

INTERDISCIPLINARY DOCTORAL SCHOOL

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EVALUATION AND DEVELOPMENT OF SMART SOLUTIONS FOR WOOD TRACEABILITY AND SOURCING

SUMMARY

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BRAȘOV, 2026

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LIST OF ABBREVIATIONS AND ACRONYMS

AKAZE: Accelerated-KAZE

Android: Mobile operating system

App: Application

Bias: Signed difference between paired measurements

Bluetooth: Short-range wireless communication technology

BRISK: Binary Robust Invariant Scalable Keypoints

CNN: Convolutional Neural Network

DBH: Diameter at breast height

DBSCAN: Density-Based Spatial Clustering of Applications with Noise

DNA: Deoxyribonucleic Acid

EUTR: European Union Timber Regulation

FREAK: Fast Retina Keypoint

FSC: Forest Stewardship Council

GIS: Geographic Information System

GPS: Global Positioning System

HITMAN: Acoustic tool for wood stiffness detection

Huber's formula (VH): Volume estimate using Huber's method

KAZE: Nonlinear diffusion-based keypoint detector

LiDAR: Light Detection and Ranging

MAE: Mean Absolute Error

ML: Machine Learning

ORB: Oriented FAST and Rotated BRIEF

PEFC: Programme for the Endorsement of Forest Certification

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

QR: Quick Response

RFID: Radio-Frequency Identification

RMSE: Root Mean Squared Error

SIFT: Scale-Invariant Feature Transform

SINTETIC: Single item identification for forest production, protection, and management

SURF: Speeded-Up Robust Features

INTRODUCTION

Relevance of smart solutions for wood traceability and sourcing

Forest operations involve numerous activities related to the management, harvesting, transportation, and processing of timber resources within the supply chains (Baskent et al., 2008; Abbas et al., 2014; Braghiroli & Passarini, 2020). The number of steps included, actors and stakeholders participating in these processes are increasing the risk of data loss and illegal practices (Sundström, 2016). The origin of wood is becoming increasingly important as regulatory authorities demands accountability that wood comes from sustainable forest management (Sikkema et al., 2014). For example, the European Timber Regulation (EUTR) as well as consumers requirement for sustainable harvested timber (Holopainen et al., 2015) are encouraging systems to trace timber flows (Laporte & Vandenhoute, 2016). Traceability has emerged as a new standard for running businesses and trading of wood on global markets (Tzoulis & Andreopoulou, 2013). In addition, current traceability systems and data processing techniques can provide a trade-off between sustainability and increased production through forest management and efficient wood logistics downstream. This ensures that wood products are being extracted in a climate friendly way (Mensah et al., 2022; Creutzburg & Lieberherr, 2021). By tracing timber, through setting up an information system that detect and locate legal timber and timber products, this adds value to wood product (Kaulen et al., 2023).

Traceability means “the ability to trace any product through all stages of production, processing and distribution” (Laporte & Vandenhoute, 2016; Godbout et al., 2018; Kaulen et al., 2023). Up to date, traceability systems are using traditional methods and techniques such as stamping, punching, colour marking, plastic tags, and barcoding. These methods are however affected by environmental factors and are also not secure (Tzoulis & Andreopoulou, 2013). On the other hand, certifications of origin from the Forest Stewardship Council (FSC) and the Programme for the Endorsement of Forest Certification Schemes (PEFC) still dominate the market, but they are prone to inaccuracies and security gaps that need to be contained through the use of new technologies (Kaulen et al., 2023). Furthermore, manual and paper-based systems, visual checking, and manual measurement tools, are still being applied in forestry in many regions worldwide. For example, standard field instruments such as calipers and forestry tapes (Kadzuwa & Missanjo, 2022) are still used for forest and industry inventories to provide wood volume estimation (Gülci et al., 2023), and up-to-date visual comparisons along with transport documents are employed to verify truckloads at loading and unloading points (Kravets et al., 2017). These are often vulnerable to human errors, especially in an intensive work environment, either in the forest or industry, which mostly consumes labour efforts and time (Borz et al., 2022; Borz & Proto, 2022). These limitations show the importance of supply chains to be digitized (Palander et al., 2024); thus, automated and advanced smart solutions are needed for supporting accurate timber traceability and sourcing in real work conditions (Pichler et al., 2022). Recently, technology-driven innovations have opened new opportunities for enhancing wood traceability through the use of big data collection (Taylor et al., 2020), processing, and transmission in real time and in a more accessible format that makes monitoring the wood supply chain simpler (Pichler et al., 2022; Figorilli et al., 2018). For instance, the development of smartphone applications has offered a wide range of services related to wood supply chain management (Kärhä et al., 2019; Odstrčil et al., 2024). Smartphones equipped with LiDAR scanners, sensors, and high-quality RGB cameras are useful for close-range photogrammetry and remote sensing (Magnuson et al., 2024) that are effectively used to measure variables such as

diameter at breast height (DBH), tree height, basal area (BA), volume, and log biometrics, thus having the possibility to enhance forest inventories accuracy and efficiency (Borz et al., 2022; Niță & Borz, 2023; Tatsumi et al., 2023). However, to achieve high-standard digitalization in forestry, mobile applications should meet several requirements. These include performing accurately with efficient time and having the ability to store, process, and transfer data instantly, with the most important being the integration with other wood traceability technologies (Figorilli et al., 2018; Häkli et al., 2013; He & Turner, 2021) which consider shortcomings in many applications (Borz et al., 2022; Niță & Borz, 2023; Tatsumi et al., 2023). Tracking wood along the supply chain using advanced technologies is not a new concept. In parallel with traditional methods, several approaches have been utilized over time each having its advantages and limitations such as the quick response (QR) codes that are printed on the ends of logs, trucks, and wood products, to store information related to the species, harvesting area, etc. Even though this method is considered low cost, reading the codes can be challenging (Dykstra et al., 2002; Häkli et al., 2013; Tzoulis and Andreopoulou, 2013). RFID technology has gained significant attention as a practical and scalable method for tracing wood (Kaakkurivaara, 2019; Picchi, 2020), offering an automatic log identification system that is less susceptible to environmental factors and ensures high readability, as radio waves do not necessitate a line of sight and can penetrate most materials (Häkli et al., 2013). RFID tags can be placed on each log as well as on the vehicle's chassis, engine, and other parts. This makes it possible to follow the logs in real time as they are being moved (Tsioras et al., 2022). But RFID tags and readers are still quite expensive (Häkli et al., 2013; Pichler et al., 2017). DNA fingerprinting can identify the source of wood by analysing the genotypes of wood samples (Tzoulis and Andreopoulou, 2013). While this experimental method has shown reliability as a verification tool, it is often too costly and challenging to implement (Boner et al., 2019). The integration of geographical information systems (GIS) technology with the Global Positioning System (GPS) devices that are installed in most trucks have been successfully tracking the movement of timber in real time (Devlin et al., 2008). However, one obstacle with GPS tracking is that signals can be obstructed in areas with dense forests (Abdi et al., 2014), and GPS itself is not totally accurate for certifying truckload conformity. Additionally, the advancements in machine learning (ML), deep learning (DL), and computer vision (CV) techniques have emerged as powerful tools for supporting wood identification. Convolutional neural networks (CNNs) and feature detection algorithms (Ji et al., 2024; Martinetto et al., 2025) have been employed to fingerprint and match images of sawn boards, wood products, and cross-sectional logs (Pahlberg et al., 2015; Hu et al., 2015; Sun et al., 2022; Hwang et al., 2022; Ji et al., 2024; Martinetto et al., 2025) pertinent to various wood-based industries. These instruments use visual data, eliminating the need for wearable devices in some applications, but their performance depend on the data quality (Sun et al., 2021). This thesis intends to develop and evaluate new intelligent solutions for timber traceability and sourcing, given the necessity for legal, accountable, transparent, and sustainable wood supply chains. The development of these smart solutions needs large datasets, including reference and digital measurements, image records, mobile scanning, quality data, and documentation along supply chain stages for robust validation and comparative analysis. Moreover, the integration of these technologies into traceability systems in forest and industrial workflows needs to address some practical constraints under real work conditions.

Aim and objectives

The aim of this thesis is to improve wood traceability and sourcing systems along the supply chain through testing and evaluating novel tools and approaches such as application-based smartphones and digital instruments. In addition, the thesis also develops and introduces new methods based on computer vision and machine learning. By the recognition of the limitations of conventional practices, this research addresses the challenges associated with current traceability system by developing new methods that can improve transparency, efficiency, productivity, and the quality of data collection in the wood supply chain. The specific objectives of the thesis were as follows:

- O1. To perform a comprehensive state of the art of existing procedures and technologies used for wood traceability and sustainable transport management and the outcomes of adopting these developments, as well as to identify current limitations and gaps for future innovations.
- O2. To evaluate the performance of the TreeScanner (TS) application, a LiDAR-based smartphone for log volume estimation;
- O3. To assess the accuracy of the CIND's Timspec® technology used in sawmills for estimating the roundwood solid volume in truckloads;
- O4. To introduce the use of several feature detection algorithms and evaluate their performance for fingerprinting truckloads and matching them based on images taken at their ends;
- O5. To disseminate the results.

Organization of the thesis

The PhD thesis is organized into manuscript-style chapters, each concentrating on the following topics:

Chapter 1: Timber Traceability and Sustainable Transportation Management: A Review of Technologies and Procedures

This study presented a systematic literature review that explored the procedures and up-to-date technologies used for timber traceability and sustainable transportation management. The review analysed 125 scientific papers published between 1993 and 2023 that answered critical research questions like, what are the advantages of these procedures and technology?, What are the environmental, economic, and social outcomes of their adoption, and finally, what are the challenges of implementing traceability-based technology in the forestry sector?, laying the groundwork for future research.

Chapter 2: Accuracy of a Novel Smartphone-Based Log Measurement App in the Prototyping Phase

This study evaluated the performance of the Tree Scanner (TS) application, a LiDAR-based smartphone in its prototyping phase, for direct estimation of log volume. A dataset of 155 coniferous logs was measured both manually and digitally by two operators. Each operator took repeated measurements to check intra- and inter-user reliability. The TS app estimated volumes using two sampling densities, 0.5 m and 0.1 m.

Chapter 3: Wood Measurement at the Factory Gate: A Comparison Study to Evaluate the Accuracy of a State-Of-The-Art Digital Truckload Measurement System

The study investigates the accuracy of CIND Timspec® digital system in estimating roundwood volume in truckloads at the sawmill gate. A comprehensive assessment was done using a dataset of 1,292

truckloads comparing CIND measurements with data sourced by manual measurements performed in the forest and Microtec® measurements carried out in the sawmill yard.

Chapter 4: Truckload Traceability: The Performance of Different Image Matching Algorithms and Prospects for Online Applications

This study introduces the use of several feature detection algorithms—SURF, SIFT, ORB, AKAZE, BRISK, and FREAK—for fingerprinting truckloads and matching them based on images taken at their ends. Eight experiments consisting of a total of 2,084 image comparisons were designed and conducted to evaluate the algorithms' performance.

CHAPTER 1. TIMBER TRACEABILITY AND SUSTAINABLE TRANSPORTATION MANAGEMENT: A REVIEW OF TECHNOLOGIES AND PROCEDURES

1.1. MATERIALS AND METHODS

In this research, a methodical review was adopted on the techniques and processes used in tracing wood and transporting timber sustainably. To boost the quality of the review, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) technique for systematic reviews was used. Following the PRISMA methodology, 125 papers were incorporated into the study, as shown in Figure 1.1.

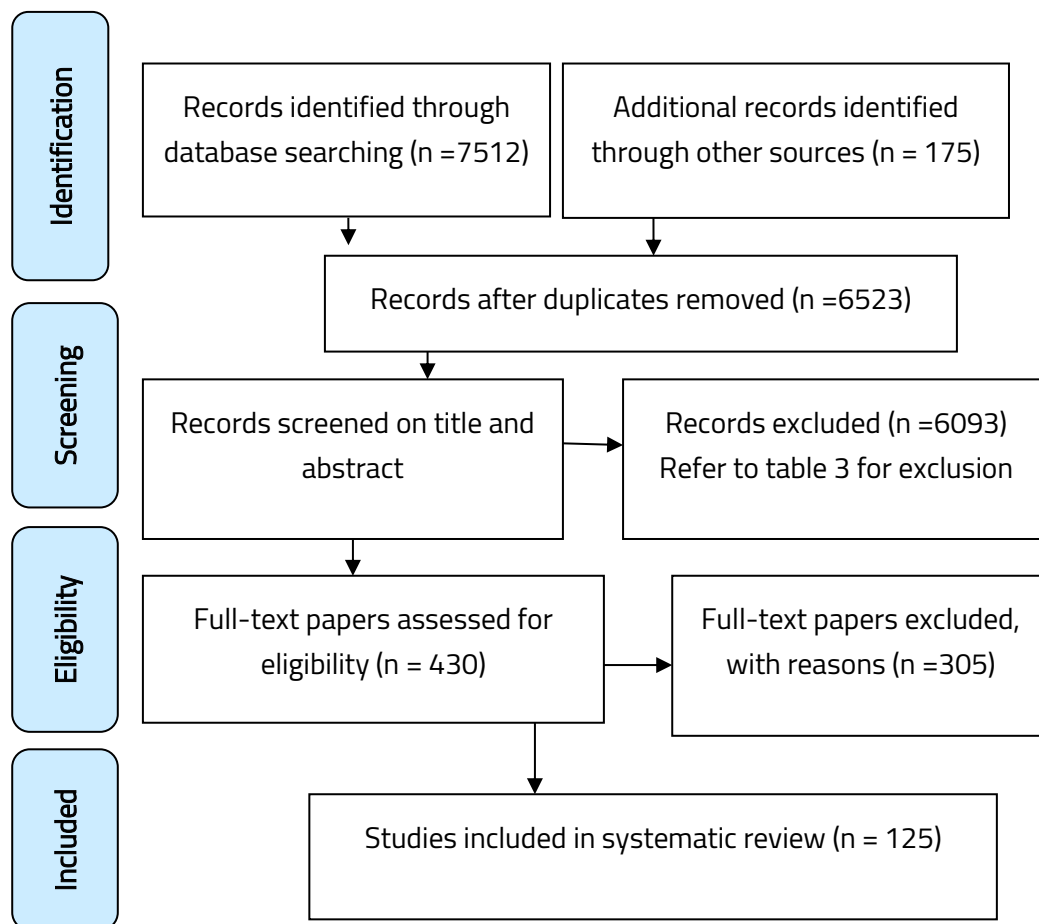


Figure 1.1. Flowchart of the systematic literature review, following the PRISMA 2020 guidelines.

1.2. RESULTS AND DISCUSSIONS

1.2.1. Overview of Studies

Based on the outcomes of this systematic literature review, the findings are presented in this section. The review included 125 papers published in 87 academic journals, three published theses, 32 conference papers, one book, and two reports. According to the objective of this review, the selected papers were categorised based on different attributes such as the year of publication, the countries from which the papers came, the used technology, results, and outcomes that seemed relevant.

Figure 1.2 shows the year-wise distribution of the 125 selected papers from 1993 until 2023.

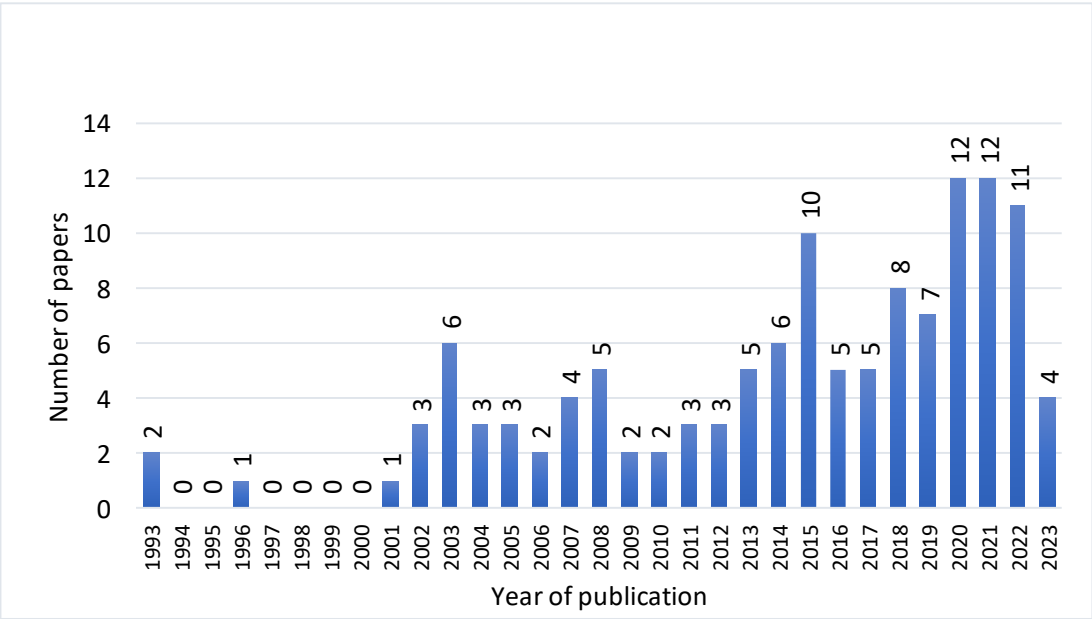


Figure 1.2. The distribution of papers categorised by their year of publication.

Figure 1.3 shows the countries where the selected papers were sourced. The sources were comprehensive worldwide, and included Europe, Asia, Africa, South and North America. Figure 1.4 illustrates the distribution of papers by mentioning the technologies used for traceability. Based on the data extracted from the studies, the predominant technologies identified in the studies were RFID, barcodes, QR codes, DNA fingerprinting, and blockchain technology.

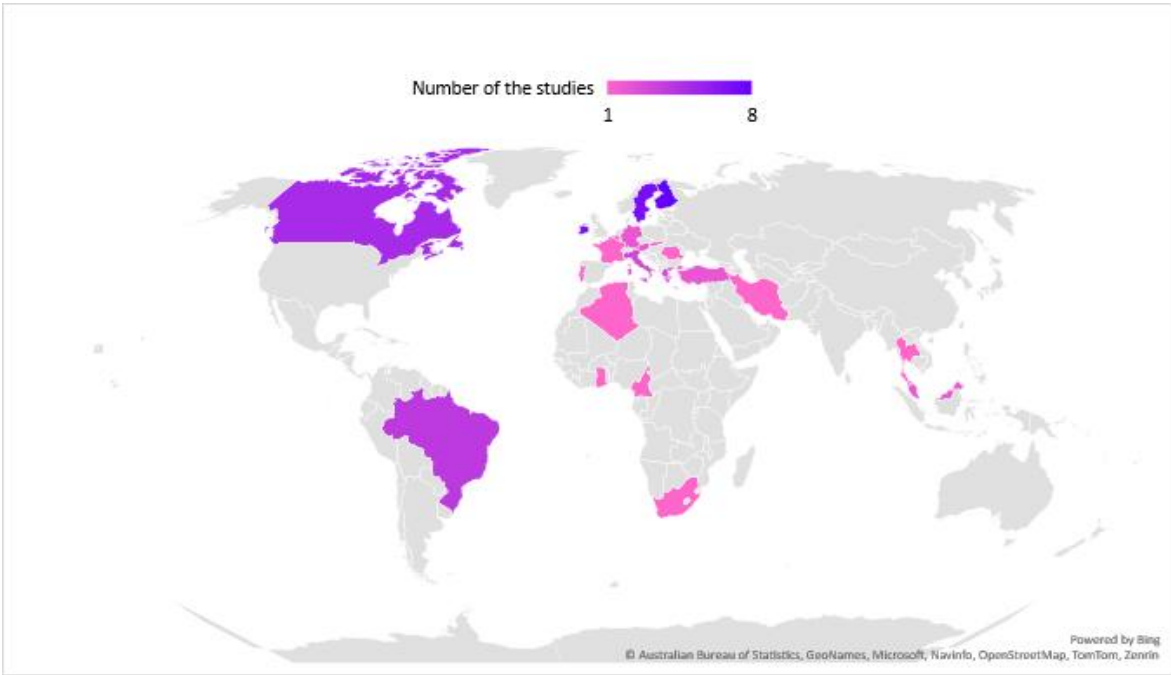


Figure 1.3. Number of the selected papers in each country.

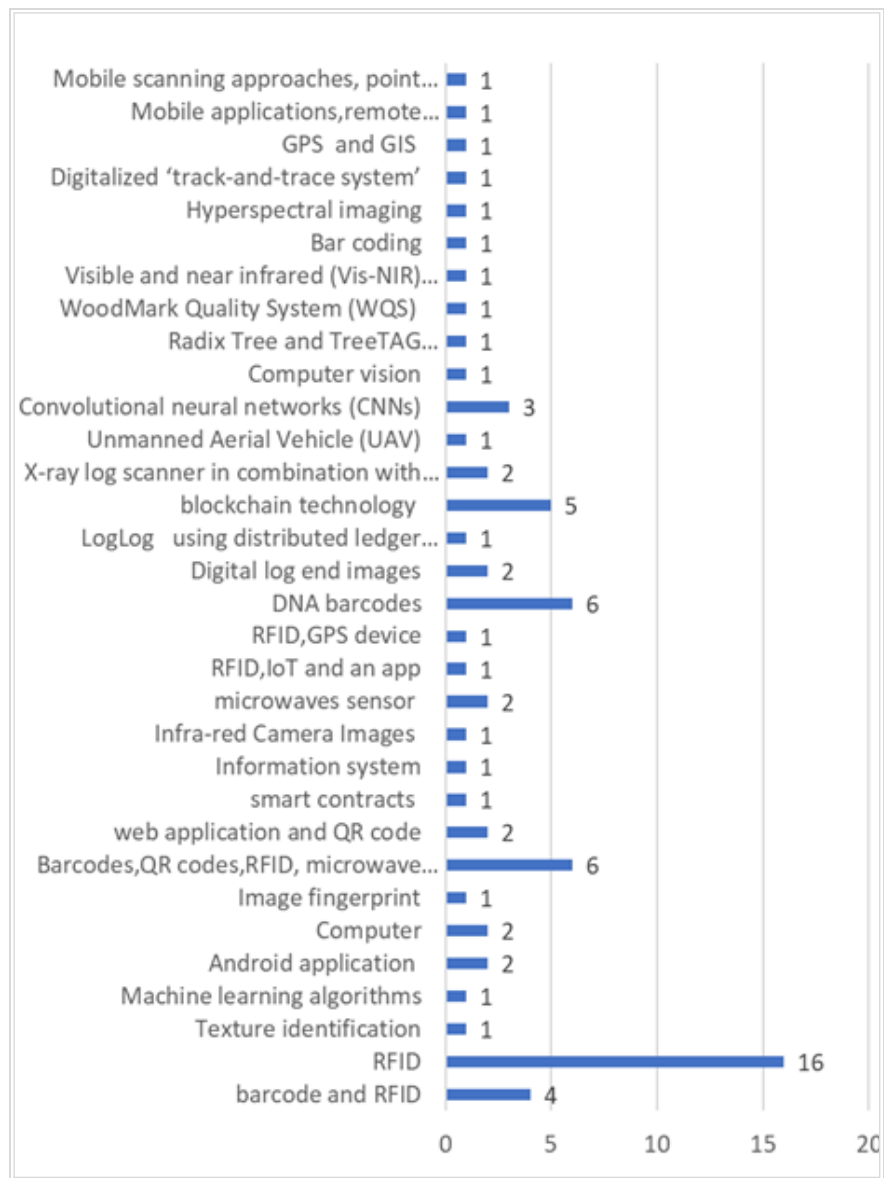


Figure 1.4. Numbers of papers mentioning each technology.

Table 1.1 in the source document details the utilisation, efficiency, features, and challenges of these technologies.

Table 1.1. The utilisation of the most popular technologies, their efficiency, and their features.

Technology	Utilisation	Efficiency	Features	Challenges
Stamping	Marking logs	Less efficient	Easy to use	Environmental factors, not secure
Paint	Marking logs	Less efficient	Easy to use	Environmental factors, not secure
Smart marking (coding system)	Marking logs	Less efficient	Easy to use	Environmental factors, not secure
Barcode	Tracing logs and wood product	Less efficient	Simple and cheap	Not secure
QR code	Tracing logs and wood product	Less efficient	Easy to use	Not secure
DNA fingerprinting	Verify timber origin	Reliable efficient	Database of samples	Expensive
Microwave sensor	Automated identification of wood product	Experimental	Finding wood attributes	Experimental
RFID	Identifying logs and wood products	Reliable efficient	Difficult to cheat	Expensive but the price per tag is predicted to reduce
Biometric method	Identifying logs	Reliable efficient	Secure and high precision	Large dataset
Oriented briefing (ORB)	Tracing Logs	Reliable efficient	Quik and effective image comparable	Large dataset
Blockchain	Tracing logs and wood products	Reliable efficient	Comprehensive and unchangeable data	Large dataset
Smart Tree APP	Collecting data from marking trees to cutting phases	Reliable efficient	Identify tree location through GPS	It needs available Internet

1.2.2. The Strategic Outcomes

The importance of sustainable transportation management in the context of long-term ecological and economic sustainability emphasises the optimization of logistics, technologies, systems, procedures, and tools in order to achieve economic savings, reduce environmental impacts, and enhance social sustainability (Wilkerson et al., 2008).

1.2.3. The Challenges

The outcomes of the research demonstrate plenty of hurdles that must be handled to establish trustworthy and efficient traceability systems with the aid of technology in wood. Such difficulties arise because of factors such as costs, the absence of necessary infrastructure, interoperability constraints, data management and confidentiality issues, uptake and adherence to standards or laws, as well as capabilities needed on the part of people involved in different stages of timber processing until final

clients. Overcoming these challenges is important for ensuring the effective adoption and use of traceability technology in the wood sector.

1.3. CONCLUSION

The findings demonstrate that wood traceability can be significantly enhanced in terms of speed, accuracy, and reliability through the use of various technologies throughout the supply chain. These technological advancements help manage, monitor, and reinforce traceability from origin to end product, allowing consumers to make informed choices about wood products. This can lead to better control over deforestation, lawful logging, and other hidden activities. While the review acknowledges that the technologies discussed are not yet operationalised, it highlights their potential to promote responsible and sustainable wood usage.

Benefits include improved product quality and differentiation, regulatory compliance, worker safety, stakeholder participation, and ethical consumer choices, contributing to a sustainable forestry industry. The paper also discusses limitations and challenges in implementing traceability technology, such as costs, infrastructure obstacles (data management, adoption and compliance, and stakeholder engagement), and other drawbacks. Addressing these issues is crucial for the future of the forestry industry, as traceability systems will pave the way for more sustainable practices and higher quality wood products.

CHAPTER 2. ACCURACY OF A NOVEL SMARTPHONE-BASED LOG MEASUREMENT APP IN THE PROTOTYPING PHASE

2.1. MATERIALS AND METHODS

2.1.1. App Description and Data Used in This Study

Tree Scanner (hereafter referred to as TS) is a smartphone-based application currently under development as part of the Sintetic (Single Item Identification for Forest Production, Protection, and Management) project (<https://sinteticproject.eu/>). The goal of this project is to harness the potential of digital technologies in supply chains that are still largely reliant on manual methods.

The app enables users to measure the biometrics of trees and logs, process and save results on local devices, and transfer and store geo-referenced data in dedicated databases using state-of-the-art remote server connection technologies. For log measurement, it allows users to create measurement instances, take reference diameters at the ends of logs using deep learning models to recognize their profiles, and scan the logs using dedicated sensors. In addition to estimating timber volume, the app is equipped with other essential functionalities. These include Bluetooth connectivity with the HITMAN acoustic tool for detecting wood stiffness and an RFID (radio frequency identification) tag reader to uniquely identify every tree or piece of wood.

2.1.2. Location of the Study

The site setting and the arrangement of logs were chosen to limit the background noise as much as possible, because the presence of understory or grass would create artifacts in the collected point clouds or obstructions on the ground during measurement, which, in turn, could affect the computational workflow of the app and the time-consumption measurements. The species group was controlled as well by including in this study only coniferous logs to limit the number of variables. This study was conducted in the log yard of an important wood processing company based in Romania, which is designated by the red dot in **Figure 2.1 a**. The company handles material sourced both from domestic and foreign forests and typically works with short logs in the range of 3 to 4 m in length. A batch of logs representing a part of the sample used to take the measurements is illustrated in **Figure 2.1 b**, while descriptive statistics of the sample, including volume estimates based on Huber's formula, are provided in **Figure 2.1 c**.

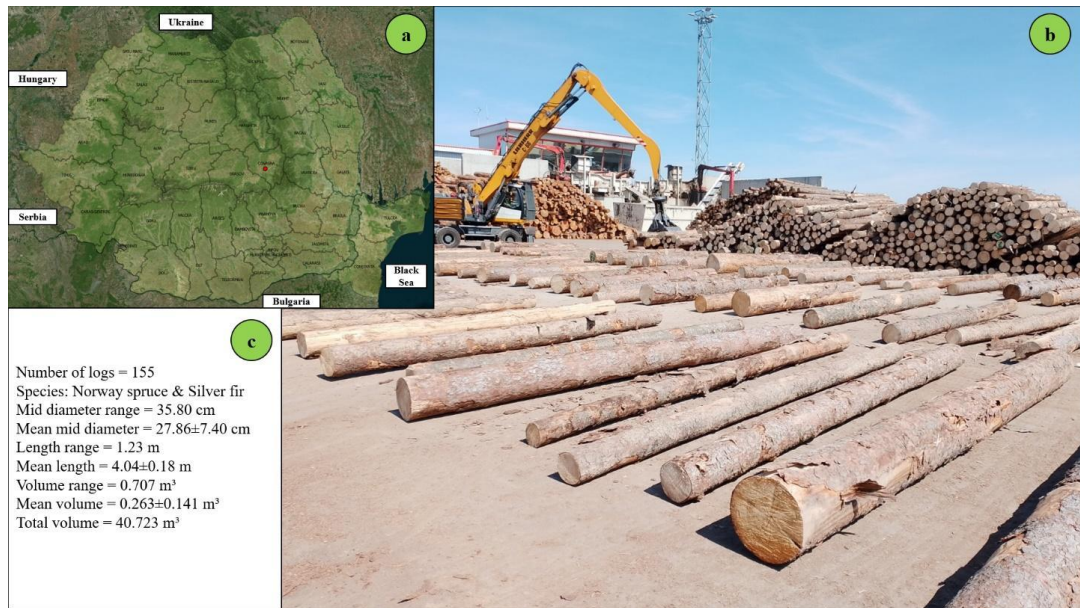


Figure 2.1. Location of the study area and characteristics of the sample used in this study: (a) national level map showing the study site (red dot), (b) sample logs used for measurement (c) summary statistics of the sample, with volume estimates based on Huber's.

2.1.3. Experimental Design and Data Collection

The design of this study was primarily comparative, and the data were collected using both manual and digital measurements. Two researchers, hereafter referred to as Subject 1 (S1) and Subject 2 (S2), measured the logs as described in Figure 2.2. Both subjects conducted the measurement tasks in two replications.

Workflow	Persons	Tools used	Measurement accuracy	Measurement steps, work object: single log	Data storage	Data transfer	Office storage	Sample size and variables	Abbreviation of the dataset
Manual measurement	RM	RM, Tape measure	Nearest millimeter Nearest centimeter	1 2 3 4	Paper	Manual	X	155 obs. Ds Dm DI L VH VS	REF
Digital measurement by S1, R1	R1	Smartphone	App default	1 2 3	Smartphone	Bluetooth	X	155 obs. VAPP1_S1R1 VAPP2_S1R1	VAPP1_S1R1 VAPP2_S1R1
Digital measurement by S1, R2	R2	Smartphone	App default	1 2 3	Smartphone	Bluetooth	X	155 obs. VAPP1_S1R2 VAPP2_S1R2	VAPP1_S1R2 VAPP2_S1R2
Digital measurement by S2, R1	R1	Smartphone	App default	1 2 3	Smartphone	Bluetooth	X	155 obs. VAPP1_S2R1 VAPP2_S2R1	VAPP1_S2R1 VAPP2_S2R1
Digital measurement by S2, R2	R2	Smartphone	App default	1 2 3	Smartphone	Bluetooth	X	89 obs. VAPP1_S2R2 VAPP2_S2R2	VAPP1_S2R2 VAPP2_S2R2
Time consumption for manual and digital measurement	All	Smartphone	Nearest second	Log 1 Log ... Log n	Paper	Manual	X	155 obs. TM TS1R1 TS1R2 TS2R1 TS2R2	TM TS1R1 TS1R2 TS2R1 TS2R2

Figure 2.2. Description of the testing workflows implemented in the field.

2.2. RESULTS

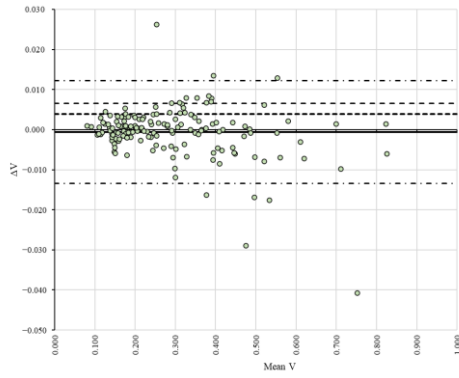
2.2.1. Trends, Agreement, and Differences in the Algorithm's Estimates

Table 2.1 summarizes the values of the slopes (C) and coefficients of determination (R^2) derived from the trend models developed using regression through the origin for both the actual values and the differences between the actual values.

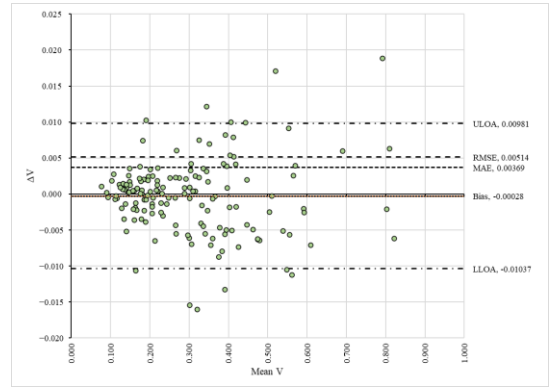
Table 2.1. Summary statistics of trends in data between the algorithm's estimates.

Dependent Variable	Independent Variable	Number of Observations	Parameters of the Model for Actual Values	Parameters of the Model for Differences
VAPP2_S1R1	VAPP1_S1R1	155	C = 1.0041 $R^2 = 0.9996$	C = -0.0041 $R^2 = 0.0430$
VAPP2_S1R2	VAPP1_S1R2	155	C = 1.0006 $R^2 = 0.9998$	C = -0.0006 $R^2 = 0.0014$
VAPP2_S2R1	VAPP1_S2R1	155	C = 1.0035 $R^2 = 0.9999$	C = -0.0035 $R^2 = 0.0844$
VAPP2_S2R2	VAPP1_S2R2	89	C = 0.9994 $R^2 = 0.9996$	C = -0.0006 $R^2 = 0.0009$

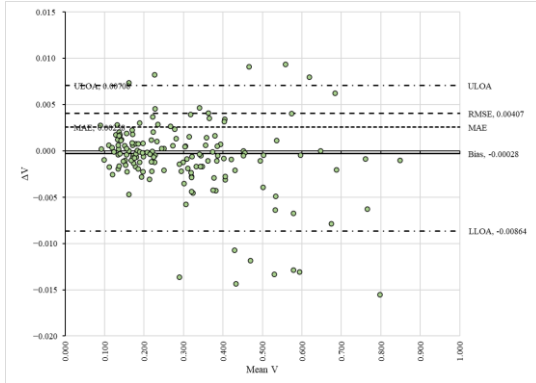
The regression models developed for the differences in the data reveal two key points: the slope was consistently close to zero, indicating a constant trend line, and the coefficients of determination suggested a poor explanation of variability (**Table 2.1**). Similar findings are presented in **Figure 2.3**, where the Bland–Altman plots indicate a high degree of agreement in the estimates, as the data points fall within the agreement limits and show a narrow range of values for these limits.



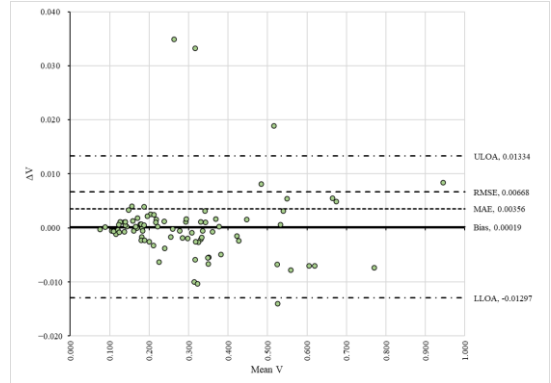
(a)



(b)



(c)



(d)

Figure 2.3. Bland–Altman plots of the compared variables for the algorithm’s estimates: (a) comparison between VAPP1_S1R1 and VAPP2_S1R1; (b) comparison between VAPP1_S1R2 and VAPP2_S1R2; (c) comparison between VAPP1_S2R1 and VAPP2_S2R1; (d) comparison between VAPP1_S2R2 and VAPP2_S2R2.

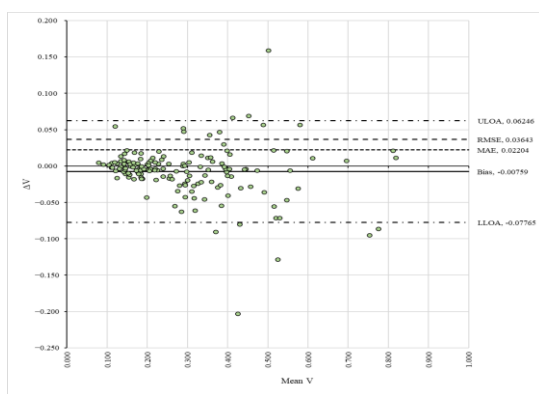
In these plots (Figure 2.3), the signed differences (ΔV) between the reference (VAPP1_S1R1—panel (a), VAPP1_S1R2—panel (b), VAPP1_S2R1—panel (c), VAPP1_S2R2—panel (d)) and compared (VAPP2_S1R1—panel (a), VAPP2_S1R2—panel (b), VAPP2_S2R1—panel (c), VAPP2_S2R2—panel (d)) data are plotted against their mean values (Mean V) in a space delimited by the upper (ULOA) and lower (LLOA) limits of agreement, along with figures such as the fixed bias (Bias), mean absolute error (MAE) and root mean squared error (RMSE).

2.2.2. Trends, Agreement, and Differences in the Replicates

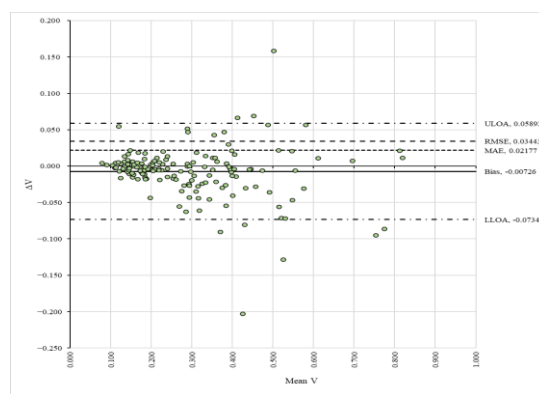
The results on the trends, agreement, and differences in the replicates are summarized similarly to those reported in Section 3.2. Table 2.2 presents the values of the slopes (C) and coefficients of determination (R^2), while Figure 2.4 displays the Bland–Altman plots along with the error metrics. Panels (a) to (d) show the signed differences (ΔV) between the reference (VAPP1_S1R1—panel (a), VAPP2_S1R1—panel (b), VAPP1_S2R1—panel (c), VAPP2_S2R1—panel (d)) and compared (VAPP1_S1R2—panel (a), VAPP2_S1R2—panel (b), VAPP1_S2R2—panel (c), VAPP2_S2R2—panel (d)) data plotted against their mean values (Mean V) in a space delimited by the upper (ULOA) and lower (LLOA) limits of agreement, along with figures such as the fixed bias (Bias), mean absolute error (MAE), and root mean squared error (RMSE).

Table 2.2. Summary statistics of trends in data between the replicates.

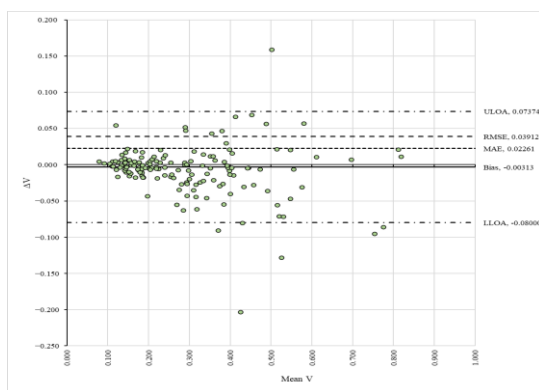
Dependent Variable	Independent Variable	Number of Observations	Parameters of the Model for Actual Values	Parameters of the Model for Differences
VAPP1_S1R2	VAPP1_S1R1	155	$C = 1.0231$ $R^2 = 0.9888$	$C = -0.0231$ $R^2 = 0.0431$
VAPP2_S1R2	VAPP2_S1R1	155	$C = 1.0199$ $R^2 = 0.9900$	$C = -0.0199$ $R^2 = 0.0364$
VAPP1_S2R2	VAPP1_S2R1	89	$C = 1.0117$ $R^2 = 0.9867$	$C = -0.0017$ $R^2 = 0.0098$
VAPP2_S2R2	VAPP2_S2R1	89	$C = 1.0082$ $R^2 = 0.9886$	$C = -0.0082$ $R^2 = 0.0057$



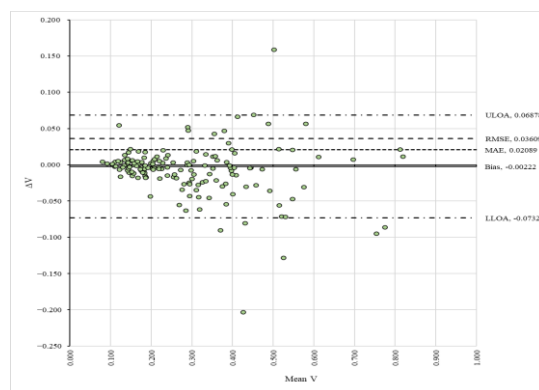
(a)



(b)



(c)



(d)

Figure 2.4. Bland–Altman plots of the compared variables between replicates: (a) comparison between VAPP1_S1R1 and VAPP1_S1R2; (b) comparison between VAPP2_S1R1 and VAPP2_S1R2; (c) comparison between VAPP1_S2R1 and VAPP1_S2R2; (d) comparison between VAPP2_S2R1 and VAPP2_S2R2.

2.2.3. Trends, Agreement, and Differences Between the Raters

Regarding inter-rater consistency, **Table 2.3** summarizes the values of the slopes (C) and coefficients of determination (R^2), while Figure 5 presents the Bland–Altman plots alongside the error metrics. Panels (a) to (d) show the signed differences (ΔV) between the reference (VAPP1_S1R1—panel (a), VAPP2_S1R1—panel (b), VAPP1_S2R1—panel (c), VAPP2_S2R1—panel (d)) and compared (VAPP1_S1R2—panel (a), VAPP2_S1R2—panel (b), VAPP1_S2R2—panel (c), VAPP2_S2R2—panel (d)) data plotted against their mean values (Mean V) in a space delimited by the upper (ULO) and lower (LLO) limits of agreement, along with figures such as the fixed bias (Bias), mean absolute error (MAE), and root mean squared error (RMSE). The systematic bias generally exhibited values indicating greater differences (**Figure 2.5**), and the mean absolute error (MAE) was slightly higher compared to intra-rater consistency. Furthermore, the root mean squared error (RMSE) suggested the presence of larger-magnitude differences, particularly for the last two compared datasets (**Figure 2.5**).

Table 2.3. Summary statistics of trends in data between raters.

Dependent Variable	Independent Variable	Number of Observations	Parameters of the Model for Actual Values	Parameters of the Model for Differences
VAPP1_S2R1	VAPP1_S1R1	155	C = 1.0432 $R^2 = 0.9884$	C = -0.0432 $R^2 = 0.1270$
VAPP2_S2R1	VAPP2_S1R1	155	C = 1.0431 $R^2 = 0.9898$	C = -0.0431 $R^2 = 0.1417$
VAPP1_S2R2	VAPP1_S1R2	89	C = 1.0321 $R^2 = 0.9732$	C = -0.0458 $R^2 = 0.0737$
VAPP2_S2R2	VAPP2_S1R2	89	C = 1.0338 $R^2 = 0.9773$	C = -0.0102 $R^2 = 0.0083$

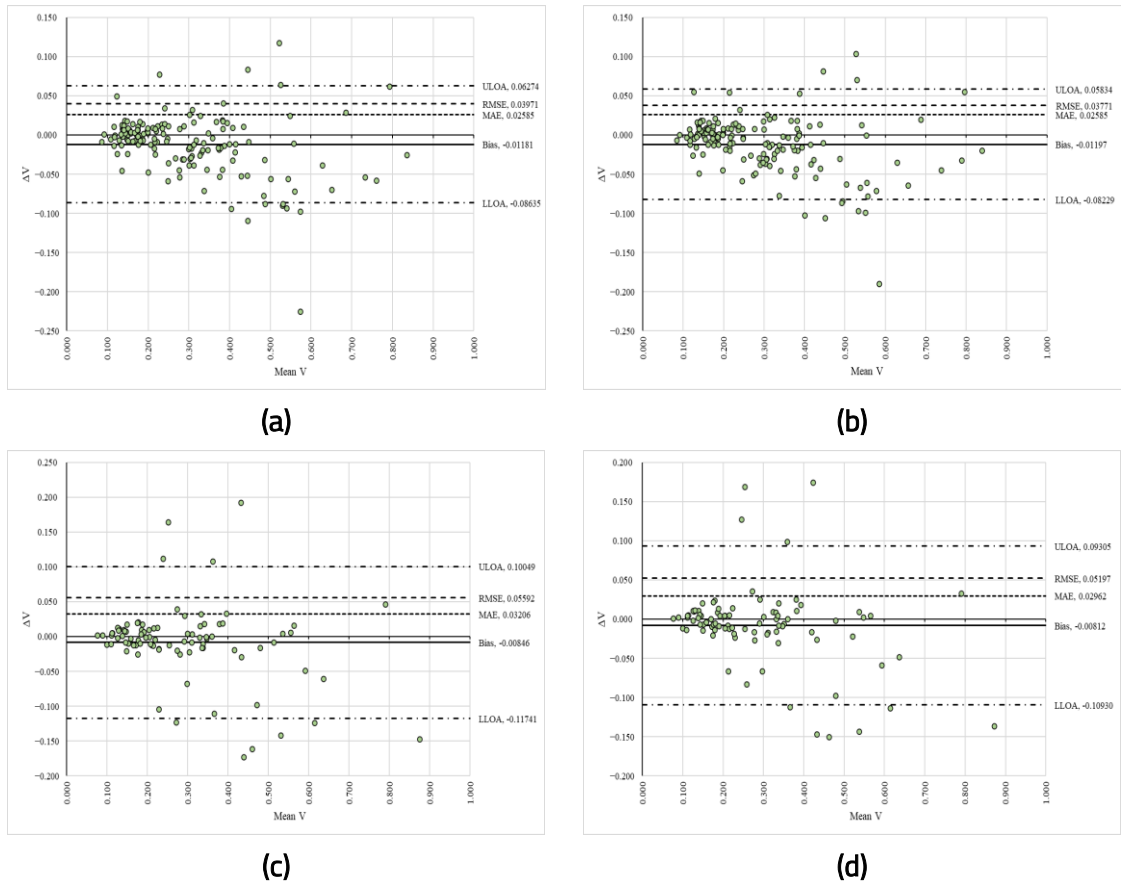


Figure 2.5. Bland–Altman plots of the compared variables between the raters: (a) comparison between VAPP1_S1R1 and VAPP1_S1R2; (b) comparison between VAPP2_S1R1 and VAPP2_S1R2; (c) comparison between VAPP1_S2R1 and VAPP1_S2R2; (d) comparison between VAPP2_S2R1 and VAPP2_S2R2.

2.2.4. Agreement Between Digital and Manual Data

When comparing the digital estimates to the manually based reference data, the developed models exhibited varying slopes and coefficients of determination, as presented in **Table 2.4**. There was similarity in the slopes (C) for the same subject and replication across different sampling densities, and the values for fixed bias (Bias), mean absolute error (MAE), and root mean squared error (RMSE) demonstrated similar behavior (**Table 2.5**).

Table 2.4. Summary statistics of trends in digital data against the manually based estimates.

Dependent Variable	Independent Variable	Number of Observations	Parameters of the Model for Actual Values
VAPP1_S1R1	VH	155	C = 1.0924 R ² = 0.9848
VAPP2_S1R1	VH	155	C = 1.0978 R ² = 0.9860
VAPP1_S1R2	VH	155	C = 1.1236 R ² = 0.9843
VAPP2_S1R2	VH	155	C = 1.1248 R ² = 0.9849
VAPP1_S2R1	VH	155	C = 1.1509 R ² = 0.9928
VAPP2_S2R1	VH	155	C = 1.1551 R ² = 0.9929
VAPP1_S2R2	VH	89	C = 1.1659 R ² = 0.9806
VAPP2_S2R2	VH	89	C = 1.1664 R ² = 0.9824

Table 2.5. Error metrics of the digital data when compared with manually based estimates.

Dependent Variable	Independent Variable	Number of Observations	Bias	MAE	RMSE
VAPP1_S1R1	VH	155	-0.0286	0.0353	0.0489
VAPP2_S1R1	VH	155	-0.0292	0.0357	0.0487
VAPP1_S1R2	VH	155	-0.0362	0.0406	0.0559
VAPP2_S1R2	VH	155	-0.0364	0.0405	0.0557
VAPP1_S2R1	VH	155	-0.0404	0.0430	0.0536
VAPP2_S2R1	VH	155	-0.0412	0.0437	0.0546
VAPP1_S2R2	VH	89	-0.0417	0.0495	0.0668
VAPP2_S2R2	VH	89	-0.0416	0.0492	0.0654

2.2.5. Time Efficiency

The main descriptive statistics for the time-consumption data are presented in **Table 2.6**. Based on the median value, the time consumption for manual measurements was higher by 7 s per log. Additionally, the coefficient of variation (**Table 2.6**) indicated greater dispersion in the manual time-consumption dataset compared to the digital measurements.

Table 2.6. Descriptive statistics of time consumption data.

Variable	Minimum Value	Maximum Value	Mean Value	Median Value	Coefficient of Variation
TM (s)	21	89	31.11	29.00	25.19
ATM (s)	17	29	20.94	21.00	10.22

2.3. DISCUSSION

This study evaluated the performance of the Tree Scanner (TS) app, a LiDAR-based smartphone tool, during its prototyping phase for log volume estimation. The findings are promising, indicating the app's potential as an accurate, reliable, and efficient alternative to traditional manual methods, though several considerations and limitations exist. The TS app demonstrated a high degree of accuracy in estimating log volumes when compared to the manual reference data that was evaluated using Huber's formula. The strong agreement, evidenced by R^2 values consistently exceeding 0.98 and a low overall RMSE (below 0.067 m^3), with minor systematic underestimation (Bias approx. -0.0417 m^3), positions the TS app favorably against other mobile solutions.

2.4. CONCLUSION

This study aimed to evaluate the performance of the prototype Tree Scanner (TS) app, a LiDAR-equipped smartphone application, for direct log volume estimation. The results demonstrate that the TS app is a promising digital measurement tool, exhibiting strong agreement with conventional manual methods while offering a significant improvement in time efficiency. The app maintained consistent accuracy and high reliability across two different sampling densities (0.1 m and 0.5 m) and between different users. The TS app represents a notable advancement by providing instant volume estimates directly on a mobile device, streamlining field data collection. Its ease of use by a single operator and its design integrating features for Bluetooth device connectivity, remote server access, and potential for species identification position it as a valuable component for enhancing forest operations and integrating into comprehensive wood traceability systems. However, as a prototype evaluated under controlled conditions, further research is essential. Future work must focus on assessing the TS app's performance and robustness in diverse and challenging real-world forest environments and across a wider variety of tree species and log irregularities.

CHAPTER 3. WOOD MEASUREMENT AT THE FACTORY GATE: A COMPARISON STUDY TO EVALUATE THE ACCURACY OF A STATE-OF-THE-ART DIGITAL TRUCKLOAD MEASUREMENT SYSTEM

3.1. MATERIALS AND METHODS

3.1.1. 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, m³) 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). 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, m³). Such manual measurements are commonly practiced in Romania and globally.

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.

3.2. RESULTS

3.2.1. Measurement Agreement

Figure 3.1, **Figure 3.2** and **Figure 3.3** illustrate the compared datasets by considering the location and magnitude of signed differences, whereas **Table 3.1**. provides the synthetic data on the considered error metrics. As shown in **Figure 3.1**, **Figure 3.2** and **Figure 3.3**, there were trends of different degrees in the signed differences related to the magnitude of the considered reference measurements. On average (**Table 3.1**), VTS overestimated manual measurements by about 0.5 m³ ($\text{BIAS}_{\text{VMA-VTS}} = -0.47 \text{ m}^3$). For the same compared datasets, mean absolute error was close to 2.5 ($\text{MAE}_{\text{VMA-VTS}} = 2.33$), and the root mean squared error was close to 3 ($\text{RMSE}_{\text{VMA-VTS}} = 3.06$). 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 3.1**). 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 3.1**).

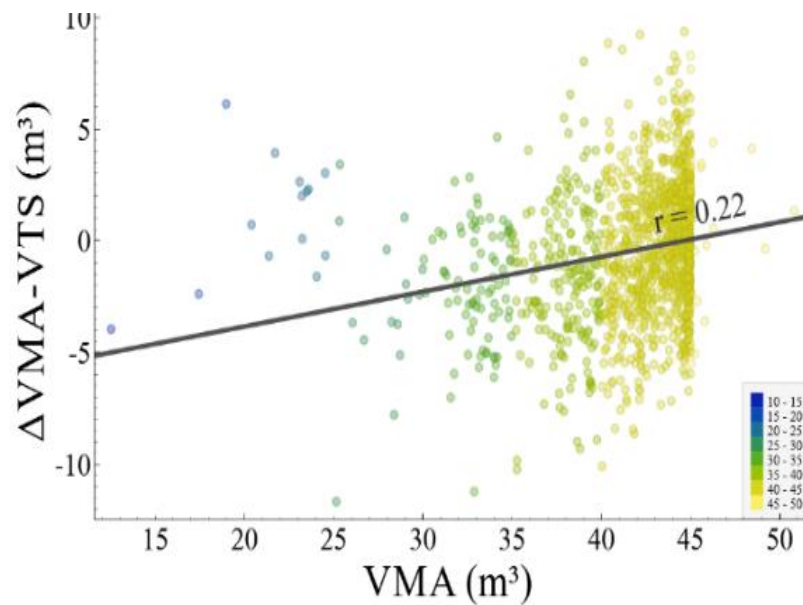


Figure 3.1. Signed differences between VMA and VTS ($\Delta VMA-VTS$, m³), plotted against VMA (m³), indicate a moderate trend in magnitude ($r = 0.22$) in relation to the magnitude of VMA. Note: The numerical legend denotes categories of magnitude in VMS (m³), and data points are scaled by the magnitude of the signed differences.

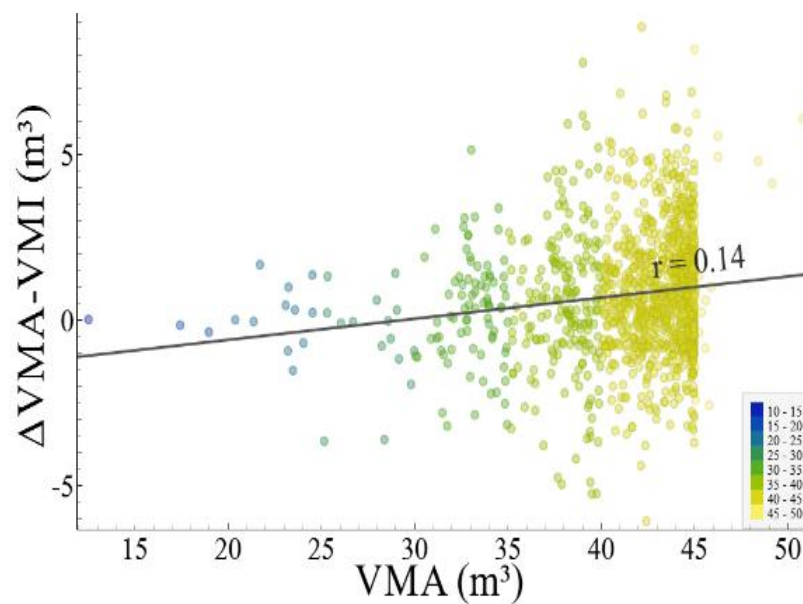


Figure 3.2. Signed differences between VMA and VMI ($\Delta VMA-VMI$, m³), plotted against VMA (m³), indicate a low trend in magnitude ($r = 0.14$) in relation to the magnitude of VMA. Note: The numerical legend denotes categories of magnitude in VMI (m³), and data points are scaled by the magnitude of the signed differences.

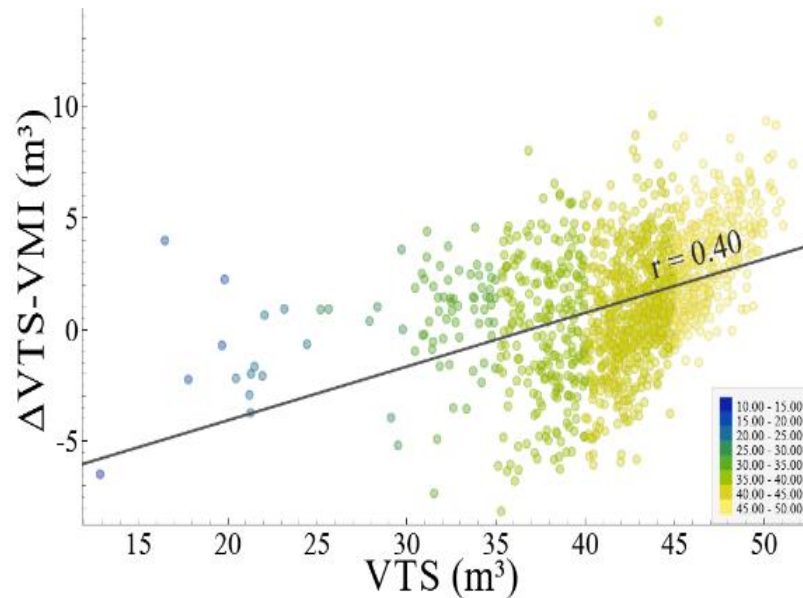


Figure 3.3. Signed differences between VTS and VMI ($\Delta\text{VTS-VMI}$, m^3), plotted against VTS (m^3), indicate a high trend in magnitude ($r = 0.40$) in relation to the magnitude of VTS. Note: The numerical legend denotes categories of magnitude in VMI (m^3), and data points are scaled by the magnitude of the signed differences.

Table 3.1. 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	$p_{BP} < 0.001$ $p_W < 0.001$

Finally, **Table 3.2** 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 $\pm 2\text{m}^3$. 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 $\pm 2\text{m}^3$. Very large differences, accounting for more than $\pm 5\text{m}^3$ (see also **Figure 3.1**, **Figure 3.2** and **Figure 3.3**), accounted for about 10% for VMA–VTS and VTS–VMI, respectively, and were low as share when comparing VMI against VMA (**Table 3.2**).

Table 3.2. Distribution of signed difference on categories of magnitude.

Compared data	Share of signed differences on categories of magnitude (%)						
	$\pm 1 \text{ m}^3$	$\pm 1\text{-}2$ m^3	$\pm 2\text{-}3$ m^3	$\pm 3\text{-}4$ m^3	$\pm 4\text{-}5$ m^3	over $\pm 5 \text{ m}^3$	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

3.3. DISCUSSION

The results of this study are generally promising, indicating overall a high degree of agreement among the measurement systems under 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 by the system as empty spaces. 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%). 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.

3.4. CONCLUSION

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.

CHAPTER 4. TRUCKLOAD TRACEABILITY: THE PERFORMANCE OF DIFFERENT IMAGE MATCHING ALGORITHMS AND PROSPECTS FOR ONLINE APPLICATIONS

4.1. MATERIALS AND METHODS

4.1.1. Data Sourcing and Preprocessing

Image data was procured by taking photographs of the truckload ends at a large wood processing company located in Romania. In total, 72 different truckloads were photographed twice using a Realme C53 mobile device, operating an Android version 13, following two rules. For each truckload, a photograph was taken at approximately 20 meters, with the field of view oriented perpendicularly to the truckload end, while avoiding camera rotation. Then, the second photograph was taken from about the same distance, but after repositioning the field of view, aiming this way to produce a different instance of the same truckload. Subsequently, these image datasets and their derivatives, following preprocessing, were labelled as 1 and 2, respectively. Images taken at the sourcing point (forest) were also obtained from the company's wood traceability system. However, these images were captured using different mobile devices, which resulted in a different scale, and most of them suffered from other distortions such as blurring.

Figure 4.1 illustrates the logic of data organization in folders, along with examples of images corresponding to each created folder. A parent folder was established to store the image data specific to each truck (denoted as TR_i , where TR stands for truckload and i ranges from 40 to 111). Within each truck-level folder, two child subfolders were created: FO and FA. The FO subfolder was used to contain the images and their preprocessing derivatives collected by various devices in the forest (at the sourcing point), while the FA subfolder stored the corresponding images collected at the factory. Within both the FO and FA subfolders, three additional subfolders were created: OR, BR, and LR.

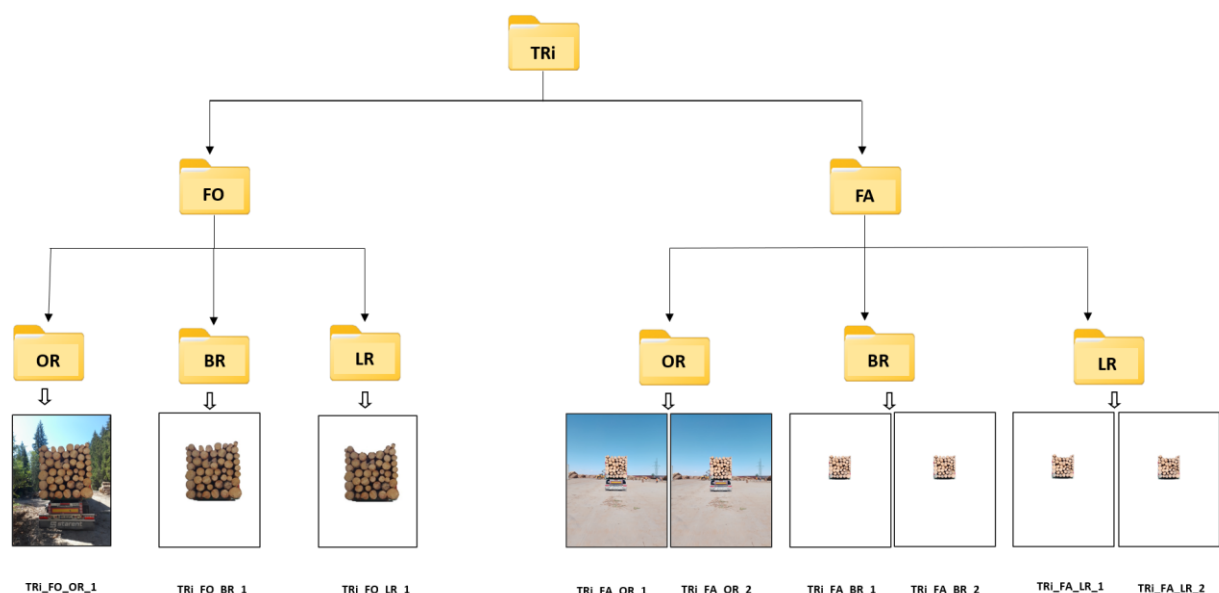


Figure 4.1. Organization of the image data. Legend: TR_i – parent folder containing images for truckload i , FO and FA – subfolders containing the original (OR), background removed (BR) and log removed (LR) images taken at the sourcing and destination points, respectively. Note: FA contained two image instances of the same truckload organized in the OR, BR and LR subfolders.

4.1.2. Experimental Design and Data Analysis

In total, eight experiments were conducted to evaluate the performance of the algorithms in fingerprinting and matching truckload images. The design of the experiments was guided by the main research questions, as illustrated in **Figure 4.2**. For the first two questions, both true positive and false positive experiments were established. A true positive experiment involved using images of the same truckload for both reference (Ref) and comparison (Com). In contrast, false positive experiments were designed to compare reference images of a specific truckload against randomly selected images of different truckloads. This approach assumed that, by chance, some truckloads in the Com datasets might be incorrectly matched with those from the Ref datasets. The experiments were conducted by first comparing the images taken in the forest with those from the factory, followed by a comparison of the images from the two datasets (1 and 2) taken at the factory.

Question	Type of experiment	Image datasets	Rule	Image data examples and number of comparisons				Performance metrics				
1	True positive	Ref TRI_FO_BR_1 Com TRI_FA_BR_1	Same truckload in Ref and Com		against		15 × 15	RVP	MKR	MKC	NMK	MT
	False positive	Ref TRI_FO_BR_1 Com TRI_FA_BR_1	Randomly selected truckload in Com		against		15 × 15	RVP	MKR	MKC	NMK	MT
2	True positive	Ref TRI_FA_BR_1 Com TRI_FA_BR_2	Same truckload in Ref and Com		against		72 × 72	RVP	MKR	MKC	NMK	MT
	False positive	Ref TRI_FA_BR_1 Com TRI_FA_BR_2	Randomly selected truckload in Com		against		72 × 72	RVP	MKR	MKC	NMK	MT
3	True positive	Ref TRI_FO_LR_1 Com TRI_FA_BR_1	Same truckload in Ref and Com & logs missing in Ref		against		15 × 15	RVP	MKR	MKC	NMK	MT
	True positive	Ref TRI_FO_BR_1 Com TRI_FA_LR_1	Same truckload in Ref and Com & logs missing in Com		against		15 × 15	RVP	MKR	MKC	NMK	MT
	True positive	Ref TRI_FA_LR_1 Com TRI_FA_BR_1	Same truckload in Ref and Com & logs missing in Ref		against		72 × 72	RVP	MKR	MKC	NMK	MT
	True positive	Ref TRI_FO_BR_1 Com TRI_FA_LR_1	Same truckload in Ref and Com & logs missing in Com		against		72 × 72	RVP	MKR	MKC	NMK	MT
								RVP	MKR	MKC	NMK	MT
								RVP	MKR	MKC	NMK	MT
4	Best image fingerprinting algorithm with the lowest image matching time							RVP	MKR	MKC	NMK	MT

Figure 4.2. Experimental design showing the question to be answered, type of experiments, datasets and rules used, examples of images and number of observations along with the performance metrics used. Note: 15 × 15 and 72 × 72 stand for the number of images in the Ref and Com datasets.

For the third question of the study, only true positive experiments were set up to consistently compare the Ref images against the Com images of the same truckload. These experiments involved comparing images taken in the forest with those taken at the factory, as well as comparing images from the two datasets captured at the factory.

4.2. RESULTS

4.2.1. Effect of Source Image Quality on the Fingerprinting and Matching Performance

As shown in **Figure 4.3**, when using low-quality images as reference data, the results were not encouraging. For instance, the ratio of valid points (RVP) was particularly low, averaging about 0.15,

irrespective of the type of experiment (Figure 4.3 a, b). Moreover, there was no consistency in the results, as both types of experiments yielded similar outcomes that were algorithm-dependent (i.e., BRISK and FREAK had higher RVPs compared to the other algorithms).

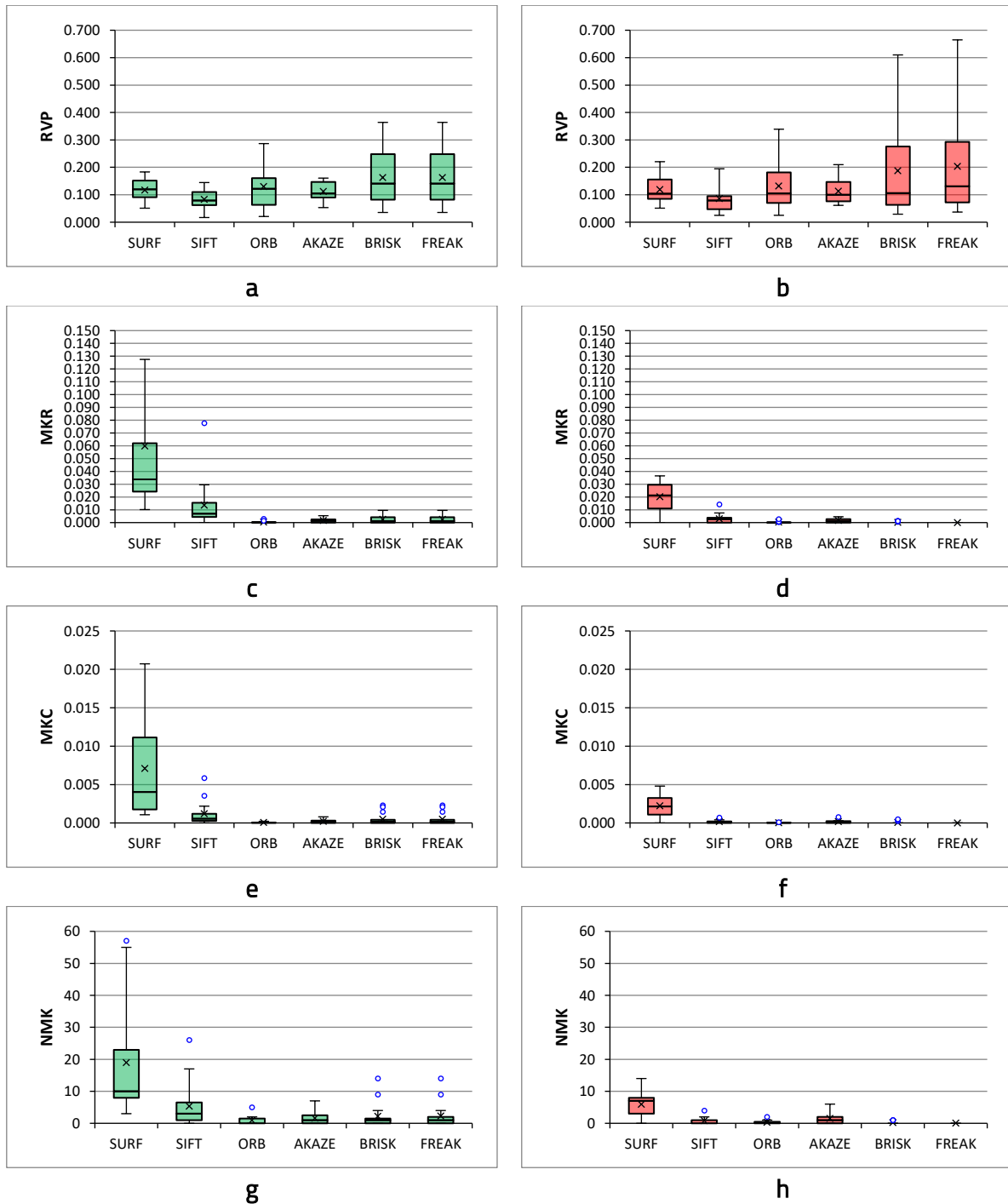


Figure 4.3. Fingerprinting and matching performance among the used algorithms for low quality of the source image: a, c, e, g – true positive experiments, b, d, f, h – false positive experiments, RVP – ratio of valid points in reference and compared image, MKR – ratio of the matched keypoints to valid points in the reference image, MKC – ratio of the matched keypoints to valid points in the compared image, NMK – number of matched keypoints.

4.2.2. Fingerprinting and Matching Performance on Images Sharing Similar Data Acquisition Features

The algorithms produced mean ratios of (RVPs) close to 1 when the same truckloads were compared based on high quality images (Figure 4.4 a). Moreover, the ratio of (MKR) closely aligned with the ratio of (MKC) for all the used algorithms (Figure 4.4 c, e), and these ratios were above 0.1.

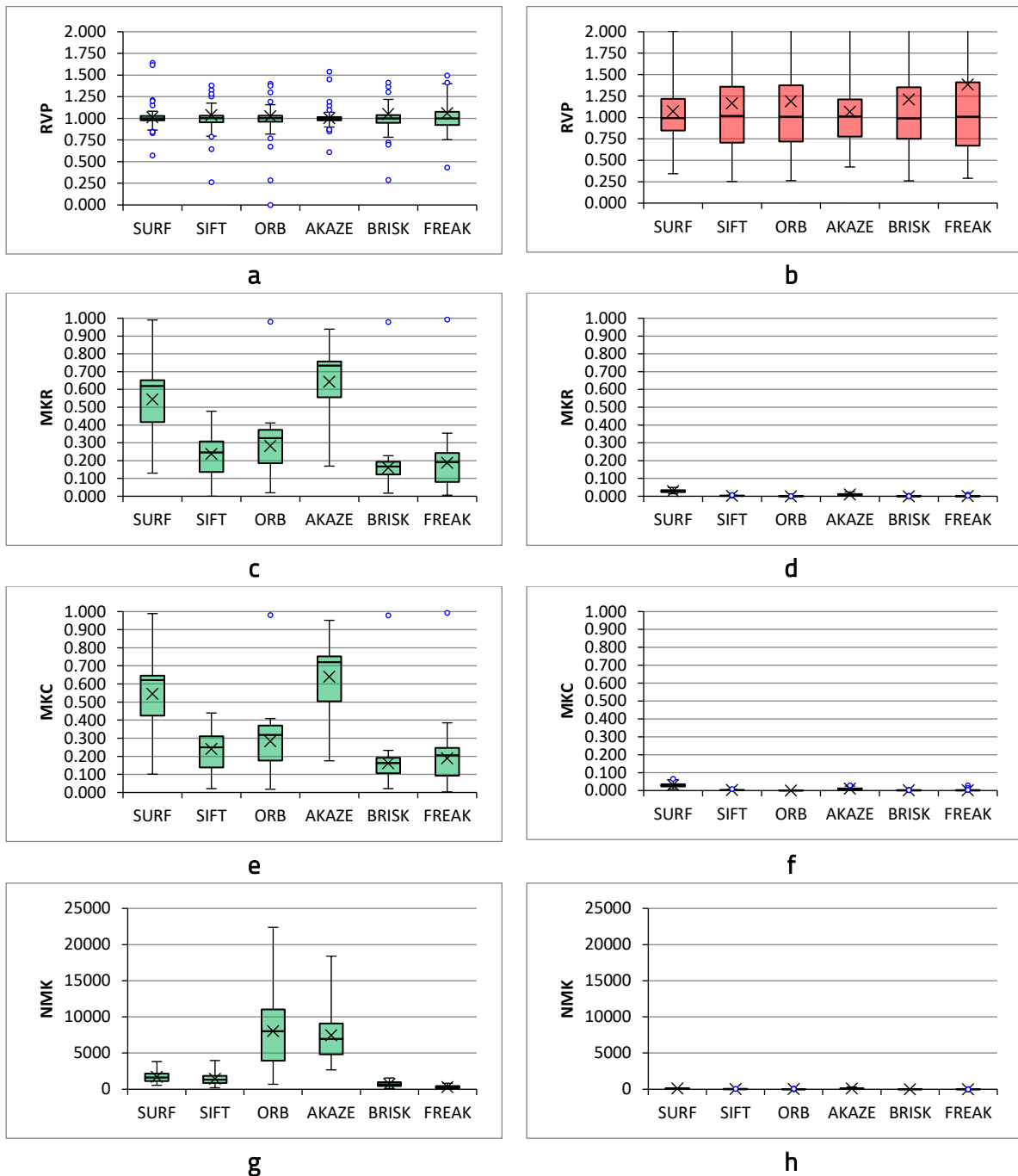


Figure 4.4. Fingerprinting and matching performance among the used algorithms for images sharing a similar quality: a, c, e, g – true positive experiment, b, d, f, h – false positive experiments, RVP – ratio of valid points in reference and compared image, MKR – ratio of the matched keypoints to valid points in the reference image, MKC – ratio of the matched keypoints to valid points in the compared image, NMK – number of matched keypoints.

Notably, SURF and AKAZE had consistently high MKR and MKC values. On other hand, the total number of matched keypoints for ORB and AKAZE was significantly higher than other algorithms (**Figure 4.4 g**). The images used in the false positive experiment were of the same quality but differed in their content (different truckloads). In this case, the results were different since the range of the ratios of valid points were wider and not as consistent as in the true positive experiment (**Figure 4.4 b**). Moreover, the MKR and MKC values were close to zero as shown in **Figure 4.4 d, f**, and the number of matched keypoints was significantly lower compared to the true positive experiment (**Figure 4.4 h**). These parameters showed sharp contrasts between the two experiments that used similar quality images for comparisons.

4.2.3. Fingerprinting and Matching Performance on Images Sharing Different Data Acquisition Features and a Different Number of Logs in the Reference and Compared images

Similar results were observed during the comparison of images of similar truckloads that varied in the number of logs (missing logs in reference or in compared images) and that utilized low-quality reference images in the two true positive experiments. As shown in **Figure 4.5 a, b**, the ratio of valid points of all the algorithms was very low, averaging about 0.13.

In addition, the ratio of matched keypoints in reference and in compared images was also significantly low. Moreover, the MKR and MKC were slightly lower in these experiments compared to the previous experiment that used low quality images but with the same number of logs. Compared to other algorithms in dealing with low-quality images, SURF algorithm demonstrated a better performance. It could identify and match better based on detected keypoints (**Figure 4.5 c-h**).

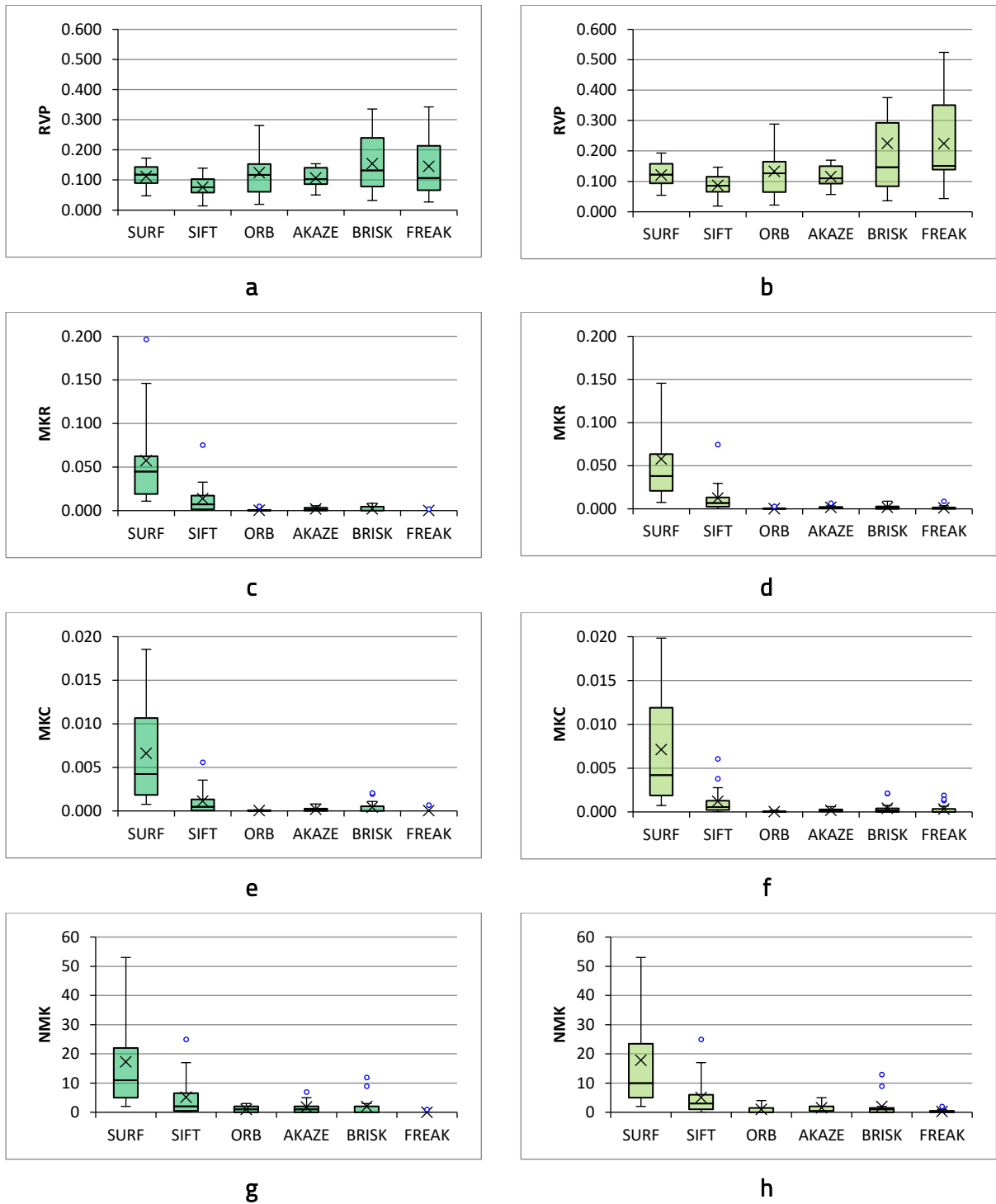


Figure 4.5. Fingerprinting and matching performance among the used algorithms for low quality of the source image: a, c, e, g – true positive experiment with missing logs in reference images, b, d, f, h – true positive experiment with missing logs in compared images, RVP – ratio of valid points in reference and compared image, MKR – ratio of the matched keypoints to valid points in the reference image, MKC – ratio of the matched keypoints to valid points in the compared image, NMK – number of matched keypoints.

4.2.4. Fingerprinting and Matching Performance on Images Sharing Similar Data Acquisition Features and a Different Number of Logs in the Reference and Compared Images

The analysis of the performance of the algorithms used in detecting and matching images of the same quality but with varying numbers of logs showed that the algorithms had a stability in ratio of valid points, except FREAK (**Figure 4.6 a, b**). The AKAZE followed by SURF achieved the highest mean MKR and MKC in both scenarios (missing logs in reference or compared images) as shown in **Figure 4.6 c-f**. In terms of the number of matched keypoints, ORB was the superior with approximately 7200 keypoints, followed by AKAZE with 6800 keypoints. SURF and SIFT demonstrated moderate performance with 1500 and 1200 keypoints, respectively, while BRISK and FREAK detected and matched 600 and 200 keypoints, respectively as shown in **Figure 4.6 g, h**.

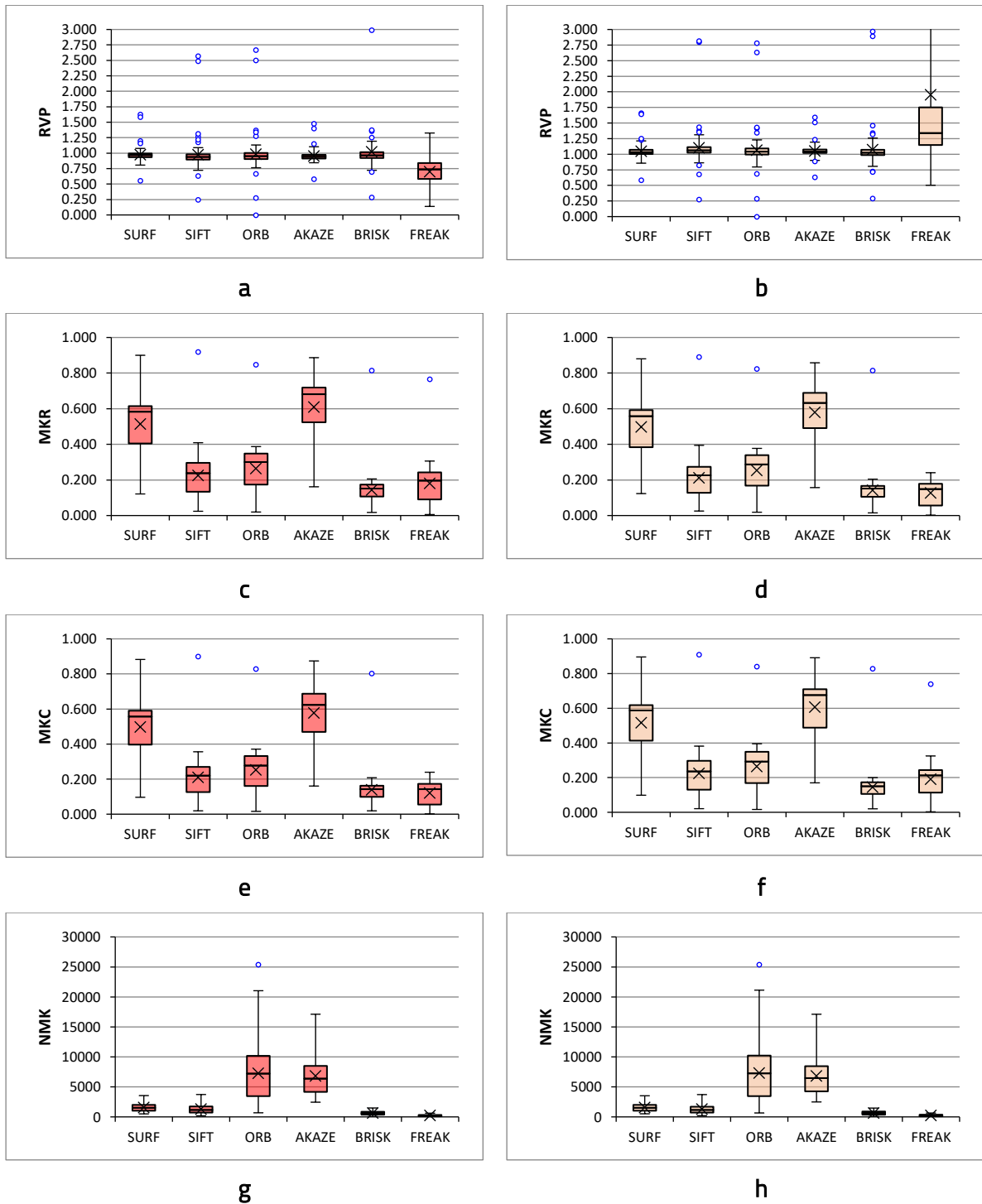


Figure 4.6. Fingerprinting and matching performance among the used algorithms for images sharing a similar quality: a, c, e, g – true positive experiment with missing logs in reference images, b, d, f, h – true positive experiment with missing logs in compared images, RVP – ratio of valid points in reference and compared image, MKR – ratio of the matched keypoints to valid points in the reference image, MKC – ratio of the matched keypoints to valid points in the compared image, NMK – number of matched keypoints.

4.2.5. Fingerprinting and Matching Time

The observations indicated that ORB recorded the longest mean matching time across all experiments as shown in **Figure 4.7**.

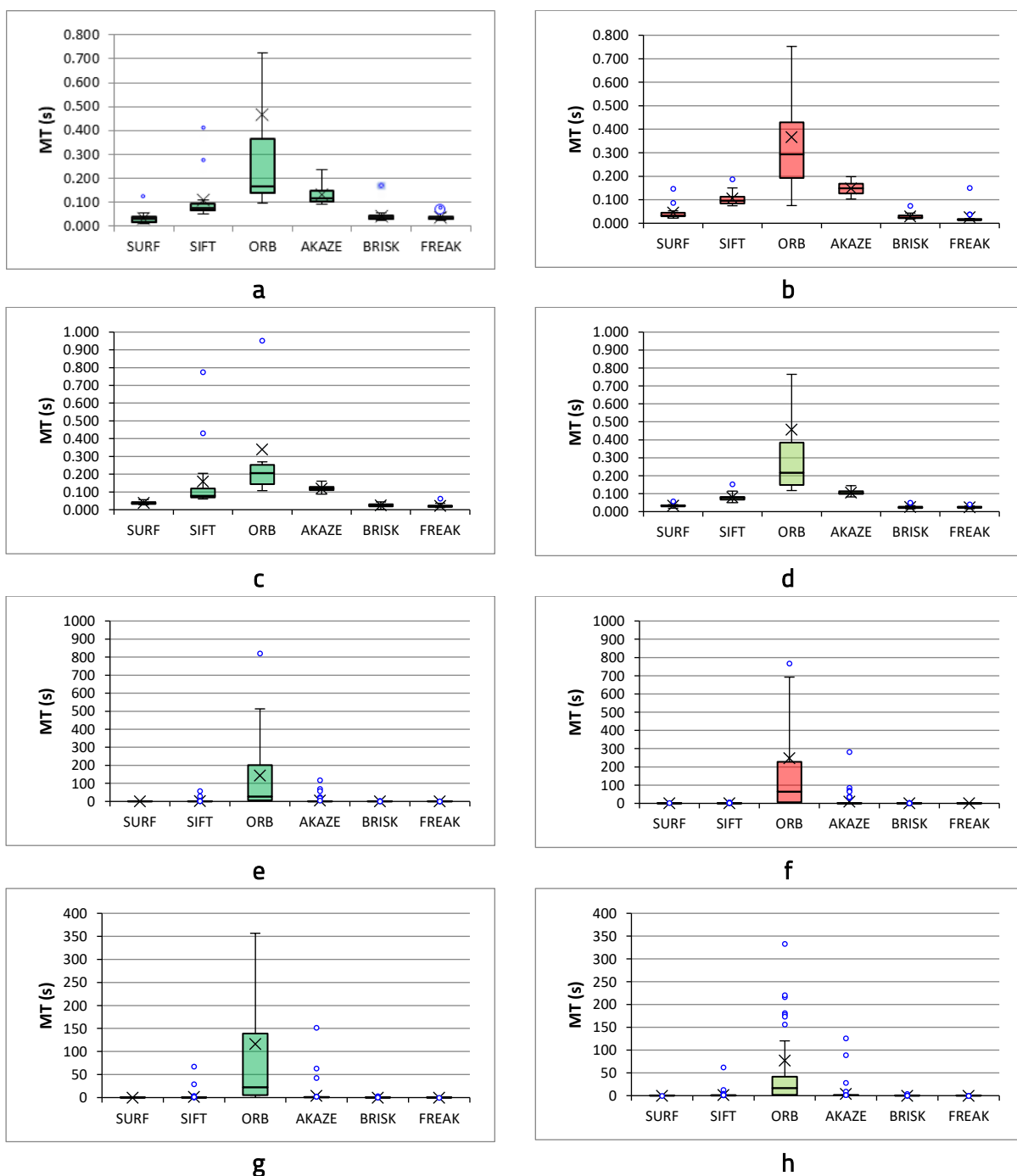


Figure 4.7. Fingerprinting and matching time: a – true positive experiment with low quality of source images, b – false positive experiment with low quality of source images, c – true positive experiment with low quality of source images missing logs, d – true positive experiment with low quality of source images having surplus logs, e – true positive experiment with images having the same quality, f – false positive experiment with images having the same quality, g – true positive experiment with images having the same quality and missing logs in source images, h – true positive experiment with images having the same quality and surplus logs in source images.

4.3. DISCUSSION

This experimental study was carried out to examine the performance of the SURF, SIFT, ORB, AKAZE, BRISK and FREAK algorithms in fingerprinting and matching truckloads based on images taken at their ends. Notably, no previous studies have specifically addressed this problem, which is highly relevant for truck transportation. The study results showed that the performance of these algorithms depends on the image quality. Notably, the SURF algorithm can work to some extent with low-quality images even if they are slightly different in the scale and content; it demonstrated that it is more effective in establishing matches, even in low-quality image scenarios. When comparing two images that shared the same quality, the performance of the algorithms depends on whether the used algorithm is sensitive to slight variations in scale of the compared images.

4.4. CONCLUSION

This study was carried out to examine the performance of the feature detection algorithms to fingerprint and match truckloads based on images taken at their ends. The results showed that the matching performance depends on the quality of the images, especially blurring, which has a negative effect on the capabilities of these algorithms. Among the tested algorithms, SURF demonstrated to some extent the capability of matching low-quality images. Additionally, the performance of these algorithms depends on how the images were taken. SURF and AKAZE perform excellently even if the images are not taken precisely from the same point of view. Conversely, SIFT, ORB, BRISK, and FREAK algorithms are more sensitive if the field of view of the images was not exactly the same, despite following the same procedure. A drawback of AKAZE is that it is time-consuming, whereas SURF is faster. Furthermore, these algorithms are able to identify the differences in the truckloads, such as missing or surplus logs. SURF could be the most effective smart solution for implementation in mobile units with constrained computing power to fingerprint truckload images, assuming that images of similar and high quality could be provided at the sourcing and destination points.

CHAPTER 5. CONCLUSIONS. ORIGINAL CONTRIBUTIONS. DISSEMINATION OF RESULTS

5.1. CONCLUSIONS

This PhD thesis highlights the importance of integrating smart solutions into wood traceability and sourcing systems, solving the growing worldwide demand for transparency, legality confirmation that can promote sustainable forest management. The review of current technologies discloses the speedy advancement in marking tools, digital platforms, identification techniques and monitoring instruments, while shading light on obstacles related to cost, infrastructure and stakeholder acceptance. The research proves that latest digital tools extending from the advancement methods identified through a comprehensive literature review to the tested methods like the LiDAR based-smartphone application, the digital industrial CIND system and the algorithmic matching instruments can importantly support the integrity and efficiency of the wood supply chain. The evaluated TreeScanner application showed that a LiDAR based smartphone can provide high reliable instant log volume estimation, that can be an efficient and practical alternative to traditional field measurement tools. Moreover, the assessment of CIND digital system of measuring roundwood solid volume, demonstrated fast, accurate estimate of the truckload at the factory gate, reducing human error, enhancing operational control, and improving monitoring of wood flow that can address many challenges related to timber transportation. This technology ensures legal compliance in the forest industry. Furthermore, the tested feature matching algorithms provided for the industry evidence of a valuable idea of integrating this smart solution for tracing timber truckloads from forest to sawmill with the advantage of exposing stolen or illegal logs in the loads. The findings of this thesis prove that digitalisation can alter wood traceability and sourcing systems by reducing manual effort, improving data accuracy and supporting dependable sourcing practices. Regardless of limited datasets and the necessary of comprehensive field validation, this research set up a strong footing of knowledge for future improvements. Future work can focus on combining other technology like sensor data, testing other algorithms with broad datasets, enhancing interoperability between field and industrial systems, developing merged platforms able to monitor overall chain of custody. These efforts can increase the efficiency and transparency of forestry sector that meet the global sustainable objectives.

5.2. ORIGINAL CONTRIBUTIONS

This PhD thesis has significantly advanced the domain of wood traceability and sourcing by developing and assessing innovative smart solutions that enhance supply chain transparency and efficiency. An essential aspect of this thesis is the development of an understanding base through the systematic literature review of 125 scientific papers, thus creating one of the most updated and complete literature review on the processes and technologies used in timber traceability and sustainable transportation management, as well as the results obtained in the environmental, economic, and social fields. This review not only synthesizes the current understanding but also reveals the existing gaps and opportunities in terms of inventions, thus creating a remarkable reference.

Another important contribution is the evaluation of the TreeScanner application, which is considered to be one of the first studies that applies the phone-based LiDAR technology to directly estimate log volume in the sawmill yard. The study has generated a high-quality dataset that includes both manual and digital measurements. The results demonstrate that the TreeScanner app provides accurate and consistent measurements across two different sampling densities (0.1 m and 0.5 m) and between different operators, enabling a practical and efficient alternative to conventional methods by improving productivity (38%), as the digital measurements took a median time of 21 s per log compared to 29 s per log with manual measurements. This research promotes the integration of this LiDAR-based application into wood traceability systems, as it features many functionalities, such as Bluetooth transfer, remote server services, the provision of instant volume estimates, compatibility with RFID tags, and the ability to document the geographic location of measurements.

The thesis contributes to the development of industrial traceability with an evaluation of CIND technology in the context of the sawmill environment to determine the volume of timber transported in truckloads. It focuses on the potential offered by this technology to provide precise measurements as the truck arrives at the gate. This study highlights the operational benefits that can be obtained from the integration of smart solutions, which may be beneficial in terms of the interoperability between the field and the industry traceability systems.

This thesis introduces the use of feature detection algorithms to fingerprint truckloads and match them based on images taken at their ends as a notable, significant, original contribution. The comprehensive dataset contained 2,084 images used to evaluate the performance of six algorithms in fingerprinting images, which were as follows: SURF (Speeded-Up Robust Features), SIFT (Scale-Invariant Feature Transform), ORB (Oriented FAST and Rotated BRIEF), AKAZE (Accelerated-KAZE), BRISK (Binary Robust Invariant Scalable Keypoints), and FREAK (Fast Retina Keypoint). The study demonstrates that these algorithms can trace transported timber from forest to sawmills and help prevent illegal logs from entering the supply chain through transportation using the advantages of these algorithms in identifying the differences in the truckloads, such as missing or surplus logs. The research highlights SURF as the most effective smart solution among the tested algorithms. This research gives the industry an idea of integrating this smart solution into timber traceability systems. Collectively, these contributions set up a multi-layered framework for improving wood traceability through merging systematic knowledge, validation of digital measurements, assessment of industrial technology, and presenting and testing novel smart solutions. This thesis provides an important foundation for future innovations and practical implementation of digitalization in forestry.

5.3. DISSEMINATION OF RESULTS

5.3.1. Scientific Publications Based on this PhD Thesis

A. Papers Published in BDI Journals

1. Elias, M. (2024). Timber traceability and sustainable transportation management: A review of technologies and procedures. Bulletin of the Transilvania University of Brasov. Series II: Forestry ■ Wood Industry ■ Agricultural Food Engineering, 11-52. Available online at: https://webbut.unitbv.ro/index.php/Series_II/article/view/7874/5925
DOI: 10.31926/but.fwiafe.2024.17.66.1.2

B. Papers Published in Journals Indexed by Clarivate Analytics (former ISI Web of Science)

1. Elias, M., Forkuo, G. O., Picchi, G., Nati, C., & Borz, S. A. (2025). Accuracy of a novel smartphone-based log measurement app in the prototyping phase. *Sensors*, 25(18), 5847. Available online at: <https://www.mdpi.com/1424-8220/25/18/5847,DOI:10.3390/s25185847>
2. Elias, M., & Borz, S. A. (2025). Wood measurement at the factory gate: a comparison study to evaluate the accuracy of a state-of-the-art digital truckload measurement system. *Annals of Forest Research*, 68(2), 85-96. Available online at: <http://afrjournal.org/index.php/afr/article/view/4151/1349,DOI: 10.15287/afr.2025.4151>

5.3.2. Papers Presented at Scientific Conferences Based on this PhD Thesis

A. Papers Presented at National Scientific Conferences

1. Elias, M., Borz, S.A., 2023. Wood traceability and sourcing technologies: a systematic review. celei de-a VIII-a Sesiuni Naționale de Comunicări Științifice Studentești pe Teme de Silvicultură și Protecția Mediului Vatra Dornei, 26-27 Mai 2023. Available online at: https://silvic.usv.ro/avizier/2023_mai_simoz_national.pdf
2. Elias, M., Borz, S.A., 2024. Tracing the Timber from Forest to the Mill: An Application of the SURF Algorithm to Fingerprint Truckloads Based on Photographs Taken at their Ends. Graduates in Front of Companies (AFCO) 2024. Available online at: https://afco.unitbv.ro/2024/images/Documente/AFCO_2024_Lucrari_inscris_e_.pdf
3. Elias, M., Borz, S.A., 2024. Tracing the Timber from Forest to the Mill: An Application of the SURF Algorithm to Fingerprint Truckloads Based on Photographs Taken at their Ends. DoCo2024. Available online at: <https://www.unitbv.ro/en/research/doctoral-studies/2024-doctoral-conference.html>. Conference program details are available online at: https://www.unitbv.ro/Detailed_Programme.pdf

B. Papers Presented at International Scientific Conferences

1. Elias, M., Borz, S.A., 2024. Tracing the timber from forest to the mill: an application of the SURF algorithm to fingerprint truckloads based on photographs taken at their ends. In Book of Abstracts of the 11th 4369 International Symposium on Forest and Sustainable Development, FSD 2024. Available online at: https://silvic.unitbv.ro/images/conferinte/fsd2024/Book_of_abstracts_FSD_2024c.pdf
2. Elias, M., Borz, S.A., 2024. Tracing The Timber From Forest To The Mill: An Application of The Surf Algorithm To Fingerprint Truckloads Based On Photographs Taken At Their Ends. In Book of Abstracts of the 56th International Symposium on Forest Mechanization (FORMEC), Gdańsk, Poland 2024. Available online at: https://www.formec.org/images/proceedings/2024/Proceedings_FORMEC_2024_Gdansk_02.pdf
3. Borz, S.A., Elias, M., Forkuo, G.O., Picchi, G., Nati, C., 2025. Performance of a Novel Smartphone – Based Measurement App Prototype in Log Volume Estimation. Book of Abstracts: Proceedings of the 57th International Symposium of Forest Mechanization (FORMEC), Finland. Available online at: <https://erepo.uef.fi/server/api/core/bitstreams/2dd5580c-e499-4590-a04f-aebea21969d4/content>

5.3.3. Scientific Publications Based on the Results Produced by Participation in Research Teams External to the PhD Thesis Scope

A. Papers Published in Journals Indexed by Clarivate Analytics (former ISI Web of Science)

1. Stopfer, L., Buss, E., Kaulen, A., Berendt, F., De Miguel-Díez, F., Püls, Elias, M., Borz, S. A, & Purfürst, T. Sustainability Assessment of Blockchain Systems in Timber Supply Chains: Environmental and Economic Impacts. *Frontiers in Blockchain*, 9, DOI:10.3389/fbloc.2026.1745200

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2. Abdi, E., Mariv, H. S., Deljouei, A., & Sohrabi, H. (2014). Accuracy and precision of consumer-grade GPS positioning in an urban green space environment. *Forest science and technology*, 10(3), 141-147. DOI:10.1080/21580103.2014.887041
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ACKNOWLEDGEMENTS

I give all the glory and thanks to my lord and saviour Jesus Christ for his love and grace and for fulfilling the wish of my heart to have a doctoral degree.

With much respect and admiration, I am deeply thankful to my supervisor, Prof. Dr. Eng. Stelian Alexandru BORZ, whose expertise and mentorship, invaluable insights, patience, and support guided me through every stage of this research.

I am also indebted to the members of my Supervisory Committee, Prof. Dr. Petrișan Ion Cătălin, Assoc. Prof. Dr. Marcu Marina Viorela, Assoc. Prof. Dr. Iordache Eugen and Assoc. Prof. Dr. Nicușor Boja, for their constructive feedback, thought-provoking questions, and steadfast encouragement during the various stages of this research.

I would like to thank the Department of Forest Engineering, Forest Management Planning, and Terrestrial Measurements, Faculty of Silviculture and Forest Engineering, Transilvania University of Brasov for providing the equipment needed for this research.

I would like to acknowledge the invaluable scholarship provided by Transilvania University of Brasov enabled this research endeavour. I thank to the rector of the Transilvania University of Brasov, prof. Ioan Vasile ABRUDAN and the dean of the Faculty of Silviculture and Forest Engineering, prof. Alexandru Lucian CURTU and all the professors for their useful teaching during the PhD program.

Special thanks to my colleagues and friends for their kindness and support in different stages of my academic program: Obaida Alhousrya, Tinashe Chamunorwa, Ronald Musona, Malsha Mayoshi, Vladimir Bulatnikov, Lukas Stopfer, Alexandra reyes. I appreciate the efforts of my friends and colleges: Jenny Morocho, Gabriel Forkuo, Alfaro Dylan, Bolash Andras, Darius Naiman and Necolai Talagai who helped with data collection.