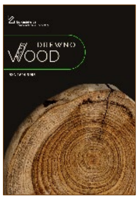
Article citation info:
Borz S.A., Marcu M.V., Iordache E. 2025. Postural Risk Assessment in Wood Measurement: A Follow-Up Study To Explore New Measurement Options And To Check The Repeatability of Outcomes When Using Digital Options. *Drewno. Prace naukowe. Doniesienia. Komunikaty* 68 (215): 00039. https://doi.org/10.53502/wood-195843

Łukasiewicz
Poznań Institute of Technology

Drewno. Prace naukowe. Doniesienia. Komunikaty
Wood. Research papers. Reports. Announcements

Journal website: https://drewno-wood.pl/



Postural Risk Assessment in Wood Measurement: A Follow-Up Study To Explore New Measurement Options And To Check The Repeatability of Outcomes When Using Digital Options

Stelian Alexandru Borz
Marina Viorela Marcu[*]
Eugen Iordache

Transilvania University of Brasov, Romania

Article info
Received: 2 July 2024
Accepted: 12 November 2024
Published online:
15 January 2025

Keywords
wood supply chain
close range sensing
ergonomics
health risk
comparison

Technological development and digitalization have brought new opportunities in many industrial sectors, including forestry. Wood measurement is an important process which in many regions is shifting from manual methods to the use of digital tools, and the validation of new approaches is necessary to ensure the sustainability of the sector. This study was set up mainly as a follow-up attempt to validate results concerning postural risks when using digital tools to measure logs. In addition, the study explores the postural implications of a new measurement option, namely scanning of wood loaded into trucks. Generally, the digital measurement options involving the use of smartphones and professional LiDAR scanners generated lower postural risks, results which are consistent with and validate previous findings. Although the studied measurement options displayed statistically significantly different profiles in terms of postural conditions, manual wood measurement remains challenging in terms of postural risk. From a postural assessment perspective, transition to digital tools in wood measurement seems to be a sustainable option in the long run, but it will require the further development of existing algorithms so as to be able to extract useful information from the collected data.

DOI: 10.53502/wood-195843
Published by Łukasiewicz Research Network – Poznań Institute of Technology.

Introduction

Wood measurement is a common activity in the timber supply chain, because it provides information about the quantity and quality of the wood (Leahu, 1994), which supports research and decision-making (Müller et al., 2019). Traditionally, the measurement of logs in various places along the supply chain has been done manually. With the development of completely mechanized harvesting systems and the integration of the latest technology into machines, the measurement tasks have been transferred to a computer fed by sensors, contributing to an increase in measurement efficiency and to the ability to transfer measurement data along the supply chain (Kemmerer & Labelle, 2021). However, mechanized harvesting is so far used only to a certain extent worldwide (Lundbäck et al., 2021; Moskalik et al., 2017), which

[*] Corresponding author: viorela.marcu@unitbv.ro

constrains the practice of wood measurement to the use of manual tools in many regions of the world.

With advancements in technology such as LiDAR and photo-optical sensing, there has been increased momentum in the testing, developing and marketing of technologies that are increasingly replacing traditional measurement methods. To date, several platforms and technologies have been tested with good results in capturing the biometrical features of logs, such as mobile LiDAR scanners (de Miguel-Díez, 2022) and various smartphone applications (Borz et al., 2022a; Niță & Borz, 2023; Tomaštíc et al., 2017). These technologies have shown a great deal of potential in saving time and effort (Borz & Proto, 2022), but few studies have addressed the ergonomic conditions of their use (Borz et al., 2022b). The basic principle of their operation is scanning, which is characterized by a series of continuous movements that are usually done smoothly (Forkuo & Borz, 2023) at a low walking speed; in contrast, the use of conventional tools such as callipers may require a higher proportion of stationary work. The weight carried by the operator also depends on the tools used, with the smartphone platforms demonstrating a high potential to reduce carrying effort.

At first glance, these new tools may appear very promising from an ergonomic point of view, since no direct contact with the measured object is required, and their weight is low (Borz et al., 2022a). However, they may require quite frequent changes in working posture so as to cover the logs by scanning. The literature on the topic is still underdeveloped, with just one study that assessed postural risk in wood measurement tasks (Borz et al., 2022b). This comes in a context where biomechanical exposure is one of the main concerns today, mainly because it can lead to musculoskeletal disorders, disabilities, and an increase in health-related costs (Helander, 2006). In particular, forestry work is known to lead to health problems such as low back pain (Gallis, 2006; Grzywinski et al., 2016). Most manual and motor-manual forest operations are known to generate increased risks of developing musculoskeletal disorders due to factors such as the postures assumed by the workers (Cheța et al., 2018; Spinelli et al., 2018). Conventional wood measurement is no exception, as indicated by a previous study (Borz et al., 2022b). This is because measurements are typically taken on logs placed on the ground, which may require uncomfortable postures of the back and legs, or on logs placed in piles, which may require uncomfortable arm postures. Additionally, there may be a need to carry measurement tools such as forest callipers and tapes, which are heavier than a smartphone.

The risk of developing musculoskeletal disorders is commonly evaluated by a postural assessment method. To date, there are several postural assessment methods used in industry (David, 2005), of which the OWAS method (Karhu et al., 1977) has been widely adopted due to its low complexity, ease of use, coverage of all body parts, and usability in various work environments, including forestry (Corella Justavino et al., 2015; Calvo, 2009). One of the main concerns related to the use of postural assessment methods is their validity (David, 2005), where the repeatability of outcomes is important to validate their results.

This work was designed mainly as a follow-up study. As a first objective, the study checked the repeatability of results on postural assessment when using digital tools to measure wood, by considering new datasets which were collected by observing several subjects in new work conditions. A second objective of the study was to explore and evaluate the postural implications of a new way of measuring wood, namely the scanning of logs loaded into trucks. The objectives were operationalized by computing the postural risk indices and the frequencies of activities per action category. This was complemented by a detailed description of the frequencies of body part postural conditions according to the OWAS method, as well as statistical comparison tests to check for significant differences in the outcomes of postural assessment factored by the measurement method used.

Materials and methods

1. Measurement instrumentation and data collection

Data supporting this study were collected between 14 February and 12 May 2022 in Romania, at the wood storage facility of HS Timber Group Reci, located at 46°4'34"N, 25°54'16"E. Four types of activities were covered by this study, reflecting the use of conventional and advanced wood measurement options. Table 1 gives a description of the activities divided into elemental tasks, with abbreviations for the compared datasets based on the type of measurement method (scanning – S; manual measurement – MM), location of the logs (on the ground – G; loaded in a truck – T), and the platform used for measurement by scanning (professional LiDAR – Z; scanner and smartphone – P).

The logs used in the study were mostly sourced from Norway spruce trees harvested from Romanian forests, predominantly in thinning operations. The timing relative to the stands' age, and the time span between the interventions, commonly generate large variability in the harvested tree sizes. Typically, the logs processed by the company have a length of about 3 or 4 meters, and a mid-diameter ranging from about 20 to 40 cm.

Table 1. Description of the observed activities

Activity (abbreviation)	Description	Tasks (abbreviation)
Scanning groups of logs at the ground by a professional Li-DAR scanner (SLGZ)	The subject prepares the instrument, runs the effective scanning by surrounding groups of logs (50 to 250 logs) placed at the ground at a distance of approximately 60 cm each other	The subject prepares the instrument for scanning (P) The subject uses the instrument to effectively scan the logs (GS) The subject saves the data in the memory of the instrument (SD)
Scanning piles of logs in the trucks by a professional Li-DAR scanner (SLTZ)	The subject prepares the instrument, runs the effective scanning by surrounding a given truck and, when the case, moves to another location for scanning	The subject prepares the instrument for scanning (P) The subject uses the instrument to effectively scan the logs (GS) The subject moves to another place of work (M) The subject saves the data in the memory of the instrument (SD)
Scanning individual logs at the ground by a smartphone (SLGP)	The subject prepares the instrument, runs the effective scanning by surrounding each log from a group of logs (50 to 250 logs) placed at the ground at a distance of approximately 60 cm each other	The subject prepares the instrument for scanning (P) The subject uses the instrument to effectively scan a given log (PS) The subject saves the data in the memory of the instrument (SD) The subject carries on other tasks which are not related to the scanning work (PD)
Measuring manually individual logs at the ground by a calliper and a tape (MM)	The subject prepares the instruments and runs the effective measurements on each log from a group of logs (50 to 250 logs) placed at the ground at a distance of approximately 60 cm each other	The subject prepares the instruments for measurement (P) The subject moves to another log or place of work (M) The subject measures the log (ML) The subject carries on other tasks which are not related to the measuring work (PD)

The logs were scanned individually with a smartphone, measured individually by manual tools, or scanned as groups. As regards location, the logs were either placed on the ground or as piles into trucks. A professional LiDAR scanner (Zeb Revo, GeoSLAM) was used to scan groups of logs placed on the ground or loaded into trucks, due to its capability in terms of scanning range, which is up to 30 m. A Huawei P40 Pro equipped with the Forest Design Scanner application (https://forestdesign.ro/index.php/ro/) was used to scan the logs individually, with a shorter scanning range of typically less than 5 m. Finally, manual measurements were taken by a calliper and a tape on individual logs, following a protocol developed in the Hypercube 4.0 project (see, for instance, Niță & Borz, 2023), which aimed to collect reference biometric figures to check the accuracy of digital measurements. Examples of the methods used for measurement are shown in Figure 1.

Four subjects were observed during the field data collection. However, no differentiations were made to identify a given subject working in a given type of task. GoPro Hero 10 video cameras were set up to collect video files continuously so as to record the observed tasks. The collected films were each 12 minutes in length, and they covered all of the tasks carried out on a given day. In total, 80 high-quality films, covering all of the observed wood measurement activities, were selected for data processing.

a b c d

Fig. 1. Examples from measurement activities taken into study: a – scanning groups of logs at the ground by a professional LiDAR scanner (SLGZ), b – scanning piles of logs in the trucks by a professional LiDAR scanner (SLTZ), c – scanning individual logs at the ground by a smartphone (SLGP), d – measuring manually individual logs at the ground by a caliper and a tape (MM)

2. Data processing

Frames were extracted from each film, resulting in about 709 still images extracted from each file. This step was carried out using the Free Video to JPG Convertor software (https://www.dvdvideosoft v 5.1.1), resulting in 82 sets of still images. Sets of random numbers between 1 and 180 were then generated in Microsoft Excel and used to select images from each dataset based on their identification number. A total of 14,940 still images were extracted and checked for usability in the postural analysis (Table 2). Of these, all images that failed to show all of the body parts required by the analysis were removed from the dataset. The retained images accounted for 28% to 71% of the original datasets, and overall close to 49% of the data (Table 2). The percentages of valid images for measurement methods and their elemental tasks are given in Table 3. As shown, images depicting effective measurement were dominant, accounting for close to 60% in the case of scanning of individual logs with a smartphone, and close to 70% for the remaining measurement methods.

Valid images were evaluated, and codes for the posture of the back, arms and legs, and for the level of force exertion were assigned to each image, in accordance with the OWAS method (Karhu et al., 1997; Helander, 2006; Corella Justavino et al., 2015). Postural codes included a text code characterizing the task, as described in Table 1. The OWAS method includes four possible postures of the back, three postures of the arms, seven postures of the legs, and three levels of force exertion. These are combined in a four-digit sequence based on which a given instance is assigned to one of the four possible action categories (ACs). The four action categories describe the severity of postural condition in terms of the timing of ergonomic interventions to be taken. According to the first AC, no ergonomic intervention is required, whereas the second, third and fourth ACs indicate respectively that corrective actions are required in the near future, as soon as possible, and immediately (Karhu et al., 1997; Helander, 2006; Corella Justavino et al., 2015). Since the tools used for measurement involved either carrying a smartphone or a mobile LiDAR scanner in a backpack while using the scanning device with the arm, or carrying and using a calliper, the force exertion was assumed to be less than 10 kg in all cases.

Table 2. Description of the used data

Activity	Number of observed subjects	Number of films	Film length (s)	Number of extracted frames	Number of valid frames	Share of valid frames (%)
SLGZ	4	21	14.901	3780	1175	31.08
SLTZ	3	21	9.448	3780	2684	71.01
SLGP	2	20	14.193	3780	1079	28.54
MM	2	20	14.195	3600	2370	65.83
Total	4	82	52.737	14940	7308	48.92

Table 3. Share of data on activities and elemental tasks

Activity	Task[1]						
	GS	M	ML	P	PD	PS	SD
SLGZ	69.02			7.49			23.49
SLTZ	68.77	0.37		5.84	25.02		
SLGP				8.01	11.07	61.85	19.07
MM		15.99	74.22	0.13	9.66		
Total							

Note: [1] The tasks abbreviated in Table 3 are described in Table 1.

3. Data analysis

Data analysis was carried out in Microsoft Excel at the elemental task and measurement method levels. Based on the codes attributed to each body part, the action category of each image was determined by means of Visual Basic for Applications code developed in the Visual Basic Editor of Microsoft Excel. The matrix used to place a given instance in an action category is described, for instance, in Calvo (2009). The data on action categories were sorted by elemental task and measurement method, and analysed at those levels of data organization. To characterize the ergonomic risk for elemental tasks and measurement methods, the postural risk index (PRI) was used, as described for instance by Zanuttini et al. (2005). This metric weights the action categories by their relative frequency in a dataset, and provides a numerical result between 100 and 400 to characterize the overall risk of a task or activity. Based on the analysis steps described, the data was organized by elemental task and measurement method in the form of graphics showing the relative frequencies of action categories and the computed postural indices. To detect potential statistical differences between the distributions characterizing the four datasets at the action category level, the Real Statistics add-in running under Microsoft Excel was used to implement nonparametric statistical comparison tests. In the statistical comparison, a given measurement method was included as a nominal input variable, whereas the action category was included as an ordinal outcome variable, since it describes actions to be taken in increasing order of urgency. Comparisons were implemented between each possible pair of datasets, characterizing the action category data using a Mann–Whitney test, with the confidence threshold to detect differences set at $\alpha = 0.05$ ($p<0.05$). Mann–Whitney tests were implemented using (i) tie correction, since the likelihood of ties was large, (ii) a continuity correction, since the data were limited to four ordinal values, and (iii) an effect size statistic (effect r), which basically explains the differences in variance. For instance, values of 0.3 to 0.5 indicate a medium to large effect size.

Results and discussion

1. Postural risk

The main results of this study are shown in Figs. 2 to 5. Overall, measuring the logs by scanning returned the best postural condition, irrespective of the platform used, location, and degree of grouping of the logs (Figs. 1 to 3). The postural risk indices were 147 for SLGZ (Fig. 2), 159 for SLTZ (Fig. 3) and 167 for SLGP (Fig. 4). Clearly this is an effect of the dominance of the first action category in these datasets. However, the first option (SLGZ) gave the best postural condition. This can be attributed to the way in which effective scanning is performed. For instance, the frequencies of action categories differed between SLGZ and SLTZ, with a higher frequency of the second action category in the latter dataset. Here, the way in which the instrument is used differs mainly in terms of the posture of the arms, since it is required to point the scanning devices upwards to cover the logs piled into trucks. This means that, in some cases, the posture of the arms was changed sufficiently that changes in the action category occurred. Scanning individual logs on the ground using a smartphone is far easier in terms of weight carried. However, to properly cover the logs by scanning, some back bending may be required, given the location of the measured objects and the scanning range capabilities. This is made clear in Fig. 4, which shows the completely different distribution of the action categories, where the first action category accounted for slightly less than 50% of the data.

Instrument preparation and data saving are elemental tasks that entail different approaches in the way that the instruments are used. In the first two activities (SLGZ, SLTZ) the instrument is usually operated from near the ground when it is set up and when the data are saved (Borz & Proto, 2022). In contrast, preparation of the instrument and data saving after scanning with a smartphone are usually done from a standing position (based on the data supporting this study), while the effective scanning process is similar to that used with a professional LiDAR scanner, by scanning in a closed loop (Niță & Borz, 2023). These differences may be clearly seen in the postural risk indices and distribution of data on action categories, as shown for elemental tasks P and SD in Figs. 2 to 4. For the first two activities (SLGZ, SLTZ), the postural risk indices for preparation (P) and saving data (SD) were respectively 238 and 243, and 290 and 260. For the third activity, the postural risk indices of these elemental tasks were 213 and 114, respectively.

Compared with a previous study on the postural assessment of manual and scanning options in log measurement (Borz et al., 2022b), the results indicate a certain degree of similarity in terms of postural risk indices. In this study, scanning groups of logs placed on the ground with a professional mobile LiDAR scanner returned a postural risk index of 147, whereas Borz et al. (2022b) reported a postural risk index of 150. Also, scanning individual logs with a smartphone produced a postural risk index of 213 in this study, which was close to the value of 180 reported by Borz et al. (2022b). In addition, this study evaluated the postural implications of scanning piles of logs located in a truck using a mobile LiDAR scanner. Although this was similar to the case of scanning of logs placed on the ground, it returned a higher value for the postural risk index (159) and indicated assignment of this activity to the second action category.

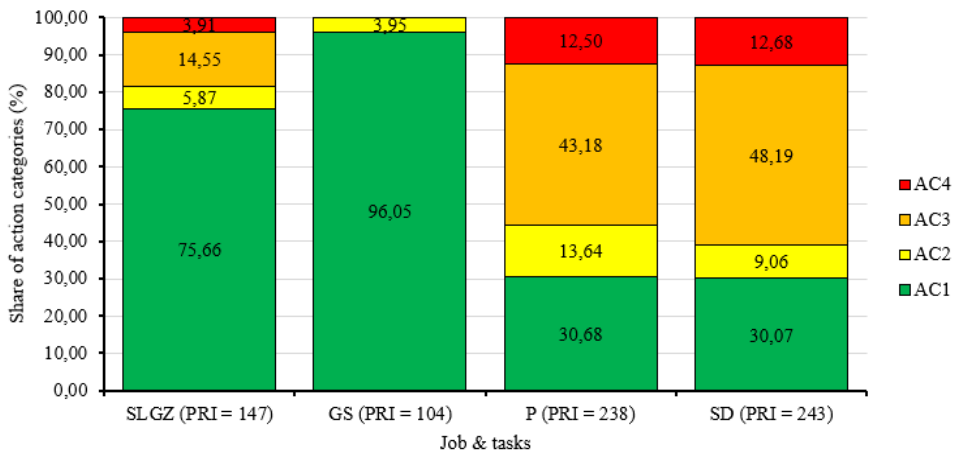


Fig. 2. Share on action categories and postural risk index when scanning groups of logs at the ground by a professional LiDAR scanner (SLGZ). Legend: AC1 to AC4 stand for the action categories 1 to 4. Note: GS – effective scanning by the instrument, P – preparing the instrument for scanning and SD – data saving

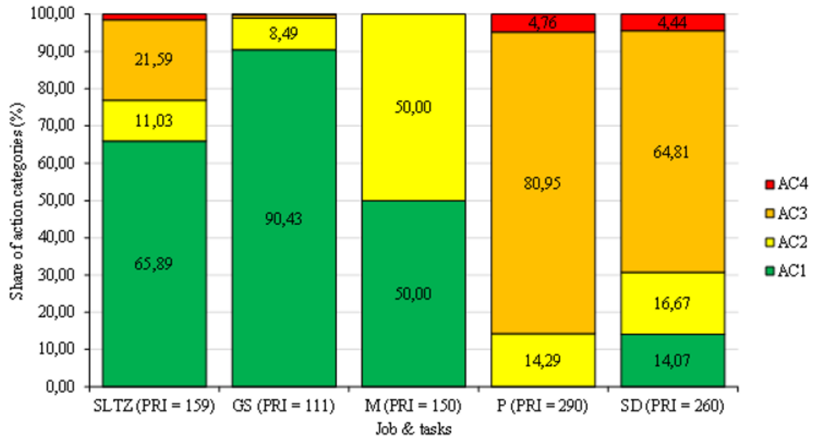


Fig. 3. Share on action categories and postural risk index when scanning piles of logs into a truck by a professional LiDAR scanner (SLTZ). Legend: AC1 to AC4 stand for the action categories 1 to 4. Note: GS - effective scanning by the instrument, M – moving to another place of work, P - preparing the instrument for scanning and SD - data saving

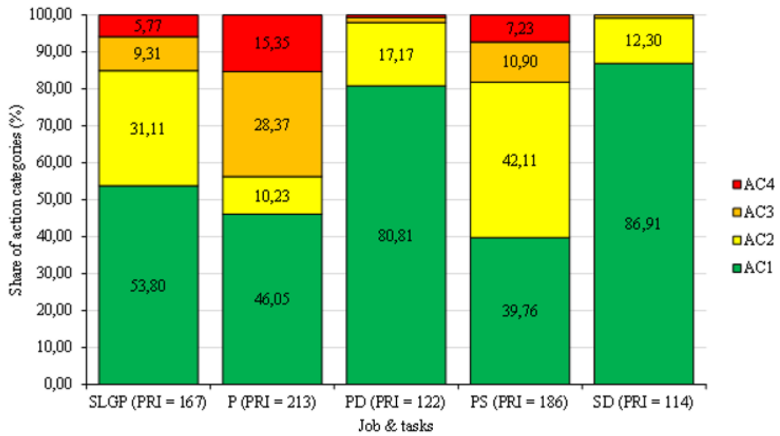


Fig. 4. Share on action categories and postural risk index when scanning individual logs at the ground by a smartphone (SLGP). Legend: AC1 to AC4 stand for the action categories 1 to 4. Note: P - preparing the instrument for scanning, PD – carrying on other tasks not related to the work, PS – effective scanning by the smartphone and SD - data saving

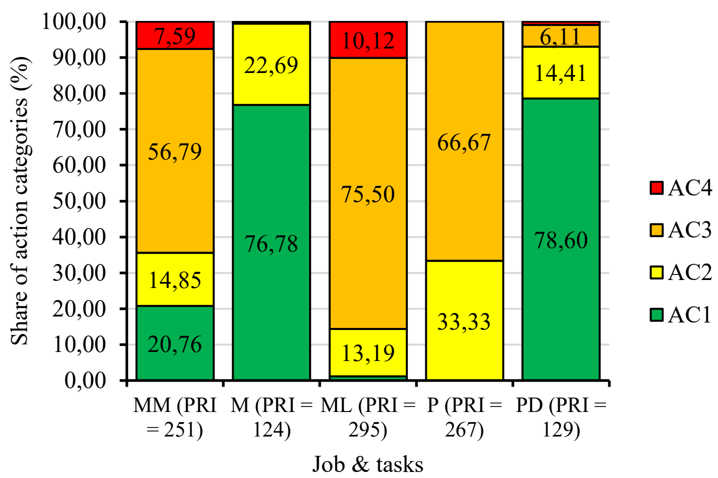


Fig. 5. Share on action categories and postural risk index for manual measurement (MM). Legend: AC1 to AC4 stand for the action categories 1 to 4. Note: M - moving to another log or place of work, ML - measuring the log, P - preparing the instruments for measurement, and PD – carrying on other tasks not related to measuring work

Similarly as in the study by Borz et al. (2022b; PRI = 250.5), manual measurement returned the highest postural risk index in this study, equal to 251, resulting largely from effective measurement and preparation of tools (Figure 5), which were tasks generally assigned to the second and third action categories. Altogether, the first three activities seem to require no urgent corrective actions, indicating insignificant risks of developing musculoskeletal disorders. Consistently with the work of Borz et al. (2022b), however, it was found that manual measurement appears to require corrective measures as soon as possible. By visual analysis of the data in the frequency domain, the distribution of data indicates clear differences between the two first (SLGZ, SLTZ) and two last (SLGP, MM) datasets. The former appeared to be similar in terms of the distribution of instances to action categories, whereas the third and fourth action categories indicated different relative distributions.

2. Body part posture

Frequencies of postures of body parts are given in Table 4. As shown, scanning by a smartphone led to a significant proportion of cases with the back being bent and twisted, or bent forward and sideways, which is consistent with the way in which the scanning was done. This comes mostly from the data covering preparation and effective scanning tasks (data not shown here). When scanning piles of logs loaded into trucks, most of the changes in arm postures occurred in a significant proportion of the analysed images in which at least one arm was at or above shoulder level. However, these occurred mostly with a straight back. For manual measurement, there was a higher proportion of cases where the back was bent forward, which is natural when diameters of logs are measured with a calliper, as well as a significant proportion of images in which one or both arms were at or above shoulder level.

Table 4. Share of data on activities and elemental tasks

Activity	Postural codes of the body parts[1]													
	B1	**B2**	**B3**	**B4**	**A1**	**A2**	**A3**	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**
SLGZ	36.7	15.3	42.5	5.5	98.2	1.1	0.7	-	0.5	8.9	19.2	2.2	-	69.2
SLTZ	64.3	25.7	8.5	1.5	60.6	23.6	15.8	-	1.9	7.0	25.8	3.9	-	61.4
SLGP	45.8	25.4	11.1	17.7	98.3	1.0	0.7	2.1	2.4	26.1	4.7	13.3	-	51.4
MM	27.3	63.5	4.1	5.1	84.2	9.8	6.0	-	4.2	5.8	47.4	26.3	-	16.3

Note: [1] Postural codes of the body parts according to the OWAS method: B1 - straight, B2 - bent forward or backward, B3 - twisted or bent sideways, B4 - bent and twisted or bent forward and sideways, A1 - both arms below shoulder level, A2 - one arm is at or above the shoulder level, A3 - both arms are at or above shoulder level, L1 - sitting, L2 - standing with both legs straight, L3 - standing with the weight on one straight leg, L4 - standing or squatting with both knees bent, L5 - standing or squatting with one knee bent, L6 - kneeling on one or both knees, L7 - walking or moving.

Table 5. Results of comparison tests between the measurement methods

Compared variables[1]	Results of the Mann-Whitney test		
	α	**p-value[2]**	**effect r[3]**
SLGZ-SLTZ	0.05	0.00001	0.092
SLGZ-SLGP	0.05	0.00000	0.159
SLGZ-MM	0.05	0.00000	0.482
SLGP-SLTZ	0.05	0.00003	0.068
SLGP-MM	0.05	0.00000	0.440
SLTZ-MM	0.05	0.00000	0.430

Note: [1] The values of action categories were considered ordinal variables since they designate, from 1 to 4, increasing concerns and ergonomic interventions to be taken; [2] p - values of less than 0.05 indicate significant statistical differences ($\alpha = 0.05$, $p < 0.05$) in terms of distribution on action categories in the compared datasets; [3] values of the effect r are judged against the commonly used comparison scales where 0.1 is a small effect, 0.3 is a medium effect and 0.5 is a large effect.

Except for manual measurement, all of the measurement methods involved a high degree of movement (L7 for the legs). However, because scanning with a smartphone was done piece by piece, it produced less leg movement during scanning. For reference, according to the classification matrix of the OWAS method, a posture for the back coded with 2, 3 or 4, coupled with a posture of the arms coded with 2 or 3, and with a posture of the legs coded with 4 or 5, leads to assignment to the fourth action category (Calvo, 2009; Corella Justavino et al., 2015). The present results confirm and validate the finding that measuring logs by mobile scanning carries less risk than manual measurement. This finding is also supported by the median values of the action category data, which were always 1 for measurement methods based on scanning and 3 for the manual measurement (explicit data not shown here). The comparison tests indicated significant differences between all pairs of measurement methods, as shown in Table 5. However, the effect sizes were consistently larger (> 0.4) when comparing the distribution of data from MM against any of the scanning-based measurement methods (Table 5).

In addition, wood measurement by scanning appears to carry less risk than motor-manual felling (Cheța et al., 2018; PRI = 275), motor-manual willow felling with brush cutters (Borz et al., 2019; PRI = 191–192), manual cultivation of poplar (Marogel-Popa et al., 2019; PRI = 179.9), and manual planting of poplar seedlings and cuttings (Marogel-Popa et al., 2020; PRI = 250–259), and similar or greater risk compared with wood debarking (Spinelli et al., 2018; PRI = 114–150). Also, the results confirm the repeatability of outcomes, as similar data for postural risk indices were obtained for three wood measurement options. Scanning the logs piled into trucks, however, seems to be at an intermediate position in terms of postural risks, placing this activity between the scanning of logs placed on the ground using a professional mobile LiDAR scanner and similar scanning using a smartphone.

With the advancement in close-range sensing technologies and intelligent algorithms, the near future will probably see the elimination of the need for humans to undertake manual wood measurement tasks. Until then, this study provides documented information on the potential risks of developing musculoskeletal disorders when carrying out wood measurement tasks, validates the repeatability of the results, and evaluates the risk associated with the scanning of logs piled into trucks.

Conclusions

The assignment of the risk of developing musculoskeletal disorders, as evaluated by the OWAS method, to the first and at most the second action category is valid, based on the results of this study for activities such as scanning groups of logs placed on the ground by means of mobile professional LiDAR scanners and smartphones. In other words, the postural risk indices computed based on the data from this study confirm previous findings on the risks of developing musculoskeletal disorders in such tasks. Also, scanning the logs piled into trucks seems to be at the boundary between the first and the second action category based on the computed postural risk index, meaning that no significant postural risks were identified for this measurement option.

The proportions of postures of body parts were consistent with the way of performing the work in all of the studied measurement methods, whereas the distribution of data on action categories indicated that the measurement methods have their own particularly features. In other words, the distribution of data was specific to each method of measurement, generating statistically significant differences between any two methods under comparison. However, the effect size of comparison tests was large only when comparing the data for manual measurement against any of the scanning-based methods.

Acknowledgements

The authors would like to acknowledge the support of the Hypercube 4.0 project's team members who were actively involved in collecting and processing the data required in this study. The authors would like to thank to the Department of Forest Engineering, Forest Management Planning and Terrestrial Measurements for supporting this study.

Funding source

This work was supported by a grant of the Romanian Ministry of Education and Research, CNCS – UEFISCDI, project number PN-III-P4-ID-PCE-2020-0401, under PNCDI III. One of the objectives of the Hypercube 4.0 project is to test the ergonomic efficiency of advanced technologies for wood measurement against the traditional manual options.

Data availability statement

Interested readers can be provided with the database supporting this study upon a reasonable request to the first author.

Informed consent

The subjects who participated in this study were the team members of the Hypercube 4.0 project. They were informed about the goal of the study and the intended use of the data, according to the project grant and to the contractual specifications; they agreed verbally to participate as subjects in the study based on a non-identity disclosure clause.

References

Borz, S.A., Talagai, N., Cheţa, M., Chiriloiu, D., Gavilanes Montoya, A.V., Castillo Vizuete, D.D., Marcu, M.V. 2019. Physical strain, exposure to noise and postural assessment in motor-manual felling of willow short rotation coppice: Results of a preliminary study. Croat. J. For. Eng. 40, 377–388.

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. Agr. 197, 106990.

Borz, S.A., Morocho Toaza, J.M., Forkuo, G.O., Marcu, M.V., 2022a. Potential of Measure app in estimating log biometrics: A comparison with conventional log measurement. Forests 13, 1028.

Borz, S.A., Papandrea, S., Bacenetti, J., Proto, A.R. 2022b. Postural assessment of three measurement options by the OWAS method: Digital solutions seem to be better. Forests 13, 2007.

Calvo, A. 2009. Musculoskeletal disorders (MSD) risks in forestry: A case study to propose an analysis method. Agric. Eng. Int., 11, 1–9.

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.

Corella Justavino, F., Jimenez Ramirez, R., Meza Perez, N., Borz, S.A. 2015. The use of OWAS in forest operations postural assessment: advantages and limitations. Bull. Transilvania Univ. Braşov 8, 7–16.

David, G.C. 2005. Ergonomic methods for assessing exposure to risk of factors for work-related musculoskeletal disorders. Occup. Med-C. 55, 190–199.

de Miguel-Díez, F., Reder, S., Wallor, E., Bahr, H., Blasko, L., Mund, J.-P., Cremer, T. 2022. Further application of using a personal laser scanner and simultaneous localization and mapping technology to estimate log's volume and its comparison with traditional methods. International Journal of Applied Earth Observations and Geoinformation 109, 102779.

Forkuo, G.O., Borz S.A. 2023. Accuracy and inter-cloud precision of low-cost mobile LiDAR technology in estimating soil disturbance in forest operations. Front. For. Glob. Change 6,1224575.

Gallis, C., 2006. Work-related prevalence of Musculoskeletal symptoms among Greek forest workers. Int. J. Ind. Ergonom. 36, 731–736.

Grzywinski, W., Wandycz, A., Tomczak, A., Jelonek, T., 2016. The prevalence of self-reported musculoskeletal symptoms among loggers in Poland. Int. J. Ind. Ergonom. 52, 12–17.

Helander, M., 2006. A Guide to Human Factors and Ergonomics, 2nd ed.; CRC Press: Boca Raton, FL, USA.

Karhu, O., Kansi, P., Kuorinka, I. 1977. Correcting working postures in industry: a practical method for analysis. Appl. Ergon. 8, 199–201.

Kemmerer, J., Labelle, E.R., 2021. Using harvester data from on-board computers: a review of key findings, opportunities and challenges. Eur. J. For. Res. 140 (1), 1–17.

Leahu, I. 1994. Dendrometrie. Editura Didactică şi Pedagogică Bucureşti, 374 p.

Lundbäck, M., Häggström, C., Nordfjell, T., 2021. Worldwide trends in methods for harvesting and extracting industrial roundwood. International Journal of Forest Engineering 32, 202–215.

Marogel-Popa, T., Cheţa, M., Marcu, M.V., Duţă, C.I., Ioraş, F., Borz, S.A. 2019. Manual cultivation operations in poplar stands: A characterization of job difficulty and risks of health impairment. Int. J. Env. Res. Pub. Health 16, 1911.

Marogel-Popa, T., Marcu, M.V., Borz, S.A. 2020. Postural risk in manual plating operations of poplar: two options compared. Sustainability 12, 5531.

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. Croat. J. For. Eng. 38, 231–241.

Müller, F., Jaeger, D., Hanewinkel, M., 2019. Digitization in wood supply-a review of how Industry 4.0 will change the forest value chain. Comput. Electron. Agr. 162, 206–218.

Niță, M.D., Borz S.A., 2023. Accuracy of a Smartphone-based freeware solution and two shape reconstruction algorithms in log volume measurements. Comput. Electron. Agr. 205, 107653.

Spinelli, R., Aminti, G., Magagnotti, N., De Francesco, F. 2018. Postural risk assessment of small-scale debarkers for wooden post production. Forests 9, 111.

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. Agr. 141, 109–117.

Zanuttini, R., Cielo, P., Poncino, D. 2005. The OWAS method. Preliminary results for the evaluation of the risk of work-related musculo-skeletal disorders (WMSD) in the forestry sector in Italy. For. Riv. Selvico. Ecol. For. 2, 242–255.