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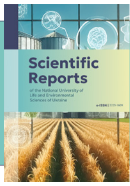

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Analysis of wood defects in *Pinus sylvestris* L. using digital scanning

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Abstract. Given the growing demand for wood and the need for its rational use, determining the quality of raw materials becomes particularly relevant, for which digital scanning of wood is promising, which allows automated identification and assessment of its shortcomings, but visual assessment method is mainly used in Ukraine. The main goal of the current study was to empirically assess wood defects in *Pinus sylvestris* L. on a sample of lumber by digital scanning and comparing the data with the results obtained by conventional visual diagnostics. Statistical analysis included comparing the results between methods, assessing the degree of their compliance, and analysing the nature of discrepancies using a paired t-test for dependent samples, an intra-class correlation coefficient, and Bland-Altman

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analysis. The use of the digital method showed higher values for all assessed wood defect parameters, including the number and diameter of knots, the number of resin pockets, grain slope, pith eccentricity, compression, curvature, convergence, and both the length and relative size of cracks. Statistical analysis confirmed the presence of statistically significant differences between the two methods in all the parameters under study ($p < 0.001$). The intra-class correlation coefficient showed a moderate, high or very high level of consistency (in the range of 0.72-0.91). The Bland-Altman analysis revealed a systematic bias between digital and visual methods, but the absence of a pronounced proportional bias and a stable distribution of differences in indicators indicated an acceptable level of consistency between approaches within the parameters under study. The practical significance of the results obtained lies in the possibility of using the digital scanning method as an additional tool to traditional visual analysis to improve the accuracy, objectivity and reproducibility of wood quality assessment. The results can be used in production activities, and in the creation and implementation of automated quality control systems for lumber

Keywords: lumber quality; digital image processing; consistency of methods; intra-class correlation; forestry of Ukraine

Introduction

Scots pine (*Pinus sylvestris* L.) is one of the main forest species in Ukraine. It forms a significant part of the raw material base for the woodworking and construction industries due to its wide distribution, rapid growth, and high performance. The qualitative potential of pine wood largely depends on its properties, which are determined by the presence of defects, physical and mechanical characteristics and anatomical structure. In particular, the presence of defects such as knots, cracks, curvature, etc., directly affects the modulus of elasticity and strength of lumber, which determines its suitability for structural applications (Meshkova, 2021). The study by A. Terentiev *et al.* (2023) analysed the current state and productivity of modal stands of Scots pine in the Forest-Steppe zone of Ukraine based on tax data, and established structural differences by growth regions and the main characteristics of areas and stocks of stands divided into four groups, providing findings that may support the refinement of forest management standards and forest-use planning.

In the context of growing demand for wood and the need for its rational use, the issue of accurate assessment of the quality of raw materials becomes extremely relevant. Disadvantages of wood, both natural (for example, the presence of knots) and pathological (in particular, resin accumulation or rot), significantly reduce its technological value and economic efficiency of processing (Kulak *et al.*, 2023). Special attention should be paid to internal defects that remain invisible with conventional inspection methods, but have a significant impact on the quality of finished products. For example, biotic damage that causes resin accumulation leads to reduced lumber yields and significant economic losses for the woodworking industry.

In this context, the use of digital technologies for analysing wood defects is becoming increasingly important, which allows automating the evaluation process and increasing the objectivity of product quality control. Despite the active introduction of such methods in international practice, the traditional visual approach still dominates in Ukraine, and research in the field of digital wood analysis remains insufficiently systematised. In this regard, it is important to conduct additional empirical studies to assess the accuracy and reliability of digital methods for determining wood defects.

Conventional approaches to wood quality assessment are based primarily on visual analysis, but such methods have a number of disadvantages: they are subjective, time-consuming, and characterised by insufficient accuracy, since they allow detecting only surface defects. That is why in the contemporary scientific literature, more and more attention is paid to research related to the use of digital technologies for automated analysis of wood defects. For example, S. Hwang & J. Sugiyama (2021) pointed out that computer vision, machine learning, and digital image analysis techniques, including X-ray computed tomography, have significant potential for automated detection and evaluation of wood structural features, creating prerequisites for their use in the study of its defects.

Y. Huang *et al.* (2024) in their paper investigated the use of X-ray computed tomography to analyse the internal structure of Scots pine wood. The researchers found that X-ray and CT scans allow non-destructive diagnostics of the internal characteristics of wood and obtain detailed information about the density distribution, the presence of knots, cracks and other structural defects. The study also noted that the use of digital tomography contributes to the creation of a "virtual log model", which allows optimising sawing processes and predict the quality of finished products, which indicates the significant potential of digital methods to improve the efficiency of woodworking production. M. Wieruszewski *et al.* (2022) analysed the relationship between the strength properties of Scots pine (*Pinus sylvestris* L.) sawn timber on specific wood defects, establishing that defects (knots, cracks, irregularities) have a statistically significant effect on the mechanical strength of the product, which is of practical importance for the classification and technical assessment of timber in the woodworking industry.

The main goal of the current study was to empirically assess wood defects of *Pinus sylvestris* L. by digitally scanning the lumber and comparing the data with the results obtained by traditional visual diagnostics. The main tasks were: 1) to conduct a visual assessment and digital scanning of a representative sample of Scots pine lumber samples, obtaining quantitative parameters of wood defects; 2) to determine the defects of wood samples based on scanning data and compare with the results of visual evaluation; 3) to assess the degree of convergence of the two methods and their discrepancies, and to determine the mean absolute error (MAE) and root-mean-square error (RMSE). The scientific originality of the study consists in conducting an empirical investigation aimed at comparing the traditional visual method for assessing the defects of Scots pine wood with a contemporary digital approach.

Literature Review

Since 2019, Ukraine has implemented a timber classification system harmonised with European standards, according to which the quality of wood was determined by classes: from A to D (State Forest Resources Agency of Ukraine, 2019). The key criterion for determining whether wood belongs to a certain class is the quantitative and qualitative assessment of its defects, which directly affect the operational properties of the material. The current classification system often does not consider the specific features of Ukrainian forest resources, which often leads to controversial issues in the quality assessment process and makes it necessary to develop additional technical regulations. In Ukraine, research in the field of wood defect analysis using digital technologies remains fragmented, and the main method is visual quality assessment. This approach, for all its accessibility and simplicity, requires significant time resources and is significantly affected by the subjective factor (Wan *et al.,* 2021).

Digital scanning of wood, including the methods of computer vision, laser scanning, and X-ray tomography, is almost not used in Ukraine. The main obstacles to this are a combination of technological, economic, and organisational factors, in particular: expensive equipment, lack of software and algorithms for local conditions, insufficient scientific research, lack of implementation of digital tools for determining wood defects at the state level. Despite this, the potential for the development of this area in Ukraine is significant, since the integration of contemporary approaches opens up opportunities for more accurate detection of defects, minimises the subjective factor, and ensures more rational use of forest resources. The actual implementation of digital wood scanning procedures and its accuracy in comparison with the classical (visual) method remain relevant.

B. Jambreković *et al.* (2024) investigated the effectiveness of machine learning algorithms and deep image analysis in the process of automatic detection of oak wood defects. The researchers found that computer vision algorithms significantly increase the speed and accuracy of identifying knots, cracks, and other defects compared to traditional approaches, and also noted that digital systems work better with clearly defined defects, while complex heterogeneous structures can be determined less stably, which indicates the prospects for integrating artificial intelligence elements into wood quality assessment processes. In turn, A. Rais *et al.* (2017) analysed the possibilities of statistical models of segmentation of digital images to identify complex wood defects and came to a similar conclusion that modern segmentation methods enable better recognition of individual types of defects even in conditions of heterogeneous surface texture of the material. The issue of stability of algorithms in cases of changes in lighting and the quality of digital images was ignored by the study, which can significantly affect the results of the analysis. D. Lopes *et al.* (2025) in a review of factors determining resin production in pine species, systematised the effects of biotic, abiotic and silvicultural (forestry) practices on the development of the quantity and quality of resin, emphasising the role of physiological properties of wood for technological and economic aspects of forest management and processing.

V.-T. Nguyen *et al.* (2021) investigated the use of LiDAR technologies and three-dimensional scanning to assess the geometric characteristics of a tree trunk and detect surface defects. In their study, the researchers concluded that remote sensing technologies allow automating individual stages of wood quality assessment and ensure high accuracy in measuring geometric parameters. J. Pyörälä *et al.* (2026) noted that the relationship between the external characteristics of wood and the internal properties of wood remains limited. The study also noted that evaluating only external parameters does not allow accurately predicting the quality of the internal structure of the material, which makes it necessary to integrate several digital analysis methods. S. Joevenller *et al.* (2025) studied the detection features of resin accumulation and internal structural changes in Scots pine wood using X-ray computed tomography. The researchers noted that certain types of defects, in particular resin pockets, remain difficult for stable automatic identification. In a follow-up study, S. Joevenller *et al.* (2026) proposed a hybrid approach to image segmentation that combined statistical models and digital processing algorithms. The researchers concluded that the accuracy of digital analysis significantly depends on the specifics of defects, the quality of scanning, and the parameters of processing algorithms.

In general, as previous studies show, the prospects of digital methods for analysing wood defects are significant, but the issues of their practical accuracy, consistency with conventional methods of assessment and adaptation to the conditions of the Ukrainian woodworking industry remain insufficiently investigated.

Materials and Methods

The study involved the use of a comparative experimental approach aimed at evaluating the effectiveness of digital scanning in detecting *Pinus sylvestris* L. defects compared to the visual diagnostic method. The methodology included successive steps: sampling, visual analysis, digital scanning, image processing, and subsequent statistical evaluation of the data obtained. The objects of the study were Scots pine lumber from wood harvested in one of the Ukrainian forestry enterprises, the sample consisted of 100 samples taken from different parts of the trunk – lower, middle, and upper. The geometric parameters of the samples were as follows: length – 1.0-1.5 m, width – 100-150 mm, thickness – 25-50 mm. Before starting work, the samples were cleaned of contamination and brought to an air-dry state (humidity 10-12%) under controlled laboratory conditions at a temperature of 20-22°C and a relative humidity of 50-60%. Wood assessment was carried out according to timber classification standards agreed with European requirements (classes A-D), considering the permissible limits of major defects (Podkorytov, 2015; State Forest Resources Agency of Ukraine, 2019). In the evaluation process, a system of quantitative and qualitative indicators was used:

- knots (quantity – units, diameter – cm);
- resin pockets (quantity – units/section);
- slope of growth fibres (cm/m);
- core displacement (%);
- compression (%);
- curvature (cm/m);
- convergence (cm/m);
- cracks (length – cm; relative size – fraction of the diameter Ø).

The same characteristics were checked during digital analysis, but their assessment was carried out automatically by processing digitised images. Visual assessment of wood was carried out by a group of independent experts ($n = 3$) who had a higher education in forestry and wood commodity science, and at least five years of practical experience in the field of wood and lumber quality assessment. Experts previously participated in the sorting assessment of wood in accordance with national standards and regulations in force in Ukraine. Before starting research, they received additional training aimed at clarifying the assessment procedure and standardising the criteria for fixing wood defects. Each sample was evaluated separately during a sequential review. A caliper (accuracy 0.1 mm), a ruler (accuracy 1 mm), and a protractor for determining the slope of the fibres were used to measure the defect characteristics. In case of disagreement in the results of 3 experts, a consensus approach was used: the sample was re-examined, after which the final value was determined.

Digital scanning of wood samples and analysis of their defects was performed using digital image analysis technology, which included sequential application of algorithms for pretreatment, filtering, contour selection, and segmentation of damage zones using the method of M. Özkan & C. Özcan (2024). The working area looked like a closed structure measuring 220×220×175 cm, within which the research object was located (Fig. 1). To ensure uniform illumination, two light sources with a power of 30 W and 20 W, respectively, were used, supplemented with a system of diffusers in the form of rectangular prisms covered with paper to minimise shadows and glare. The primary image was obtained by digital photography using a Fujifilm X-S1 camera with a resolution of 12 MP. It was fixed in a stable position on the side of the test sample, which provided standardised images of the wood surface. After photographing, the images were transferred to a digital environment for further processing. At the first stage, the resulting images were converted to greyscale, which simplified the analysis of surface texture and pixel intensity. The next step was to correct the brightness by adjusting the pixel intensity, which helped to improve the contrast of the defective areas compared to the rest of the wood surface. A median filter was used to eliminate noise from the digital image, and a value of 13×13 was recognised as the most effective for removing noise without losing important information about defects (Özkan & Özcan, 2024). The Canny edge detection algorithm was used to identify damage contours, which identifies boundaries based on brightness gradients (Canny, 1986). The algorithm included several steps: image smoothing, calculating horizontal and vertical gradients, suppressing non-maximal values, and applying double threshold filtering.

The thresholds selected based on experimental data were 20 (lower threshold) and 185 (upper threshold), which ensured high sensitivity of the algorithm to defect limits.

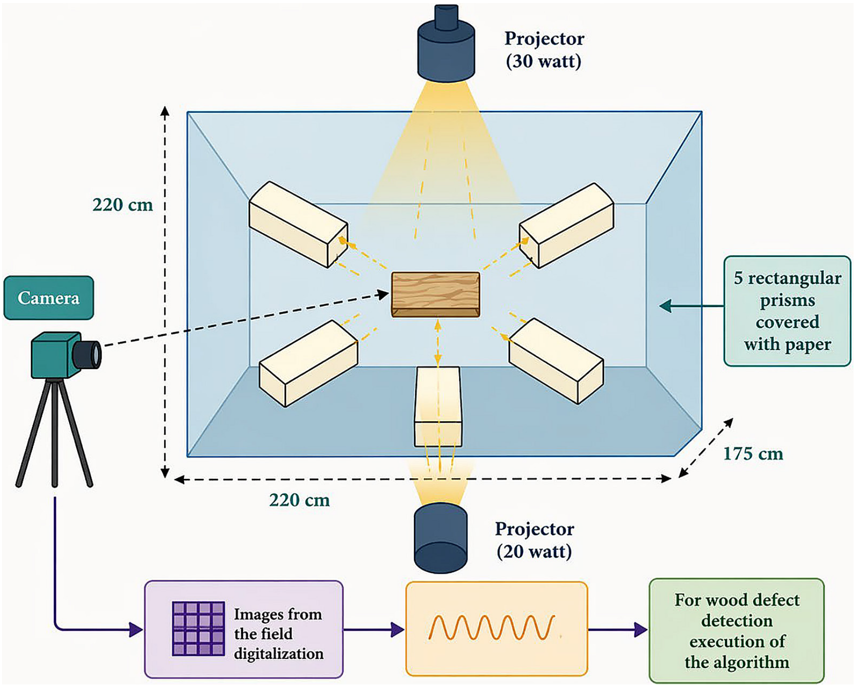

Figure 1. *Diagram of wood defect analysis using digital scanning in the current study*
Source: compiled by the authors

After determining the contours, the image was cropped based on the coordinates obtained as a result of the specified algorithm, which allowed selecting only certain areas of wood, excluding non-functional background elements. Segmentation of damage zones was performed in the Hue-Saturation-Value (HSV) colour model, where the following thresholds were used: hue – from 23 to 50, saturation – from 70 to 255, values – from 170 to 255. Based on these indicators, a binary mask was formed, which helped to identify areas of defects and separate them from undamaged areas of wood. Figure 2 shows an example of detecting wood defects using digital processing. The final step of the procedure was quantitative analysis of defects using pixel counting, for which the ratio of the number of pixels of the defect zones to the total number of pixels in the image was calculated, helping to calculate the percentage of the affected surface.

Statistical analysis was performed using IBM SPSS Statistics 27, and the statistical significance level was set at $p < 0.05$. Descriptive statistical methods were used to analyse the quantitative parameters of wood defects, including the number and diameter of knots, the number of resin pockets, grain slope, pith eccentricity, compression, curvature, convergence, and the length and relative size of cracks. In particular, the average values, standard deviations, and minimum and maximum values were calculated. To identify statistically significant differences between the indicators obtained by the two methods, a paired t-test was used for dependent samples. The degree of consistency of the results between visual and digital methods was estimated based on the intra-class correlation coefficient (ICC). The level of consistency was set according to generally accepted criteria (Koo & Li, 2016). In addition, an analysis using the Bland-Altman method was performed to determine systematic deviations between methods and set limits on their consistency.

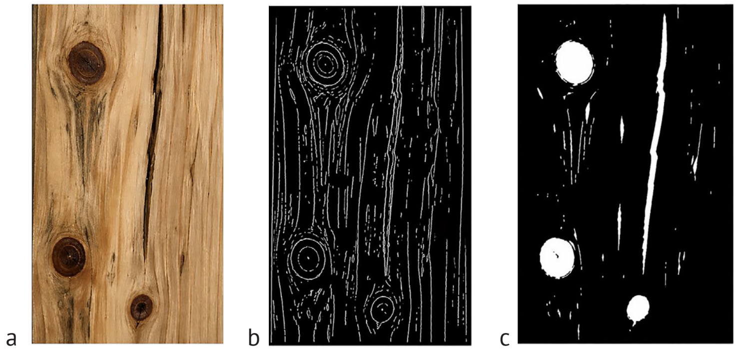

Figure 2. *Example of detecting wood defects using digital photo processing*

Note: a – original image, b – Canny edge detection, c – segmented defect mask

Source: compiled by the authors

For additional evaluation of the accuracy of the digital method, the error indicators relative to the results of the visual assessment taken as the reference value are calculated. Specifically, MAE and RMSE were calculated to quantify the discrepancies between the results obtained using the two methods and to complement the agreement analysis by assessing measurement. To do this, the following equations were used:

$$MAE = (1/n)\,\Sigma\,|X^{d}_{i} - X^{v}_{i}|; \quad (1)$$

$$RMSE = \sqrt{[(1/n)\,\Sigma\,(X^{d}_{i} - X^{v}_{i})^2]}. \quad (2)$$

In these equations, X^d_i denotes the value of a certain wood defect index obtained by digital scanning, whereas X^v_i corresponds to the value of the same indicator determined by the visual method, which in the context of this study is considered as a reference. Index i was used to identify individual observations in the sample, and n indicated the total number of such observations. The difference between X^d_i and X^v_i displayed the degree of deviation of the results of the two methods for each individual sample. The calculation of MAE and RMSE indicators was carried out in the IBM SPSS Statistics 27 software environment, where operations were performed to calculate the differences between actual and predicted values, determine absolute and squared deviations, and calculate the corresponding averages and the square root of the obtained values.

Results and Discussion

For the initial analysis of the results obtained, a descriptive statistical assessment of the characteristics of wood defects determined using the visual method and the digital scanning method was performed. The results are presented in Table 1.

Table 1. *Descriptive statistics of lumber defect parameters determined by visual method and digital scanning method (n = 100)*

Indicator	Method	Average	Standard deviation	Minimum	Maximum
Knots (quantity, units)	Visual	4.07	1.40	2	6
	Digital	4.53	1.53	2	7

***Table 1.** Continued*

Indicator	Method	Average	Standard deviation	Minimum	Maximum
Knots (diameter, cm)	Visual	2.22	0.52	1.30	3.20
	Digital	2.39	0.51	1.37	3.43
Resin pockets (units/section)	Visual	0.91	0.84	0	2
	Digital	1.38	1.02	0	3
Fibre slope (cm/m)	Visual	4.47	1.12	2.56	6.46
	Digital	4.77	1.14	2.75	6.81
Core displacement (%)	Visual	6.64	2.18	3.10	9.90
	Digital	7.61	2.15	3.90	11.10
Compression (%)	Visual	4.24	1.23	2.00	6.00
	Digital	4.55	1.22	2.40	6.40
Curvature (cm/m)	Visual	1.26	0.36	0.72	1.97
	Digital	1.39	0.36	0.86	2.08
Convergence (cm/m)	Visual	0.98	0.28	0.55	1.49
	Digital	1.10	0.29	0.62	1.63
Cracks (length, cm)	Visual	13.71	3.76	7.10	20.00
	Digital	14.93	3.74	7.80	20.90
Cracks (relative size, fraction Ø)	Visual	0.17	0.06	0.08	0.28
	Digital	0.20	0.06	0.09	0.31

Source: compiled by the authors

For most parameters, there is a tendency for higher indicators when using the digital scanning method compared to the visual method. For example, the average number of knots in digital analysis was 4.53 units, while the visual score showed 4.07 units. Similar dynamics are also noticeable for the parameter the diameter of knots (2.39 cm vs. 2.22 cm), the number of resin pockets (1.38 vs. 0.91), and the length of cracks, which according to scanning data was 14.93 cm compared to 13.71 cm for the visual method. Higher values using the digital method are also observed for growth indicators: fibre slope (4.77 cm/m vs. 4.47 cm/m), core displacement (7.61% vs. 6.64%), compression (4.55% vs. 4.24%), curvature (1.39 cm/m vs. 1.26 cm/m), and convergence (1.10 cm/m vs. 0.98 cm/m). To identify statistically significant differences between the indicators obtained by the two methods, a paired t-test was used for dependent samples (Table 2).

***Table 2.** Results of a paired t-test to compare the characteristics of wood defects determined by visual and digital scanning (n = 100)*

Indicator	Average difference	Standard deviation	95% CI (lower)	95% CI (upper)	t	p
Knots (quantity)	-0.46	0.50	-0.56	-0.36	-9.18	<0.001
Knots (diameter)	-0.16	0.09	-0.18	-0.14	-17.21	<0.001
Resin pockets	-0.47	0.50	-0.57	-0.37	-9.37	<0.001
Fibre slope	-0.31	0.12	-0.33	-0.29	-25.04	<0.001
Core displacement	-0.97	0.30	-1.03	-0.91	-32.75	<0.001
Compression	-0.31	0.12	-0.33	-0.28	-25.40	<0.001
Curvature	-0.13	0.04	-0.13	-0.12	-30.59	<0.001
Convergence	-0.12	0.04	-0.13	-0.11	-29.07	<0.001
Cracks (length)	-1.22	0.45	-1.31	-1.13	-27.14	<0.001
Cracks (relative size)	-0.03	0.01	-0.03	-0.03	-23.78	<0.001

Note: CI – confidence interval

Source: compiled by the authors

The results indicate statistically significant differences between the data obtained by visual and digital scanning for all wood defect parameters studied ($p < 0.001$). The average difference for all characteristics has negative values, which shows a tendency for higher indicators in the results obtained by digital scanning compared to visual evaluation. The most pronounced differences were found in core displacement (-0.97), crack length (-1.22), and the number of resin pockets (-0.47). Consistency with the visual method and digital scanning of wood defects was further evaluated using ICC. The results are shown in Table 3.

Table 3. *Calculation of consistency between visual and digital scanning of wood defects according to ICC (n = 100)*

Indicator	ICC	Consistency level
Knots (quantity)	0.84	High
Knots (diameter)	0.87	High
Resin pockets	0.72	Moderate
Fibre slope	0.91	Very high
Core displacement	0.81	High
Compression	0.88	High
Curvature	0.91	Very high
Convergence	0.86	High
Cracks (length)	0.87	High
Cracks (relative size)	0.82	High

Source: compiled by the authors

The ICC ranged from 0.72 to 0.91, which, according to the recommendations, indicates moderate, high and very high levels of consistency (Koo & Li, 2016). The highest level of consistency was recorded for parameters such as fibre slope and curvature (ICC = 0.91), while the lowest level was recorded for resin pockets (ICC = 0.72), which may be due to the complexity of their detection and increased variability of manifestations. Figure 3 shows a Bland-Altman graph for additional verification of the consistency of the results of the visual method and the digital scanning method. The abscissa (X) axis shows the average values of both methods for each sample, and the ordinate (Y) axis shows the difference between them (visual method minus digital). The black dashed line represents the average difference between the methods (offset), the red line represents the regression line, and the upper and lower black lines, together with the blue zones, indicate the consistency limits (mean ± 1.96 standard deviation) and their confidence intervals, in which most values are located. The green zone illustrates the confidence interval for the average shift. Most of the points are located below the zero line, which indicates a systematic bias. The average deviation between methods, which is indicated by a dashed black line, is negative and remains stable over the entire range of values. The upper and lower coherence limits (solid black lines), together with the corresponding confidence intervals, cover most of the observations, indicating that there are no significant random deviations and an acceptable level of variation between the methods. The distribution of points looks uniform, without a pronounced slope, and the regression line remains close to horizontal, which indicates that there is no proportional displacement. To evaluate the accuracy of the digital method compared to the visual approach, a scatter plot was created, where MAE and RMSE were calculated (Fig. 4).

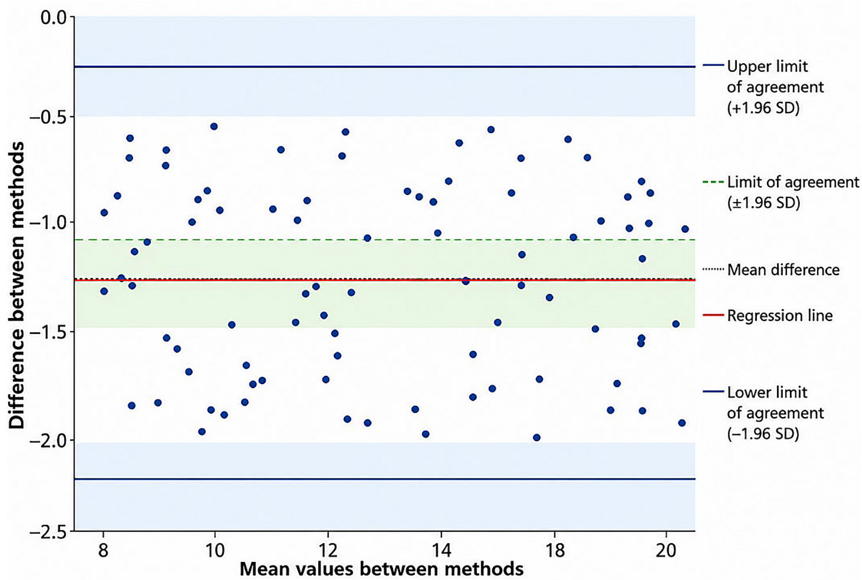

Figure 3. *Bland-Altman graph for checking the consistency between visual evaluation and digital scanning*

Source: compiled by the authors

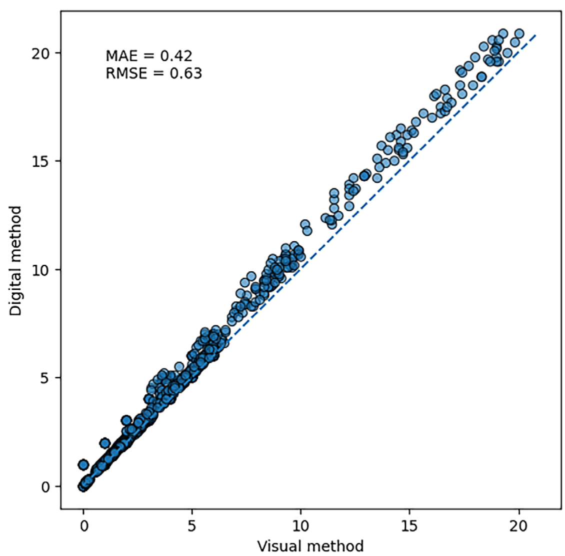

Figure 4. *Scatter plot for MAE and RMSE*

Source: compiled by the authors

The diagonal dashed line (y = x) represents a reference for evaluating the correspondence between the two methods, and the proximity of most points to it indicates high consistency. There is a moderate spread of values around the diagonal, which reflects some discrepancies. These deviations coincide with the results of quantitative analysis, in particular, the values of the mean absolute error (MAE = 0.42) and the root-mean-square error (RMSE = 0.56), which indicate that the errors are relatively insignificant, that is, the digital method provides sufficient accuracy for estimating wood defects.

The results obtained suggest that digital scanning can provide relevant indicators of the characteristics of defects in Scots pine lumber in comparison with traditional visual assessment in the conditions of application in Ukraine. The systematic bias found in the current study may not even be an error in the classical sense, but rather demonstrates the difference in approaches to obtaining and interpreting information. Similar results were observed by Y. Huang *et al.* (2024) using computed tomography, where digital technologies have shown the ability to analyse in detail the internal structural characteristics of wood: we are talking about knots, deviations in density or fibres that remain inaccessible on surface examination. This coverage of a wider range of properties may explain the tendency to get higher values when scanning digitally. Despite statistically significant differences between assessment approaches, ICC analysis showed a high level of consistency in most parameters. This is consistent with the study by A. Rais *et al.* (2017), where automated and manual estimates were compared: although the absolute values may vary slightly, the overall correlation between the methods was high. Notably, the level of consistency of parameters depended on the nature of the defect, since that study showed relatively low correlation indicators for resin pockets, which may be due to the complexity of their identification. The study by S. Joevenller *et al.* (2026) noted that such defects often have properties that are difficult to distinguish from natural wood variations even with digital methods, which can lead to higher variability in results and requires additional attention in the diagnostic process.

The current results show interesting data from the paired t-test, which revealed statistically significant differences between the visual method and the digital scanning method for all the parameters under study. At first glance, such results may seem contradictory due to the high ICC values, but this apparent contradiction is probably due to the different statistical nature of the analysis methods used. In particular, the paired t-test is designed to detect systematic discrepancies between the average values of data groups, while the ICC evaluates the degree of consistency or correspondence between two sets of measurements. Within the framework of the study, the digital method showed a tendency to obtain slightly higher values compared to the visual one, which could lead to statistically significant differences, but simultaneously, maintaining a proportional relationship between the results of both methods ensures a high level of their consistency, which corresponds to conventional approaches to interpreting similar statistical indicators. This highlights the importance of applying an integrated approach to statistical analysis to better understand the nature of the existing discrepancies between the assessment methods used.

Previous research by M. Nocetti & M. Brunetti (2024) indicated certain limitations of the visual evaluation method, in particular, it was noted that this approach is subjective, depends on the experience of the expert and does not consider data on the internal structure of the material. In turn, this can also serve as an explanation for the tendency to underestimate the values obtained in the visual method. The current results are also consistent with the processes of automated image analysis, which prove the effectiveness of algorithmic methods in detecting defects, but their accuracy, as one of the paper points out, varies significantly and depends on the characteristics of wood defects and the quality of the initial data (Özkan & Özcan, 2024). Similar conclusions were drawn by B. Jambreković *et al.* (2024), where neural network-based systems have demonstrated unequal efficiency in detecting different types of defects. For example, they worked better with well-defined defects, such as knots, than with complex or heterogeneous structures that are identified with less stability. It is worth noting that the study focused specifically on classification accuracy, while the current paper evaluated metric consistency between methods, which may explain the differences in conclusions, because high classification indicators do not always show the absence of systematic measurement errors. An important aspect may also be the natural variability of wood as a material, because the study by T. Ravoajanahary *et al.* (2025) emphasised that wood parameters can vary greatly even within a single sample. This factor may partially explain the spread of values in the Bland-Altman graphs, indicating that the difference between the methods may be due not only to measurement errors, but also to material heterogeneity. T. Ravoajanahary *et al.* (2025) analysed the variability of wood quality and material moisture using industrial X-ray scanning and concluded that wood properties can vary significantly even within a single sample, which complicates the automated assessment process. Furthermore, the study noted that digital technologies allow identifying patterns that remain inconspicuous in traditional visual analysis, which emphasises the need to combine several methods of analysis to improve the accuracy of wood defects diagnostics.

Taking these limits into account, the current results require further verification in real-world industrial use conditions to ensure their practical relevance. In future studies, special attention should be paid to the analysis of potential complications associated with the introduction of digital scanning, since the quality of the resulting images can significantly depend on a number of unstable factors, in particular, the texture variation of wood, the degree of surface contamination, and lighting conditions during scanning. The introduction of new technologies is accompanied by significant financial costs, in this regard, a promising area of further research is the assessment of the economic efficiency and financial feasibility of integrating digital scanning into production processes. In addition, the results obtained have the prospect of influencing broader methodological aspects of research related to wood quality assessment, in particular, the use of an approach that combines the analysis of systematic differences with the assessment of consistency between methods opens up the possibility for more comprehensive validation of digital technologies. In the future, this approach can be adapted to other methods of wood quality control, where it is important not only to ensure the accuracy of measurements, but also the stability and repeatability of the results obtained in a variety of conditions.

The practical significance of the current study lies in the prospect of introducing digital scanning as an auxiliary tool for traditional visual analysis, which seems promising for improving the objectivity and reproducibility of the wood quality control process. The findings can be used in woodworking enterprises and in the timber processing industry when implementing automated quality control systems for lumber. In addition, they have the potential to be used in scientific research in the fields of forestry and materials science, in particular, for the development and improvement of image processing algorithms designed to identify defects. Current data can also be integrated into the educational process of training specialists of the relevant profile and is of practical interest to engineers, technologists, quality control specialists, and software developers involved in the creation and implementation of digital solutions in the field of wood analysis.

Conclusions

The study conducted an empirical analysis of the effectiveness of two approaches – the visual method and digital scanning – to assess defects in Scots pine wood (*Pinus sylvestris* L.) on a sample of lumber (n = 100). The results showed that the digital method showed higher values of such indicators of wood defects as the number and diameter of knots, the number of resin pockets, the slope of fibres, core displacement, compression, curvature, convergence, and the length and relative size of cracks. Statistical analysis confirmed the presence of significant differences between the two methods in all the parameters studied. The ICC showed moderate, high, or very high levels of consistency between the two methods. The highest level of consistency was found for fibre slope and curvature, and the lowest – for resin pockets, which is probably due to the complexity of their determination and greater variability of manifestation. The Bland-Altman analysis revealed a systematic bias between the methods: digital scanning results tended to show slightly higher values compared to visual evaluation. The absence of a pronounced proportional bias and a stable distribution of differences in indicators indicate an acceptable level of consistency between approaches within the parameters under study. The accuracy analysis, based on the MAE and RMSE indicators, also showed that the digital method generally provided an acceptable level of accuracy in determining wood defects. This gives reason to consider digital scanning not as a substitute for visual analysis, but as an effective complement to it, which can increase the objectivity, reproducibility and accuracy of wood defect assessment.

The scientific relevance of the current study lies in the quantitative comparison of the traditional visual method for assessing defects in Scots pine wood with the contemporary digital scanning approach based on the use of a set of statistical methods (in particular, the pair t-test, the ICC, and the Bland-Altman analysis). The results clarify the differences between the two methods, indicating the existence of a systematic bias, while demonstrating an acceptable level of consistency, which, in turn, contributes to a deeper understanding of the possibilities and limitations of using digital technologies in wood research. The paper also made a significant contribution to improving existing approaches by focusing not only on identifying wood defects, but also on quantifying them and comparing the results of different measurement approaches.

Current results should be considered with a number of limitations in mind. First of all, the sample was quite narrow and covered only specific conditions for growing Scots pine, which makes it difficult to extrapolate the results to other conditions. In addition, the analysis was carried out exclusively on lumber, which limits the ability to fully consider the characteristics of wood that does not fall under this category. In addition, it is worth noting that the methods used in the current study were based only on surface analysis, which reduces the efficiency of detecting defects located in the deep layers of the material. In addition, the accuracy of digital scanning is always determined by a number of factors that must be considered, in particular, the shooting conditions (lighting, quality of the resulting images, parameters of segmentation algorithms, etc.). Furthermore, the method of visual assessment, although carried out with the consent of 3 experts, remains partially subjective and largely depends on the qualifications and experience of specialists. Future research should focus on expanding sampling, improving digital scanning techniques and image processing algorithms, and evaluating the efficiency and economic feasibility of implementing digital technologies in real-world production environments.

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Conflict of Interest

None.

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Аналіз вад деревини *Pinus sylvestris* L. із застосуванням цифрового сканування

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Анотація. З огляду на зростання попиту на деревину та необхідність її раціонального використання, особливо актуальним стає визначення якості сировини, для чого перспективним є цифрове сканування деревини, що дозволяє автоматизовано виявляти та оцінювати її вади, проте в Україні переважно застосовується метод візуальної оцінки. Основною метою поточного дослідження було емпірично оцінити вади деревини *Pinus sylvestris* L. на вибірці пиломатеріалів шляхом цифрового сканування та порівняти дані із результатами, що отримані традиційною візуальною діагностикою. Статистичний аналіз охоплював порівняння результатів між методами, оцінку ступеня їхньої відповідності та аналіз характеру розбіжностей за допомогою парного t-тесту для залежних вибірок, коефіцієнта внутрішньокласової кореляції та аналізу за методом Бленда-Альтмана. Застосування цифрового методу показало вищі значення усіх показників вад деревини (кількість і діаметр сучків, кількість смоляних кишеньок, нахил волокон, зміщення серцевини, крінь, кривизна, збіжистість, а також довжина і відносний розмір тріщин). Статистичний аналіз підтвердив наявність статистично значущих відмінностей між двома методами за всіма досліджуваними параметрами ($p < 0{,}001$). Водночас коефіцієнт внутрішньокласової кореляції продемонстрував помірний, високий або дуже високий рівень узгодженості (в межах 0,72-0,91). Аналіз Бленда-Альтмана виявив систематичне зміщення між цифровим та візуальним методами, однак відсутність вираженого пропорційного зміщення та стабільний розподіл різниці в показниках вказали на прийнятний рівень узгодженості між підходами у межах досліджуваних параметрів. Практичне значення отриманих результатів полягає у можливості застосування методу цифрового сканування як додаткового інструменту до традиційного візуального аналізу для підвищення точності, об'єктивності та відтворюваності оцінки якості деревини. Результати можуть бути використані у виробничій діяльності, а також під час створення й впровадження автоматизованих систем контролю якості пиломатеріалів

Ключові слова: якість пиломатеріалів; цифрова обробка зображень; узгодженість методів; внутрішньокласова кореляція; лісові господарства України