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Accuracy of two LiDAR-based augmented reality apps in breast height diameter measurement

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ABSTRACT

Accurate measurement of the diameter at the breast height (DBH) is essential in forestry-related science and practice, but its measurement is currently done by labor-intensive tools such as calipers or devices designed to measure the girth. With the development in light detection and ranging (LiDAR) and augmented reality (AR) technologies, and their integration in low-cost mobile platforms, affordable proximal measurement applications were released on the market. This study examines the accuracy in DBH measurement of Arboreal Forest (hereafter DA) and Measure (hereafter DM) apps, by taking as a reference the measurements done by an accurate forestry caliper (hereafter DC). A number of 615 trees were considered, of which 395 were broadleaved (DBH between 10 and 73 cm, averaging 39.73 ± 9.91 cm) and 220 were coniferous (DBH between 25 and 89 cm, averaging 52.47 ± 12.81 cm), and measurements were taken under sunny, cloudy and rainy weather. Comparison was done in terms of agreement (Bland and Altman's method), dependence (least square simple ordinary and regression through origin), correlation (Spearman's, Pearson's and Kendall's tests), and difference (mean absolute error - MAE, root mean squared error - RMSE, and bias - BIAS). Besides a close-to-perfect fit, strong association in data, and a good degree of agreement, the results indicated the presence of centimeter-level differences when comparing DM against DC (MAE = 0.715 cm, RMSE = 0.879 cm, BIAS = 0.333 cm) and DA against DC (MAE = 0.953 cm, RMSE = 1.246 cm, BIAS = -0.108 cm). When comparing DA against DM the differences were slightly higher (MAE = 1.175 cm, RMSE = 1.531 cm, BIAS = –0.446 cm). The magnitude in differences found is rather caused by the application used and not by the environmental conditions. Further studies may consider larger data samples to provide better estimates as well as checking the limits in measurement capabilities of these apps.

1. Introduction

Diameter at the breast height (DBH) is essential in single tree and stand measurement, spanning a wide range of applications, from traditional forestry to carbon accounting, ecology, inventories and forest monitoring (Kershaw et al., 2017; Van Laar and Akça, 2007). Although they can provide instant readings, traditional DBH measurement methods still rely heavily on mechanical measurement, and often lack the capability of storing, transferring and, therefore, making a better use of the collected data. In addition, they may take a longer measurement cycle time and may provide poorer ergonomic (Borz et al., 2022a) and safety conditions, mainly because they imply a direct contact measurement, and make use of rather heavy to carry tools; operating costs could be another good reason when checking for their economic performance, since they typically require more human resources as compared to digital tools (Borz and Proto, 2022). These characteristics make them rather incompatible with the modern concepts of sustainable forestry (Heinimann, 2007; Marchi et al., 2018), at least under economic and ergonomics points of view. In addition, they cannot provide the data in the required format and information flows as specific to Forestry 4.0 (Costa et al., 2018; Müller et al., 2019) and individual tree detection and measurement (Keefe et al., 2022). In turn, individual tree detection and Forestry 4.0 concepts are promising in forestry because they are better fitted to the management of digital data, and they are being expected to overcome many of the issues of traditional forest management, particularly when the latter is less efficient due to the high share of

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conventional data transfer (Rauch and Borz, 2020).

The latest developments in proximal sensing technology, as well as the integration of advanced sensors in smart portable devices have provided new opportunities for measuring tree biometrics at affordable costs and with minimal inputs of resources. Technologies such as those developed by Google for Android-based platforms (Hyyppä et al., 2017; Niţă and Borz, 2023; Tomaštík et al., 2017), or by Apple for iPhone and iPad platforms (Borz and Proto, 2022; Ucar et al., 2022) have already been tested in measuring the main biometrics of trees and logs with promising results. These were complemented by studies that tested or described the capabilities of professional LiDAR scanners (Balenović et al., 2020; de Miguel-Díez et al., 2022; Giannetti et al., 2018; Panagiotidis and Abdollahnejad, 2021;) and which concluded that such devices may reach a high accuracy when used in forestry applications, including for the measurement of main biometrics of the trees or logs.

Still, the main challenges of using professional LiDAR scanners are those related to the investments in equipment, which remained high over the last years, as well as in a lower portability, which make them less suitable when working in rough terrain. In some data collection configurations, one may add the occlusion effects, which may lead to loosing important data. Obviously, the use of low-weight and highly mobile devices such as the smartphones may overcome many of these limitations but, irrespective of the device used, instant readings of the measurement results, as well as the capability to store, document and transfer the data are important features to consider when choosing a measurement solution (Borz et al., 2022b). These requirements constrain the available set of digital DBH measurement solutions to couple of software applications such as the Arboreal Forest (Arboreal Forest, 2023) developed by Arboreal (http://www.arboreal.se/en/) and Measure App developed by Apple (https://apps.apple.com/us/app/measure/id1383426740). Both of them take the advantage of close-range LiDAR sensing and Augmented Reality technology, which comes handy for orientation and effective operation, and provide instant readings of the measurement results as opposed to the use of rather resource intensive algorithms to obtain the results in an offline approach (e.g. Gollob et al., 2021; Niţă and Borz, 2023; Tomaštík et al., 2017). Measure App comes as a freeware solution but it lacks advanced data transfer protocols, although the data can be shared by e-mail or messaging; Arboreal Forest app comes at a subscription price and features several advanced features such as those related to species recognition, DBH and height measurement, and setting of inventory plots, in addition to a dedicated platform for data transfer and storage.

Despite their promising features, the accuracy of these apps received far less attention in the scientific research with only couple of papers published on the topic of tree and log biometrics measurement (Borz et al., 2022a; Sandim et al., 2023; Ucar et al., 2022), though they were complemented by data published in the form of reports or dissertations (Lindberg, 2020; Sveaskog, 2023). In addition, there is limited knowledge on how the accuracy of these apps may behave in various operating conditions, particularly in terms of species variability, DBH magnitude and range, and weather state during their operation, which are factors that may affect the performance of LiDAR scans (Nik Azhan Hakim et al., 2023). From these points of view, the tests with Arboreal Forest App come mostly from the north (pine, spruce and deciduous trees) and south of Europe (pine and eucalyptus), for dominant datasets on diameters in between 5 and 50 cm (Lindberg, 2020; Sveaskog, 2023; Sandim et al., 2023). In terms of DBH, the systematic bias and the root mean squared error were found by Lindberg (2020) to be of −0.4 and 1.2 cm, respectively. The report published by Sveaskog (2023) concluded that the measurements taken by Arboreal Forest were better than those taken manually with a caliper as compared to harvester-produced data, with a systematic error of <0.1 mm and an average absolute error of 4.1%; however, the report indicates a positive relation between the error and the magnitude of diameter readings. Ucar et al. (2022) have tested the Measure app in the conditions of Turkey for poplar, oak and pine trees, averaging 20 to 30 cm in DBH. They found a systematic bias in DBH measurement of <0.4 cm.

This study was setup to compare the readings on DBH as they were taken by the Arboreal Forest and Measure App to the readings taken manually by a digital caliper. The main aim of the study was to describe and characterize the accuracy of the two tested digital methods in relation to the manual method. In addition, the study checks the agreement between digital and manual methods, as well as between the digital methods themselves, for a diameter range of about 20 to 90 cm, by considering two species groups (broadleaved and coniferous) and three weather states (sunny, cloudy and rainy weather) as covariates. From these points of view, the novelty of the study lies in checking for accuracy by considering a wider DBH range as opposed to that found in available literature, while working with a reasonably high number of observations in the sample and putting the emphasis on the potential effects in accuracy and agreement of the methods as controlled by the weather condition during measurement. This study also checks for eventual heteroskedasticity in data that may indicate the presence of proportional bias in the measurements and makes use of advanced statistical methods for checking the accuracy and agreement of the DBH measurement methods.

2. Materials and methods

2.1. Study area and sampling procedure

The Răcădău Forest, located at 45°38′03″N - 25°36′25″E., near the city of Brasov (Romania), was chosen as the location for collecting the data in the field. The selection of this forest area was mainly based on a wide distribution in tree biometrics such as the diameter at the breast height (DBH). The forest is mixed and composed of several tree species such as the European beech (*Fagus sylvatica* L.), Norway spruce (*Picea abies* (Lam.) Link.) and Silver fir (*Abies alba* Mill.). Field data collection was carried out at the end of April and beginning of May 2022, during four days, and it was based on weather forecasts which aimed at having three main conditions namely, sunny, cloudy and rainy days. The data was collected in two sunny, one cloudy and one rainy day, by randomly selecting a starting point within the forest, followed by a random selection of the trees to be measured. Dominant in the sample of trees taken into study were the European beech (393 individuals, accounting for about 64% of the sample) and the Silver fir (206 individuals, accounting for about 33% of the sample).

2.2. Instrumentation and measurement protocol

Three options were used for DBH measurement purposes in this study, of which the first was the conventional manual one, and the rest were the digital tested options (Fig. 1).

The first option, which was used to procure the reference data, was that of measuring the diameter at the breast height (DBH) by the use of an accurate caliper manufactured by Haglöf AB, Sweden (https://haglofsweden.com/). In this option, the breast height diameter (hereafter DC, cm) was measured at exactly 130 cm above the ground for each of the randomly selected trees. Readings were taken to the nearest millimeter and data was noted on a field book along with a short description of the tree species and with the weather condition at the time of measurement. In a second option, the Measure App developed by Apple was used to take the diameter at the breast height (hereafter DM, cm) by taking as a reference the same height above the ground as for DC. To support this, the caliper was kept by a field researcher at the place at which it was used to measure the diameters in the first option until finishing the measurements by the app (Fig. 1). As enabled by the application, the measurements were taken to the nearest centimeter. The third option was that of measuring the diameter at the same height by the use of Arboreal Forest (hereafter, DA), which is developed by Arboreal (Sweden). With this measurement option, the diameters were taken to the nearest millimeter using the same DBH referencing

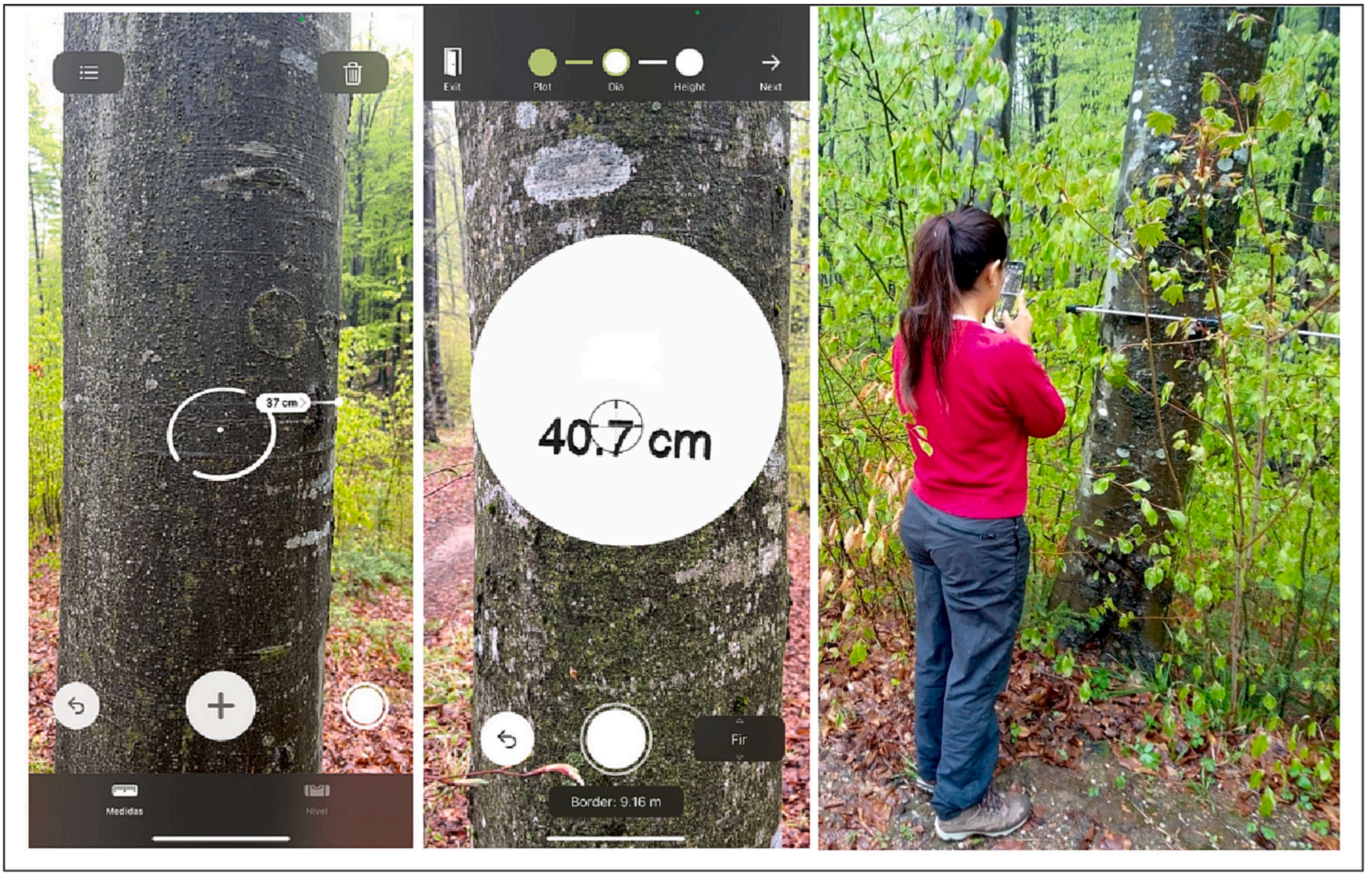

Fig. 1. Interface of the Measure App (left) and Arboreal Forest (center) during the field sampling activity which included conventional high-accuracy measurements by a caliper (right).
Note: species were not noted in the Arboreal Measure App.

procedure as for Measure App Once a tree was measured by the use of the three options, the field book data was updated. The field collected sample accounted for 615 trees. The use of the digital options was supported by an iPhone 13 Pro Max device (https://support.apple.com/kb/SP848?locale=en_US) on which they were installed in advance. The device features a LiDAR sensor which emits from a Vertical Cavity Surface Emitting Laser (MacKinnon, 2018) an array of 8 by 8 points which is diffracted in 3 by 3 grids, accounting for a total of 576 points and for a maximum scanning range of 5 m (Luetzenburg et al., 2021).

2.3. Data processing and statistical analysis

Although all of the measurement options used in this study have capabilities in saving the readings, for consistency the data was noted on paper, then it was transferred into a Microsoft Excel spreadsheet which was equipped with the Real Statistics freeware add-in (Real Statistics Using Excel, 2023). Here, the data was organized by date, species group (broadleaved and coniferous) and weather state during the measurements (sunny, cloudy and rainy). To support the statistical comparisons between the measurement options, in addition to the raw data on diameters measured at the breast height, the following were computed in the office phase of the study: absolute differences in diameters (Eq. (1)), relative differences in diameters (Eq. (2)), positive differences in diameters (Eq. (3)) and squared differences in diameters (Eq. (4)), by considering the paired data of DM - DC, DA - DC and DA - DM variables.

$$\Delta D_k = D_{ik} - D_{jk} \ (\mathrm{cm}) \tag{1}$$

$$PED_k = \left(D_{ik} - D_{jk}\right)/D_{ik} \times 100 \ (\%) \tag{2}$$

$$P\Delta D_k = |D_{ik} - D_{jk}| \ (\mathrm{cm}) \tag{3}$$

$$S\Delta D_k = \left(D_{ik} - D_{jk}\right)^2 \ \left(\mathrm{cm}^2\right) \tag{4}$$

Where:

ΔD_k is the absolute difference between diameter i (D_i) and diameter j (D_j) of a given pair of observations k, where k = 1 to N (*N* = 615); D_i = DC or DM; D_j = DM or DA when D_i = DC, and D_j = DA when D_i = DM; PED_k – relative difference in diameters; $P\Delta D_k$ – positive difference in diameters and $S\Delta D_k$ – squared difference in diameters.

Further processing steps were aimed at preparing the data for those parts of the statistical analyses that could not be automated by the used software. For instance, the upper and lower limits of agreement, as well as the bias required by the Bland-Altman analysis were computed manually based on the above-described data, and manual sorting procedures were in place to categorize the absolute differences in measurement and to compute three error metrics used for characterizing the differences. The error metrics considered by this study were the mean absolute error (MAE), root mean squared error (RMSE) and bias (BIAS). They were computed for each of the compared option by considering the group of species and weather condition, as well as for the overall data. As an error metric, MAE is computed as the ratio of the sum of absolute differences between reference and measured data to the number of observations in a given sample; RMSE is computed as the square root of the ratio of squared differences between reference and measured data to the number of observations in a given sample and, finally, the BIAS is computed as the average value of the absolute differences between reference and measured data. When the accuracy of the two sets of estimates in uncertain, these error metrics may be interpreted as differences between them, and show different sensitivities to the magnitude of differences found in data; as such, the RMSE is more sensitive to large magnitude of differences in data, as opposed to MAE (Willmott and Matsuura, 2005). BIAS, on the other hand, measures the average misestimation of the new data as compared to the reference data (Giavarina, 2015), and accounts also for the direction of misestimation.

The statistical analysis followed the complete workflow of implementing a method of measurement comparison test, and it was carried out entirely in Microsoft Excel where it was supported by the Real Statistics add-in. In terms of diameters, the main descriptive statistics were estimated at species group and weather condition level, as well as at the sample level, and they included the minimum, maximum, mean, median and standard deviation values. Checking for normality of the data was done for the diameters and for the absolute differences in diameters by the means of Shapiro-Wilk (Shapiro and Wilk, 1965) and d'Agostino-Pearson (D'Agostino and Pearson, 1973) tests which were complemented by distribution plots showing the experimental and expected-normal data of these variables. These statistical tests were carried out as prerequisites in characterizing the data and in interpreting the results of correlation, regression and method agreement tests.

For a comparison at a first glance, a complete correlation analysis was implemented by considering the same treatments and divisions in data; it was done by the Pearson's (r), Spearman's (ρ) and Kendall's (τ) tests (Zar, 2010) and it was complemented by a graphical representation of association and dependence (causation) in data and by the development of regression models by two approaches: linear regression through origin and ordinary simple linear regression (Eisenhauer, 2003; Zar, 2010). These models and their main statistics were estimated by the use of Microsoft Excel's functionalities and were used to see if there were general trends in data agreement, as well as their magnitude. These analyses were done for each level of data division, as well as at the overall sample level.

The agreement between the compared measurement options was analyzed by the method developed by Bland and Altman and by the means of the error metrics described above. Bland-Altman plots are typically used to check the agreement between two measurements of the same variable when there is no certainty that the measurements are unaffected by errors (Giavarina, 2015). This statistical method is particularly useful when there is a question whether a new measurement option will return an acceptable accuracy as compared to a reference one, as long as the acceptable limits of agreement can be set in advance (Bland and Altman, 1995; Giavarina, 2015). Typically, it plots the absolute difference between two variables against their mean values in a space defined by two limits of agreement (upper and lower limits of agreement) which includes an identity line (zero differences) and the line characterizing the mean of differences (bias). When the values of differences are grouped around the bias within two standard deviations of their mean (i.e. the limits of agreement), the measurement agreement between the compared options is usually attained. While the method assumes that the values of differences are normally distributed, their failing to do so is not as serious as in other statistical contexts. Since the method enables the estimation of fixed bias, it may require testing for heteroskedasticity in data, which can be done by several techniques (Giavarina, 2015), with the aim of verifying whether there is the case of proportional bias in it (Ludbrook, 2010; Mansournia et al., 2021). The statistical steps taken in this study to see if there is an agreement between the measurement methods were those of *i)* checking the normality of data in absolute differences, *ii)* checking for homoscedasticity in data and *iii)* developing the Bland-Altman plots. As it was recommended by previous work (Mansournia et al., 2021), it is useful to check whether there is a correlation between the differences and the mean values of a given pair of data compared right before running a Bland-Altman analysis. This statistical step has used the same correlation metrics as mentioned above for all the compared data sets. Checking for homoskedasticity in data may be done by the use of Breusch-Pagan's (Breusch and Pagan, 1979) and/or White's (White, 1980) tests; the main difference between the two is that the later can be used to detect non-linear forms of heteroskedasticity. Statistical analyses concerning the agreement of methods by the Bland-Altman method were done at the sample level.

Where relevant for the statistical tests used in this study, a confidence level of 95% ($\alpha < 0.05$) was assumed. Artwork describing some of the statistical results of this study was developed in Microsoft Excel. Some of it supposed the use of Real Statistics, as a more advanced option of getting meaningful representations. For instance, histograms showing the experimental and expected-normal distributions were supported by this add-in.

3. Results

3.1. Summary statistics

A summary of descriptive statistics for the three measurement options is given in Table 1 by considering the main data divisions used in this study. The main differences in the number of observations were those related to the number of individuals measured in the broadleaved and coniferous species groups. In total, there were 615 trees included in the study, of which 395 were broadleaved and 220 coniferous. Two thirds (66%) of them were measured during sunny weather conditions, 21% during cloudy conditions and the rest (13%) during rainy conditions. In the broadleaved species group, the reference DBH varied between approximately 18 and 73 cm, averaging 39.73 ± 9.91 cm, while in the coniferous species group it ranged between approximately 25 and 89 cm, averaging 52.47 ± 12.81 cm (detailed data not shown herein). None of the three datasets characterizing the DBH measurement options (DC, DM, DA), neither the differences found between the measurements, passed the normality check. Table S1 shows the results of normality tests carried out for the diameters and for the absolute differences between each pair. Fig. S1, on the other hand, shows the distributions in experimental data for the three modes of measurement, as well as the normal distributions which were fitted based on the area of the histograms in experimental data.

Overall, the samples of the three measurement options were characterized by DBH ranges in between approximately 18 and 90 cm, with low differences between the minimum and maximum values. In addition, they returned comparable values for the mean, median and standards deviation, as shown in Table 1. By the design of the study, it was impossible to have a balance on the number of observations categorized by diameters, species groups and weather conditions, a reason for which the last two factors were accounted as co-variates.

3.2. Data association

Figs. 2–4 show the main trends in data association for the three comparisons made in this study. The main results of the correlation analysis are shown in Table 2. In addition, Table S2 shows the main parameters of the regression models fit over the data by the two considered approaches: regression through origin and ordinary regression.

As shown in Fig. 2, the data of DC and DM was more grouped together around the identity line, indicating lower magnitudes in differences between the two options of measurement. Correlation results indicated a similar trend (Table 2), placing the values of the two options in the closest association. Similar trends may be observed for the regression statistics shown in Table S2, from where the response in DM as a linear function of DC was found to return the highest coefficients of determination ($R^2 = 0.991–1.000$, Table S2), slopes close to 1 and an intercept which was close to 0. In contrast, the results shown in Figs. 3 and 4, indicate a higher degree of scattering in the compared values around the identity lines. These seemed to have a higher magnitude in upper ranges of diameters, in general for those over 30 cm.

Association in data was found to be less sensitive to the species group

Table 1
Mains descriptive statistics of the measurements.

Variable	Species group	Weather condition	Descriptive statistics					
			Number of observations	Minimum value	Maximum value	Mean value	Median value	Standard deviation
DC	Broadleaved	Rainy	64	25.3	72.4	40.12	37.85	8.69
		Cloudy	127	18.2	67.2	38.54	38.40	9.07
		Sunny	204	19.8	73.0	40.34	38.85	10.71
DC	Coniferous	Rainy	13	30.3	70.3	48.98	50.70	12.29
		Cloudy	4	53.6	80.5	68.75	70.45	12.55
		Sunny	203	24.9	88.5	52.37	51.60	12.67
DM	Broadleaved	Rainy	64	26.0	72.0	39.66	38.00	8.65
		Cloudy	127	18.0	67.0	38.11	38.00	9.01
		Sunny	204	19.0	72.0	40.22	39.00	10.69
DM	Coniferous	Rainy	13	29.0	68.0	47.85	48.00	12.05
		Cloudy	4	54.0	80.0	68.25	69.50	12.34
		Sunny	203	24.0	88.0	52.00	51.00	12.60
DA	Broadleaved	Rainy	64	25.8	73.0	40.30	38.70	9.06
		Cloudy	127	17.9	68.2	38.48	38.10	9.43
		Sunny	204	19.1	74.3	40.28	39.20	10.95
DA	Coniferous	Rainy	13	29.6	73.3	49.18	49.10	12.83
		Cloudy	4	53.6	81.0	69.75	72.20	12.95
		Sunny	203	24.0	92.1	52.72	52.30	13.14
DC	All	All	615	18.2	88.5	44.29	42.40	12.61
DM	All	All	615	18.0	88.0	43.95	42.00	12.53
DA	All	All	615	17.9	92.1	44.39	42.20	13.01

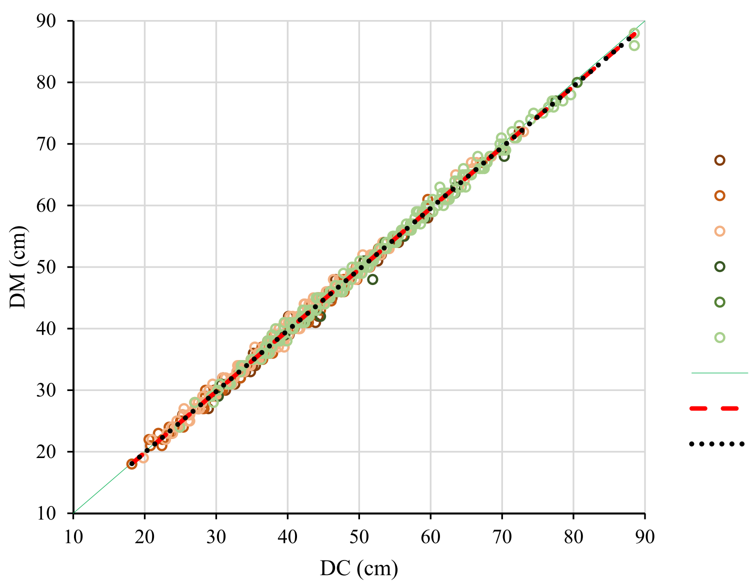

Fig. 2. Association between DM and DC: DCM – association between diameter measured by caliper and diameter measured by Measure app, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions, green line – identity (1:1) line, red dashed line – simple linear regression through origin line, black dotted line – simple ordinary regression line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and weather conditions, since the coefficients of correlation were close in value. In addition, the correlation between the compared variables seemed to be rather linear, indicating a proportional change in the compared variable as the reference data has changed. This applied to all the three options compared and it is supported by the comparison of the values returned by both Pearson's (r) and Spearman's (ρ) coefficients of correlation, which were close in value (Table 2). Since the data of the diameter measurements failed to pass the normality test, the Spearman's (ρ) coefficient of correlation could be more robust in characterizing the association between the compared data. Regression trends shown in Fig. 2–4, indicate an underestimation of DC by DM, an overestimation of DC by DA and an overestimation of DM by DA. Linear regression through origin, for instance, is assumed to have no intercept; in this case, a slope of exactly one unit will indicate a general deterministic trend in which the increment in a response variable perfectly fits the increment in an independent variable. Slopes of DM-DC comparisons were <1, while DM-DC and DA-DM comparisons returned, in general, slopes higher than 1. Differences brought by species group and weather conditions were minor (Table S2).

At a first glance, these results also indicate a good agreement in data, particularly when comparing DM against DC (Fig. 2). Missing data from Table 2 was due to the fact that too few observations were available for the coniferous group in cloudy conditions so as to be able the compute the correlation metrics by the used software.

3.3. *Agreement of the measurement options*

The main results of agreement between the measurement options are

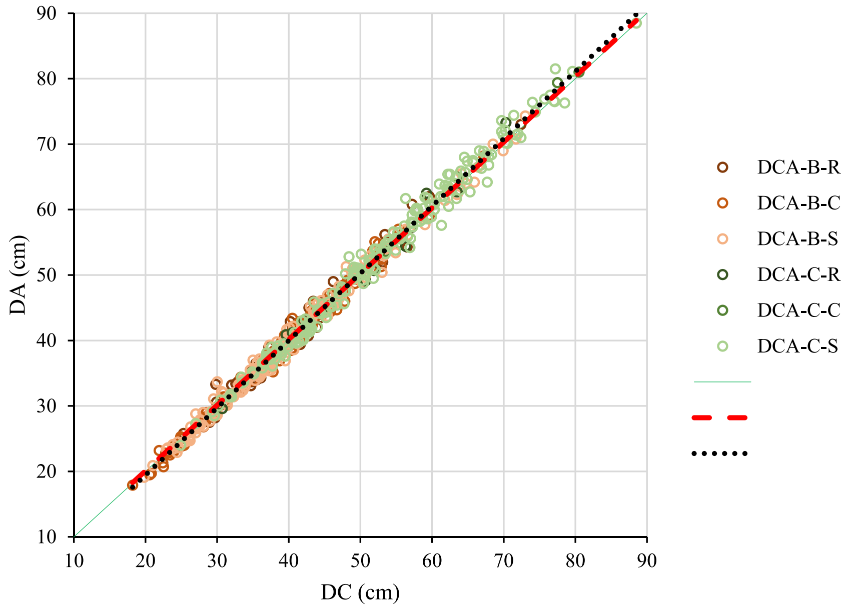

Fig. 3. Association between DA and DC: DCA – association between diameter measured by caliper and diameter measured by Arboreal Forest app, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions, green line – identity (1:1) line, red dashed line – simple linear regression through origin line, black dotted line – simple ordinary regression line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

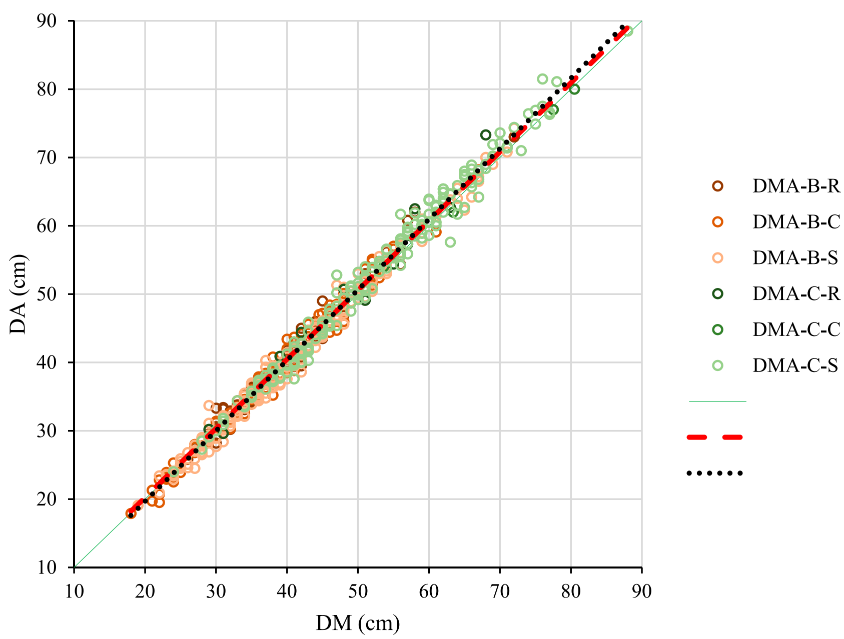

Fig. 4. Association between DA and DM: DMA – association between diameter measured by Measure app and diameter measured by Arboreal app, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions, green line – identity (1:1) line, red dashed line – simple linear regression through origin line, black dotted line – simple ordinary regression line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

given in Fig. 5–7, Table 3 and Fig. 8. Supporting data and supplementary results are included in Table S2, and in Fig. S3-S8. Fig. 5–7 describe the Bland-Altman plots of the three compared options. The correlation analysis between the differences and the mean values of the measurement returned low values of the correlation coefficients, although they were statistically significant (data not shown herein). In the DM-DC comparison, the general trend was that of overestimation, which on average, was characterized by a bias of 0.333 cm. That is, in relation to the reference measurements (DC), DM measurement underestimated, on average by 0.333 cm. Only for this comparison treatment and only for the absolute differences, the normality check was passed by the d'Agostino-Pearson test (Table S1), and no trends were found to indicate heteroskedasticity in data (Table S3). There were, however, several compared pairs well outside the agreement limits set, and only 26 observations were identified as exact matches (Fig. 8). Also, 73% of the observations were in a difference range of ±1 cm and most of them

Table 2
Treatment-wise correlation metrics.

Species group	Weather condition	Compared variables	Abbreviation	Correlation metrics		
				Pearson (r)	Spearman (ρ)	Kendall (τ)
Broadleaved	Rainy	DC, DM	DCM-B-R	0.994	0.989	0.938
		DC, DA	DCA-B-R	0.989	0.986	0.913
		DM, DA	DMA-B-R	0.988	0.983	0.909
Broadleaved	Cloudy	DC, DM	DCM-B-C	0.997	0.996	0.964
		DC, DA	DCA-B-C	0.995	0.992	0.933
		DM, DA	DMA-B-C	0.991	0.989	0.931
Broadleaved	Sunny	DC, DM	DCM-B-S	0.997	0.996	0.960
		DC, DA	DCA-B-S	0.996	0.994	0.943
		DM, DA	DMA-B-S	0.993	0.991	0.938
Coniferous	Rainy	DC, DM	DCM-C-R	0.998	1.000	1.000
		DC, DA	DCA-C-R	0.993	0.993	0.970
		DM, DA	DMA-C-R	0.988	0.993	0.970
Coniferous	Cloudy	DC, DM	DCM-C-C	–	–	–
		DC, DA	DCA-C-C	–	–	–
		DM, DA	DMA-C-C	–	–	–
Coniferous	Sunny	DC, DM	DCM-C-S	0.998	0.998	0.973
		DC, DA	DCA-C-S	0.994	0.994	0.940
		DM, DA	DMA-C-S	0.993	0.993	0.941
All	All	DC, DM	DCM-C	0.998	0.997	0.966
		DC, DA	DCA-C	0.996	0.995	0.945
		DM, DA	DMA-C	0.994	0.993	0.942

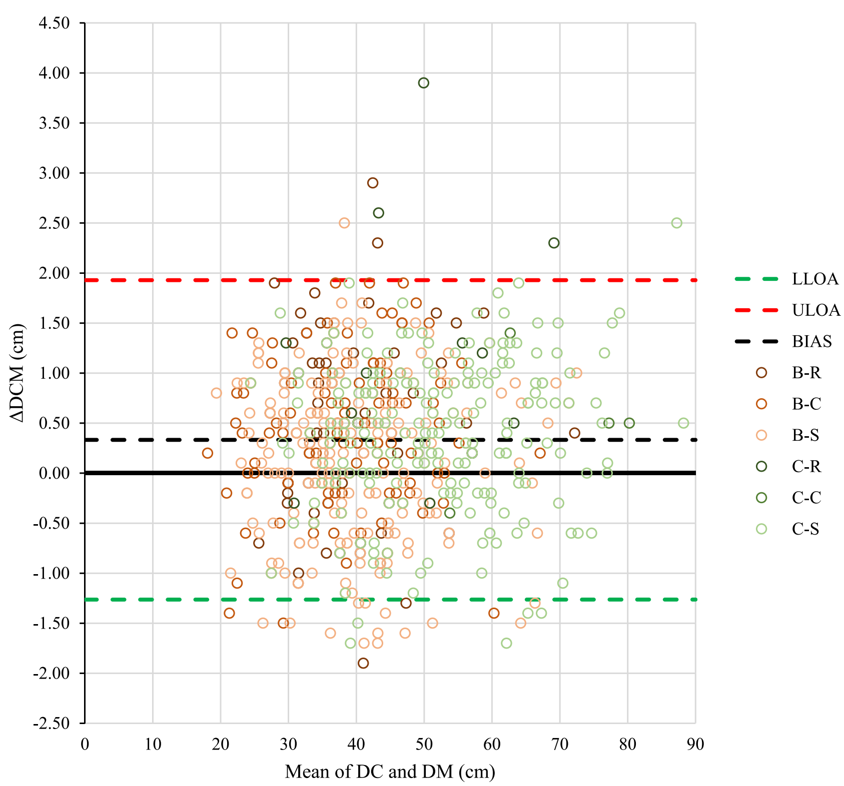

Fig. 5. Bland-Altman plot of the agreement between DM and DC: ΔDCM – absolute differences between DM and DC taking as a reference DC, LLOA – lower limit of agreement built by considering two standard deviations, ULOA – upper limit of agreement built by considering two standard deviations, BIAS – bias of the comparison, built as the average in the absolute differences, black continuous line – identity line, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions.

(99%) were in a range of ±2 cm. (See Table 4.)

As opposed to the results shown in Fig. 5, those from Figs. 6 and 7 indicate overestimations of DA in relation to DC and DM. On average, DA overestimated DC and DM by 0.108 cm and 0.446 cm, respectively. Fig. 8 indicates that the exact matches between DA, DC and DM were of 28 and 24, respectively. Following the DA-DC comparison, 62% of the observations were found to lie in between ±1 cm and 91% in between ±2 cm. In the DA-DM comparison, the differences found in the range of ±2 cm accounted for 84%. Table S3, on the other hand, indicate the presence of heteroskedasticity in data, which was characteristic to the last two comparisons.

Table 3 gives the main results on the differences found in the compared measurement options by the commonly used error metrics. When comparing the DM against DC for the data sample taken into

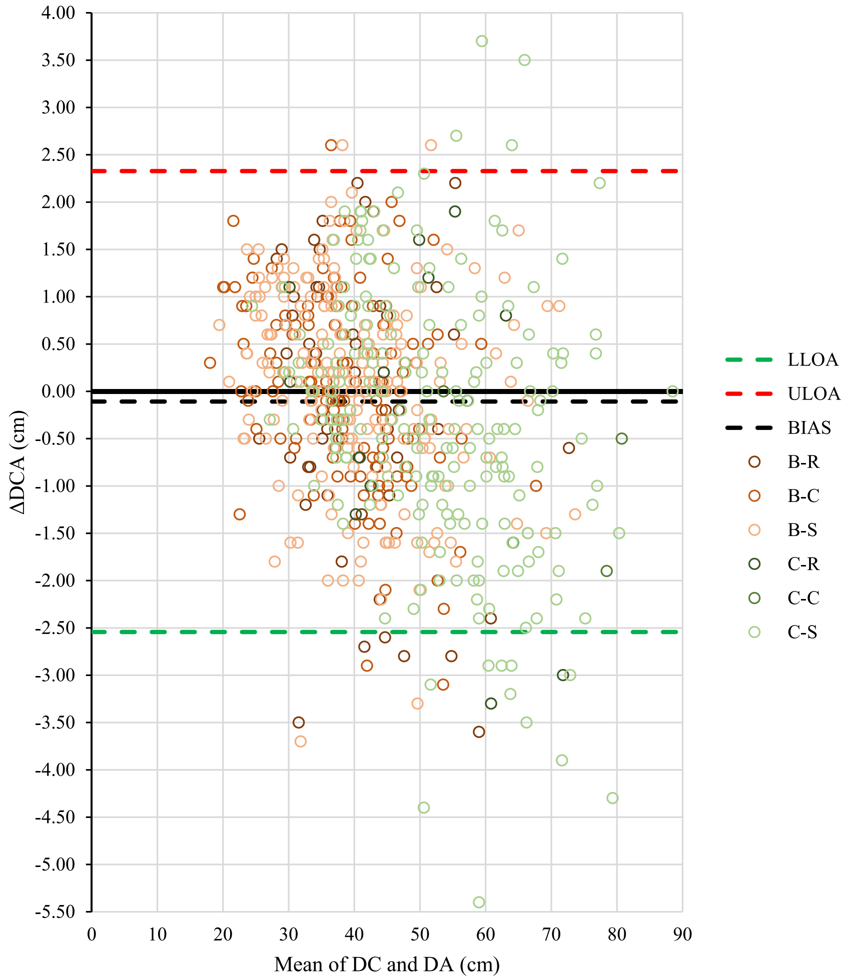

Fig. 6. Bland-Altman plot of the agreement of DA and DC: ΔDCA – absolute differences between DA and DC taking as a reference DC, LLOA – lower limit of agreement built by considering two standard deviations, ULOA – upper limit of agreement built by considering two standard deviations, BIAS – bias of the comparison, built as the average in the absolute differences, black continuous line – identity line, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions.

study, these error metrics returned values of <1 cm. The highest differences were measured by the RMSE when comparing DA to DM, and accounted for close to 1.5 cm. At sub-treatment level, the error values varied in a wide range, with lower errors in cloudy and sunny conditions when comparing DM against DC. Figs. S6 – S8 show the distribution of relative (percentual) errors of the three compared measurement options. These were in range of ±7% for DM taking as a reference DC, ±12% for DA taking as a reference DC and ± 17% for DA taking as a reference DM. Particularly for broadleaves, there was an increment trend in percentual error as the diameter decreased, which was more obvious in the first of the compared measurement options.

4. Discussion

The results of this study indicate a high accuracy of the two digital options used to measure the diameter at the breast height. By the BIAS metric, for instance, the Measure app underestimated, on average, by less than half centimeter. A BIAS of 0.33 cm was found in this case, which is consistent with the results reported by Ucar et al. (2022). For the measurement of log diameters, however, Borz et al. (2022) have found a bias of 0.2 cm, probably due to the fact that the diameters were taken by the Measure App from a much closer range (up to 0.5 m), as well as due to the fact that the starting and ending points of the measurement were much more easier to establish in their approach. On the other hand, one needs to account for the fact that Measure App has provided the measurement results rounded to the nearest centimeter, probably affecting the results reported herein on the error metrics, as well as the comparisons between the two digital options. As of this study, we believe that the differences cannot be attributed solely to the distance between the device used for taking the measurements and the tree. This is because the measurements were taken form a rather close range while the caliper was on the tree, guiding the filed researcher in the attempt of hitting the measurement's starting and ending points. However, with the Measure App, hitting the exact starting and ending points where the caliper touches the trees may be affected by subjectivity, particularly in the case of large trees characterized by an uneven bark profile at these points. For Arboreal Forest app, the systematic bias was even lower, accounting for −0.108 cm when compared to the manual option. Overall, by the mean absolute error and by the root mean squared error, this method of measurement returned accuracies of about 1 cm in this study. By comparison, the study of Sandim et al. (2023) has found bias values in between −0.13 and 2.04 cm, and root mean square values in between 1.22 and 6.87 cm. From this point of view, our results on the performance of Arboreal Forest are comparable to those reported by Lindberg (2020) who found a bias of −0.4 cm and a root mean squared error of 1.2 cm.

For both digital methods, it seems that the best conditions for measurement were met when the weather was either sunny or cloudy. These

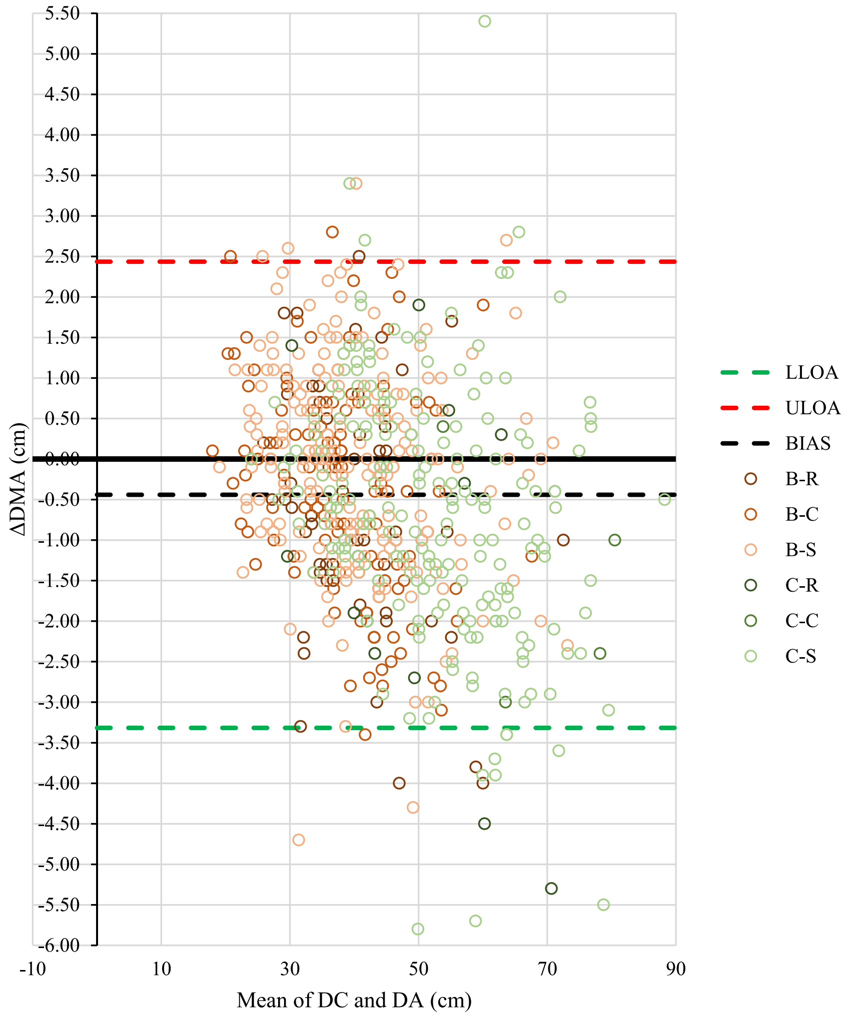

Fig. 7. Bland-Altman plot of the agreement of DA and DM: ΔDMA – absolute differences between DA and DM taking as a reference DM, LLOA – lower limit of agreement built by considering two standard deviations, ULOA – upper limit of agreement built by considering two standard deviations, BIAS – bias of the comparison, built as the average in the absolute differences, black continuous line – identity line, B-R – broadleaved trees measured in rainy conditions, B—C – broadleaved trees measured in cloudy conditions, B—S – broadleaved trees measured in sunny conditions, C-R – coniferous trees measured in rainy conditions, C—C – coniferous trees measured in cloudy conditions, C—S – coniferous trees measured in sunny conditions.

Table 3
Differences between measurement options by the error metrics.

Species group	Weather condition	Compared variables	Abbreviation	Error metrics		
				MAE	RMSE	BIAS
Broadleaved	Rainy	DC, DM	DCM-B-R	0.864	1.044	0.461
		DC, DA	DCA-B-R	1.048	1.363	−0.192
		DM, DA	DMA-B-R	1.228	1.563	−0.717
Broadleaved	Cloudy	DC, DM	DCM-B-C	0.671	0.824	0.433
		DC, DA	DCA-B-C	0.791	1.001	0.057
		DM, DA	DMA-B-C	1.059	1.331	−0.376
Broadleaved	Sunny	DC, DM	DCM-B-S	0.679	0.817	0.129
		DC, DA	DCA-B-S	1.508	1.051	0.069
		DM, DA	DMA-B-S	0.977	1.265	−0.060
Coniferous	Rainy	DC, DM	DCM-C-R	1.231	1.621	1.138
		DC, DA	DCA-C-R	1.254	1.583	−0.192
		DM, DA	DMA-C-R	1.977	2.449	−1.331
Coniferous	Cloudy	DC, DM	DCM-C-C	0.700	0.809	0.500
		DC, DA	DCA-C-C	1.000	1.267	−1.000
		DM, DA	DMA-C-C	1.700	1.995	−1.500
Coniferous	Sunny	DC, DM	DCM-C-S	0.698	0.849	0.379
		DC, DA	DCA-C-S	1.129	1.480	−0.342
		DM, DA	DMA-C-S	1.369	1.775	−0.721
All	All	DC, DM	DCM-C	0.715	0.879	0.333
		DC, DA	DCA-C	0.953	1.246	−0.108
		DM, DA	DMA-C	1.175	1.531	−0.446

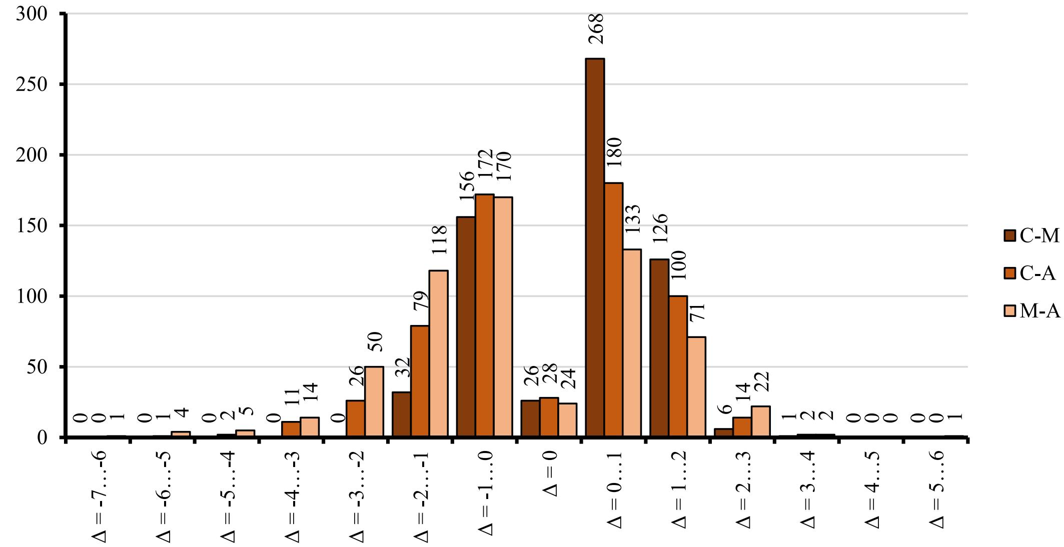

Fig. 8. Histogram showing the frequency of absolute differences between the compared options: C – caliper, M – Measure App, A – Arboreal Forest.

Table 4
Workflow of the research design.

Step No.	Input	Performer	Step	Description	Output
1	Maps of forest stands Description of forest stands Documentation on the approaches used in comparative tree measurements	Authors	Documentation of the experiment	Collecting information on the forest stands to be covered by measurements based on the maps, description of the species and main biometrics, and the protocols used in comparative studies	List of forest stands Map for the field experiments Method for measurement Field book
2	Digital weather forecasts	Authors	Documentation of weather conditions	Collecting forecasting data about the weather to cover the three main states from the study design	List of days for measurement
3	Smartphone Arboreal license Conventional caliper Field book List of days for measurement	Authors	Taking comparative measurements	Taking the comparative measurements and noting down the descriptions relevant for the study such as the measurement results, species, and weather state	Updated field book
4	Updated field book Microsoft Excel	Authors	Transferring data	Transferring the data from paper in a purposely designed Microsoft Excel workbook	Initial digital database
5	Initial digital database Microsoft Excel	Authors	Data post-processing	Organizing the data and computing the additional variables required for statistical analysis	Processed digital database
6	Processed digital database Real Statistics for Excel Microsoft Excel	Authors	Statistical analysis	Running the statistical analyses aiming at comparing the measurement options, including checking for assumptions, effective comparison and artwork development	Results of comparison Artwork of the study

outcomes confirm some of the limitations of the smartphone LiDAR based operations (Nik Azhan Hakim et al., 2023), particularly under rainy conditions, and may be related to the fact that some of the stems were wet during the measurements. Since this study indicates such trends based on categorical data, perhaps it would be useful to run similar studies by an improved experimental design to relate the measurement errors to measured light conditions. The main challenge of such studies would be that of repeatability in readings, particularly when no reference marks are placed on the measured trees.

Also, one needs to take into account that the diameter at the breast height may be a subjective measure, particularly when comparing the outcomes of several measurement methods, or when it is taken by different people. When comparing methods of measurement, the main challenge is to exactly match the measurement points. Then, the principle of measurement may be quite different between the LiDAR- and manually-based measurements, all of which would lead to some differences between these options. One of the underlying concepts of Bland and Altman analysis is that it assumes measurement errors in both methods used for comparison, therefore it fits well in research questions such as those from this study. Agreement between the methods may be characterized to some extent by the coefficient of correlation (Mansournia et al., 2021), which was largely the case of this study; also, the Bland-Altman method seeks for the agreement between alternative methods by allowing for measurement errors in the variable used as a reference, which is not the case of insights provided by the regression analysis. From these points of view, most of the data compared in this study agreed in a range of ± 2 cm, and provided a high degree of certainty that this range can be preserved for 91–99% of the observations. When considering applications that use data aggregated from multiple observations, one can account even for lower (aggregated) levels of error, therefore the digital options studied herein are suitable for such attempts.

Looking at the extremes of the possible DBH ranges, previous studies have indicated higher deviations in measurement errors (Sandim et al., 2023; Sveaksog, 2023), particularly for diameters of $<$10 and of $>$50 cm. This was the case of this study, particularly in the range of 50 to 90 cm. Also, the relative differences in measurement errors (Fig. S6-S8) were consistent with those reported by previous studies (Sveaksog, 2023), showing higher relative errors in the lower range of DBH. In these diameter ranges, it is likely that those differences come from the capabilities of the LiDAR sensor. For instance, the used sensor has some limitations when dealing with small objects (Luetzenburg et al., 2021), whereas for large trees it may produce higher absolute differences (Sveaskog, 2023). By the findigs of this study, there was also a proportional bias in the data, particularly for the Arboreal Forest app, as proven by the results of the heteroskedasticity tests.

Future studies should be framed around experimental designs that should check the repepatability of the measurements and reliability of the devices used, and should consider much bigger samples that are wider in the range of the covered diameters, so as to be able to clarify the trends in the proportional bias and the exact capability limits of the digital measurement options. Also, the resources spent in digital measurement operations need to be more precisely quantified. For instance, there are no quantifications on the cycle time for digital measurement of DBH, which would be helpful in better understanding the economics of these options. Comparing the effects brought on the accuracy and agreement by different factors such as species group or weather conditions would be important to better understand the expectations and to better plan the field effort for digital measurement. In this study it was not possible to use parametric comparsion tests since they make assumptions such as the normality of data and homogeneity of variance; for the normality assumption, the tests used in this study failed. In turn, the use of nonparametric comparison tests is known to be a less robust approach to the problem. However, the methods used in this study were able to clarify the accuracy and agreement trends of the compared measurement options.

5. Conclusions

The digital DBH measurement options supported by affordable mobile platforms equipped with LiDAR and AR technologies are accurate and compatible with the DBH measurement requirements when compared to the manual option. As found by this study, they can provide sub-centimeter level accuracy when considering aggregated data sets. For individual measurement, most of the results agreed in a range of ±2 cm. These accuracy features make them suitable for many applications in forestry, when one considers the limitations of manual measurement in terms of accuracy, difficulty of work and economics. Further studies should explore the capability limits of these technologies by accounting for repeatability, larger datasets and wider diameter ranges. In addition to finding better methods to provide reference data, such studies should account also for the resources spent in measurement and reliability of the devices.

Founding source

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CRediT authorship contribution statement

Stelian Alexandru Borz: Writing – original draft, Visualization, Validation, Supervision, Resources, Investigation, Funding acquisition, Data curation, Conceptualization. **Jenny Magali Morocho Toaza:** Methodology, Investigation, Formal analysis, Data curation. **Andrea Rosario Proto:** Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors report no declarations of interest.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102550.

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