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ORIGINAL ARTICLE

Comparison of non-destructive tools for measuring MOE of southern pine trees

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Abstract

Various non-destructive evaluation (NDE) technologies increasingly used to assess log stiffness and support sorting, segregation and processing decisions. However, comprehensive comparative evaluations of various NDE tools across the wood value chain remain limited. Therefore, this study compared several NDE methods for estimating modulus of elasticity (MOE) in southern pine grown in Queensland, Australia, at three processing stages: standing trees pre-harvest, felled logs post-harvest, and boards produced from those logs. Standing trees measurement included ultrasound MOE assessment on increment cores (USMOE) and Director ST300 (ST300_MOE) and IML-Resi PD-400 resistance drilling (Resi_MOE). Felled log measurements were obtained using Beam Identification by Non-destructive Grading (BING_MOE) and the resonance acoustic tool Hitman HM200 (HM200_MOE). These measurements were then related to log MOE, log density, and the average MOE and modulus of rupture of boards cut from the same trees. Finally, log stiffness measurement tools were compared in terms of deployability, efficiency, and predictive power. NDE tools applied to standing trees pre-harvest generally exhibited lower predictive power in estimating log and board MOE than tools applied to felled logs. For log MOE, HM200_MOE showed the strongest relationship with BING_MOE (R^2 =0.78) followed by USMOE ($R^2 = 0.67$), ST300_MOE ($R^2 = 0.61$), and Resi_MOE ($R^2 = 0.57$). BING_MOE explained the highest variability in the average board MOE ($R^2 = 0.84$), followed by USMOE ($R^2 = 0.71$), HM200_MOE ($R^2 = 0.69$), ST300_MOE ($R^2 = 0.64$), and Resi_MOE ($R^2 = 0.43$). These results highlight a clear trade-off between predictive performance and operational practicality. BING and HM200 provided better accuracy and precision, but unsuitable for standing tree assessment. Among the standing trees methods, USMOE provided best balance between precision and accuracy and potential field use but are slower and more expensive. ST300 and Resi were faster and more practical for pre-harvest sorting their lower predictive performance underscores the need for improved calibration or modelling. Overall, tool selection depends on the required balance between predictive performance, operational efficiency, sampling requirement and cost.

1 Introduction

Assessing the quality of logs in forest plantations is essential for optimising resource allocation, utilisation, and processing efficiency. Non-destructive evaluation (NDE) methods often involve no or minimal sampling from standing trees without causing significant damage to the tree (Ondrejka et al. 2021; Schimleck et al. 2019). Early-age NDE assessment can also aid genetic selection for improved structural timber (Lindström et al. 2002). Over the past few decades, significant advancements have been made in the NDE methods and tools for measuring the Modulus of Elasticity (MOE) in logs. Lindström et al. (2002) demonstrated strong agreement between destructive (static) and NDE (dynamic) MOE (R^2 = 0.85–0.91) for early age radiata pine trees. Several NDE methods are available for evaluating tree and log

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quality, which can be broadly categorised into two main groups based on whether tree felling is required: (a) NDE tools on standing trees and (b) NDE tools on felled trees such as stems or logs. NDE tools on felled trees-based resonance acoustic methods such as Hitman HM200 (Fibre-gen, Christchurch, New Zealand), Beam Identification by Non-destructive Grading (BING) (CIRAD, France), and other resonance frequency measurement methods (Edlund et al. 2006) can provide high predictive performance.

The NDE methods on standing trees can be further categorised into two methods:

1. Lab-based NDE on standing trees: These methods require small samples such as cores taken from standing trees, with measurements conducted in laboratory settings. Examples include measurement and/or estimation of density and MOE from core samples using ultrasound (Kumar et al. 2021), near-infrared (NIR) spectroscopy (Schimleck et al. 2018), SilviScan (Evans et al. 2000), and DiscBot (Lee 2024).
2. Field-deployable NDE on standing trees: These methods enable direct measurements on standing trees in situ and are portable for use in forest. These include resistance drilling (IML-RESI Power Drill™ and the RESISTOGRAPH™) (Downes and Lausberg 2016; Downes et al. 2018; Rinn et al. 1996), Pilodyn 6J Forest (Proceq, Schwerzenbach, Switzerland), ST300 (Fibre-gen, Christchurch, New Zealand), and Fakopp Microsecond Timer (Fakopp Kft., Sopron, Hungary).

In lab-based NDE on standing trees, the increment borer is a fundamental tool for assessing the wood quality of forest resources. This tool extracts cores from living trees and the core is then stored and transported to a laboratory for further analysis, where wood density and stiffness can be determined (Gao et al. 2017). Increment cores extracted from standing trees can also facilitate measurement of many other wood properties, including basic density, modulus of elasticity (MOE), dendrochronological analysis, fibre length, and microfibril angle using various techniques such as ultrasound (Kumar et al. 2021), X-ray imaging, near-infrared (NIR) spectroscopy, (Downes et al. 1997; Gao et al. 2017; Gendvilas et al. 2022), SilviScan® (Buksnowitz et al. 2007; Evans et al. 2000; Schimleck et al. 2002; Wessels et al. 2011), DiscBot (Ondrejka et al. 2021). Dahlen et al. (2018) found that, although non-destructive SilviScan outputs are useful, calibration based on sonic resonance overestimated MOE by approximately 25%; therefore, calibration against destructive (static) testing is required for accurate absolute predictions.

Internal radial variation of the wood properties obtained from core can also be used to predict MOE of logs and the boards (Kumar et al. 2021; Psaltis et al. 2021). However, this process can present challenges, such as reaching the pith in large trees and core extraction difficulties can arise in denser trees (Gao et al. 2017; Grissino-Mayer 2003). In contrast, field deployable NDE on standing trees allow for faster data collection and processing with minimal or no lab work. Among them, 'time of flight' acoustic techniques are widely employed and commercially viable due to their affordability, speed, robustness, and practicality for field applications. These tools have been used in assessing standing trees before harvesting, facilitating effective resource management, planning, harvesting, and wood processing to maximise the resource's value extraction potential (Ondrejka et al. 2021; Schimleck et al. 2019). These methods measure stress wave speed propagating through the stem, typically generated by tapping one end with a light hammer. The Time of Flight (TOF) of the acoustic wave is precisely determined between the transmitter probe and receiver probe (Wang and Ross 2002; Wessels et al. 2011). Subsequently, acoustic wave speed and a dynamic MOE are calculated from the TOF measurements and the wood density data. Some examples of these devices are Fibre-gen Director ST300 Tool, ArborSonic 3D Acoustic Tomograph, IML Impulse Hammer, and FAKOPP company tools (Microsecond Timer, Resonance Log Grader, ArborElectro Impedance Tomograph).

Another notable field deployable tool on standing trees is the resistance drilling technology developed in the early 1990s. There are two commonly used drilling resistance machines: IML-RESI Power Drill™ (IML - Instrumenta Mechanik Labor System GmbH, 2022) and the RESISTOGRAPH™ (Rinntech, 2023). Primarily used to detect rot in trees and poles, it is gaining popularity due to its affordability for field use, digital data collection capability, and relatively high-resolution data output (Gao et al. 2017; Rinn et al. 1996). It operates by driving a specialized 3 mm diameter drill (needle) through a tree at specified feed and rotation speeds while measuring the resistance to rotation (torque). This process generates a profile of resistance at 0.1 mm intervals, which is correlated with wood density and stiffness (Downes and Lausberg 2016; Downes et al. 2018; Rinn et al. 1996). Pilodyn, an older technology, is also used in standing trees, however its accuracy and reliability for tree selection, especially in breeding programs, is questioned due to its limited evaluation of outermost wood rings, making it unrepresentative of stem mean density (Cown 1978; Gao et al. 2017).

NDE methods that enable efficient evaluation of relatively large numbers of trees, balancing sampling rates, cost-effectiveness, and field operational speed can deliver valuable information to the forest industries for log or forest sorting. The various NDE methods mentioned above have been used to assess log quality, comparing MOE estimates between standing trees, logs, and boards, yielding varying degrees of accuracy in their results. Ultrasonic measurement on cores was used to predict log MOE, explaining 64–79% of the variance (Kumar et al. 2021) and board MOE, explaining 47–53% of the variance (Psaltis et al. 2021). Carter et al. (2007) used HM200 for sorting logs or lumber and concluded that HM200 can provide good estimations of mean MOE of boards. Moreover, dry HM200 velocity was better than green velocity for estimating air-dry MOE of boards due to uncertainties and variation in green density. Similarly, Edlund et al. (2006) reported weak relationships between visual grade classes and log MOE (resonance based), but good agreement between log MOE and the proportion of higher structural-grade sawn timber. Downes et al. (2022) found good correlation between resistance drilling with outerwood density data derived from SilviScan.

Duchesne et al. (2025) investigated the relationship between acoustic velocity (AV) measurement at multiple levels using ST300 for standing trees and HM200 for stems and sawlogs and boards for lodgepole pine. They also evaluated the ability of AV measurement to estimate a board's static bending stiffness (MOE) and strength (MOR). As expected, the AV between log and stem showed the strongest relationship. However, no or weak relationships were found between board AV and tree/stem AVs. Board bending properties and tree AV at all levels were also poorly correlated. Similar findings were reported by Todoroki and Lowell (2016), who developed predictive mixed-effects models for tree, bole, and log MOE and demonstrated acoustic velocity alone is insufficient for accurate MOE estimation and tree segregation, and that incorporating wood density and stem taper is necessary to improve predictive accuracy. In contrast, Butler et al. (2017) found a moderate relationship between mean MOE of boards and log AV ($R^2=0.49$), and a weak relationship between lumber MOR and log AV ($R^2=0.20$) in loblolly pine. Auty and Achim (2008) compared ST300 log MOE with the MOE and MOR of 300 mm × 40 mm × 40 mm clear specimens obtained from the same trees, reporting moderate relationships between acoustic velocity and MOE ($R^2 = 0.53$) and between acoustic velocity and MOR ($R^2 = 0.59$). Grabianowski et al. (2006) found good correlations in AV between tree, log, and board MOE, showing that older trees with stiffer outerwood displayed higher acoustic velocities than young plantation-grown Radiata Pine. AV was also a better predictor than specific gravity for both MOE and MOR of boards, indicating the potential of using AV in future tree breeding, as well as for product segregation (Filipescu et al. 2017). MOE of boards obtained from static bending also showed a moderate relationship between log AV for black spruce ($R^2=0.78$) and balsam fir ($R^2=0.58$) (Duchesne et al. 2025). Amishev and Murphy (2008) reported strong correlations between stand-level acoustic measurements (ST300, HM200) and veneer grade recovery ($R^2 = 0.91$ and 0.82).

However, multilevel comparisons across standing trees, logs, and boards using different methods and instruments are rarely reported in the literature due to high costs, extensive labour requirements, and methodological complexity, particularly when sawing and static bending tests are involved (Legg and Bradley 2016). For Sitka spruce, studies have examined relationships between logs and boards (Searles and Moore 2009; Simic et al. 2019). Tree-to-log relationships have been reported for radiata pine, red pine, Sitka spruce, loblolly pine, western hemlock, and jack pine (Bucur 2023; Olaoye and Ojo 2022), Douglas fir, Norway spruce, and Sitka spruce (Krajnc et al. 2019) while log-to-board relationships have been investigated for loblolly pine (Butler et al. 2017), as well as more generally for softwood species (Wang 2013). For hardwoods, multilevel relationships have been examined between logs and boards in shining gum (Balasso et al. 2022) and between logs and small clear samples (Sirswal et al. 2025). Rais et al. (2014) assessed MOE at the tree, log (using ST300), and board levels in Douglas-fir and found that felled-tree measurements provided more reliable pre-grading or sorting information than standing-tree assessments. To date, limited comprehensive multilevel comparisons have been reported using for Southern pine, particularly when considering the range of contemporary tools and techniques now available. Therefore, the objectives of this study are threefold: First, to investigate the correlation between log MOE measured using various NDE tools on felled and standing trees, log density, and the MOE and MOR of sawn boards. Second, to assess the accuracy of the log MOE measurement tools in predicting log MOE and the average MOE of sawn boards derived from these logs. Finally, NDE tools were compared with a focus on measurement accuracy and precision, efficiency, predictive capability, and operational practicality.

2 Methodology

Data were collected from a total of 68 trees/sawlogs, each 3.9 m in length, extracted from a height of 2.4–6.3 m above the stump, from trees harvested from plantation forests in Tuan, Beerburrum and Toolara in southeast Queensland (SEQ), Australia. All trees were from the locally developed hybrid between slash pine (*Pinus elliottii* var. *elliottii*) and Caribbean pine (*P. caribaea* var. *hondurensis*), known as the PEE × PCH hybrid, from a range of germplasm types and silvicultural regimes. The sample set comprised.

- 30 F_2 hybrid trees from Tuan, aged 28 years, with a mean diameter at breast height (DBH) of 36.33 cm (SD = 4.51), originating from open-pollinated seedlings and grown at a final crop stocking density of 388 stems per hectare;
- 30 F_1 hybrid trees from Beerburrum, aged 19 years, with a mean DBH of 33.43 cm (SD = 8.25), including an F_1 hybrid full-sib family and two clonal varieties, C625 and C887, with stocking densities ranging from 200 to 1000 stems per hectare; and,
- 8 F_1 hybrid trees from Toolara, aged 24 years, with a mean DBH of 26.84 cm (SD = 3.41) all of clonal variety C887, with stocking densities ranging from 1006 to 2660 stems per hectare.

After completing the standing tree sampling and log measurements, the 3.9 m logs were sawn using industry-prescribed sawing patterns to nominal structural framing dimensions (96 mm × 40 mm and 72 mm × 40 mm). The resulting boards were kiln dried. Samples for static bending to determine MOE or MOR were taken randomly from one end of the 3.9 m sawn boards, with the length of the test sample determined by the cross-sectional dimensions of the board. For 96 mm × 40 mm studs, the test sample length was 2 m, whereas for 72 mm × 40 mm studs it was 1.5 m. Each test sample was taken from either the butt or top end of the board, with the end selected randomly. On average, each tree contributed approximately 9– 10 boards, with the number of boards per tree ranging from a minimum of 3 to a maximum of 24. A total of 662 boards were tested. Density of the boards for static bending tests were measured from dimension and mass.

Non-destructive evaluations were performed at three processing stages along the wood value chain - standing tree (pre-felling), log (post-felling), and board (post-processing), standing tree, log, and board, using complementary NDE tools to estimate or measure modulus of elasticity (MOE) and related wood properties. This multistage approach enables the linkage of stiffness estimates from standing trees to final board properties. Table 1 summarises the NDE tools and measurements applied at each of the three stages in this study and Fig. 1 illustrates the application of these NDE tools at the standing tree, log, and board levels.

Table 1 Material levels and NDE tools used for MOE and density assessment

Processing stage	NDE measurement/estimation tools
Standing tree (pre-felling)	Resi (PD-400), ST300, USMOE
Log (post-felling)	HM200, BING, log density
Board (post-processing)	Static bending (MOE & MOR), density

2.1 NDE of log MOE on standing tree

2.1.1 Lab based NDE on standing tree

Bark to bark cores of dimensions approximately 16 mm ×16 mm were extracted from logs at 2.4 m height and cores were cut into 20 mm segments. The segments (approximately 16 mm ×16 mm × 20 mm) were then air dried and their extracted density was estimated using air density and resin content measured using wet chemistry and near infrared (NIR). Then ultrasonic transmission velocity (UTV) was measured for each segment (Fig. 2).

From UTV and extracted density, MOE of each segment was calculated. A five-parameter logistic (5PL) function was used to describe the radial variation of MOE obtained from segment data.

The 5PL model used in this study for fitting radial MOE variation of segments is given by:

$$m\left(r\right)=A+\frac{B\text{-}A}{\left(1+\left(\frac{r}{C}\right)^{D}\right)^{E}}. \tag{1}$$

Here, r (m) is the radial position for the segment from the pith, A is the asymptotic maximum, B is the asymptotic minimum, C is the inflection point midway between A and B (when $E=1$), D is the slope factor which characterises the steepness of the curve, and E is the asymmetry factor (Kumar et al. 2021).

The area weighted average of the segment's ultrasonic MOE and extracted log density were used to estimate the MOE (hereafter referred to as 'USMOE') and extracted density of the logs (hereafter referred to as 'Extr_Log_Den_Est') was then calculated using mean value theorem shown in Eq. 2.

$$USMOE \vee Extr\_log\_Den\_Est=\frac{2}{R^2}\int_0^R m\left(r\right)rdr. \tag{2}$$

where $m\left(r\right)$ is the MOE or extracted density at radial coordinate r given by the fitted 5PL curve in Eq. 1. MATLAB™ was used to calculate this integral (Baillères et al. 2019; Kumar et al. 2021).

2.1.2 Field deployable NDE on standing tree

'ST300_MOE' was calculated using time of flight (ToF) acoustics wave velocity method using the Director ST300 (Fibre-gen, Christchurch, New Zealand) on standing trees and using a constant green density of 1000 kgm^{-3}.

A Resi trace was collected at breast height avoiding branches and visible defects using the IML-RESI Power

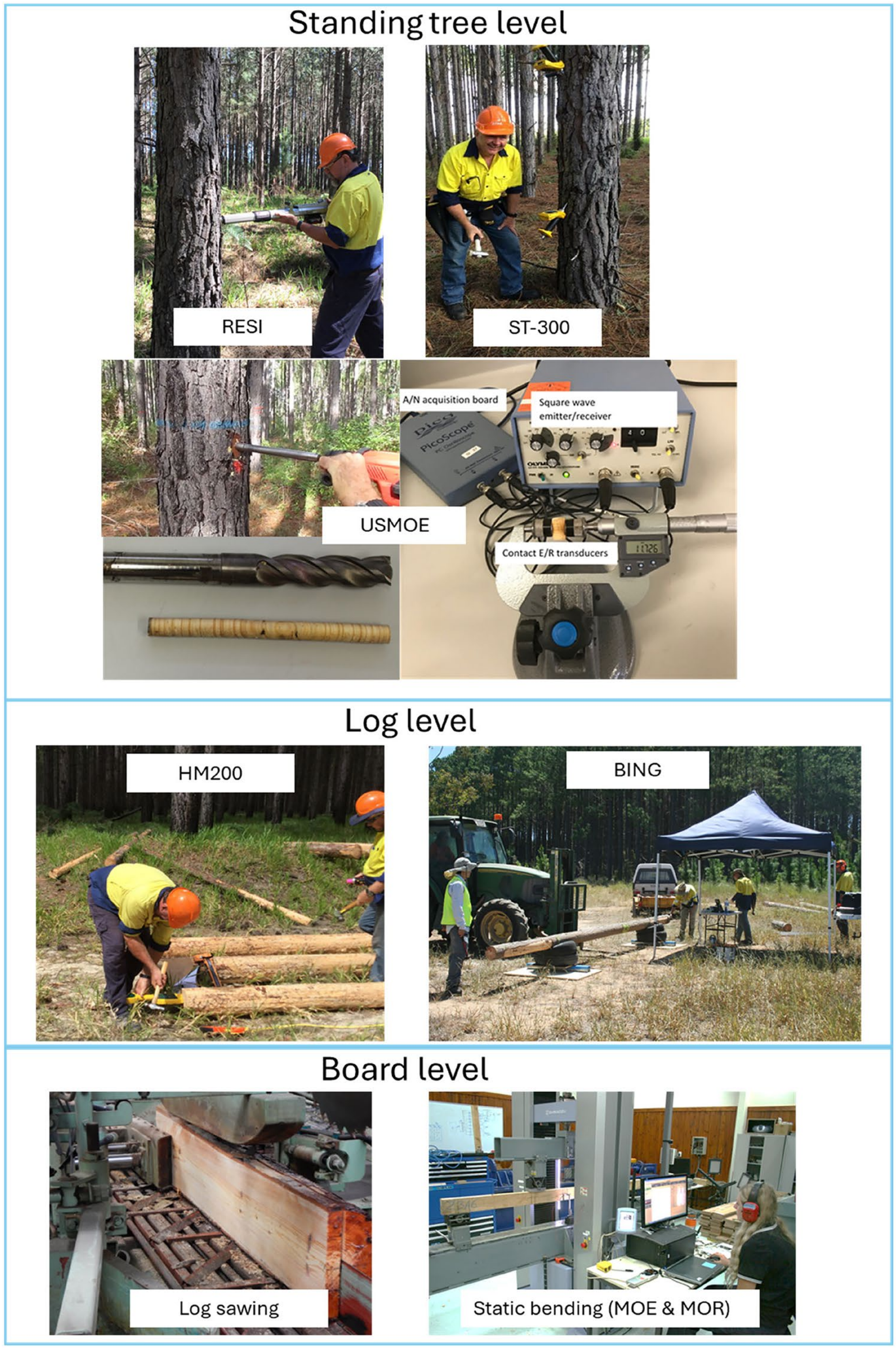

Fig. 1 Overview of the NDE tools used at standing tree, log and board level

Drill™ (Resi) PD-400 (IML System GmbH, Wiesloch, Germany). Pith to bark traces were collected with a forward speed of 200 cm/min and a rotation speed of 2500 RPM (Downes 2023) on felled trees for convenience and improved accuracy; however, comparable results would be expected if measurements were taken on standing trees. The current recommendation to pine species is to collect bark to bark resistance drilling traces to increase the accuracy of the sampling (Downes 2023).

MOE was estimated using a random forest model developed from a range of metrics extracted from the Resi trace to predict log MOE values derived from over 2,000 individual radiata and southern pine logs (Downes et al. in preparation). These were sourced from multiple sites, representing different ages, site qualities and positions-within-tree across

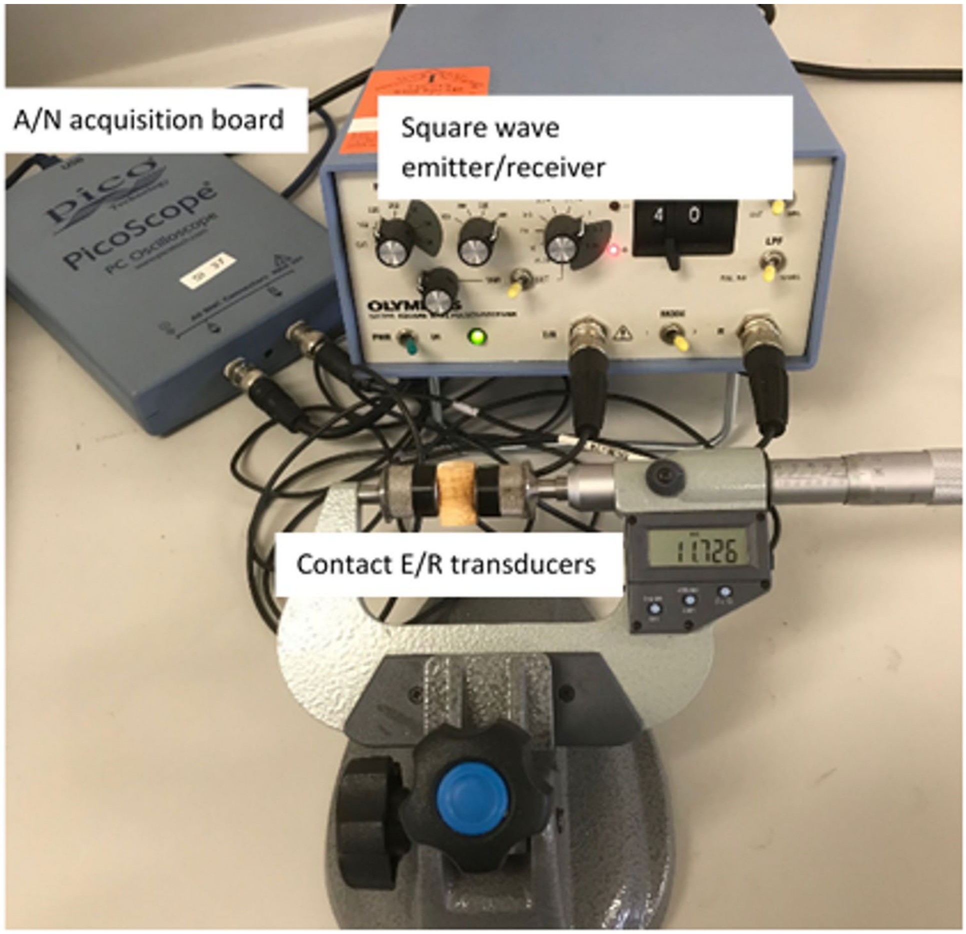

Fig. 2 Ultrasound apparatus for calculation of wood stiffness properties (US-MOE)

many regions in Australia. The model was validated against independent data sets and performed well. Resi traces were processed using web-based software (https://forestquality.shinyapps.io/FWPA-5/) (accessed on 10 November 2024) for processing and to estimate 'Resi_MOE' and 'Resi_Density'.

2.2 NDE of Log MOE on logs (felled trees)

Two NDE tools were used on felled trees. First was the Beam Identification by Non-destructive Grading (BING) tool, a resonance acoustic method for estimating MOE (Paradis et al. 2017) hereafter referred to as 'BING_MOE'. It consists of a microphone, an acquisition card (Pico Technology), two elastic supports and a hand-held hammer (Baillères et al. 2009; Brancheriau 2014; Faydi et al. 2017; Kumar et al. 2021). For longitudinal vibrations, the following equation was used to determine the MOE:

$$BING\_MOE = 4L^2\rho\left(\frac{f_n}{n}\right)^2. \tag{3}$$

Here, L is the length of the beam (m), ρ is the density (kg/m^3), and f_n is the vibration frequency of rank n *(1/s)*.

The BING_MOE had the highest correlation with the board's average MOE (discussed in the results section) and therefore was used for comparison with other NDE measurements.

The second NDE on felled logs was another resonance acoustics measurement tool the Hitman HM200 (Fibre-Gen Ltd., Christchurch, New Zealand), hereafter refereed as 'HM200_MOE' (Fibre-gen, Christchurch, New Zealand). First the length of the logs was entered into the handheld HM200 tools, then the sensor was pressed against the logs cross section and by hitting the logs with hammer. HM200 calculates the acoustic velocity in km/s using travel time of the acoustic wave through the entire log and measured stem length entered in the device. The MOE was then calculated using density acoustic velocity using

$$HM200\_MOE = density \times \ veclocity^2 \tag{4}$$

The density of the green logs referred to as 'Green_Log_Density' was measured from dimension and weight of the logs and was used to estimate BING_MOE and HM200_MOE.

2.3 Board MOE, MOR and density

The Modulus of Elasticity (MOE) and the Modulus of Rupture (MOR) of the boards were determined by four point edgewise static bending testing in accordance with (AS/NZS 4063.1 2010). The average board MOE, MOR, and density obtained from each log, referred to as 'Avg_Board_MOE', 'Avg_Board_MOR', and 'Avg_Board_Den' respectively, were calculated by averaging the MOE, MOR, and density values of individual boards from each log.

2.4 Statistical analysis

All analyses were prepared in R using RMarkdown (Allaire et al. 2023) within the RStudio environment (Core Team 2015). Pearson correlation coefficients were used to examine relationships among density, log MOE measurements obtained using different tools at multiple points from trees and logs to board-level MOE and MOR. Linear regression analyses were then performed to evaluate relationship between log MOE measurements, board MOE and MOR with BING_MOE.

The results from regression analysis were used to investigate the precision and bias of estimating log MOE and average board MOE from the NDE tools. The coefficient of determination (R^2) served as an estimate of precision, indicating the proportion of variance explained by the independent variable, while the slope and intercept of linear regression lines reflect bias, indicating whether the model systematically underpredicts or overpredicts (accuracy or bias). Differences in regression slopes between BING_MOE and four NDE-derived MOE measurements (HM200, ST300, Resi, and USMOE) were evaluated using a linear model including MOE, measurement method, and their interaction. Slope differences were tested via ANOVA on the interaction term, with pairwise comparisons conducted using estimated marginal trends and Tukey-adjusted p-values. Finally, the overall comparison between the tools regarding their predictive performance, operational capability and efficiency is presented.

3 Results and discussion

3.1 Correlations between all MOE and density measurement

Figure 3 shows the Pearson correlation coefficients (r) between log MOE measured by various NDE tools, density measurement (green log density and estimated extracted log density), average board MOE and MOR. BING_MOE exhibited moderate to strong positive correlations with other MOE measurement tools, ranging from $r = 0.75$ to 0.88. The highest correlation with BING_MOE was observed with HM200_MOE (r =0.88), likely due to both being resonance-based methods applied to felled logs. This was followed by USMOE (r =0.82), ST300_MOE ($r = 0.78$) and Resi_MOE ($r = 0.75$).

However, these correlation coefficients alone do not determine which tools are superior, as multiple additional factors need to be considered for measuring or predicting log MOE. These factors include measurement time, accuracy or bias as defined above, sampling speed, and whether the tools are field-deployable for use in standing trees and commercial settings (discussed further in Sect. 4.4).

The average MOE of the boards (Avg_Board_MOE), representing an average performance of the final product (sawn boards), exhibited a strong correlation with BING_MOE ($r = 0.92$), USMOE ($= 0.84$), and HM200_MOE ($r = 0.83$) (Fig. 3), indicating these methods can provide reliable predictions of average board quality. Since BING_MOE showed the strongest correlation with the quality of the sawn boards (final product), it was selected as the reference measure for comparison with the other NDE-derived MOE estimates. ST300_MOE also showed a moderate correlation ($r = 0.80$), while Resi_MOE demonstrated a weaker relationship ($r = 0.66$) with the Avg_Board_MOE. However, this value represents only the average MOE of all boards extracted from each log and may not accurately reflect grade recovery. While MOE is an important parameter for grade recovery, other factors are also critical, including initial log volume, distribution of board's MOE, visual stress grading based on defects and board quality, and machine stress grading in accordance with Australian Standards which is beyond the scope of this paper (AS/NZS 1748:2006; Baillères et al. 2019). The relatively lower predictability of Resi_MOE may be attributed to its dependence on calibration models and its measurement principle (resistance to drilling), primarily linked to the wood density, which doesn't provide a direct account of the microfibril angle (MFA) contribution to MOE. Further analysis could explore the underlying causes of variability in prediction accuracy among these tools, particularly for pre-harvest NDE tools such as ST300 and Resi. These results suggest that the degree of log MOE measured on felled trees were better correlated with the average board MOE than the log MOE measured on standing trees using the NDE tools used in this study.

The green log density displayed low correlation with all the MOE and density measurements. This result is likely influenced by variations in moisture content (MC) of the logs. MC decreases due to partial drying during transportation, handling, and storage, as well as differences in resin

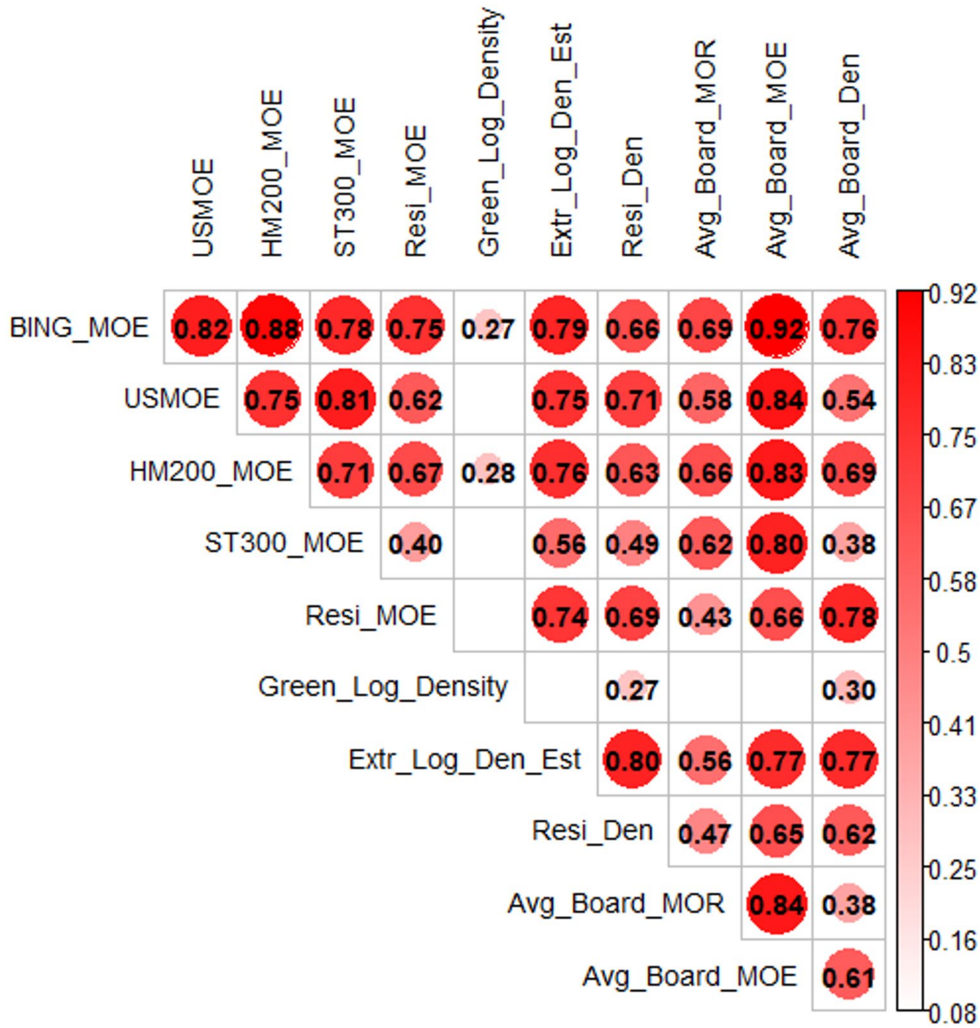

Fig. 3 Pearson correlations coefficient (r) between log MOE, density (easured using different tools), average board MOE, MOR, and density. Statistically insignificant correlations ($p>0.05$) are left blank. Positive correlations are represented in red and negative correlations in blue, with the intensity and circle size proportional to the strength of the correlation (colour figure online)

content within the logs and thus MC variation can impact the green density values. Conversely, extracted log density (Extr_Log_Den_Est) showed strong to moderate correlation coefficients (r)values ranging from 0.56 to 0.79 (r=0.56 for ST300, 0.75 for USMOE, 0.76 for HM200 and 0.79 for BIN_MOE). Extr_Log_Den_Est also exhibited a moderate positive correlation with average board MOE ($r = 0.77$) and average board density ($r = 0.77$).

This indicates that extracted log density is a more reliable metric for predicting both board and log MOE in southern pine species specially where resin and extractives are present, making it a preferable choice over green log density. Resi_Den is as good as BING_MOE at predicting Extr_Log_Den_Est.

As expected, there was a strong correlation between the NDE measurement using Resi i.e. Resi_Density and Resi_MOE (r=0.69) as they are not statistically independent. The average board MOR shows a strong relationship with the average board MOE ($r = 0.84$). However, average board MOR exhibited only weak correlations with log MOE measurements (r values ranging from 0.43 to 0.69), with the strongest correlation observed with BING_MOE. This suggests that while log MOE can serve as a reliable predictor for average board MOE, it is not an effective predictor for average board MOR, which can be impacted by knots, grain angle and other features such as compression failure.

3.2 Comparison of log MOE using linear regression

Figure 4 shows the regression between BING_MOE and other log MOE metrics measured using various destructive and non-destructive tools differentiated by germplasm.

When compared with BING MOE, HM200_MOE exhibited the highest precision ($R^2 = 0.78$), followed by the lab-based non-destructive method applied on standing trees (USMOE, $R^2 = 0.67$). The field-deployable NDE tools used on standing trees showed comparatively lower, yet still meaningful, predictive performance, with ST300_MOE ($R^2 = 0.61$) slightly outperforming Resi_MOE ($R^2 = 0.57$). These results suggest that while portable NDE tools may

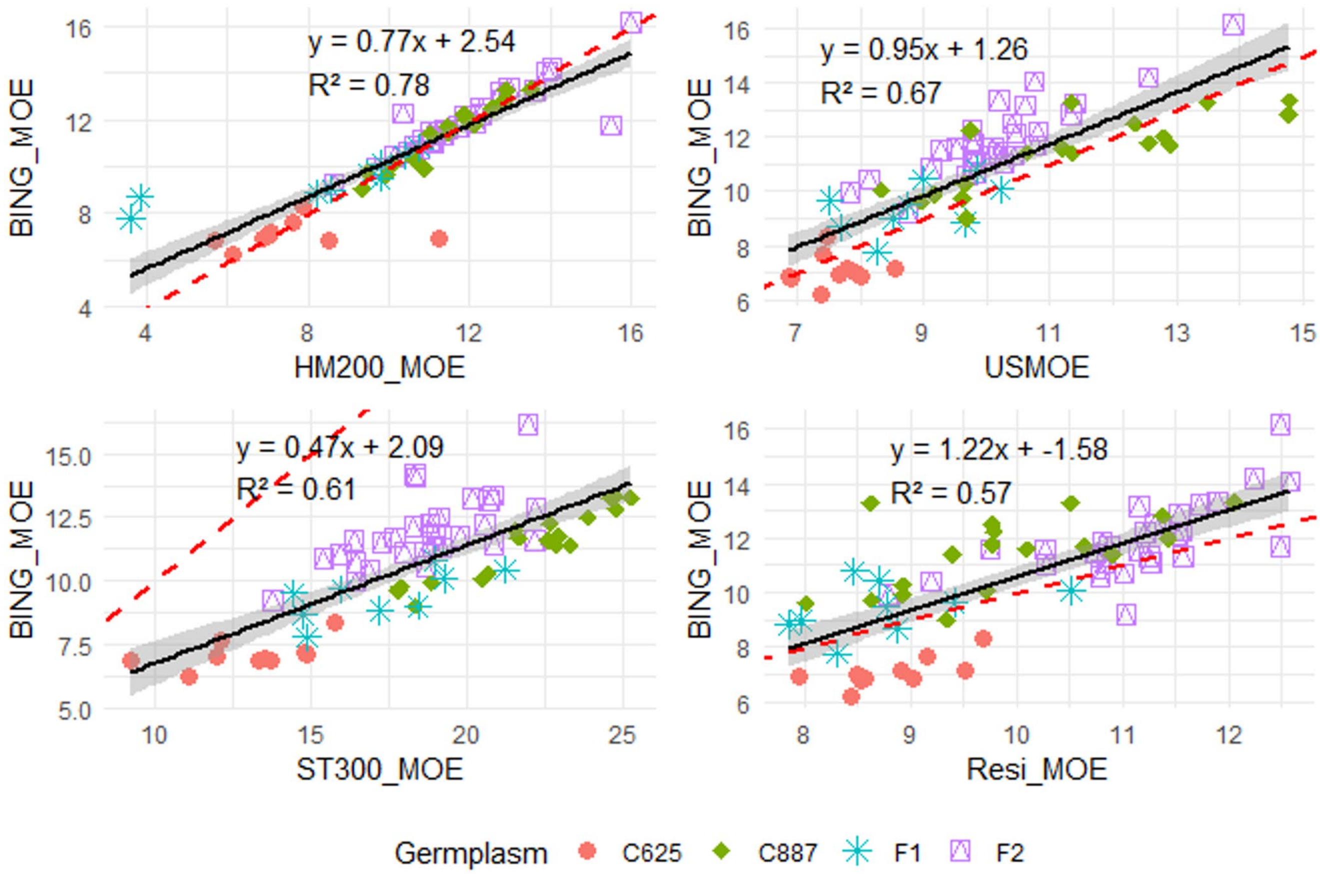

Fig. 4 Linear regression between BING_MOE and MOE measured using various tools (e.g., USMOE, HM200, ST300, and Resi), differentiated by Germplasm. Regression analysis includes red lines and text indicating regression through the origin (zero intercept) and blue lines representing ordinary regression with an intercept. Marker shapes and colours represent different Germplasm groups, with a single shared legend for all plots. The red dashed line represents the 1:1 reference line, indicating perfect agreement between measured and predicted values (colour figure online)

sacrifice some accuracy relative to laboratory or log-based measurements, they retain substantial potential for operational tree-level assessment. The observed strength of the relationships aligns well with previous studies using comparable measurement approaches. Searles and Moore (2009) reported a similar coefficient of determination ($R^2 = 0.60$) between MOE measurements obtained from standing trees using acoustic tools and those from felled logs. Likewise, Wang et al. (2002) found moderate relationships between static bending MOE and dynamic log MOE, with R^2 values of 0.60 for jack pine (*Pinus banksiana*) and 0.53 for red pine (*Pinus resinosa*). Some previous studies have reported stronger relationships between acoustic velocity (AV) measurements obtained from standing trees and logs, with coefficients of determination ranging from $R^2 = 0.75$ to 0.91 (Chauhan and Walker 2006; Chauhan and Aggarwal 2011). The higher correlations observed in these studies are likely attributable to the use of comparable acoustic wave velocity measurements at both scales, rather than a comparison among NDE tools based on different physical principles. In contrast, the present study evaluates multiple NDE technologies- including stress wave, resonance, and drilling resistance methods (e.g., ST300, BING, and Resi), which inherently differ in measurement mechanisms and sensitivity to wood heterogeneity. These methodological differences may partially explain the comparatively lower, yet still meaningful, relationships observed between standing-tree measurements and reference MOE values.

When comparing the regression slopes (Fig. 3), the USMOE demonstrated the lowest bias (slope = 0.95, close to 1), indicating a strong predictive power followed by HM200_MOE (a slope of 0.77). ST300_MOE exhibited the lowest accuracy or higher bias (slope = 0.47), significantly overpredicting the actual MOE values by approximately 50%, likely due to the assumption of a constant tree green density of 1000 kg m^{-3} and only sampling the outerwood of the trees. Conversely, Resi-MOE with a slope of 1.22 underpredicted the BING_MOE by 22%, potentially due to calibration dependencies. The Resi-MOE and the HM200_MOE are biased by about the same degree but in the opposite direction. These results indicate that the felled tree measurement outperformed standing tree tools in predicting BING_MOE, having both higher precision and lower bias. However, these results are for limited data set of only 68 trees. Regression slopes differed significantly among NDE tools ($p<0.001$). The slope for HM200 differed significantly from Resi ($p=0.0058$) and ST300 ($p=0.0006$), but not from USMOE ($p=0.32$). Resi exhibited a significantly steeper slope than ST300 and USMOE (both $p<0.0001$), while ST300 also differed significantly from USMOE ($p<0.0001$).

One of the four sampled genotypes, clonal variety C625 (orange circles in Fig. 3), exhibited consistently low log MOE values, below 8,000 MPa. This resulted in reduced prediction accuracy and higher deviations from the regression lines, particularly for USMOE and Resi_MOE. The poor prediction performance for this germplasm may be attributed to its unique characteristics, such as growth characteristics (e.g. large juvenile wood proportion). Downes et al. (2017) previously reported similar issues, attributing this to the abnormal behaviour of this specific clone. However, there were only 10 data points from C625. A larger dataset with more trees would provide better insight into these effects and overall comparison of the log MOE predictions.

3.3 Comparison of average board MOE via linear regression

Figure 5 shows linear regression models predicting average board MOE (Avg_Board_MOE) from NDE tools on felled tree (BING_MOE and HM200_MOE), and standing tree (USMOE, ST300_MOE and Resi_MOE). Among these, BING_MOE exhibited the highest precision ($R^2 = 0.84$), followed by USMOE ($R^2 = 0.71$) and HM200_MOE ($R^2 = 0.69$). For the field deployable NDE tools on standing trees, ST300_MOE, showed a stronger relationship ($R^2 = 0.64$) compared to Resi_MOE ($R^2 = 0.44$). Overall, the higher coefficients of determination observed for BING_MOE, USMOE, and HM200_MOE indicate their superior capability for predicting board-level stiffness. These findings are broadly consistent with previous studies reporting moderate to strong relationships between acoustic-based NDE measurements and board MOE. Tsehaye et al. (2000) found moderate correlations between log acoustic velocity (comparable to standing-tree measurements) and mean board MOE, with R^2 values of 0.45–0.56. Butler et al. (2017) for instance, reported a moderate correlation between log acoustic velocity and board MOE ($R^2 = 0.49$). However, predictive accuracy is known to vary by species for example Duchesne (2009) observed a strong relationship for black spruce ($R^2 = 0.78$) but a weaker one for balsam fir ($R^2 = 0.58$). In contrast Kovryga et al. (2020) found the species-independent strength grading for both bending strength and tensile strength. More recently, Duchesne et al. (2025) reported a strong correlation between acoustic velocity measured in logs and stems ($R^2 = 0.87$), yet a weak relationship between log and board acoustic velocity ($R^2 = 0.125$). Auty and Achim (2008) demonstrated moderate correlations between acoustic velocity and both MOE ($R^2 = 0.53$) and MOR ($R^2 = 0.59$) in clear specimens obtained from the same trees. They also suggested that automated acoustic-based sorting systems could be implemented for industrial log grading, either in the forest or at the sawmill. MOEdyn sensors can be integrated into harvester heads to assess wood quality during logging or applied at mill intake. As strength grading in green timber yields results comparable to dry timber, early sorting enables sawmills to reject low-quality logs before the costly drying process. The position of the recovered boards can also influence correlation strength. For example, Grabianowski et al. (2006) found that external log or standing-tree measurements correlated strongly with outerwood lumber ($R^2 = 0.89$) but more moderately with corewood lumber ($R^2 = 0.74$).USMOE demonstrated the least bias, with a slope of 0.97, followed by Resi_MOE (slope = 1.04) and BING_MOE (0.91), slope closer to 1, indicating that its predictions closely align with actual measured values (better accuracy). This makes USMOE, Resi_MOE and BING_MOE a reliable non-destructive alternative for predicting average board stiffness. In contrast, HM200_MOE exhibited moderate bias (slope = 0.71), suggesting a tendency to overestimate MOE, particularly for higher values. The highest bias was observed in ST300_MOE (slope = 0.47), indicating that it significantly overestimates actual average board MOE (Fig. 5).

Similar to the log MOE predictions, one of the four sampled genotypes, clonal variety C625 (indicated by orange circles), exhibited the greatest deviation from the regression line, particularly for USMOE and Resi.

While the NDE tools on felled trees such as BING and HM200 had high predictive performance, they cannot be used in standing trees before felling. Lab-based NDE measurement on standing tree studies, such as USMOE measurement on cores, bridges the gap between accuracy and non-destructiveness. However, USMOE needs laboratory-based ultrasound speed and density measured which can be time-consuming and limits its field portability. Emerging technologies such as integrated sensors and industrial artificial intelligence systems will enhance both the efficiency and usability of these systems. In contrast, portable tools like resistance drilling and ST300 provide immediate, in-situ measurements, allowing for large-scale, economical assessments (Baillères et al. 2019). A similar conclusion was reported by Rais et al. (2014), who found that pre-grading

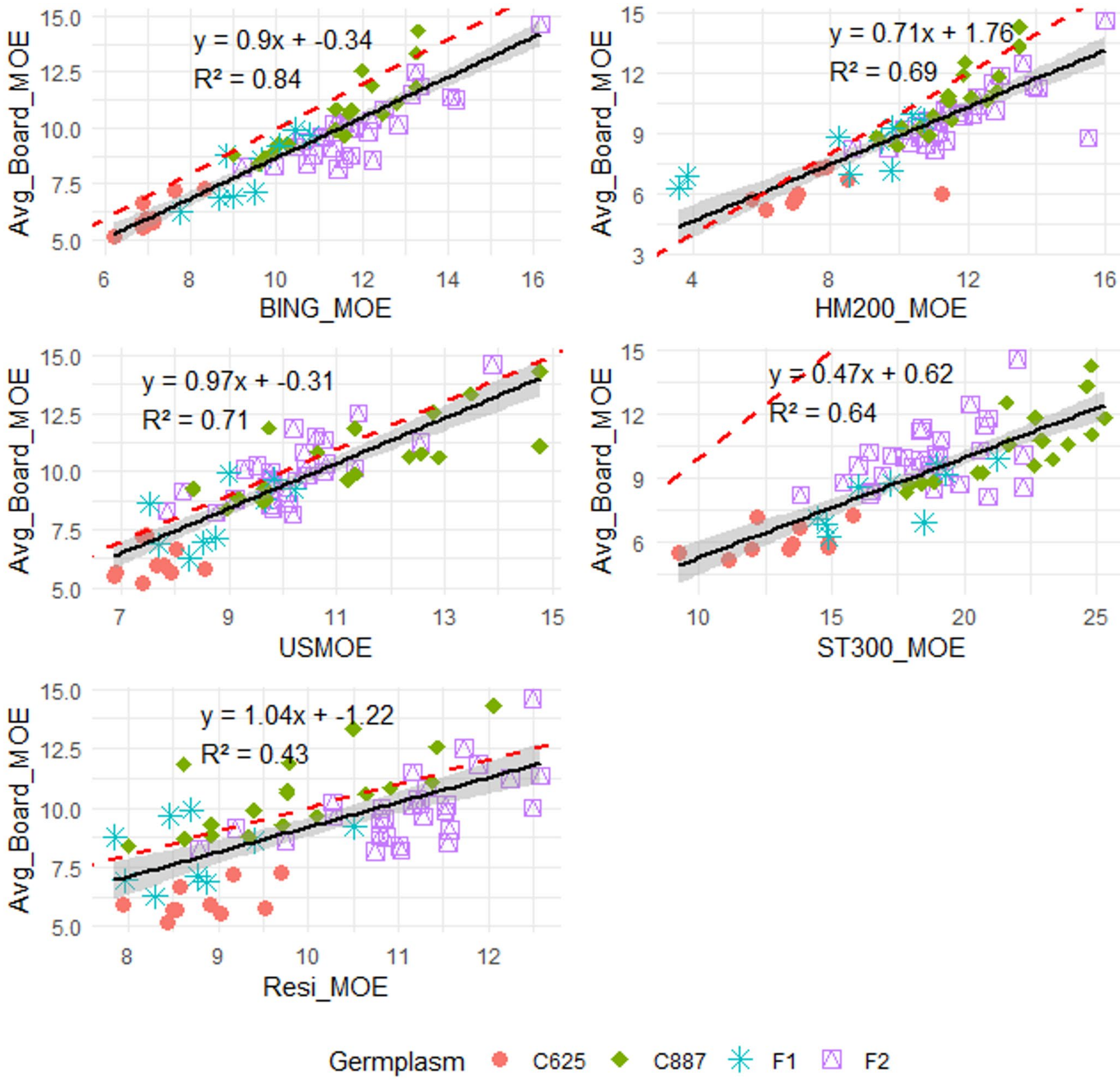

Fig. 5 Linear regression between averaged board MOE and measured log MOE using various tools (e.g. USMOE, HM200, ST300, and Resi). The red dashed line represents the 1:1 reference line, indicating perfect agreement between measured and predicted values (colour figure online)

or sorting is more effective at the log level, while measurements on standing trees provide only a rough guide.

The results must be interpreted in with consideration that this study sampled multiple plantings of varying genetic material and stocking (sph). This may have impacted upon the relative usefulness of the different methods. Field-deployable tools like ST300 and Resi offer practical solutions for operational forestry, but the lower predictive accuracy of Resi highlights the need for improved metrology, calibration techniques and predictive models for MOE. These findings underscore the trade-offs between accuracy and operational efficiency when selecting tools for predicting Avg_Board_MOE.

3.4 Overall comparison

Table 2 provides a comprehensive comparison of destructive and non-destructive tools based on their measurement efficiency, operational capabilities, and predictive power (precision and bias or accuracy). As highlighted earlier, the destructive methods (BING_MOE and HM200_MOE) require tree felling and are not field-deployable, limiting

Table 2 Comparison of destructive and non-destructive tools for log stiffness measurement for clearfall age southern pine trees

Point of comparison	BING (felled tree level)	HM200 (felled tree level)	USMOE (standing tree level)	Resi (standing tree level)	ST300 (standing tree level)
Tree felling required	Felling required	Felling required	Measures standing trees	Measures standing trees	Measures standing trees
Field deployable	Field-deployable on felled trees	Field-deployable on felled trees	Field-deployable but lab work needed	Field-deployable, no lab needed	Field-deployable, no lab needed
Type of MOE measurement	Direct measurement, not calibration-based	Direct measurement, not calibration-based	Direct measurement, not calibration-based	Calibration-based (requires training samples)	Calibration-based (requires approximate density)
Sampling rate (contiguous trees per hour)	Moderate: approximately 5 trees/hour	Moderate: approximately 5 trees/hour	Slow: approximately 4 trees/hour	Fast: approximately 50 trees/hour	Fast: approximately 20 trees/hour
Data analysis speed	Fast	Fast	Moderate	Fast	Fast
Radial variation measurement	No	No	Yes	Yes	No
Full radial analysis (e.g., age, density, extractives)	No	No	Yes, full analysis possible (e.g., cores used for extractives, age, MFA, density)	Yes, partial analysis possible (e.g. density variation)	No
Precision of log MOE prediction	High	High	High	Moderate	Moderate
Bias of log MOE Prediction	Moderate	Moderate	Low	Moderate	High
Precision of individual board MOE (board level)	Not possible	Not possible	Possible	Possible	Not possible
Precision of average board MOE prediction	High	Moderate to high	Moderate to high	Low to moderate*	Moderate
Bias of average board MOE prediction	Low	Moderate	Low	Low	High

*Resi accuracy may be improved through calibration and improved predictive models for MOE and collection of bark to bark traces

their use in commercial forestry operations despite their high accuracy.

In terms of bias for log MOE prediction, USMOE (0.95) demonstrated the lowest bias, followed by HM200_MOE (0.77). Resi_MOE (1.22) exhibited a similar level of bias to HM200 but in the opposite direction, while ST300_MOE (0.47) had the highest bias, significantly overestimating log MOE. For predicting board MOE, USMOE (0.97) and Resi_MOE (1.04) exhibited the lowest bias, whereas ST300_MOE (0.47) had the highest bias, significantly overestimating board MOE. HM200_MOE (0.71) showed moderate bias, slightly underpredicting board MOE.

Resi and ST300 excel in their operational efficiency, with faster sampling rates and no requirement for laboratory work, making them highly suitable for field applications where rapid assessment is prioritised. Stress-wave propagation measured by the ST300 is influenced by log geometry and reflects the global mechanical properties of the wood between the two measurement points (Liu et al. 2021). However, informal industry feedback suggests that the ST300 is becoming increasingly difficult to service, and its availability from suppliers is gradually declining. The Resi tools rely on statistical or machine leaning models for MOE prediction which rely on training samples. This approach can introduce uncertainty in the predictive power. Therefore, the type of calibration techniques and the number and quality of training samples are crucial. USMOE, another non-destructive method, requires laboratory measurements of density and ultrasound velocity, making it less practical for large-scale field operations. However, USMOE can provide more accurate estimation (low bias and high precision) of log MOE and average board MOE. It can also generate useful calibration data for developing predictive models from Resi traces.

However, with ongoing technological advancements, USMOE could become more efficient if density and ultrasonic transmission velocity are measured faster or if alternative methods, such as segmental MOE measurement using NIR can be used (Downes et al. 2014). Improvements in coring technology, including increased speed, reduced effort, greater portability, and innovative drilling techniques, would also make this approach better suited for field measurements.

Among the tools compared, only USMOE allow for the measurement of radial MOE variation. As a direct measurement method, USMOE offers additional capabilities such as the prediction of individual board MOE (Psaltis et al. 2021) and enabling detailed analyses such as within-tree variation and growth trends. This makes it particularly valuable for research applications requiring a deeper understanding of wood properties. Meanwhile, Resi calibration could be improved to provide radial MOE profiles for suitable species, potentially expanding its analytical applications (Gendvilas et al. 2024). Additionally, the cores obtained from standing trees can also be used for other technical traits or research purposes, such as dendrochronology-related investigations; other useful measurements, such as resin content, chemical composition analysis, and predictions of quality of products derived from those trees, can be made using the cores if necessary. For example, Psaltis et al. (2021) used the segment's MOE measured by ultrasound to predict the individual board MOE that can be obtained from a forest. In this study, the USMOE, using a 2D integration approach, can reconstruct an estimate of MOE for individual boards that can be sawn from trees with moderate accuracy (R^2=0.53) and low bias (2%).

Overall, the choice of tool depends on the specific application context:

- NDE tools on felled logs (BING and HM200) are ideal for research, better accuracy and high-precision applications but measurement and log segregation are not possible before tree felling.
- USMOE bridges the gap between accuracy and potential field applicability, with future advancements likely to enhance its practicality.
- Resi and ST300 are better suited for large-scale commercial operations, offering efficiency and portability despite their relatively lower accuracy on standing trees.

Further research should focus on improving the calibration models for accuracy of field-deployable tools like Resi and ST300 and on advancing USMOE toward a fully field-compatible solution. These developments could significantly enhance the efficiency and accuracy of non-destructive log quality assessments. In particular, the ability to segregate and sort trees prior to felling would allow standing-tree NDE tools to support pre-harvest decision-making, reduce operational risks, and enable more effective allocation of forest and processing resources.

4 Conclusion

This study compared and evaluated the performance of various NDE tools for log MOE and board MOE estimation of plantations grown Southern Pine. The study included log MOE measurement using two NDE tools applied to felled trees, BING and HM200, along with three NDE tools can be applied to standing trees: one lab-based (USMOE) and two field-deployable (ST300 and Resi).

Overall, NDE tools on standings trees were less accurate than NDE tools on felled trees. When the log MOE measurement were compared with BING_MOE, the HM200_MOE had the highest correlation ($R^2 = 0.78$) followed by *USMOE* ($R^2 = 0.67$), *ST300_MOE* ($R^2 = 0.61$) and *Resi_MOE* ($R^2 = 0.57$). BING_MOE explained the highest variance (R^2=0.84) and lower bias in the average boards MOE from logs. USMOE than HM200_MOE also had higher precision and lower bias compared to the tools that sampled standing tree (Resi and ST300) in predicting average board MOE. Additionally, clone C625 consistently exhibited low log MOE values (<8,000 MPa), leading to reduced prediction accuracy, particularly for USMOE and Resi_MOE. These deviations align with prior reports attributing this behaviour to unique characteristics of this specific clone. While extracted log density exhibited strong correlations with both log MOE and average board MOE for this species, green log density had a very weak correlation. A limitation of this study is that BING_MOE, used as a comparative benchmark due to its strong relationship with average board MOE, represents a predictive NDE estimate rather than a direct mechanical measurement of log stiffness.

The choice of tool depends on the specific application requirements. For high accuracy in research or precision-demanding operations, NDE tools on felled trees remain the most reliable. For NDE tools on standing trees USMOE, Resi and ST300 offer a practical balance between predictive power and operational efficiency. Future research should focus on improving the calibration models for NDE tools on standing trees to enhance their accuracy and consistency across diverse field conditions.

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Declarations

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