industrial round-wood losses associated with harvesting systems in Russia. Croatian J. Forest Eng. 31, 111–126.
Giavarina, D., 2015. Lessons in biostatistics. Understanding Bland Altman analysis. Biochemia Medica 25 (2), 141–151.
Gollob, C., Ritter, T., Kraßnitzer, R., Tockner, A., Nothdurft, A., 2021. Measurement of forest inventory parameters with apple IPad pro and integrated LiDAR technology. Remote Sens. 13, 3129. https://doi.org/10.3390/rs13163129.
Heinimann, H.R., 2007. Forest operations engineering and management - the ways behind and ahead of a scientific discipline. Croatian J. Forest Eng. 28 (1), 107–121.
Iheaturu, C.J., Akinyemi, F.O., Hepner, S., Batchelor, J.L., Wingate, V.R., Agonvonon, G. A., Speranza, C.I., 2024. Integrating UAV LiDAR and multispectral data to assess forest status and map disturbance severity in a west African forest patch. Eco. Inform. 84, 102876. https://doi.org/10.1016/j.ecoinf.2024.102876.
iPhone 13 Pro Max - Technical Specifications. Available at: https://support.apple.com/kb/SP848?viewlocale=en_US&locale=ro_RO. accessed on 3rd of November, 2023.
Jourgholami, M., Abari, M.E., 2017. Log damage and value loss following motor-manual tree harvesting in the Hyrcanian Forest, Northern Iran. Eur. J. For. Res. 3, 31–43.
Jourgholami, M., Majnounian, B., Zargham, N., 2013. Performance, capability and costs of motor-manual tree felling in Hyrcanian hardwood forest. Croatian J. Forest Eng. 34, 283–293.
Kerbes, E.L., McIntosh, J.A., 1969. Conversion of trees to finished lumber - the volume losses. In: The Forestry Chronicle, October, pp. 348–353. Available at https://pubs.cif-ifc.org/doi/pdf/10.5558/tfc45348-5. retrieved on 6th of October, 2023.
Knobloch, C., Richter, L., Erler, J., 2023. Tree felling with a drill cone. Croatian J. Forest Eng. 44, 275–288. https://doi.org/10.5552/crojfe.2023.2015.
Koger, J.L., 1983. Observed methods for felling hardwood trees with chainsaws. United States Department of Agriculture, Forest Service, Southern forest experiment station. Res. Note so-297, 1–7.
Ludbrook, J., 1997. Comparing methods of measurement. Clin. Exp. Pharmacol. Physiol. 24, 193–203.
Luetzenburg, G., Kroon, A., Bjork, A.A., 2021. Evaluation of the apple iPhone 12 pro LiDAR for an application in geosciences. Sci. Rep. 11, 22221. https://doi.org/10.1038/s41598-021-01763-9.
Lundbäck, M., Häggström, C., Nordfjell, T., 2021. Worldwide trends in methods for harvesting and extracting industrial roundwood. Int. J. For. Eng. 32, 202–215. https://doi.org/10.1080/14942119.2021.1906617.
Lyons, K., Sessions, J., Wimer, J., 2012. Effect of undercut style and post hinge behavior in tree felling. For. Sci. 58, 547–558.
Marchi, E., Chung, W., Visser, R., Abbas, D., Nordfjell, T., Mederski, P.S., McEwan, A., Brink, M., Laschi, A., 2018. Sustainable forest operations (SFO): a new paradigm in a changing world and climate. Sci. Total Environ. 634, 1385–1397.
Melemez, K., 2015. Risk factor analysis of fatal forest harvesting accidents: a case study in Turkey. Saf. Sci. 79, 369–378. https://doi.org/10.1016/j.ssci.2015.07.004.
Microsoft, 2023a. Microsoft Excel. Available at: https://www.microsoft.com/ro-ro/microsoft-365/excel. accessed on 3rd of November, 2023.
Microsoft, 2023b. Microsoft Powerpoint. available at: https://www.microsoft.com/ro-ro/microsoft-365/powerpoint. accessed on 3rd of November, 2023.
Moskalik, T., Borz, S.A., Dvorák, J., Ferencik, M., Glushkov, S., Muiste, P., Lazdinš, A., Styranivsky, O., 2017. Timber harvesting methods in eastern European countries: a review. Croatian J. Forest Eng. 38, 231–241.
Neely, G., Wilhelmson, E., 2006. Self-reported incidents, accidents, and use of protective gear among small-scale forestry workers in Sweden. Saf. Sci. 44, 723–732. https://doi.org/10.1016/j.ssci.2006.03.002.
Nikooy, M., Naghdi, R., Ershadifar, M., 2013. Survey of directional felling and analysis of effective factors on felling error (case study; Iranian Caspian forests). Caspian J. Environ. Sci. 11, 177–184.
Niţă, M.D., Borz, S.A., 2023. Accuracy of a smartphone-based freeware solution and two shape reconstruction algorithms in log volume measurements. Comput. Electron. Agric. 205, 107653. https://doi.org/10.1016/j.compag.2023.107653.
Noll, F., Lyons, C.K., 2010. A novel method for manually falling trees. For. Chron. 86, 608–613.
Obabiire, A.A., Agboolla, J.O., Ajao, I.O., Adegbiillero-Iwarii, O.E., 2020. Comparison of different tests for detecting heteroscedasticity in datasets. Ann. Comp. Sci. Ser. 18, 78–85.

Oprea, I., 2008. Timber Harvesting Technology [in Romanian]. Transilvania University Press, Brasov, p. 237.
Oprea, I., Borz, S.A., 2007. Planning of the Felling Site [in Romanian]. Transilvania University Press, Brasov, p. 130.
Papandrea, S.F., Cataldo, M.F., Zimbalatti, G., Grigolato, S., Proto, A.R., 2022. What is the current ergonomic condition of chainsaws in non-professional use? A case study to determine vibrations and noises in small-scale agroforestry farms. Forests 13 (11), 1876. https://doi.org/10.3390/f13111876.
Poje, A., Potočnik, I., Košir, B., Krč, J., 2016. Cutting patterns as a predictor of the odds of accident among professional fellers. Saf. Sci. 89, 158–166. https://doi.org/10.1016/j.ssci.2016.06.011.
Potočnik, I., Poje, A., 2017. Forestry ergonomics and occupational safety in high ranking scientific journals from 2005–2016. Croatian J. Forest Eng. 38, 291–310.
QGis, 2023. Available at: https://www.qgis.org/en/site/. accessed on 3rd of November, 2023.
Real Statistics Using Excel, 2023. Available at: https://real-statistics.com/. accessed on 3rd of November, 2023.
Shapiro, S.S., Wilk, M.B., 1965. An analysis of variance test for normality (complete samples). Biometrika 52, 591–611.
Tomaštíc, J., Saloň, S., Tunák, D., Chudy, F., Kardoš, M., 2017. Tango in forests – an initial experience of the use of new Google technology in connection with forest inventory tasks. Comput. Electron. Agric. 141, 109–117. https://doi.org/10.1016/j.compag.2017.07.015.
Tsioras, P., Rottensteiner, C., Stampfer, K., 2014. Wood harvesting accidents in the Austrian State Forest Enterprise 2000–2009. Saf. Sci. 62, 400–408. https://doi.org/10.1016/j.ssci.2013.09.016.
Wang, J., LeDoux, C.B., Vanderberg, M., McNeel, J., 2004. Log damage and value loss associated with two ground-based harvesting systems in Central Appalachia. Int. J. For. Eng. 15, 61–69. https://doi.org/10.1080/14942119.2004.10702490.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48, 817–838.
Williams, R., 2020. Heteroskedasticity. Available at: https://www3.nd.edu/~rwilliam/stats2/l25.pdf. retrieved on 3rd of November, 2023.
Wilmott, C.J., Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean squared error (RMSE) in assessing the average model performance. Clim. Res. 30, 79–82. https://doi.org/10.3354/cr030079.
Wu, F., Wu, B., Zhao, D., 2023. Real-time measurement of individual tree structure parameters based on augmented reality in an urban environment. Ecol. Inform. 77, 102207. https://doi.org/10.1016/j.ecoinf.2023.102207.
Yun, T., Li, J., Ma, L., Zhou, J., Wang, R., Eichhorn, M.P., Zhang, M., 2024. Status, advancements and prospects of deep learning methods applied in forest studies. Int. J. Appl. Earth Obs. Geoinf. 131, 103938. https://doi.org/10.1016/j.jag.2024.103938.