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Wood measurement at the factory gate: a comparison study to evaluate the accuracy of a state-of-the-art digital truckload measurement system

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Abstract Precise wood measurement and traceability are important for increasing supply chain efficiency and guaranteeing legal compliance in the forest industry. Digitalization has emerged as a transformative trend globally, offering significant potential to address current challenges associated with wood transportation. This study investigates the accuracy of the CIND's Timspec ® system in measuring the roundwood solid volume at the factory gate. It compares the system's performance using data from a number of 1,300 truckloads, of which 1,292 were retained after outlier removal, and were compared to data sourced by manual measurements performed in the forest and Microtec® measurements carried out in the sawmill yard. The study followed a comprehensive methodological framework from outlier removal using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm to statistical analysis and heteroskedasticity tests to assess the reliability of the system. The results indicate a high degree of agreement among the used measurement systems. However, it highlights the differences in volume estimations produced by these systems, revealing that while the Timspec system tends to overestimate wood volumes by approximately 0.5 m³ overall, which is likely attributed to operational factors such as truckload gaps and moving speed, Microtec system underestimates by about 0.8 m³ overall, primarily due to observable factors such as bark loss during mechanical handling in the sawmill yard. Based on the findings, Timspec® system can be used to effectively check the conformity regarding the quantity of wood delivered to the processing industry by those in charge with tactical and strategic decision making, mainly due to speed, effectiveness, and coverage of measurements. Following improvements, this digital system may stand as an effective tool for the wood supply chain, allowing for fast and accurate estimates of the truckload-based wood deliveries, as well as automation of the measurement processes at the factory gate.

Keywords: transportation, supply chain, estimates, agreement, digital systems, traceability, decision making.

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Introduction

Forests offer a diverse range of products and services that support economic development, societal welfare, and environmental balance (Ritter & Dauksta 2013, Brockerhoff et al. 2017, Nesbitt et al. 2017, Bjärstig & Sténs 2018). Currently, the lignocellulosic biomass they produce has numerous applications worldwide (Nanda et al. 2015, Ullah et al. 2015, Okolie et al. 2021), and wood utilization has historically played a crucial role in the development of humankind (Bisby & Frangi 2015).

New trends in consumption patterns (Bais et al. 2015, Wang & Haller 2024), combined with the complexity of the wood supply chain (Larsson et al. 2016), make wood procurement particularly challenging. Although wood consumption trends have continued to rise, innovations in the supply chain aimed at overcoming effectiveness bottlenecks are relatively rare (He & Turner 2021), with only a few examples of advanced technologies being used to enhance performance. Additionally, new challenges have emerged from the need to implement effective traceability systems, further complicating efforts to improve supply chains (Dasaklis et al. 2022).

Digitalization is a new trend in wood-based industry across many parts of the world, holding significant unexplored potential to overcome the current challenges in wood procurement (Gnacy & Werbińska-Wojciechowska 2023). More effective allocation of resources, information, and data flows – along with the ability to accurately document the source of wood and track it through the supply chain – represent both important benefits and key challenges that require effective solutions (Scholz et al. 2018).

Wood measurement and grading are typically required and used to support commercial transactions, produce statistics, and document the flow of wood to the markets (Eriksson et al. 2023). Depending on various factors, such measurements are employed at many points in the supply chain (Sandberg et al. 2023). The sequential flow of wood between different stakeholders is commonly facilitated by economic transactions, which, in the best case, may be based on trust. However, due to legal regulations or a lack of trust, these transactions often necessitate quantitative measurements (Borz & Proto 2022, Liu et al. 2022). A typical example that interlinks several stakeholders is the wood transportation process, as there are often bi-directional economic transactions between harvesting contractors, transporters, and sawmills. Therefore, when selling, buying, or transporting wood, quantitative assessments are essential for economic reasons, trust, traceability, and legal compliance (Saikouk & Spalanzani 2016, Mena-Reyes et al. 2024).

The latest statistics on the topic indicate a dominance in the use of road transportation, which relies on various trucks with differing configurations and capacities; for instance, capacity may vary significantly across the world due to factors such as management practices, road infrastructure, and transportation regulations (Palander et al. 2020, Lyons et al. 2023, Kärhä et al. 2024, Palander et al. 2024). To date, measuring the wood before delivering it to the market is generally performed in the forest, either by using data provided by fully mechanized harvesting systems (Kemmerer & Labelle 2021), or through manual measurement (Borz et al. 2022). However, the use of fully mechanized harvesting systems is limited in scope (Lundbäck et al. 2021, Spinelli et al. 2021), and some stakeholders may be reluctant to utilize the quantitative data they generate. Manual measurement, on the other hand, is time-intensive, less safe and requires highly skilled labor (Borz et al. 2022).

The developments in advanced sensing technology based on photo-optical, LiDAR, and other principles have brought new opportunities for wood measurement. Studies have already shown that it is possible to obtain accurate estimates for individual pieces, such as logs (de Miguel-Díez et al. 2022, Niţă & Borz 2023), as well as for wood piles (Tomczak et al. 2024) and truckloads (Acuna & Sosa 2019). However, these new approaches are still in the experimental stage and have consistently demonstrated one key point: while they are reliable enough, they still require significant computing and processing effort to achieve accurate estimates, therefore they are less effective in terms of time resources required to produce the results. Nevertheless, truckload measurement offers scalable advantages and may serve as a useful alternative to build trust in estimates – particularly when stakeholders agree on a checkpoint and the estimates produced at that checkpoint, such as the sawmill gate. This approach not only will limit the resources required to measure the wood but will also enhance the effectiveness of the supply chain by removing bottlenecks introduced by waiting times.

Companies focused on developing technologies for the wood supply chain have already presented advanced solutions to address measurement accuracy and overall effectiveness. For example, portal-like sensor-based systems have been developed by companies such as LASE (https://lase-solutions.com/products/wood-industry/) and CIND (https://www.cindsolutions.com/timspect). Similar systems have also been documented in a few scientific studies focused on the theory of measurement and reconstruction based on LiDAR scanning (David et al. 2016, Sikora et al. 2019). CIND, for instance, offers Timspec ®, which is a scalable solution that claims to automatically, accurately, and effortlessly measure the bulk and solid roundwood transported by trucks. This system is designed to operate independently of weather conditions and can function while trucks are moving, utilizing advanced sensing and 3D software. Despite their significant potential, the available scientific information on the accuracy of these systems remains limited. In particular, data covering extended time periods, or a high number of truckloads is lacking, which is essential for a broader understanding the systems' behavior and accuracy. Furthermore, the workflows and algorithms underlying these systems are often proprietary technologies of their developers, which typically restricts evaluation efforts to empirical studies.

In 2022, a large wood processing company located in Romania had the initiative of testing the CIND's Timspec ® solution for a time period large enough to collect highly detailed data, which provided the opportunity to estimate its accuracy in relation to manually measured data. In addition, the company operated at the time a Microtec ® system to measure the logs individually before entering on the sawmilling lines, which provided another opportunity to check the accuracy in data. As such, the main aim of this study was to estimate the accuracy of the CIND's Timspec ® system in measuring the roundwood solid volume by i) quantifying the magnitude in differences between the three datasets, ii) checking if the differences are affected by the size of the truckload, and iii) documenting the potential factors affecting such differences.

Materials and Methods

Data sourcing

A large dataset was compiled at the company headquarters from early March to the end of June 2022. This dataset included three measurements taken from a total of 1,300 trucks. The first measurement was taken manually (hereafter referred to as VMA, m^3) at the truck loading site in the forest, conducted by individuals responsible for such tasks, including harvesting contractors and transporters. These personnel are mandated by relevant Romanian law to measure and report the results of wood measurement and grading in the national traceability system before transportation (Ministry of Environment, Waters and Forests, 2021). Accordingly, the measurement was performed in accordance with the national regulations for roundwood measurement and grading that were in effect in Romania at the time of the study (Government of Romania, 2020). These regulations specify that volume estimates are generally based on measurements taken from each log, specifically in terms of length and mid-diameter. The data reported in the traceability system includes the assortment, species, mid-diameter (cm), and length (m), leading to the issuance of a document that describes the truckload, including the quantity transported, which was one of the inputs of this study (VMA, m^3). Such manual measurements are commonly practiced in Romania and globally. However, several errors can affect the accuracy of manual measurements, such as incorrect human reading or recording of measurements, instrument misalignment, measuring over bumps or branch stubs, incorrect tensioning of tapes and calipers, and rounding mistakes in numbers, which can all impact measurement results (Strandgard 2009, Figorilli et al. 2024). Additionally, factors such as local topography can hinder workers from taking precise measurements (Stereńczak et al. 2019).

The second truckload measurement was taken using the CIND Timspec® system (hereafter referred to as VTS, m³), a proprietary automated 3D sensing portal installed at the factory gate. This model-based system provides nearly real-time, automated measurements without specific human assistance. The vehicle is scanned within seconds as it moves through the gate, and the system's program employs a series of algorithms to dynamically identify the truck's load. A 3D model is generated while 2D images are simultaneously captured for additional processing. The software utilizes the collected data to compute the truckload volume and other features. The third measurement was conducted using the Microtec® system (hereafter referred to as VMI, m³) in the sawmill yard. Microtec employs sensors installed on the log sorting line, scanning each log individually and computing its volume based on sensor determinations of the diameter and length of each log.

A specific protocol was followed by the study to match the truckloads across measurements, implemented with the support of the factory personnel. Upon arrival at the factory, the document issued by the traceability system - stating the quantity of wood loaded onto the truck based on individual log measurements taken manually in the forest - was paired with the readings taken by the CIND's Timspec system. After passing through the gate, the truck was unloaded in a designated area of the log yard to ensure the resulting pile of wood was readily identifiable. In some instances, this included marking the piles with paint. Once these requirements were fulfilled, the wood from that truck was fed into the log sorting line, and the individual measurements taken on each log were summarized for all logs corresponding to a specific truck.

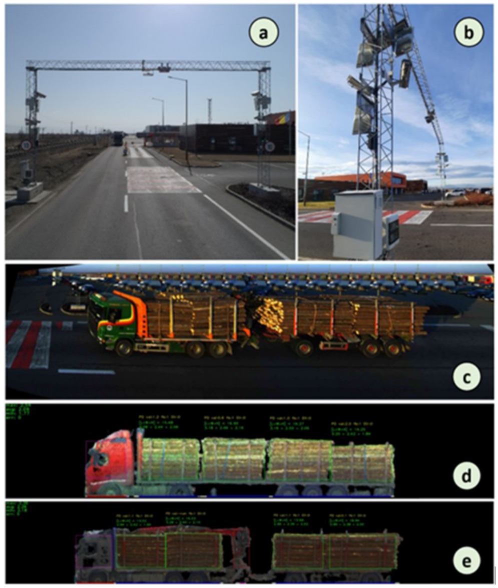

Figure 1 Main features of the system: a and b – scanning portal installed at the sawmill gate, c – scene taking during scanning, d and e – measurement summaries for a truck, and a truck with a trailer. Complements to CIND.

Statistical design and data analysis

Basic statistics

As a first step, the three datasets were used to compute the signed, absolute, and squared differences between each pair of measurements. Manual measurement data were taken as a reference to compare the results from the Timspec and Microtec systems. A comparison was also made between the Timspec and Microtec systems themselves. Signed, absolute and squared differences were then computed for the VMA-VTS, VMA-VMI, and VTS-VMS variables.

Given the uncertainty in some data estimates, which may have been caused by reporting errors, an arbitrary outlier removal procedure was implemented on the initial dataset. To achieve this, the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm was used, taking as features the volume measurements from the three systems (VMA, VTS, and VMI, in m³) and the number of shipment documents (ND). This approach aimed to find a clustering solution based on the signed differences in all the compared datasets (ΔVMA-VTS, ΔVMA-VMI, and ΔVTS-VMI). Specifically, DBSCAN is a density-based unsupervised clustering algorithm that effectively identifies arbitrarily shaped clusters (Ester et al. 1996).

DBSCAN has been successfully applied in forestry-related studies for various purposes, including the classification of tree components from 3D LiDAR point clouds and noise removal (Ferrara et al. 2018, Fu et al. 2022, Zhang et al. 2022, You et al. 2023, Xie et al. 2025, Zhang et al. 2025). It can detect and map specific clusters formed by closely packed points, while also identifying points in low-density regions as outliers (i.e., outliers are considered noise). According to its developers (Ester et al. 1996) the algorithm uses two parameters: the radius of the neighborhood around a given data point (*eps*) and the minimum number of points required within that radius to form a dense region (*np*). Typically, *eps* is determined based on a k-distance graph as the point corresponding to the first significant valley in the graph, while the minimum *np* is commonly selected based on the dimensionality of the analyzed dataset, where *np* = number of dimensions + 1 (Ester et al. 1996). The algorithm operates by classifying points into three categories: core points, which have enough neighbors within the *eps* distance; border points, which lack enough neighbors to be core points; and noise points, which are those located outside the clusters at the time a clustering solution has been reached.

Following the clustering process, a data curation step was implemented to remove unsuitable data, such as the outliers. This step was based on the *eps* distance identified at the first valley in the k-distance graph, retaining only the data that formed a suitable, dense cluster for further statistical analysis.

Advanced statistics

For the first objective of the study, commonly used error metrics – specifically, bias (hereafter referred to as BIAS), mean absolute error (hereafter referred to as MAE), and root mean squared error (hereafter referred to as RMSE) – were utilized to estimate the mean systematic bias, absolute difference, and the impact of large discrepancies between the datasets.

Typically, BIAS is useful for detecting the direction of the difference, thus allowing for evaluation of whether a given measurement system underestimates or overestimates the values on average. On the other hand, MAE characterizes the magnitude of differences (Willmott & Matsuura 2005), highlighting expected maximum differences. RMSE is particularly useful for assessing whether and how large differences may affect the estimates (Chai & Draxler 2014). In other words, theoretically, two datasets may exhibit a null BIAS while still presenting differences when evaluated using MAE. Furthermore, the usefulness of MAE can be cross-validated by considering RMSE, as similar values indicate lower anomalies attributed to the magnitude of the differences.

For the second objective of the study, common descriptive statistics were computed, along with plots to illustrate how the signed differences distribute in relation to reference measures such as VMA or VTS. Specifically, ΔVMA-VTS, ΔVMA-VMI, and ΔVTS-VMI were plotted against VMA and VTS, respectively, along with regression lines to indicate their trends and supporting data to illustrate their magnitude and relationship to the other variables used for comparison. These statistics were supplemented by heteroskedasticity tests to determine whether proportional bias was present in the data and, if so, to characterize its type. Specifically, the Breusch-Pagan and White tests were implemented to detect the presence of linear and/or other types of proportional bias.

It was expected that differences would arise among the datasets being compared. However, understanding their relative magnitudes is important for assessing how a given measurement system behaves. Therefore, for the third objective of the study, the data on signed differences were categorized based on their magnitudes to provide estimates as shares for discussing the potential factors behind these differences.

Software used

Data curation through clustering and the statistical analyses were conducted using Microsoft Excel, which included a copy of Real Statistics (Zaiontz 2025) available at: https://www.real-statistics.com, as well as Orange Visual Programming software (Demšar et al. 2013). Specifically, the computation of differences and the main descriptive statistics, along with the heteroskedasticity tests, were performed in Microsoft Excel and Real Statistics. DBSCAN clustering and the artwork required for the study were developed in Orange Visual Programming software.

Results

Curated dataset

Following data clustering using DBSCAN, two main partitions were identified, as shown in Fig. 2. With an optimal Euclidean distance set at 2.03, the algorithm effectively grouped the data points into two clusters (C1 and C2) based on the signed differences among the three volume estimates. For example, Fig. 2 illustrates the clustering results based on the signed differences between VMA and VTS; however, these results were consistent across the entire range of signed differences for the considered variables. The points in the second cluster (C2, Fig. 2) exhibited high magnitudes of signed differences, particularly when comparing VMA against VTS and VTS against VMI (results not shown). In contrast, the signed differences between VMA and VMI did not reveal a specific pattern in the clustering results (results not shown). Consequently, the main outcome of the clustering was based on a subset of data points where the truckload volume was significantly overestimated by VTS. Additionally, some data points (grey data points) were not assigned to either of the two clusters by the DBSCAN algorithm (Fig. 2). Therefore, these unassigned data points, along with those from the second cluster, were removed from the dataset used for further analysis.

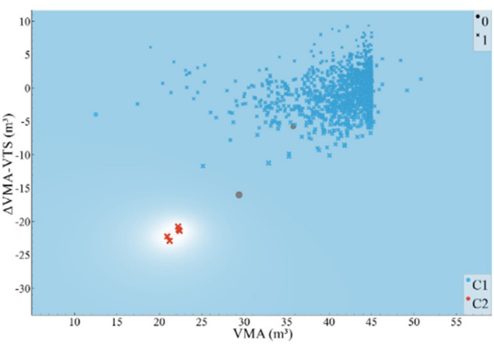

Figure 2 Results of clustering using DBSCAN. Legend: C1 – cluster no. 1, C2 – cluster no. 2, 0 – point not considered by the algorithm as core, 1 – core point, ΔVMA-VTS – signed difference between VMA and VTS (m^3). Note: the size of the datapoints is scaled based on the magnitude of ΔVMA-VTS.

Descriptive statistics

Fig. 3 illustrates the distribution of data points following data curation in the form of violin plots. The assumption of normality was not met for the volume data produced by the tree measurement systems analyzed in this study, which is reflected in the shape of the data distributions shown (Fig. 3). Each of the refined datasets contained 1,292 observations. In these datasets, VMA ranged from 12.52 to 50.81 m^3, with an average of 41.66 m^3; VTS ranged from 12.85 to 51.61 m^3, with an average of 42.13 m^3; while VMI ranged from 12.50 to 40.87 m^3, with an average of 40.87 m^3.

The distribution of the signed differences between the compared variables is illustrated in Fig. 4. As shown, the pairwise signed differences have been smoothly modeled by a normal distribution in all cases (Fig 4b). For VMA–VTS, the differences ranged from approximately –11.5 to about 9.5 m^3; for VMA–VMI, the range was narrower, spanning from about –6 to 9 m^3. In contrast, for VTS–VMI, the range shifted more towards positive differences, from approximately –8 to 14 m^3.

Measurement agreement

Figs. 5-7 illustrate the compared datasets by considering the location and magnitude of signed differences, whereas Table 1 provides the synthetic data on the considered error metrics.

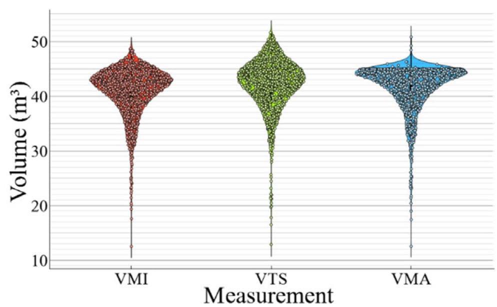

Figure 3 Violin plots, scaled by area and using a normal kernel, illustrate the distribution of data following curation, represented in the form of density dots. Legend: VMA – manual measurement; VMI – measurement taken by the Microtec system; VTS – measurement taken by the Timspec system. Note: The data failed to meet the normality assumption.

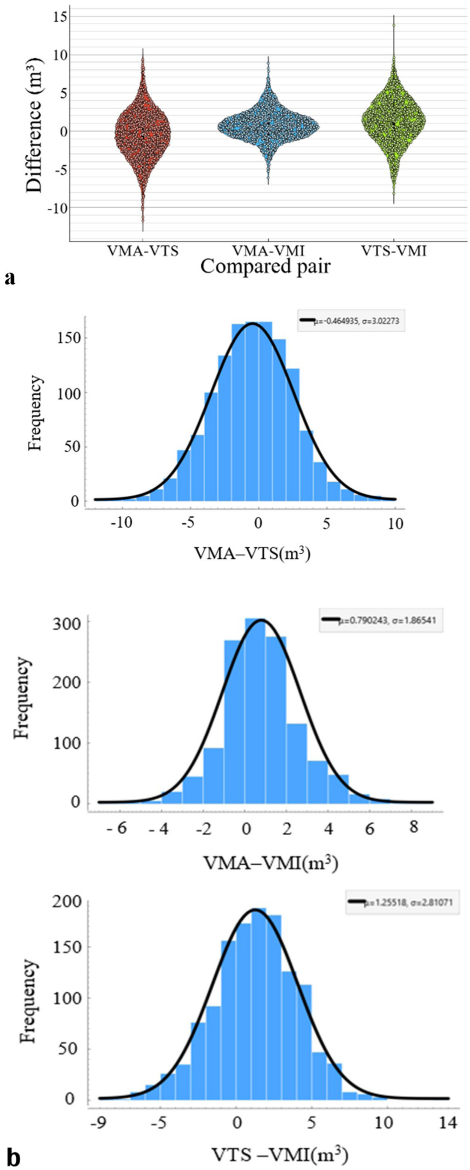

Figure 4 Violin plots, scaled by area and utilizing a normal kernel, illustrate the distribution of the signed differences data following curation, represented as density dots (a), along with data distribution of the signed differences between variables using a bin size of 1 (b). Legend: (a) VMA–VTS indicates the signed differences between manual measurements and Timspec; VMA–VMI represents the signed differences between manual measurements and Microtec; VTS–VMI denotes the signed differences between Timspec and Microtec.

Note: The data met the normality assumption as illustrated by the histograms included in (b) for the same compared variables.

As shown in Figs. 5-7, there were trends of different degrees in the signed differences related to the magnitude of the considered reference measurements. On average (Table 1), VTS overestimated manual measurements by about 0.5 m³ ($BIAS_{VMA\text{-}VTS}$ = –0.47 m³). For the same compared datasets, mean absolute error was close to 2.5 ($MAE_{VMA\text{-}VTS}$ = 2.33), and the root mean squared error was close to 3 ($RMSE_{VMA\text{-}VTS}$ = 3.06). Similarly, VMI underestimated the volumes sourced by manual measurement by about 0.8 m³, whereas the mean BIAS of VTS-VMI was of about 1.3 m³ (Table 1). All these results on error metrics indicate, on average, a high degree of agreement. However, the results of heteroskedasticity tests indicate the presence of proportional bias when considering the VMA – VTS and VTS – VMI datasets (see the results of Breusch-Pagan and White tests, Table 1).

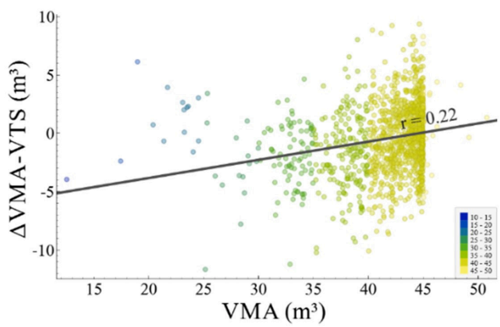

Figure 5 Signed differences between VMA and VTS (ΔVMA-VTS, m³), plotted against VMA (m³), indicate a moderate trend in magnitude (r = 0.22) in relation to the magnitude of VMA. Note: The numerical legend denotes categories of magnitude in VMS (m³), and data points are scaled by the magnitude of the signed differences.

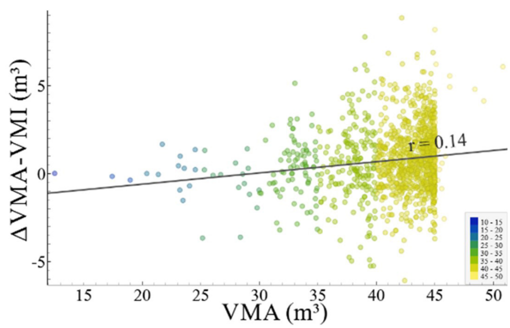

Figure 6 Signed differences between VMA and VMI (ΔVMA-VMI, m³), plotted against VMA (m³), indicate a low trend in magnitude (r = 0.14) in relation to the magnitude of VMA. Note: The numerical legend denotes categories of magnitude in VMI (m³), and data points are scaled by the magnitude of the signed differences.

Table 1 Main results on the error metrics considered in the study.

Compared datasets	BIAS	MAE	RMSE	Heteroskedasticity test
VMA – VTS (m^3)	–0.46	2.42	3.06	$p_{BP} < 0.001$ $p_W < 0.001$
VMA – VMI (m^3)	0.79	1.54	2.03	$p_{BP} = 0.802$ $p_W = 0.056$
VTS – VMI (m^3)	1.26	2.47	3.08	$p_{BP} < 0.001$ $p_W < 0.001$

Table 2 Distribution of signed difference on categories of magnitude.

Compared data	Share of signed differences on categories of magnitude (%)						
	± 1 m^3	± 1-2 m^3	± 2-3 m^3	± 3-4 m^3	± 4-5 m^3	over ± 5 m^3	Total
VMA–VTS	25.54	24.15	19.81	12.77	7.51	10.22	100
VMA–VMI	44.43	28.40	13.70	7.05	4.11	2.31	100
VTS–VMI	25.46	21.67	19.89	12.46	10.76	9.76	100

Finally, Table 2 provides an overview on the distribution of signed differences by considering categories of magnitude. When comparing VTS against VMA, close to half of the identified differences were in the range of ± 2m^3. When comparing VMI against VMA, more than 70% were in that range, and when comparing VMI to VTS, close to 47% of the differences were in range of ± 2m^3. Very large differences, accounting for more than ± 5m^3 (see also Figs. 5-7), accounted for about 10% for VMA–VTS and VTS–VMI, respectively, and were low as share when comparing VMI against VMA (Table 2).

Discussion

The results of this study are generally promising, indicating overall a high degree of agreement among the measurement systems under tests. However, none of the systems analyzed is flawless; therefore, the compared data should be interpreted with some degree of caution. Currently, most of the wood measurement digital systems are under development, and increased performance in measurement by such systems is expected in the future. For instance, Acuna & Sosa (2019) tested the accuracy of a photogrammetry-based solution and found an average deviation of 0.5 m^3, and a relative deviation of about 3%, which are comparable to some degree to that of the Timspec system in relation to manual measurements. However, manual measurements of individual logs may still be affected by many types of errors (Vasilescu 2017), which can impact the suitability of that data as a reference. In this study, it was not possible to check the accuracy of manual measurements; therefore, they were used as they were provided in the shipment documents, even though such errors may have influenced the results of the error metrics and heteroskedasticity tests. Notably, the systematic bias was the lowest when comparing Timspec data against that sourced from manual measurements, and this finding was consistent with the results related to the MAE and RMSE metrics for these two datasets.

On one hand, VTS is expected to overestimate manual measurements due to its way of operation, which may include in the volume estimates part of the empty spaces between loads on a given truck, which could have been missed as such by the system spaces. On the other hand, the speed of the truck during measurement may affect the estimates, similar to other types of sensing platforms (David et al. 2016, Sikora et al. 2019, Amorim et al. 2019). Based on informal data, CIND's Timspec system operated at its highest confidence level for truck moving speeds less than 10 km/h. Accordingly, we removed from our analysis the data pointed by the system as unreliable. In these conditions, we found a high degree of agreement between these two estimates, with average maximum differences of up to 2.5 m^3. For our datasets, the relative error (VMA - VTS) was approximately 6% and showed a decreasing trend as a function of the reference data (VMA).

On average, VMI underestimated VMA by about 0.8 m^3, but the measurements fell within a narrower average range (MAE = 1.54) and exhibited a lower relative error (about 3.5%). This again showed a decreasing trend as a function of the reference data (VMA). For VMI, the logs are scanned piece by piece when fed into the production line; therefore, the volumes of individual logs are aggregated to obtain the total volume of a given truckload, as sourced by the Microtec system. However, before the logs are fed into the production line, they undergo a series of manipulations - such as unloading, storing, moving, and feeding - that cause significant losses in terms of bark and shrinkage, which can vary depending on weather and operational conditions. Therefore, our findings are consistent with these factors, particularly our observations in the factory, which clearly indicated such losses.

Finally, VMI underestimated VTS (BIAS = 1.26 m^3) due to similar reasons. First, VTS estimates may include gaps within a given truckload. Additionally, the logs may lose bark and shrink before being fed into the production line, resulting in observable volume differences. Along with these factors, others may contribute to the differences observed, such as the general weather conditions during transport (Schulgasser et al. 2015, Fu et al. 2023), the time elapsed between taking the manual measurement and shipping the load (Trzciński et al. 2021), and specific biometrics of the logs, including the average diameter (Moskalik et al. 2022). Some of these factors may have a greater impact, particularly for coniferous wood, as noted in this study, and many of them were out of our control and quantification.

Presence of proportional bias was detected in all compared datasets excepting VMA-VMI, therefore potentially indicating one technical limit of the studied measurement system. In other words, the magnitude in differences was correlated with the magnitude of the measured variable. Since both tests indicated that heteroskedasticity is present in data, the proportional bias may propagate by rules other than linear. For reference, Figs. 5 and 7 indicate how the signed differences behaved in relation to the measured variables, showing a decreasing trend at first, then a plateau around 25-35 m^3, then again, an increment. Obviously, some exaggerations were found (VMA-VTS), with a share of about 18% of those comparisons exceeding signed differences of 4 m^3. To what degree these can be only attributed to the performance of the measurement system under study, remains open for study since we relied on manual measurements as they were. Nevertheless, about 50% of the differences stayed in a range of ±2 m^3, which is a promising result.

Keeping these findings in mind, the utility of the studied system may depend on the type of stakeholder involved, particularly under the specific conditions in Romania. The wood supply chain involves several stakeholders who are interlinked by the processes they oversee. Some have control responsibilities, while others establish economic relationships. Many share a common need: the accurate documentation of wood for both control and transactions, including the precision of quantitative estimates. The State plays a crucial role in preventing illegal logging and ensuring an efficient workflow of wood, which is essential for saving resources and enhancing the sector's competitiveness. However, existing regulations make this challenging, as measurement methods in the forest and the integration of resulting data into the mandatory traceability system are both complex and compulsory. This primarily impacts those workers responsible for measuring and grading wood in the forest before it is loaded onto trucks, since some wood processing factories can utilize their own verification systems.

Manual measurement and grading in the forest are difficult tasks, often constrained by limited space where wood is typically piled. This limitation can affect the accuracy of manual measurements. Additionally, excess length is usually produced when logs are cut. If this excess is not accounted for, and shipment documents only reflect the nominal length of the logs, it can partially explain the discrepancies observed between the studied wood measurement systems. For example, a truck carrying 100 logs, each with a nominal length of 4 m and an average diameter of about 30 cm, an excess length of 4 cm per log would yield an actual volume greater by more than 1 m^3.

Since manual measurement and grading are labor-intensive and prone to error, utilizing a system capable of automatically measuring wood at the factory gate would significantly benefit transactional processes. However, such a system must provide acceptable accuracy limits on a per-truck basis, which our findings do not fully support, likely due to factors outside our control, such as the accuracy of manual measurements. Therefore, further studies should be conducted to evaluate the system's accuracy, exploring different methods for sourcing reference data and accounting for potential improvements in the estimation algorithms of the studied system.

Conclusions

Considering the results of this study, as well as the current regulations in the country, we conclude that the studied system may provide significant benefits to the wood supply chain by checking the general conformity regarding the quantity of wood delivered to the processing industry. This would document and inform decision making at strategic and tactical level, assuming that costs of implementation would be acceptable. At the time of reporting these results, it is likely that the system has already undergone important improvements in algorithms used for estimation, and further follow-up studies are encouraged to check its accuracy. Coupled with the speed and timing of the measurement, the system provides an effective tool for the wood supply chain, allowing for fast and accurate estimates of the wood delivered, as well as automation of the measurement processes at the factory gate. For a better experimental comparison design, more accurate reference measurements are required, which may not be as readily available as one might expect due to various factors, such as the availability of tools, time resources, and volume losses from bark and shrinking between measurement points.

Conflict of interest

The authors declare no financial or personal interests could influence the work presented in this paper.

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