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MOE and MOR assessment technologies for improving graded recovery of exotic pines in Australia

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MOE and MOR assessment technologies for improving graded recovery of exotic pines in Australia

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Executive Summary

This project was designed to provide the structural softwood processing industry with the basis for improved green and dry grading to allow maximise MGP grade yields, consistent product performance and reduced processing costs. To achieve this, advanced statistical techniques were used in conjunction with state-of-the-art property measurement systems. Specifically, the project aimed to make two significant steps forward for the Australian structural softwood industry:

- assessment of technologies, both existing and novel, that may lead to selection of a consistent, reliable and accurate device for the log yard and green mill. The purpose is to more accurately identify and reject material that will not make a minimum grade of MGP10 downstream;
- improved correlation of grading MOE and MOR parameters in the dry mill using new analytical methods and a combination of devices.

The three populations tested were stiffness-limited radiata pine, strength-limited radiata pine and Caribbean pine. Resonance tests were conducted on logs prior to sawmilling, and on boards. Raw data from existing in-line systems were captured for the green and dry boards. The dataset was analysed using classical and advanced statistical tools to provide correlations between data sets and to develop efficient strength and stiffness prediction equations. Stiffness and strength prediction algorithms were developed from raw and combined parameters.

Parameters were analysed for comparison of prediction capabilities using in-line parameters, off-line parameters and a combination of in-line and off-line parameters.

The results show that acoustic resonance techniques have potential for log assessment, to sort for low stiffness and/or low strength, depending on the resource. From the log measurements, a strong correlation was found between the average static MOE of the dried boards within a log and the predicted value. These results have application in segregating logs into structural and non-structural uses. Some commercial technologies are already available for this application such as Hitman LG640.

For green boards it was found that in-line and laboratory acoustic devices can provide a good prediction of dry static MOE and moderate prediction for MOR.There is high potential for segregating boards at this stage of processing. Grading after the log breakdown can improve significantly the effectiveness of the mill. Subsequently, reductions in non-structural volumes can be achieved. Depending on the resource it can be expected that a 5 to 8 % reduction in non structural boards won't be dried with an associated saving of \$70 to 85/m^3

For dry boards, vibration and a standard Metriguard CLT/HCLT provided a similar level of prediction on stiffness limited resource. However, Metriguard provides a better strength prediction in strength limited resources (due to this equipment's ability to measure local characteristics). The combination of grading equipment specifically for stiffness related predictors (Metriguard or vibration) with defect detection systems (optical or X-ray scanner) provides a higher level of prediction, especially for MOR. Several commercial technologies are already available for acoustic grading on board such those from Microtec, Luxscan, Falcon engineering or Dynalyse AB for example.

Differing combinations of equipment, and their strategic location within the processing chain, can dramatically improve the efficiency of the mill, the level of which will vary depending of the resource. For example, an initial acoustic sorting on green boards combined with an optical scanner associated with an acoustic system for grading dry board can result in a large reduction of the proportion of low value low non-structural produced.

The application of classical MLR on several predictors proved to be effective, in particular for MOR predictions. However, the usage of a modern statistics approach (chemometrics tools) such as PLS proved to be more efficient for improving the level of prediction.

Compared to existing technologies, the results of the project indicate a good improvement potential for grading in the green mill, ahead of kiln drying and subsequent cost-adding processes. The next stage is the development and refinement of systems for this purpose.

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Introduction

In Australia, a range of native and exotic softwood forests and plantations provide an important source of fibre for sawn, round and panel products. The introduced *Pinus* species are grown in plantations managed specifically to produce high volumes of structural products primarily for the domestic construction sector. The native softwoods such as white cypress (*Callitris glaucophylla* Thompson & Johnson) and hoop pine (*Araucaria cunninghamii* Aiton ex D. Don) were not included in this study and all further reference to the term 'softwood/s' in this document, indicates plantation-grown exotic pine.

The scope of work was identified as a priority by the Australian softwood sector, and is the first study of its type conducted in Australia. Subsets of the radiata pine and Caribbean pine populations represent the range of mechanical properties of the majority of the Australian-grown exotic pine resource. This sector requires a universally applicable method to accurately and rapidly predict the strength and stiffness of green logs and boards processed for structural products. This will allow non-structural and low stiffness boards to be diverted before entering the dry chain.

There is often a high variability in wood properties of fast grown trees harvested at a young age, even within a single stem (Zobel and Buijtenen, 1989). Consequently, within a log or even within a board, the wood properties may be significantly different. Wood can be characterized as a highly heterogeneous and highly anisotropic material. Heterogeneous means that wood does not have a uniform structure and this variability can affect strength, for example knots, resin pockets and reaction wood. Anisotropic means that wood is a very oriented material, in other words directionally dependent with different properties in different planes. The strength and stiffness in the longitudinal direction of the tree are much higher than in the transverse directions. This effect can cause problems when the grain direction is not always parallel to the sawn direction of boards. High slope of grain can seriously decrease the bending strength. Because such variation is not acceptable in wood used for structural applications, it must be appropriately graded to ensure safety and performance in service.

Grading is the process by which timber is sorted into appropriate stress grades with consistent properties in each grade. Inevitably, there is a range of properties within a grade and significant overlap in properties between groups. Currently, processors undertake the grading task in the dry mill. To prevent unnecessary processing, associated costs and energy usage, for example kiln drying of low strength and ultimately non-structural boards, the grading process and subsequent segregation should be done as early as possible in the value chain. This project was initiated and designed in order to address this issue.

The main objectives of this project were:

- To improve the use of robust predictors of strength and stiffness acquired through existing in-line processing equipment such as Metriguard Continuous Lumber Tester (CLT), knot area ratio (KAR), acoustics, gamma ray and optical scanners.
- To improve the use of grading tools for upstream sorting: from logs, green boards and finally dry mill products.
- To identify if new parameters are available to refine current predictive mechanisms, and determine the most effective way to input these into prediction equations.
- To define the accuracy of the relevant parameters, or combination of parameters, for a number of technologies to independently improve grading systems.

- To develop advanced vibrational methods in order to grade softwood boards and logs for structural purposes.

The trials discussed here included three separate samples from distinct populations: stiffness limited radiata pine, strength-limited radiata pine and Caribbean pine. For each sample, logs were measured and weighed to provide density data, then tested for acoustic resonance. The resulting MOE calculations were later correlated with results from reference tests on the boards sawn from the logs.

After sawing, the green boards were subjected to a range of tests to provide relevant data as summarised below:

- Industrial acoustic test (Weyerhaeuser Thumper for MOE);
- Gamma ray (Geological & Nuclear sciences Ltd for moisture content and density);
- Metriguard Continuous Lumber Tester (MOE);
- Metriguard High Capacity Lumber Tester (MOE);
- LHG X-ray (for density and knot area ratio, strength-limited radiata pine only);
- *WoodEye*® (laser and camera optical scanner for defect type, size and position at production speed);
- Acoustic measurements (*Bing*®; longitudinal and transverse MOEs).
- Reference tests (MOE and MOR, AS 4063:1992).

Reference tests (static bending for MOE and MOR, AS 4063:1992) including both biased and random samples, were undertaken on a universal static 4-point bending test machine and visual defects were measured.

The dataset was analysed using mathematical and chemometrics' statistical tools to extract relevant parameters and to provide correlations between data sets and develop efficient strength and stiffness prediction equations. Stiffness and strength prediction algorithms were developed from raw and combined parameters using specific chemometrics' tools including multi-variate linear regression (MLR) and partial least squares (PLS).

The parameters were analysed for comparison of prediction capabilities from in-line parameters, off-line parameters (vibration analysis and manual defects measurements) and a combination of in-line and off-line parameters.

The predictors which provided the best correlations to the static MOE were used to sort the boards into MGP grades

The results from the project will allow processors to improve existing machine grading and assist in the development of next generation systems for more accurate grading of structural wood. The improved confidence in estimating strength and stiffness values for dried timber will allow for grading closer to threshold limits, thus improving structural grade yields resulting in a more efficient and profitable use of the softwood resource. This equates to greater resource optimisation, reduced costs and increased profits for the softwood sector.

Literature review

Radiata pine

Pinus radiata D. Don is marketed in Australia as radiata pine , but it is also known as Monterey pine and Insignis pine. It is easy to establish, can grow under a range of site conditions and produces large quantities of useable wood over relatively short rotations. Radiata pine from two disjunct sources *viz* south east Australia and south-west Australia, was investigated. Radiata pine is a versatile and widely planted species and in Australia there are almost 720,000 hectares (Web 1, 2003) of established radiata pine plantation forests. Native radiata pine occurs at five locations in central to north America. Three of these locations are in California: Año Nuevo, the Monterey Peninsula and Cambria. The other two are found on the two small islands off the coast of Mexico, Cedros (*Pinus radiata* var. *cedrosensis*) and Guadalupu (*Pinus radiata* var. *binata*) (Bootle, 2005).

The wood of radiata pine is pale yellow-brown and is generally straight grained with prominent growth rings formed by alternating bands of earlywood and latewood. It has low natural durability, however may be treated with preservatives for outdoor use. The wood has a good strength to weight ratio, with good nail holding and gluing ability, resistance to nail splitting and is relatively easy to saw and dry (Bootle, 2005).

The air-dry density (12% moisture content) is variable but typically is around 545 kg/m^3 and nominated strength groups are S6, SD6 (Hopewell, 2006). Wood density increases as the tree ages, and is influenced by environmental factors. New Zealand research has found that trees grown at lower altitude in warmer areas have a higher wood density than those grown at higher altitudes in cooler areas (Kininmonth and Whitehouse, 1991).

The innermost annual rings in the tree stem have a different anatomical structure compared to the wood in outer layers of the stem. The wood in the innermost rings is known as ‘juvenile wood’ and it has significantly different mechanical properties than the outer ‘adult wood’. The central core generally exhibits pronounced spiral grain, shorter fibres and lower wood density (as low as 350 kg/m^3 at 12% MC). This corewood is usually confined to the first ten to twenty growth rings only and is regarded as low-quality wood with the following characteristics (Ilic *et al*, 2003, except as noted):

- wide growth-rings;
- high grain spirality;
- low density and stiffness;
- thin cell walls and short trachieds;
- high longitudinal shrinkage;
- low transversal shrinkage
- presence of compression wood, and
- lower cellulose:lignin ratio (Bendtsen, 1978).

Radiata pine dries rapidly, and is usually kiln dried from the green condition at high temperatures e.g. 140°C. The wood is easy to dry but boards sawn from the central core zone which are prone to distortion. Improved stability of the seasoned product is achieved by pre-steaming for several hours and the use of concrete stack weights during drying (Bootle, 2005). Radiata pine has a wide range of structural and decorative uses including framing, furniture, paneling, lining, glued laminated beams, veneer, plywood and pulp. When treated with preservatives, it can be used for outdoor applications such as posts and poles (Bootle, 2005). Small diameter logs produced from thinning operations can be used for posts or pulpwood.

Caribbean pine

Caribbean pine sourced from south-east Queensland provided the balance of test material for the trials. Caribbean pine has been planted in Queensland and New South Wales where it has developed a reputation for excellent growth with minimal branching, even on poorly drained soils, resulting in desirable wood quality *viz* smaller and less frequent knots than related *Pinus* species.

Caribbean pine is pale yellow to yellow for the sapwood, and yellow to pale brown, with pink tints for the heartwood. The difference of colour between earlywood and latewood is pronounced, and the grain is straight with a coarse and uneven texture.

It has a low natural durability but can be effectively impregnated with chemical preservatives.

The air-dry density ranges from 545 to 575 kg/m³ (Hopewell, 2006). Provisional strength groups have been assigned to Caribbean pine as (S6) and (SD6).

Caribbean pine dries rapidly, and is usually kiln dried from the green condition at high to very high temperatures e.g.140-180°C without loss of strength (Siemon, 1981). The wood is easy to dry, except boards sawn from the central core zone which are prone to distortion. Improved stability of the seasoned product is achieved by reconditioning and the use of stack weights during drying.

Caribbean pine has a wide range of uses including framing, flooring, mouldings, joinery, furniture, plywood, treated landscaping and roundwood products, laminated beams, medium density fibreboard and paper production. Resin can be a problem during sawmilling as it builds up on saws and other processing equipment (Bootle, 2005).

Non-destructive testing methods

Non-destructive testing (NDT), also called non-destructive evaluation (NDE) and non-destructive inspection (NDI), is the science of identifying physical and mechanical properties of a piece of material without altering its end-use capabilities (Ross and Pellerin, 1994).

Since the 1920's, NDT methods have developed from laboratory testing to an indispensable production tool. Often components are too costly, or destructive testing is not possible, thus NDT is becoming increasingly important as a quality control management tool in almost every manufacturing process.

Today there are a large variety of NDT methods which are used worldwide to detect material characteristics such as: variation in structure, the presence of cracks or other physical or mechanical discontinuities, dimensions of products and to determine other characteristics of material. The most common methods are listed below (Bucur, 2003):

- visual and optical testing;
- ultrasonic testing;
- radiographic testing;
- impulse excitation technique;
- electromagnetic testing;
- vibration methods;

- magnetic resonance;
- laser testing;
- near-infrared.

Many of these methods originate from the medical field and have been adapted for industrial use (for example computed radiography and ultrasonic). These and other techniques are used in a wide range of industrial activities including aviation, aerospace, construction, manufacturing, pipelines and railways. Each method has advantages and disadvantages, for example radiographic methods can be used on several materials to detect the internal condition and/or properties of samples but is limited by the thickness of the test material and requires high safety precautions. Some methods are more suitable for detection and evaluation of certain flaws/properties than others. Therefore, the right choice or the combination of methods is desirable.

Using NDT to evaluate the physical properties of wood has its' origin in the need to solve practical problems without destruction of the integrity of the object under inspection (Bucur, 2003). The heterogeneity and anisotropy of wood make it difficult for manufacturers of forest products to provide a consistent quality to their customers. Many of the methods listed above have been adapted for predicting the performance of wood, but its wide variability makes it more challenging than for homogenous materials like metal and plastics (Ross and Pellerin, 1994). Therefore, research work on NDT of wood is required to determine a more accurate performance of a wood member (*Ibid*). Among the wood characteristics to be assessed non-destructively, strength and stiffness are the most important for structural applications. The only way to determine the true strength of a piece of timber is to break it. But afterwards it is of no use as a load carrying component. Therefore predicting the material characteristics of wood through NDT techniques is vital for the timber industry and has a long history of application in the wood products industry (Halabe *et al*, 1995). Moreover, the use of structural components is generally under standard applications which define the performance of the product in regard to its purpose.

It has been shown that density, knots (size, frequency, and location) and modulus of elasticity (MOE) are the most suitable parameters for wood strength prediction. The modulus of elasticity has shown the best correlation to the strength for a single parameter (Steiger, 1996). Today a wide variety of NDT methods for wood are known and available on the market including:

- radiography (X-ray and gamma-ray);
- evaluation of visual characteristics;
- near-infrared;
- microwave;
- ultrasonic;
- acoustic;
- machine stress rating (MSR);
- reference testing (quasi-static test).

Further technologies exist which are either not yet fully developed, or currently too complex or expensive to be used in commercial applications.

Radiography

In the 1980's medical X-ray and gamma ray scanners were first used on wood. Scientists soon realised that the physical properties of wood are similar to the human body and thus developed a non-medical scanner which could be used in the timber industry. X-ray and gamma ray scanning identifies internal heterogeneities and defects in logs and sawn boards (Bucur, 2003). The rays are able to penetrate material without being reflected or broken. On the basis of this feature a precise map of the internal heterogeneities is created. Depending on the system it is possible to acquire a 2D or 3D image. Such industrial wood scanner systems require a high X-ray or gamma ray source.

Gamma rays are of lower intensity than X-rays and can be used as a portable system for inspection of trees, poles and building elements (Bucur, 2003). The scan is done by irradiating the specimen from one or more sides and collecting the intensity of the transmitted radiation on the opposite side. The absorbed radiation is linked with the density and the moisture content of the material (Duff, 2005). Using this technology several strength affecting parameters like knots, density and moisture content can be determined contact free. The main advantages are that data are available in real time and a large volume of material can be rapidly inspected (Hanhijärvi *et al*, 2005). The disadvantage is that to ensure safety, the high intensity equipment has relatively large space requirements (Bucur, 2003).

Evaluation of visual characteristics

Visual inspection is one of the simplest and oldest methods of detecting exterior defects in wood members. The inspector observes the sample for parameters affecting strength such as knots, slope of grain and decay. This method requires good lighting, close attention from experienced operators and is limited to external degrade and features (Ross *et al*, 2006). Visual inspection is a relatively subjective method.

Automatic optical scanning systems allow this process at production speeds. Normally such machines are equipped with different camera and laser systems. Such cameras are also used to identify the variation in surface colour along the boards (Duff, 2005). These systems both detect the existence of the defect and its position. The data is usually sent directly to a docking machine to optimise the cutting process.

Near-infrared (NIR) methods

The spectroscopy of near-infrared waves ranges from 800 to 2500 nm. The advantage is that NIR can penetrate deeper than mid-infrared radiation and is simple to operate (minimal preparation and rapid measurement). NIR has mainly been used for non-destructive testing of organic materials such as agricultural or food products. Today it is used mainly in the medical and chemical fields, but recently NDT methods using NIR have been tested in the timber industry.

Tsuchikawa (2006) presented recent technical and scientific reports of NIR spectroscopy research in the wood and paper science industries. Others described a near-infrared method developed to predict the lignin content of solid wood. Strong correlations were found between the predicted lignin contents and the contents obtained from a traditional chemical method (Yeh *et al*, 2004). Schimleck *et al* (2002) described NIR measurements on small clear samples of *Eucalyptus delegatensis* and *Pinus radiata* to determine a number of physical properties including density, MOE, micro fibril angle and modulus of rupture (MOR). Good correlations were observed for all parameters, with R^2 ranging from 0.77 for MOR through 0.90 for MOE to 0.93 for density.

Microwave techniques

Similar to X-ray and gamma ray, microwaves penetrate the wood and on the basis of wave reflection, and checks, splits and irregularities in the test specimen can be detected. Compared to X-ray and gamma ray, this technology is less expensive, but at current production speeds the NDT of timber by microwaves is impeded/disturbed by mechanical vibrations (Bucur, 2003). Microwave testing is a contact free method that can detect defects and irregularity within the wood based on the determination of its dielectric properties which are principally due to the water content. Baradit *et al* (2006) described a microwave technique to generate and process data on knots in wood before processing.

Stress wave methods

The analysis of mechanical wave propagation in media of various complexities enables the measurement of elastic properties (Bucur, 2003). The use of acoustic methods, vibrational in the audible range (sonic) and at a frequency beyond human hearing capability (ultrasonic), for characterisation of the mechanical behavior of solid wood and wood-based composites is well documented. The velocity at which a stress wave travels in a member is dependent upon the properties of the member only. The terms sonic and ultrasonic refer only to the frequency of excitation used to introduce a wave into the member. All commercially available timing units, if calibrated and operated according to the manufacturer's recommendations, yield to comparable results.

The MOE and density are the main parameters which describe the wave propagation (Steiger, 1996). The wave speed for isotropic and homogenous material at given physical conditions is defined by the following equation:

$$\frac{\partial^2 u}{\partial x^2} = \frac{1}{V_x^2}\frac{\partial^2 u}{\partial t^2} \quad \Rightarrow \quad V_x = \sqrt{\frac{E_x}{\rho}} \qquad \text{(Equation 1)}$$

Where,

u is longitudinal displacement
t is the time measured
Ex is the modulus of elasticity
ρ is the wood density
Vx is the wave propagation speed

Basically there are two different methods to exploit stress wave velocity measurement (Krautkrämer, 1996):

- Transmission technique where the ultrasonic wave is introduced by a transmission head into the test piece and received by a second receiver head.
- The pulse echo method where a wave is reflected in a salient place (defect, surface) and the echo by the combined sending/receipt head is registered.

In the wood industry the transmission technique is more commonly used to indicate the stiffness of a sample (Steiger, 1996).

Ultrasonic

Ultrasonic describes a stress wave with a frequency greater than the upper limit of human hearing, that is, high frequency (20 kHz – 600 kHz and higher) stress wave. This technique is particularly useful to detect decay as the stress wave propagation is sensitive to the presence of degradation in wood. In general ultrasonic stress waves travel faster in high quality and stiffness material than in material that is deteriorated or of low quality (Ross *et al*, 2006). Thus the wave propagation is based on physical and mechanical characteristics such as (Bucur, 2003):

- MOE;

- density;
- moisture content;
- dimensions of the sample;
- material type;
- experimental conditions.

Timber grading using ultrasound has been discussed by Sandoz (1989) and in Steiger, (1991). It was found that by measuring spruce (*Picea* spp.) beams of 10 cm by 22 cm cross section and 4.40 m length, a correlation of $R^2 = 0.46$ between wave velocity and MOR existed. Hanhijärvi *et al* (2005) reported R^2s of 0.42 for strength and 0.57 for stiffness using a Sylvamatic strength grading machine.

Sonic

Measurement of acoustic velocity using the stress wave method is based on the same principle as the ultrasonic method. In the acoustic domain the input consists of a low frequency (approximately 1 Hz – 20 kHz) stress wave.

The wave is introduced to the material by striking the specimen with an impact hammer. A force transducer connected to the specimen records the input signal. On the other side of the specimen an accelerometer is connected which receives an output signal. The measurement of these two signals (input and output), allows the stress wave velocity to be calculated. The analysis is based on a time analysis, which doesn't require the knowledge of the boundary (Brancheriau, 2007). When striking the specimen a range of stress wave frequencies, and thus velocities, is inducted. As a consequence several velocities can be measured.

Most of the algorithms used extract the fastest speed and the average speed of the group. On the basis of the velocity and sample density the dynamic MOE can be assessed. The wave velocity is expressed as:

$$V_x = \frac{L}{t} \qquad \text{(Equation 2)}$$

Where, *Vx* is the wave propagation speed
L is the distance between the two probes (sensors)
t is the time-of-flight (TOF)

The wave velocity is linked with the MOE and density and can be calculated by Equation 1 displayed above. This expression is exact only for isotropic and homogenous materials at given physical conditions and is therefore only approximate for wood. Further parameters like energy loss can also be extracted in order to access the non-homogeneity of the tested material. A couple of commercial equipments mainly develop for standing trees stress wave velocity measurement are available (Fakkop FRS-06/00 or Director ST300 for example).

Resonance method

The most convenient method for measuring MOE with high precision depends upon measurements of the resonance frequencies in different modes (longitudinal, flexion or torsional) of simple structures for which the geometry and boundary conditions are known (Brancheriau and Bailleres, 2002). The fact that the technique is based on resonant structure ensures that frequency measurements will be precise. The technique can be extended to measure damping parameters and several signal descriptors.

To illustrate these methods consider a prismatic, homogenous and isotropic beam with a length L, height h and width w. After an impact hits the beam either longitudinally or laterally, it vibrates freely in compression or bending respectively. For a longitudinal wave (also known as compression or P-wave) the particles vibrate parallel to the direction the wave is travelling. In transversal wave (also known as shear wave or S-wave), the motion of the particles is perpendicular to its direction of propagation.

Because of these different kinds of movements, the longitudinal method is used to estimate the compression and tension characteristics, while the transversal method determines the bending characteristics. By measuring the movement of a vibrating beam the fundamental resonant frequency can be determined by a Fast Fourier Transform algorithm. The following expression shows the relationship between frequency and speed:

$$f_n = \frac{n}{2L} V_X, n \in \mathrm{N}^* \qquad \text{(Equation 3)}$$

Where, L is the length
f_n is the natural frequency (rank n)
n is the frequency rank
Vx is the wave propagation speed

The dynamic modulus of elasticity along the longitudinal direction of the beam produced by a compression stress can be calculated using the following equation (*Ibid*):

$$E = 4L^2 \rho \frac{f_n^{\ 2}}{n^2} \qquad \text{(Equation 4)}$$

Where, E is the dynamic MOE
ρ is the wood density
f_n is the natural frequency (rank n)
n is the number of frequencies

Using the transversal measurement, produced by a flexion stress, we can apply Bernoulli's model which provides a solution to calculate the dynamic modulus of elasticity. This is achieved using the following equation (*Ibid*):

$$E = 4\pi^2 \frac{\rho A L^4}{I_{Gz}} \frac{f_n^{\ 2}}{P_n} \qquad \text{(Equation 5)}$$

Where, E is the dynamic modulus of elasticity
ρ is the wood density
A is cross-section area
L is the length
f_n is the natural frequency (rank n)
P_n is solution of Bernoulli (rank n)
I_{Gz} is the moment of inertia, which can be calculated for a rectangular section as follows:

$$I_{Gz} = \frac{bh^3}{12} \qquad \text{(Equation 6)}$$

Where, *b* is base, horizontal dimension (length)
h is height, vertical dimension (length)
12 is the constant for moment of inertia of a member with rectangular cross section.

In Timoshenko's model for transversal / flexion vibration, the shear effect is no longer ignored. The solution according to Bordonné is more accurate for higher depth to length ratio beams. It allows the extraction of the shear MOE and uses more resonance frequencies information (Brancheriau and Bailleres, 2002).

Recent studies (Ross *et al*, 2005; Tsehaye *et al*, 2000; Wang *et al*, 2003) have demonstrated that predicting MOE of trees, logs and sawn timber using acoustic velocities as well as resonance methods are highly correlated with the static MOE measured. Halabe *et al* (1995) found coefficients of determinations (R^2) between static bending MOE and stress wave MOE of 0.73 and 0.74 in the green and dry stage, respectively.

Several commercial technologies are already available for acoustic grading on board such those from Microtec, Luxscan, Falcon engineering or Dynalyse AB for example.

Remark on the measured acoustic velocities

From above there are two different methods to measure the stress wave velocity:

1- By measuring the time-of-flight (TOF) according to **equation 2**. The accuracy of TOF measurement depends on accurate identification of the arrival times of the acoustic wave signals, each from a start sensor (impact hammer) and a stop sensor (accelerometer). It depends on the quality of the signal recorded and the extraction algorithm used to detect the start and the stop signals. The MOE can be calculated by applying **equation 1** provided that the density is known. The TOF method applied on standing tree is likely disturbed by dilatational or quasi-dilatational waves rather than one-dimensional plane waves. This leads to standing tree velocity being significantly higher than log velocities and skewed relationship between tree and log acoustic measurements.

2- By measuring the resonance frequency according to **equation 3**. The resonance-based acoustic method is a well-established NDT technique for measuring long, slender wood members. The inherent accuracy and robustness of this method provide a significant advantage over TOF measurement in applications such as log measurement. In contrast to TOF measurement, the resonance approach stimulates many, possibly hundreds, of acoustic pulse reverberations in a log, resulting in a very accurate and repeatable velocity measurement. Because of this accuracy, the acoustic velocity of the logs obtained by the resonance-based acoustic method is usually a better predictor than the velocity obtained by measuring the TOF. The MOE can be calculated by applying **equation 4** provided that the density is known. The constraint linked to this method is that the boundary conditions have to be perfectly known, this is not possible on standing tree.

Machine stress rating

Static bending is the foundation of MSR of timber. The development of such machines started in the 1960s and by 1963 the first industrial MSR machines were operating in the USA. These machines were characterised by a very high efficiency, but they could only sort planed timber with a maximum depth of approximately 40 mm. Therefore these machines found no practical application in Europe where larger dimensions are commonly produced and used (Krzosek, 2003).

MSR is currently the most common dynamic, mechanical load procedure. It measures the local stiffness of the material and sorts it into various MOE classes. The boards are fed through the machine flat wise, longitudinally and bent by rollers upwards and downwards in two sections. The span between the rollers is typically around 1.2 m.

Depending on the design, the machine bends the boards to a constant deflection and measures the required force or the machine bends the boards with a constant force and measures the deflection. Using the load deflection relationship, the local MOE can be determined directly by using equations sourced from fundamental mechanics of material on every point of the board except for approximately the first and last 500 mm. This test method allows the stiffness profile of a board to be determined. Boards are usually graded using a combination of the lowest MOE (Lowpoint MOE), its position and the average MOE of the boards (Duff, 2005).

Static bending

The resistance of a sample to slowly applied loads is measured by the static bending test. This procedure is generally conducted under standard conditions such as 20°C air temperature, 65% relative air humidity and 12% wood moisture content. These values vary slightly depending on the standard used. The ends of the test sample are supported on rollers and a load is applied either centrally (three point bending) or two loads are applied in the middle third of the span (four point bending). In the past, three point bending tests were used to test small clear wood samples or wood composites, whereas four point bending tests were used to test full size specimens, although four point bending can also be used for small clear wood specimens.

Because the values obtained by the different methods cannot be directly compared, Brancheriau *et al* (2002) presented an analytic formula using a crossing coefficient between 3 point and 4 point bending. The deflection and load are measured at intervals using a deflectometer and load cell respectively.

The first part of the curve is a straight line. There the deflection is directly proportional to the load and once the load is removed, the test specimen will return to its original state. This deformation is therefore in the elastic part of the beam (ε elastic). With increasing load a limit point of proportionality is reached (σp). Afterwards the deformation is no longer proportional to the load. With further load increase the material becomes plastic. This means when the load is removed, the beam will not return to its initial state (ε plastic). By increasing the stress to the point of maximum load (σu), the material begins to yield and fracture. The static MOE is determined from the slope α and the MOR value is equivalent to the maximum load attained. These values are considered as reference values.

The test span of such measurements depends on the dimensions of the specimen. Normally it is 18 times the depth of the sample. Thus, long thin specimens need to be docked to the required length. In the different standards, a variety of methods for selecting the test specimen from a piece of timber is defined (Leicester, 2004). For example in EN 408 a selection from the low point of the board is required (EN408, 1995).

Low point is the location within the board with the lowest grading modulus also known as biased position test sampling. Australian New Zealand Standard AS/NZS4063 specifies that the sample is selected randomly from a piece of timber (AS/NZS 4063, 1992). Random sampling and random position testing gives the direct comparison with the design values. However, the sampling error for strength data collected this way can be relatively high (Boughton, pers. comm.).
Random position tests are useful to provide a good approximation to population average MOE. Biased position tests can focus on the low end of the distribution more effectively and are useful to determine the effectiveness of grading systems (Leicester, 2004). However, the data from biased position tests cannot be compared directly with the Australian design values so acceptance criteria for these tests must be found from comparative testing on each size and grade of product. These two methods may lead to considerably different results of mechanical properties. Leicester *et al* (1996) studied the equivalence between different in-grade testing methods. MOE and MOR were measured on about 150, 90 x 35 mm F5 and F8 grades of radiata pine boards with a length of 4.8 m. Small but significant differences of approximately 20 percent at both the mean and the 5-percentile for strength were found.

NDT of wood for grading: results from previous studies

Brancheriau and Bailleres (2003) performed dynamic tests on 96 structural boards of larch (*Larix europeaea*). Through Partial Least Squares (PLS) analysis of acoustic vibrations in the audible frequency range, the researchers showed that the stiffness and strength could be accurately estimated. Further, they suggested that rapid, in-line grading systems could be developed relatively inexpensively through the installation of a vibration sensor, acquisition card and a computer for Fast Fourier Transforms and matrices' calculations.

One hundred southern pine (*Pinus* spp.) boards of dimension 100 x 50 mm and a length of 2.4 m were tested in green and dry states by Halabe *et al* (1995). The velocity of longitudinal stress waves and the dynamic MOE were measured with transverse vibration equipment. Ultrasonic wave speeds were also measured and the static bending MOE was determined by using a four point bending machine. The samples were then dried to 12% moisture content and the described tests were repeated for dry specimens and at the end the failure strength was determined by four point bending equipment. The result of this research showed that the relationship between dry static bending MOE versus green stress wave velocity or the corresponding green MOE can directly be used to predict the dry static bending MOE (*Ibid*).

In a study performed in New Zealand in 1998, 300 pine logs (species not reported but likely to be radiata pine) were tested using acoustics (Tsehaye *et al*, 2000). One end of each log was hit with a hammer containing an accelerometer that records the moment of impact. The sound wave passed along the 4.2 m long log and its arrival at the other end detected by a second accelerometer that was pressed against the log end. The 27-year-old pine logs from Mamaku Plateau in the Central North Island were sorted into three groups (27, 39, 27 logs), according to the speed of sound. After the measurements, the logs were sawn into 100 x 40 mm boards and then kiln dried to 12% moisture content. The MOEs of the dressed boards were determined by a stress-grading machine. The regression between the squared velocity of sound and the mean modulus of elasticity (300 logs) gave an R^2 of 0.46. Within the single groups the R^2 was between 0.45 and 0.57.

From these results it follows, that acoustic sorting of logs provides the opportunity to send only the best quality, high stiffness logs, to the sawmill (Tsehaye *et al*, 2000). In this study only two parameters, speed of sound and MOE provided by a stress-grading machine were compared. The effective strength and stiffness of the boards was not determined.

Ross *et al* (2005) conducted an investigation evaluating Douglas fir (*Pseudotsuga menziesii*) peeler cores. The longitudinal stress wave method was used to evaluate peeler cores from 111 Douglas fir stems. Then the 2.6 m long peeler cores were sawn into 90 x 40 mm boards. The dynamic MOE of each board was determined in green, as well as dry condition (6-7% MC) by using stress wave and transversal vibration techniques. Afterwards, the boards were tested to failure strength in bending to determine the static bending MOE and the modulus of rupture. This study showed that stress-wave-predicted MOE of peeler cores is a good predictor of both dynamic and static MOE of timber obtained from the cores. Very strong relationships were found between stress wave and MOE of the peeler cores and dynamic MOE (stress wave MOE and vibration MOE) as well as static MOE (bending MOE and tensile MOE) of the timber. However, the correlations between stress wave MOE of the peeler cores and the bending and tensile strength (MOR) were low. This investigation has shown that a basic grading of specimens is possible using stress wave techniques (*Ibid*).

Grabianowski *et al* (2006) performed a study about acoustic measurements on standing trees, logs and green timber of young *Pinus radiata* trees (aged 8 to 11-years-old). Thereby a time of flight tool (Fakopp® 2D) and a resonance based system (WoodSpec) were used to evaluate the stiffness of the test material. The aim of this study was to determine how well acoustic measurements of green logs, estimate the properties of timber cut from those logs. The correlation using Fakopp® 2D between the log values and those for the average of two boards from each log was 0.94. By using the resonance based system WoodSpec this relationship was 0.86. Significant correlations were found between the two tools, especially for stems (R^2 = 0.96) (Grabianoski *et al*, 2005).

During Combigrade Phase 1, Hanhijärvi *et al* reviewed the results from five previous investigations into NDT for strength prediction published between 1984 and 1997. Based on this review it was concluded that:

- Correlations (coefficient of determination, R^2) varied between studies, probably due to differing materials and methods.
- The highest correlation by any parameter tested achieved R^2=0.7.
- MOE is the best single variable for prediction of strength, followed by KAR and density.
- A combination of predictors provides greater accuracy than a single predictor.

Other relevant findings in the literature included:

- Görlacher (1984) found that the natural frequency (dynamic MOE) correlated well with static test results, as did Blass and Gard (1994) in their tests on Douglas fir.
- In separate studies Sandoz (1989) and Diebold et al (2000) found R^2=0.45 and 0.53 respectively for ultrasonic speed and strength.
- On a small number of specimens Oja *et al* (2000) found a prediction of R^2=0.41 for X-ray (density and knot volume) and strength of sawn boards.
- Similarly to the Combigrade project, Fonselius *et al* (1997) found that the accuracy of the predictors varies between species. For example in the Fonselius study it was found that knots explained 57% of the strength of pine compared to 27% for spruce.

For Phase 1 of the Combigrade project (Hanhijärvi *et a*l, 2005) approximately 100 logs each of spruce (*Picea* spp.) and pine (*Pinus* spp.) were investigated by testing them with different non-destructive testing methods. The logs were scanned by X-ray equipment and natural frequency and acoustic tomography measurements (only on 75 spruce logs, no pine logs), before they were sawn into nominal 150 x 50 mm boards. Approximately one board per log was selected and the batch was dried to an average of 10%. Final dimensions after drying and dressing were 146 x 46 mm, with a pencil round profile.

A range of data was collected for the trial boards:

- scanned for digital image analysis;
- natural frequency measurements twice (two different operators);
- X-ray scans;
- acoustic-ultrasonic measurements;
- sloping grain;
- density by gross measure and by gamma ray;
- Finnograder (gamma rays, microwaves, infrared radiation to predict strength);
- Raute Timgrader MOE;
- Compression MOE;
- Average annual ring width by image analysis.

The test material was loaded to failure in bending, and modulus of elasticity, bending strength, knot area and density were measured to determine grade.

Findings from Phase 1 of the Combigrade project are summarised below:

- Spruce and pine populations behave differently in regard to the predictors;
- Stiffness parameters had the best single-variable predictions of bending strength: MOE measured by either static method, vibration method or by ultrasonic method.
- Correlations between NDT density measurements (gross measurements, X-ray or gamma ray) and strength were within a similar range with X-ray providing the best value.
- Density is a better grade predictor for pine than for spruce.
- Knot parameters provide good predictions of strength and density for pine, but not spruce
- Irradiation equipment (X-ray and gamma ray) provide slightly better strength prediction than surface inspection such as KAR.
- Sloping grain measurements didn't have the potential to predict strength.
- Relatively strong correlations were obtained from log measurements with destructive board tests.
- Log X-ray and dynamic MOE based on natural frequency both provide R^2 of 0.60 or better for pine.
- Combinations of devices provided correlations of R^2=0.80 to 0.85 for pine and 0.60 to 0.65 for spruce.
- Combination of knot measurements with density and annual ring width provides effective predictions for strength with R^2=0.7 (pine) and 0.6 (spruce).

Based on recommendations from Phase 1 of the Combigrade project, a larger sample with replicates of different sectional sizes was tested to form the Phase 2 follow up trial (Hanhijärvi *et al*, 2008). For Phase 2 more than 1000 logs each of spruce and pine were sampled and after NDT data gathering from the logs, one board per log was selected from a mix of seven different size classes. In addition to the larger sample and range of dimensions, Phase 2 boards weren't planed after kiln drying. Results determined during Phase 2 of the Combigrade project can be summarized as:

- The two species behaved differently, similar to the small sample tested during Phase 1, with stronger correlation between predictors and strength usually achieved by pine.

- Cross-section dimensions also behaved differently, providing an insight to how size affects correlations.
- The correlation of density to MOE and MOR in bending decreases with an increase in section size.
- The results and conclusions for correlations' analyses were similar to the results from the smaller sample tested in Phase 1.

Standard requirements

The Australian Standard *AS1720.1:1997 Timber structures, Part 1: Timber properties* defines structural performance of machine graded pine (MGP) by the 5th percentile strength (MOR) of a sample population (random position tested) and by an average MOE (Standards Australia, 1997). In the current AS/NZS4063, the design properties are related to characteristic strength and MOE:

- characteristic strength is lower 75% Confidence limit of the 5th percentile strength of the population estimated from tests on a sample;
- characteristic MOE is 75% Confidence limit of the average population MOE estimated from tests on a sample.

To achieve these requirements, MGP material needs to be graded on the basis of AS/NZS1748:2003 *Timber-Stress-graded-Product requirements for mechanically stress-graded timber.* This Standard requires that every board is initially graded by a mechanical stress-grader which sorts the timber on the basis of its MOE (low point or mean or combination) and secondly by a visual inspection to detect strength-limiting and utility-limiting characteristics.

The machine stress-grader settings are determined by continuous monitoring (based on random position testing reference) of the values obtained from batches. Strength-limiting parameters are knots, resin- and bark pockets, cross- and heart shakes and splits. Utility-limiting parameters for softwood species include dimensional tolerance, squareness, knots, wane and want, machine skip, and distortion (bow/spring/twist). In the visual over-ride, high attention must be paid to the board ends, where the machine stress grader cannot determine the MOE (Standards Australia, 2003).

The European standard EN14081-1:2003 *Timber structures – Strength graded structural timber with rectangular cross section – Part 1: General requirements* requires either visual or machine graded timber. Visually graded timber accounts for:

- strength-reducing characteristics like knots, slope of grain, density, rate of growth and fissures;
- geometric characteristics like wane and warp; and
- biological characteristics like fungal and insect damage.

If the timber is machine graded the boards have to be graded on their full length. If that is not the case, as in bending type machines, the non-graded part needs to be visually examined (EN 14081-1, 2003) as for the Australian Standard.

The European standard requires a biased position test as the reference static bending test.

Study Methodology

Materials

Sampling method

Logs provided for the trials were selected from a mix of butt logs (30%) and upper logs (70%) in order to over-sample the low grades and ensure sufficient representation of the grades below MGP10 and in the lower half of the MGP10 population. Rather than sample 1 board/log and have a large number of individual logs, this project aimed to maximize the number of boards recovered from each log to provide the best experiment for comparing results from the NDT log tests and the subsequent results from board testing.

Paper log end templates based on Smith *et al* (2003) were adhered to both ends of each log to enable identification from log (Figure 1) through the green and dry chains and subsequent testing. Information provided on each label enabled the unique log number to remain on sawn boards through all stages of processing and testing as well as determining the log end (small end or large end) and relative in-log position of each board.

Figure 1. Log end template.

Stage 1 Stiffness limited radiata pine (Radiata E)

Stiffness limited *Pinus radiata*, radiata pine was sourced from 67 logs from two plantations located near the Victoria-New South Wales border and aged approximately 28-years-old. The average centre diameter for the batch was 370 mm (range 280 mm to 500 mm). From this batch the target number of board samples was 600. The sawmilling process provided 992 green boards, of which complete data sets for all trials were compiled for 517 boards. An overview of the testing conducted on this batch is provided in Figure 2.

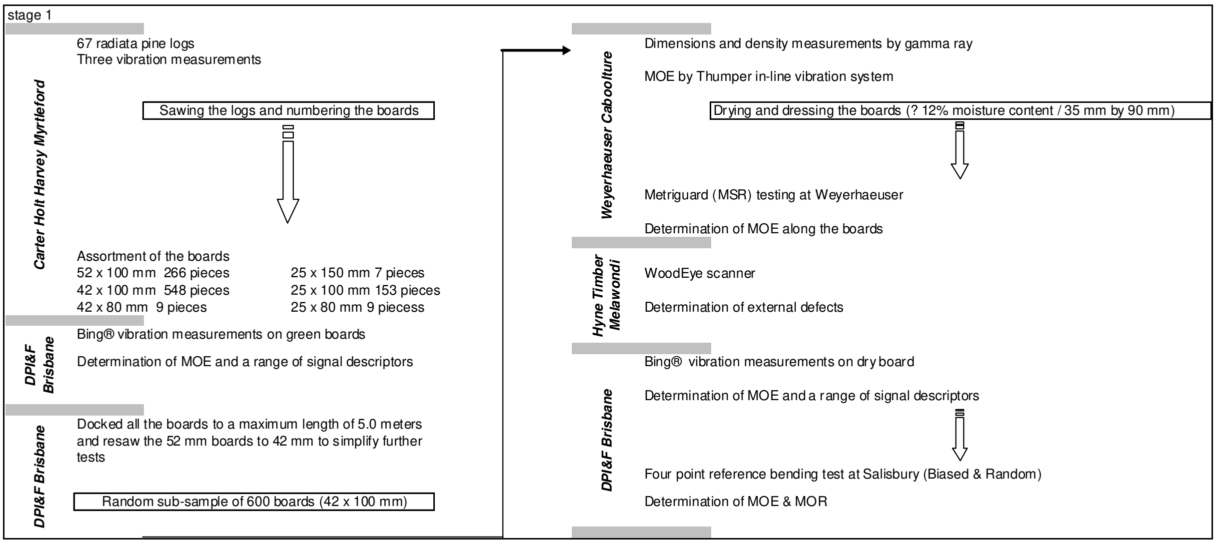

Figure 2**.** Sample flow for Stage 1, stiffness-limited radiata pine.

Stage 2 Caribbean pine (Caribbean)

One-hundred and sixteen logs representing the sub-tropical exotic pine resource of south-east Queensland were provided for the trial. The age of the source plantation was not provided by the supplier who estimated that the trees were 25- to 30-years old. The average log diameter for this batch was 250 mm (range 230 mm to 270 mm). The target number of boards from this sample was 400 and from 741 green boards, 489 were used to provide the data for the batch. An overview of the testing is provided in Figure 3 below.

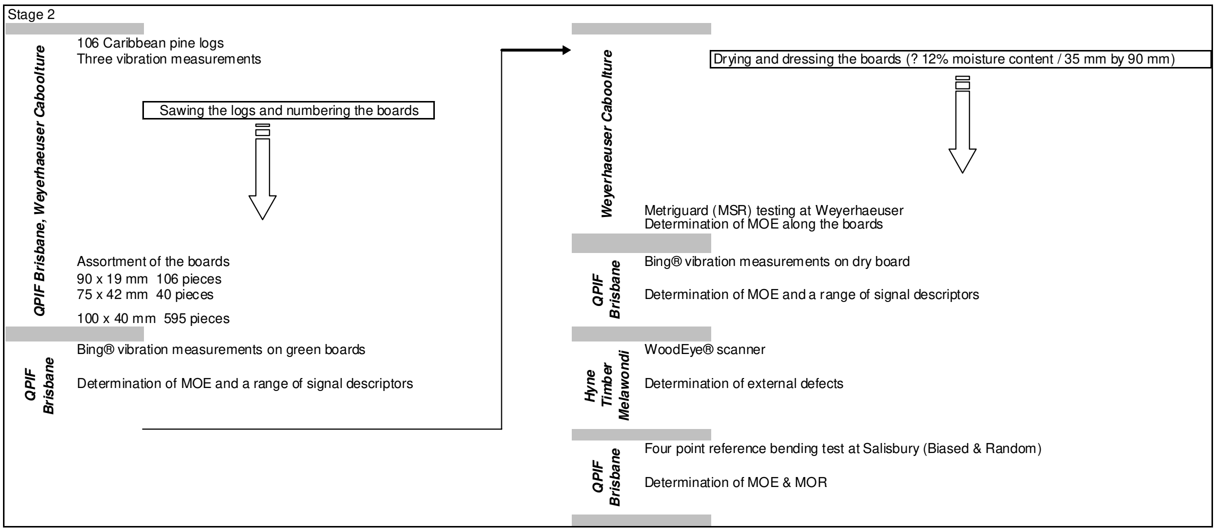

Figure 3. Sample flow for Stage 2, Caribbean pine.

Stage 3 Strength limited radiata pine (Radiata R)

Forty-seven logs with an average centre diameter of 420 mm (range 300 mm to 580 mm) representing the strength-limited radiata pine resource of Western Australia were provided for testing with a target sample of 400 dried boards. After sawing and drying, 582 boards provided the data set for this resource sample. The trial flow is depicted in Figure 4.

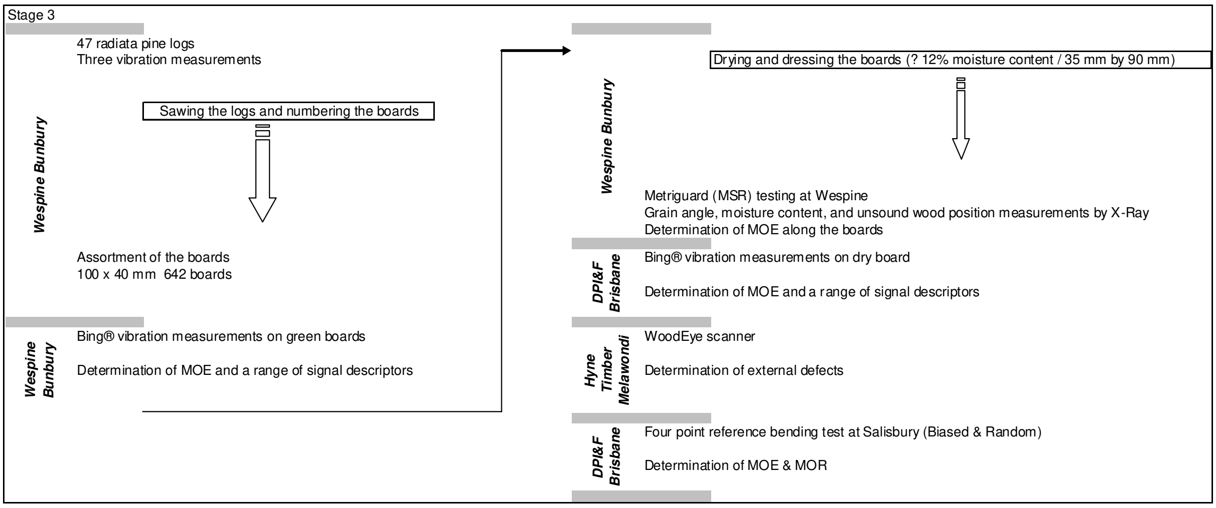

Figure 4. Overview of testing, Stage 3, strength-limited radiata pine.

Kiln drying

After completion of tests in the green (unseasoned) condition, boards were transported to a commercial softwood plant for high temperature kiln drying to a target average moisture content of 12%. After equalisation, the test boards were dressed to 90 x 35 mm.

Equipment and methods

Non destructive testing- mechanical properties measurement

Machine stress rating

Metriguard Continuous Lumber Tester (CLT 7100) equipment was used to collate MOE profiles for Stage 1 (radiata E) and Stage 2 (Caribbean) dry boards and Metriguard High Speed Continuous Lumber Tester (HCLT) for the Stage 3 (radiata R) dry boards in order to prescribe stress ratings. The boards were bent **flatwise** by rollers downward and then upward as depicted in Figure 5 below.

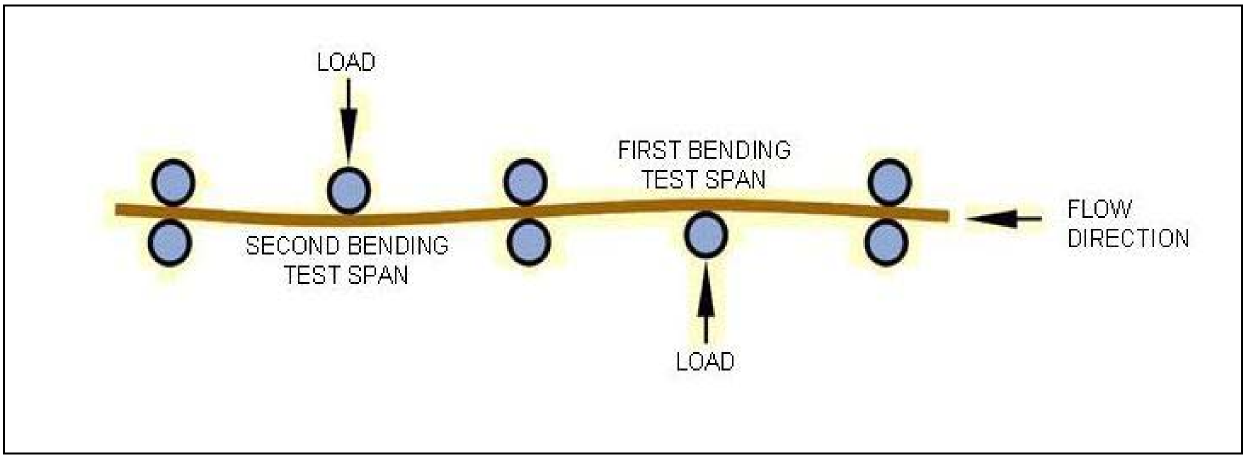

Figure 5. Schematic diagram of Metriguard CLT (source: Web 4)

Thereby the bending force and the deflection in both bending sections were measured. The local MOEs at intervals of 13.9 mm were automatically calculated, from which the average and the low point MOE were provided on the full length (excluding the leading and trailing 820 mm ends sections of boards). Additionally, the Metriguard MOE profile for the static test section was extracted to allow correlation with the static bending MOE and MOR test results.

The predictors used for the analysis were:

- full board profile extraction: **Metri_avg board** and **Metri_min board**;
- static bending span: **Metri_avg Static Test** and **Metri_min Static Test**.

In-line acoustic test

The Thumper is an in-line measurement device used to capture the longitudinal frequency and combine the data with parameters captured by the gamma-ray and laser measuring tools in the same green chain to calculate the dynamic MOE of each green board. It consists of a mechanical pneumatic cylinder that strikes the board end and a microphone which receives the signal. In front of the cylinder is a laser proximity switch which senses the presence of the board and triggers the firing of the cylinder to strike the board. The impact sets up a stress wave which travels immediately through the board and is detected by the microphone. With the vibration fundamental frequency collected by the microphone and the dimensions as well as the density provided by the gamma ray system, the dynamic MOE of each board can be calculated, allowing sorting of the green boards into stiffness classes.

The in-line Thumper system delivers a vibration MOE parameter (**Thumper_MOE**).

Off-line acoustic test

The acoustic velocity and vibration measurements were captured using *Bing*® and WISIS (Wood in Situ Inspection) products which were developed by CIRAD (http://www.xylo-metry.org/en/softwares.html).

WISIS measures the time of flight from an induced stress wave, based on a time-frequency analysis, not on a frequency analysis like the *Bing*® procedure. From the extracted results the MOE can be calculated by using Equation 1. This type of measurement can also be applied to standing trees to predict wood stiffness similar to commercial tools currently available in the forest wood quality sector. With velocity measurement, no boundary conditions are required, contrary to vibration analysis.

Bing® allows determination of the bending and compression MOE by analysis of the natural vibration spectrum of a piece of wood. The technique is also known as the resonance method as it allows determination of resonance frequencies of a beam from its response to an impact.

The two systems consist of the devices shown below in Figure 6 and associated software.

Figure 6. Equipment used for the acquisition of the off-line acoustic signals.

A	Laptop or Desktop
B	Data acquisition card (Pico Technology Type Picoscope 3224)
C	Accelerometer (Brüel & Kjaer Type 4397)
D	Impact hammer (Brüel & Kjaer Type 8206-2)
E	Conditioner (Endevco Type 4416B) for accelerometer and impact hammer
F	Low pass filter to avoid aliasing effect
G	Screw for the accelerometer attachment (magnet system)

Logs and green boards were tested using the *Bing*® for:

- longitudinal vibration-
  - compression waves,
  - frequency 2000 Hz,
  - four resonance frequencies *viz* F1 to F4, and
- transverse vibration-
  - flexion waves,
  - frequency 1000 Hz,
  - five resonance frequencies *viz* F1 to F5.

These measurements provided the following range of vibration signal descriptors: the MOEs in each configuration were calculated according to the equations described in the paragraph "Resonance method" above.

The vibration spectra were analysed in order to provide the following range of vibration signal descriptors:

- dynamic MOE associated with Fn (**MOE_n**).
- spectral centre of gravity divided by the fundamental frequency, F1 in % (**SCGravity**).
- spectral extent of gravity divided by the fundamental frequency, F1 in % (**SBandwidth**).
- spectral slope divided the fundamental frequency, F1 in % (**SSlope**).
- quality factor (inverse internal damping or friction) associated with Fn (**FacQn**).

- inharmonicity factor (IF).
- mean power in frequency sub-band; between 0 and f1; f1 and f2... (**MSPower**).
- sub-band energy ratio, between the resonance frequencies, i.e. sub-band energy/total range energy (**MSNrjRatioF_n**).
- mean power of the sub-band, resonance shoulder defined by a pass band of 20dB (**Pow_n**).
- sub-band energy ratio, resonance shoulder defined by a pass band of -20dB (**MSNrjRatioF_n**).
- MOE extraction using Timoshenko's model and Bordonné's solution (**MOET**).

A full description of the parameters is provided in Appendix 1.

<u>Maximal relative error on vibration MOEs</u>

After the signal conversion from analogue to digital, the Eigen frequencies were calculated by means of the Fast Fourier Transform. The resolution (r) is a function of sampling frequency (Fe) and of the number of measurement points (N):

$$r = \frac{f_e}{N} \qquad \text{(Equation 7)}$$

The absolute error Δf can be increased by the experimental absolute error (1 Hz) and half of the resolution. Therefore the maximal relative error for *Bing*® measurements can be determined as follows:

$$\frac{|\Delta f_i|}{f_i} = \frac{\Delta f_{i\_\exp} + 0.5 \cdot r}{f_i} \qquad \text{(Equation 8)}$$

Compression:

Resolution $r = 1.19$ Hz

$\Delta f_{i\_\exp} = 1.0\,\text{Hz}$

$f_1 = 193$ Hz $\qquad \frac{|\Delta f_1|}{f_1} = 0.83\,\%$

$f_2 = 583$ Hz $\qquad \frac{|\Delta f_2|}{f_2} = 0.27\,\%$

$f_3 = 869$ Hz $\qquad \frac{|\Delta f_3|}{f_3} = 0.18\,\%$

$f_4 = 1161$ Hz $\qquad \frac{|\Delta f_4|}{f_4} = 0.14\,\%$

Flexion:

Resolution $r = 0.3$ Hz

$\Delta f_{i\_\exp} = 1.0\,\text{Hz}$

f_1 = 10.4 Hz $\qquad \frac{|\Delta f_1|}{f_1} = 11.1\%$

f_2 = 22.6 Hz $\qquad \frac{|\Delta f_2|}{f_2} = 5.1\%$

f_3 = 54.2 Hz $\qquad \frac{|\Delta f_3|}{f_3} = 2.1\%$

f_4 = 92.1 Hz $\qquad \frac{|\Delta f_4|}{f_4} = 1.2\%$

The maximal relative error of the dynamic MOE can be calculated by the following equation:

$$\frac{|\Delta MOE_{Bing,L}|}{MOE_{Bing,L}} = \frac{|\Delta m|}{m} + \frac{|\Delta h|}{h} + \frac{|\Delta b|}{b} + \frac{|\Delta L|}{L} + 2\frac{|\Delta f_1|}{f_1} \qquad \text{(Equation 9)}$$

For the mass:	m = 5.4 ± 0.02 kg	For the width:	b = 30 ± 1 mm
For the height:	h = 90 ± 1 mm	For the length:	L = 5000 ± 20 mm

Thus the maximal relative errors on compression measurements are:

$$\frac{|\Delta MOE_{Bing,L,1}|}{MOE_{Bing,L,1}} = 6.4\%, \quad \frac{|\Delta MOE_{Bing,L,2}|}{MOE_{Bing,L,2}} = 5.3\%,$$

$$\frac{|\Delta MOE_{Bing,L,3}|}{MOE_{Bing,L,3}} = 5.1\%, \quad \frac{|\Delta MOE_{Bing,L,4}|}{MOE_{Bing,L,4}} = 5\%$$

For $MOE_{Bing,\,F,\,1\text{-}4}$ the maximal relative errors are:

$$\frac{|\Delta MOE_{Bing,F,1}|}{MOE_{Bing,F,1}} = 27\%, \quad \frac{|\Delta MOE_{Bing,F,2}|}{MOE_{Bing,F,2}} = 15\%,$$

$$\frac{|\Delta MOE_{Bing,F,3}|}{MOE_{Bing,F,3}} = 9\%, \quad \frac{|\Delta MOE_{Bing,F,4}|}{MOE_{Bing,F,4}} = 7\%$$

The data processing of the acquired digital signal involved the use of zero padding and smoothing procedures, to provide a more accurate reading of the resonance frequency.

Gamma ray

An in-line gamma-ray system (Geological & Nuclear sciences Ltd) was used to capture estimated density and moisture content data. The boards move transversely and are pushed along by lugs at 450 mm intervals on a chain conveyer system. The speed of the system can be varied up to 100 boards/minute, but is typically around 70-80 boards/minute. A system of four laser range instruments, positioned above and below the line, is used to measure the thickness, width and the length of the piece of timber. This information is combined with the gamma ray result to provide the average green density of the board. Gamma ray measurements are made simultaneously at four positions along the board by using four separate heads positioned between the chains. These measurements are combined to give average values which are used to sort the boards for subsequent kiln drying or machine stress grading.

Non destructive testing- structural properties measurement

Linear high grader (LHG)

The LHG was developed by Coe Newnes/McGehee ULC (Canada). Coe Newnes/McGehee ULC provides solutions for sawmill systems, planer mill systems, scanning and optimization technology (Web 5).

The functions of the LHG are summarised as:

- Measures wane, skip and holes.
- Measures grain angle, moisture content, and unsound wood locations.
- Determines best grade/length based on mill's grading rules.
- Marks board after scanner – ID number.
- Read boards ID.
- Sends trim and grade decision.

The LHG utilises X-ray technology to analyse density variation allowing the identification of knots within boards. Data are combined with low-point MOE results determined by Metriguard HCLT equipment to predict MOR. The LHG scanning was only used on the Radiata R resource.

LHG KAR is the LHG's estimation of knot area ratio (KAR). A second parameter was extracted from the knot position data obtained with the X-ray, called **LHG I ratio** which is the ratio of the inertia (I value) of the knots in the window to the inertia of the full cross section. The maximum value of I ratio was extracted using a Gaussian sliding-window.

LHG Weighted KAR is the same as LHG KAR, but only for knots in the outer quartile of the depth of the beam, where the outer quartile has weighting of 1.0 and the inner quartiles have weighting of 0.1, again using a Gaussian sliding-window.

LHG prediction of strength (**LHG predicted Strength)** was derived from the combination of LHG parameters and Metriguard HCLT profile from the biased and random test span. All these parameters were extracted locally from the data gathered from the static test span.

WoodEye®

A WoodEye® optical scanning system was used to record defect type, size and location features. The WoodEye® scanning system used combines:

- grey scale camera;
- RGB colour camera;
- tracheid effect LASER; and
- profile detection LASER.

The sensor-system scans each piece on all four sides for natural features such as black knot, sound knot, fibre knot as well as board geometry. Other features such as wane and pith weren't considered during this study.

For strength grading the knot categories are the most interesting. Black knot (**Bk**) and Sound knot (**Sk**) refers to knot defects created from the grey scale sensor. Fibre knot (**Fk**) is created from the laser sensor and is based on detection of a fibre disturbance. Therefore, a certain knot can give rise to both a Fibre knot and a Black/Sound knot. The sizes can differ due to the detection situation. Fibre knots tend to be larger. The contour of the combined knot silhouette (**WE**) was used as a predictor.

The beam profile construction is based on a rendering discrete process over the length of the beam with 1 cm steps. Each profile step is associated with a defects' projection of a portion on the length of the beam equivalent to two times the height of the beam. The projection window can be:

- rectangular on the entire beam portion;
- rectangular external: 1/3 of the top and bottom part of the beam height;
- rectangular interior: 1/3 of the centre part of the beam height;
- triangular according to a diamond-shaped pattern.

All the profiles are filtered with a Blackman sliding-window of which the size is equivalent to the beam height. Descriptions of the WoodEye® profiles are provided in Appendix 2.

Destructive standard static bending tests

Static bending tests were performed using a testing method in accordance with AS/NZS 4063:1992. Biased position tests were used on every board, and where the random position test location was within the useful remnant of the board after biased testing, a random position test was also performed on the same board. MOE and MOR were calculated for each test. Protocols used for the selection of biased and random samples are described in Appendix 3.

The load for the reference testing was applied and measured with a Shimadzu UDH-30 tonne (300 kN) universal testing machine depicted below (Figure 7).

Figure 7. Shimadzu UDH-30 t Universal testing machine.

The term 'universal' indicates that the machine is capable of performing a range of tests including static bending, tension, compression, shear and hardness tests on large samples. The support consists of a solid steel roller 240 mm long by 50 mm diameter and a flat mounting plate. The mounting plates have two holes which are used to locate the plate over machine bolts situated in the centre of the supports. The roller, and to a lesser extent the mounting plate, are held in place by two springs which attach to bolts protruding from the centre of the load roller. The Shimadzu UDH-30 is a 'Grade A' testing machine in accordance with Australian Standard AS 2193:2002 *Calibration and classification of force-measuring systems.*

The Australian and New Zealand Standard, AS/NZS 4063:1992 *Timber-Stress-graded-In-grade strength and stiffness evaluation*, requires that the specimens shall be conditioned to a temperature of 20 ±3°C and in an environment having a relative humidity of 65 ±5%. This conditioning shall continue until the moisture content is stable within each piece (10-15%).

Moisture content was checked using an electric resistance moisture meter to confirm that the boards had conditioned to the range specified in the standard. Bending strength and stiffness were then tested according to the methods specified in AS/NZS 4063:1992.

In the middle of the span the deflection was measured with a strain gauge type linear displacement transducer. The bending test span was 1620 mm with load applied at four points and the span-to-depth ratio was 18:1. The load deflection curve was measured up to 1.6 kN for all specimens. The modulus of elasticity can be determined from the slope of the linear relationship between the applied load (P) and the resulting deflection (ε) using the following equation:

$$MOE = \frac{23}{108} \cdot \frac{l_s^{\,3}}{bh^3} \cdot \frac{\Delta P}{\varepsilon} \qquad \text{(Equation 10)}$$

After removal of the displacement transducer, loading continued until failure of the specimen. The modulus of rupture was calculated using the following equation:

$$MOR = \frac{l_s P}{bh^2} \qquad \text{(Equation 11)}$$

The following equation gives an estimation of the relative maximal error on static bending MOE:

$$\frac{|\Delta MOE_{stat}|}{MOE_{stat}} = \frac{|\Delta b|}{b} + 3\frac{|\Delta h|}{h} + 3\frac{|\Delta l_s|}{l_s} + \frac{|\Delta k|}{k} \qquad \text{(Equation 12)}$$

The relative errors on the measurements are based on a sample of 60 specimens and are:

$$b = h = \pm 1\,\mathrm{mm}$$

$$l_s = \pm 10\,\mathrm{mm}$$

k is calculated using the 95% confidence interval from the slope of the force-deflection diagram. This method ensures the maximum relative error in the calculation of static MOE using Equation 12.

The coefficient $\frac{|\Delta k|}{k}$ is calculated as 3 % and due to the similar methodology used in this study the same value was used. Thus the maximal relative error for static MOE is:

$$\frac{|\Delta MOE_{stat}|}{MOE_{stat}} \approx 11\%$$

The maximal relative error of the MOR can be calculated by the following equation:

$$\frac{|\Delta MOR|}{MOR} = \frac{|\Delta b|}{b} + 2\frac{|\Delta h|}{h} + \frac{|\Delta l_s|}{l_s} + \frac{|\Delta P|}{P}$$

The relative error of the load applied is known as 1 % for the machine used. Therefore the maximal relative error of the modulus of rupture is:

$$\frac{|\Delta MOR|}{MOR} \approx 6\,\%$$

Biased versus random position testing

A biased test involves selection of a particular feature or position on the piece and deliberate placement in the centre of the test span in order to focus the results on the feature selected. For edge-biased bending tests, the selected feature is placed on the tension edge.

A random test is where the central position of the test span is allocated using a random number generator to determine the measurement datum along the board without consideration of any properties or features of the timber in allocating test position.

The issues of grade effectiveness must consider two opposing facts:

- AS/NZS4063 is currently being revised, but will be underpinned by evaluation of characteristic values based on random-position testing. As a result, verification testing of stress-graded products will continue to be based on random-position tests.
- The principle of stress-grading is founded on detecting the weakness in each piece to avoid failures in service where every part of most pieces will be used in some sort of role in buildings. The best grading methods will identify the lowest local strength of each piece rather than its global strength based on a random positioned test.

The implications for grade evaluation are:

- In performing normal commercial grading, the verification testing will normally use random-position tests and the test results will feed back to the threshold settings to ensure that the design characteristic values are reliably obtained by each graded product.
- In comparing grading methods, it is the correlation of grading parameter and the biased strength that is important. The most effective methods have higher correlation coefficients as they are most able to correctly predict the lowest local strength of each piece.

For this study, most use will be made of the biased position test data. Successful grading methods will have a high correlation with the biased strength. Although it is possible to achieve meaningful results from random-position tests, very large sample sizes are required. The scatter of the results is generally high, as the test span may not contain any of the limiting material that actually determined the grade of the piece.

Simulated MGP grades recovery by best predictors

The static bending values obtained from the biased samples were used to find the best correlation for each non-destructive measurement system with the collected grading modulus. These correlations were identified by simple or multiple linear regressions.

The grading modulus which provided the best correlations to the static bending data, were then used to allocate the boards into MGP grades. Thresholds were adjusted until the average of the MOE random and the 5th percentile were equal or above the standard requirements. The average and 5th percentile were calculated on the basis of the MOE and MOR obtained from the random sample tests. The outputs of various grading measures were used to group the test timber into notional grades and the test results used to confirm that the properties of each notional grade exceeded the design values.

If the thresholds were adjusted for each group, one would optimise the recovery and the grade limiting properties would be much the same for each group, but the recovery would be different between the groups. This method would be very hard to implement in practice as a producer would have to know the optimum threshold to use before starting production, so that all of the pieces could be graded to give the grade limiting property just higher than the design value.

A range of different thresholds was used and all of the results for each resource and for each prediction were plotted.

Data extraction and statistical approach

Automated data extraction was undertaken through collaboration with CIRAD Xylometry, Montpellier France. Mathematical and chemometrics' statistical tools were used to provide correlations between data sets and to develop efficient strength and stiffness prediction equations. These algorithms were derived from raw and combined parameters using multi-variate linear regression (MLR) and partial least squares (PLS).

The following discussion on MLR and PLS was modified from statsoft.com (Web 2).

For many data analysis problems, estimates of the linear relationships between variables are adequate to describe the observed data, and to make reasonable predictions for new observations. When the factors are few in number, are not significantly redundant (collinear), and have a well-understood relationship to the responses, then MLR can be a good way to turn data into information.

The MLR model serves as the basis for a number of multivariate methods such as:

- discriminant analysis, i.e. the prediction of group membership from the levels of continuous predictor variables;
- principal components regression, i.e. the prediction of responses on the dependent variables from factors underlying the levels of the predictor variables;
- canonical correlation, i.e. the prediction of factors underlying responses on the dependent variables from factors underlying the levels of the predictor variables.

These multivariate methods all have two important properties in common in that they impose restrictions such that:

- factors underlying the Y and X variables are extracted from the Y'Y and X'X matrices, respectively, and never from cross-product matrices involving both the Y and X variables, and
- the number of prediction functions can never exceed the minimum of the number of Y variables and X variables.

PLS has become a standard tool in chemometrics for modelling linear relations between multivariate measurements and is particularly suitable for monitoring and controlling industrial scenarios which may have hundreds of controllable variables and dozens of outputs. PLS represents a compromise between principal component regression (PCR) and MLR. PCR detects factors that account for the greatest amount of variance in the predictor variables. MLR seeks uncorrelated variables that best estimate the predicted variable. PLS screens for factors which account for the variance and achieve the best correlation. A great advantage of

PLS over other regression methods is that it can handle large numbers of correlated variables as predictors. The method is based on projections whereby a set of correlated variables is compressed into a smaller set of uncorrelated variables.

Partial least squares is a method for constructing predictive models when the factors are many and highly collinear. The emphasis is on predicting the responses and not necessarily on trying to understand the underlying relationship between the variables. When prediction is the goal and there is no practical need to limit the number of measured factors, PLS can be a useful tool. Partial least squares regression is an extension of the multiple linear regression model (e.g., Multiple Regression or General Stepwise Regression). In its simplest form, a linear model specifies the (linear) relationship between a dependent (response) variable Y, and a set of predictor variables, the X's, so that

$$Y = b_0 + b_1X_1 + b_2X_2 + ... + b_pX_p \qquad \text{(Equation 13)}$$

In this equation b_0 is the regression coefficient for the intercept and the b_i values are the regression coefficients (for variables 1 through $_p$) computed from the data.

Partial least squares regression is probably the least restrictive of the various multivariate extensions of MLR. This flexibility allows it to be used in situations where the use of traditional multivariate methods is severely limited, such as when there are fewer observations than predictor variables. Furthermore, PLS regression can be used as an exploratory analysis tool to select suitable predictor variables and to identify outliers before classical linear regression.

An important factor to consider when interpreting the results provided in this report is that the variation of the coefficient of determination is expressed as an **absolute** difference on a scale of 0.00 to 1.00, as opposed to a relative comparison.

Results

Static bending

Biased and random tests together

Table 1 displays basic statistics for dry density, MOE and MOR at 12% moisture content (MC) for all the boards tested (biased and random together) for the three resources. Caribbean has the highest density followed by Radiata R with Radiata E having the lowest density. The MOE follows logically the same trends, with a 5% difference between Radiata E and Radiata R and 21% between Caribbean and Radiata E. Caribbean MOR is 34% higher than Radiata R. The MOR for Radiata R is 3% lower than Radiata E MOR despite its higher MOE. The low Radiata R MOR confirms the resource quality observation by the West Australian industry which considers this resource as strength limited.

The standard deviation of Caribbean density is significantly higher than the other two resources. MOE and MOR standard deviations of Radiata R and Caribbean are very close whereas Radiata E shows comparatively low standard deviations for both properties.

Table 1. Descriptive statistics of density and mechanical properties for the three resources, biased and random combined.

Resource	Mechanical properties	Mean	Std. Deviation	N
Radiata E	Dry density (kg/m^3)	**486**	*51*	724
	MOE (MPa)	**8317**	*2450*	723
	MOR (MPa)	**33**	*16*	724
Radiata R	Dry density (kg/m^3)	**508**	*41*	689
	MOE (MPa)	**8735**	*2911*	686
	MOR (MPa)	**32**	*20*	690
Caribbean	Dry density (kg/m^3)	**563**	*71*	896
	MOE (MPa)	**10048**	*2916*	876
	MOR (MPa)	**43**	*20*	896

The bivariate Pearson's correlation coefficients between density, MOE and MOR are displayed in Table 2 below.

The MOE vs density correlations are quite different for each resource. Radiata E has the highest correlation coefficient followed by Radiata R with Caribbean having the lowest correlation coefficient. A similar trend is observed for MOE vs MOR.

Table 2. Bivariate Pearson's correlation coefficients between density and mechanical properties for the three resources, biased and random combined.

Resource	Mechanical properties	Dry density (kg/m^3)	MOE (MPa)
Radiata E	MOE (MPa)	0.68	
	MOR (MPa)	0.54	0.80
Radiata R	MOE (MPa)	0.54	
	MOR (MPa)	0.33	0.77
Caribbean	MOE (MPa)	0.31	
	MOR (MPa)	0.19	0.72

Note: All the correlations are significant at the 0.01 level (2-tailed).

Figure 8 shows the linear correlations between MOE and density for all the resources. From the scatter plot it appears that the Caribbean resource displays a significant number of outliers which have a high density with proportionally a low MOE. These outliers boards can be explained by the presence of a large quantity of resin and the occurrence of compression wood (high MFA) which both increase the density without significantly increasing the mechanical properties. Radiata E and Radiata R resources are different: the data shapes are not similar with Radiata E having a higher average MOE in the low density range.

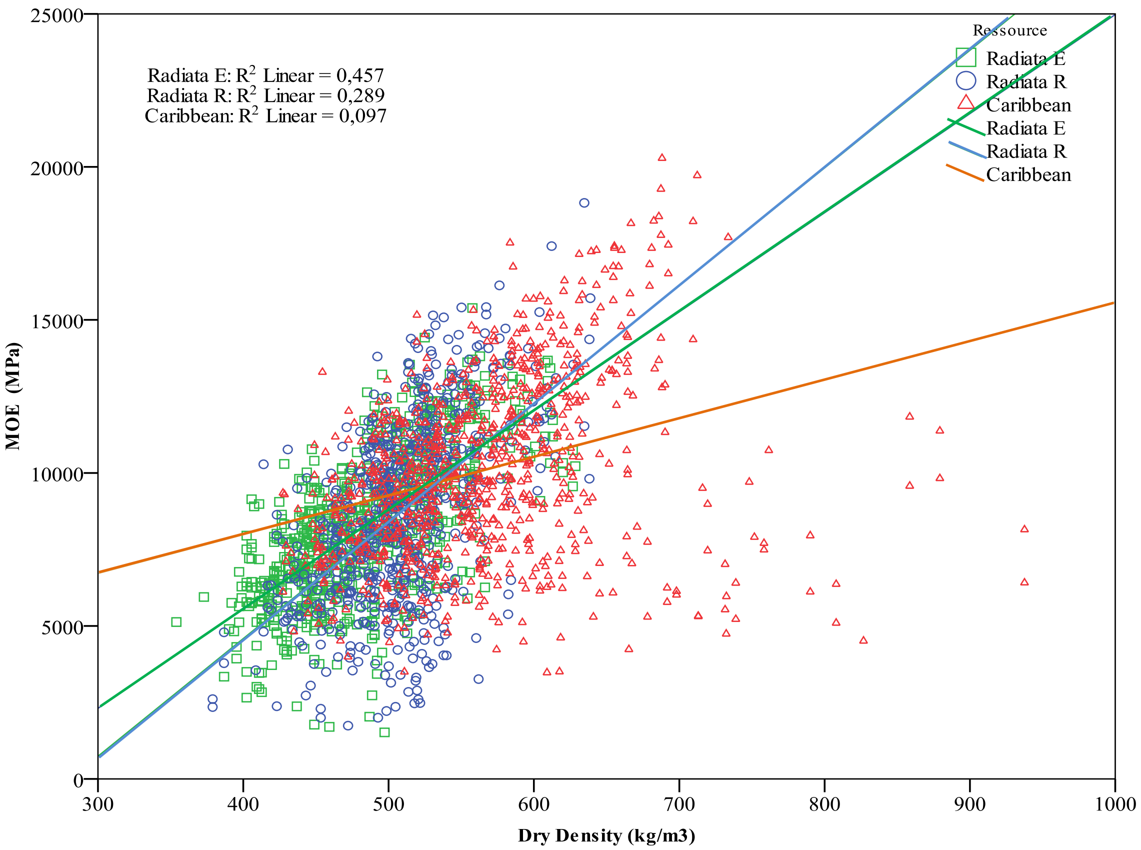

Figure 8. Linear regression between MOE and density for the three resources.

The density vs MOR correlations show the same trend but exacerbated (Figure 9).

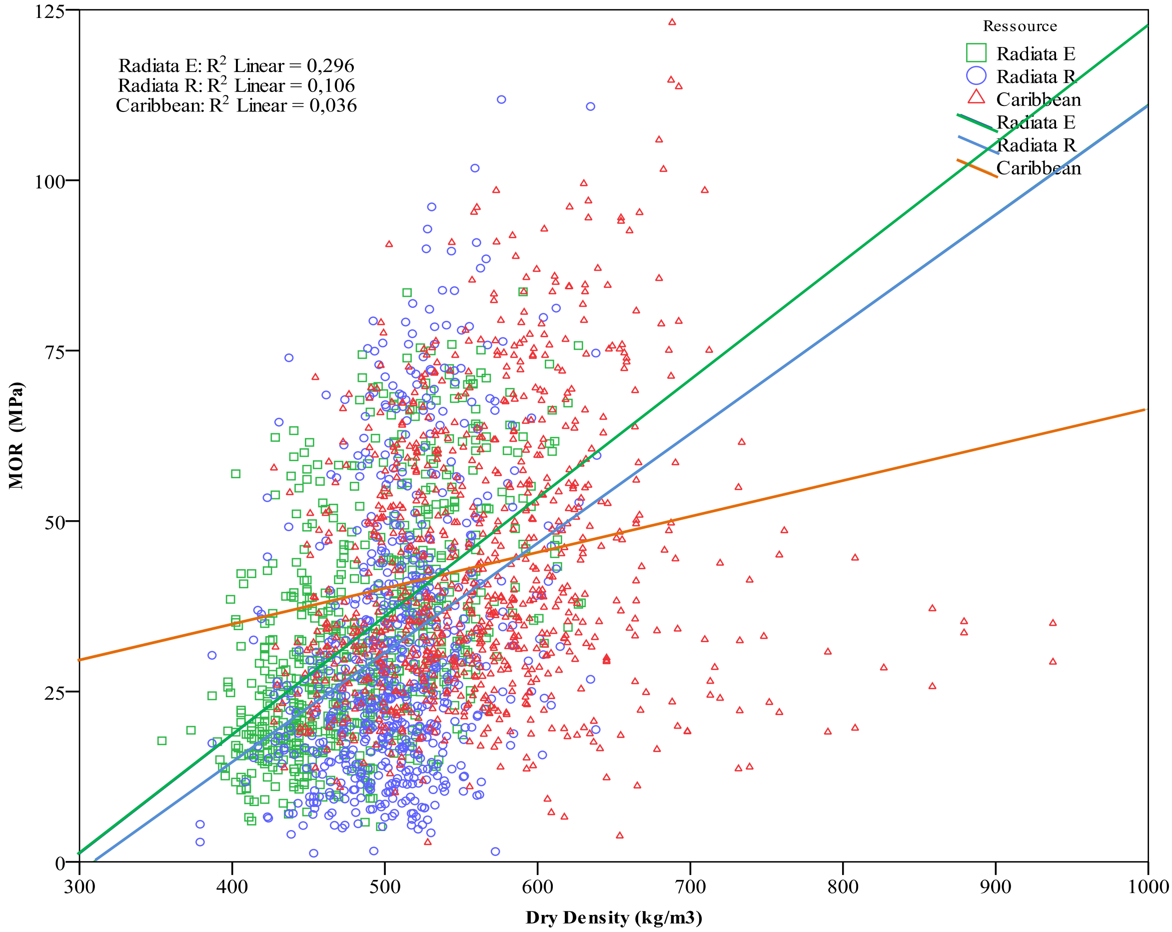

Figure 9. Linear regression between MOR and density for the three resources.

The MOR vs MOE linear correlations for all the resources are displayed in Figure 10. The general observation is the "trumpet" like shape of the data scatter points, in other words residual error on MOR increases with the MOE. This could be a source of heteroscedasticity problems (non-homogeneous variances) when developing linear regression equations.

As expected the boards with the lowest strength belong to Radiata R resource. They are spread on a quite large span of MOE, up to approximately 12000 MPa. This induces a sort of "belly" on the Caribbean resource scatter plot. This is characteristic of a strength limited resource.

The Caribbean resource has the lowest coefficient of determination which can be explained by a large variation of MOR values for a given upper range MOE (above 14000 MPa). Again the presence of a large quantity of resin associated with resin checks and the occurrence of compression wood could explain this observation.

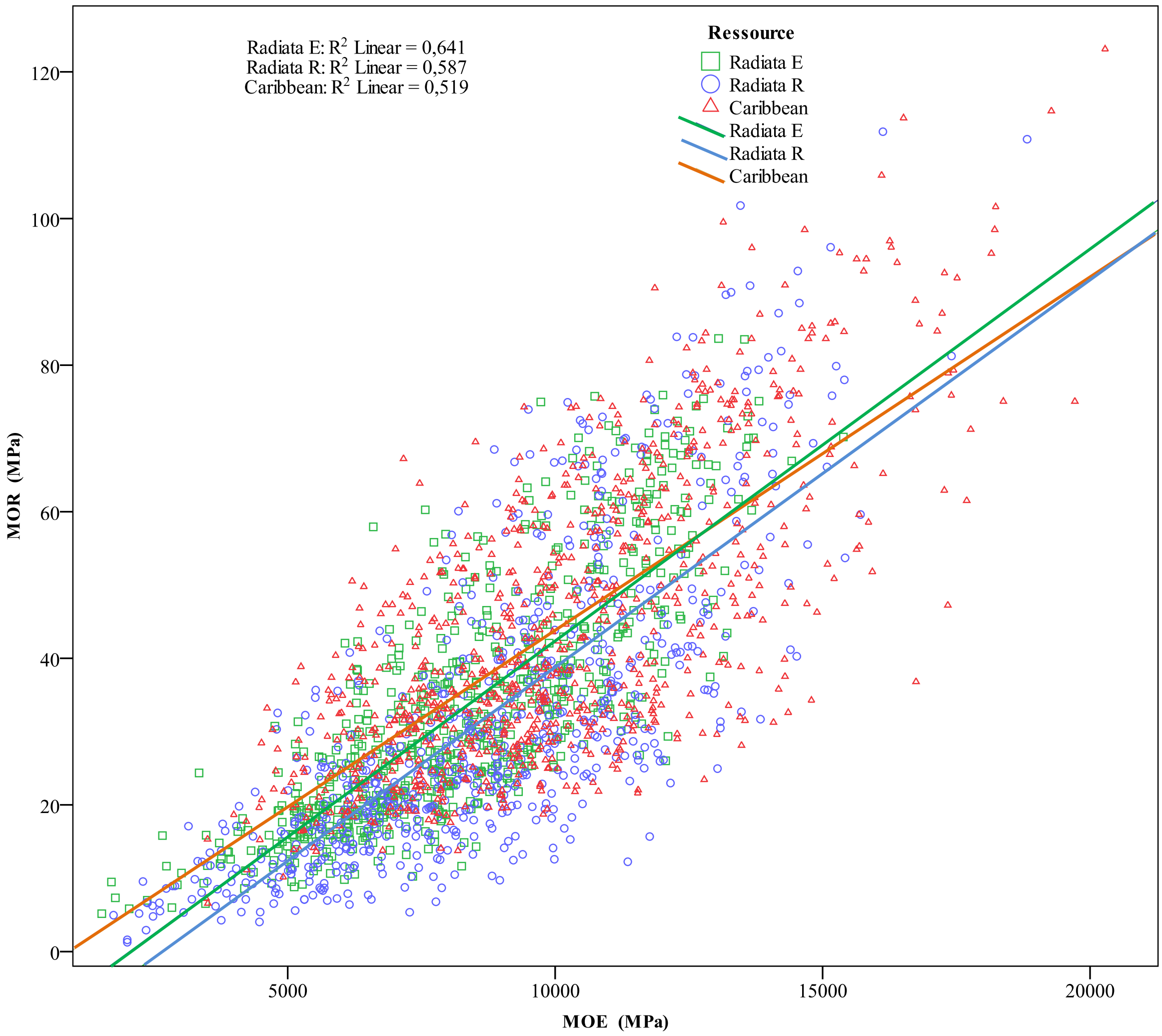

Figure 10. Linear regression between MOE and MOR for the three resources.

Random and biased

Table 3 displays the three resources' dry densities, MOEs and MORs at 12% MC for all the boards tested by random and biased tests separately.

The number of biased boards is larger than for random boards since the priority was given to biased position when performing the static bending test. The protocol was slightly different for Radiata E resource which explains the lower recovery of random boards (see Appendix 3), 40% comparing to an average of 60% for the two other resources.

The general tendencies observed when comparing the resources on all the boards taking all test positions together are similar to those observed on random or biased test positions. The mean density between biased and random is not significantly different whereas random and biased MOE and MOR are obviously quite different.

The total average MOE variations from biased to random relevant to the average MOE of all boards are 17%, 22% and 5% for Radiata E, Radiata R and Caribbean respectively. The total average MOR variations from biased to random relevant to the average MOR of all boards are 54%, 59% and 32% for Radiata E, Radiata R and Caribbean respectively. The consequence of choosing biased or random has a smaller impact on Caribbean than it does on the two Radiata resources. The greater impact is on the Radiata R resource.

Table 3. Descriptive statistics of density and mechanical properties for the three resources, biased and random separated.

Test position	Resource		Mean	Std. Deviation	N
Biased	Radiata E	Dry density (kg/m^3)	**484**	*51*	517
		MOE (MPa)	**7912**	*2349*	516
		MOR (MPa)	**28**	*13*	517
	Radiata R	Dry density (kg/m^3)	**508**	*40*	434
		MOE (MPa)	**8041**	*2706*	432
		MOR (MPa)	**25**	*15*	435
	Caribbean	Dry density (kg/m^3)	**564**	*71*	558
		MOE (MPa)	**9847**	*2842*	541
		MOR (MPa)	**38**	*17*	558
Random	Radiata E	Dry density (kg/m^3)	**489**	*51*	207
		MOE (MPa)	**9328**	*2411*	207
		MOR (MPa)	**46**	*17*	207
	Radiata R	Dry density (kg/m^3)	**508**	*41*	255
		MOE (MPa)	**9915**	*2873*	254
		MOR (MPa)	**44**	*22*	255
	Caribbean	Dry density (kg/m^3)	**561**	*72*	338
		MOE (MPa)	**10374**	*3007*	335
		MOR (MPa)	**52**	*21*	338

The histograms in Figure 11and Figure 12 illustrate the test consequence of the position choice for the three resources on MOE and MOR.

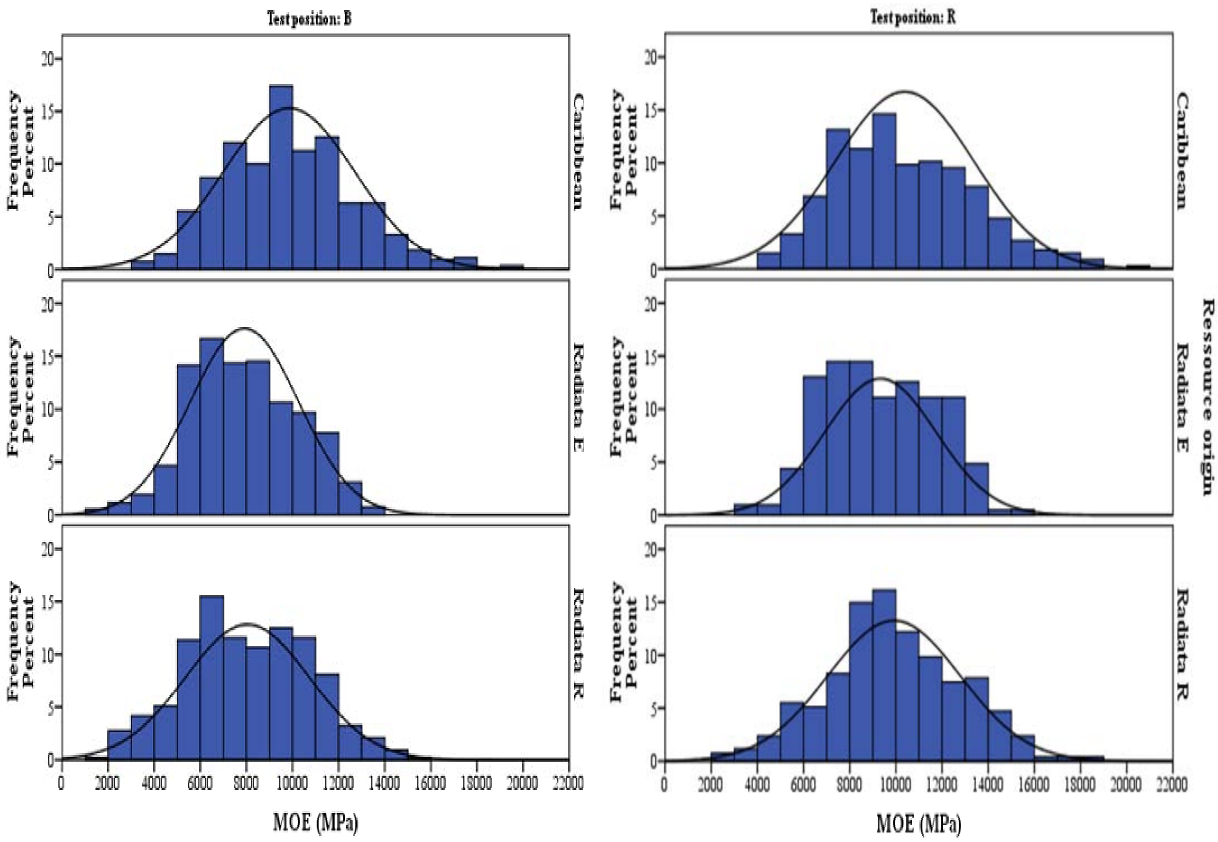

Figure 11. Biased position MOE (left), and random position MOE (right), for all resources.

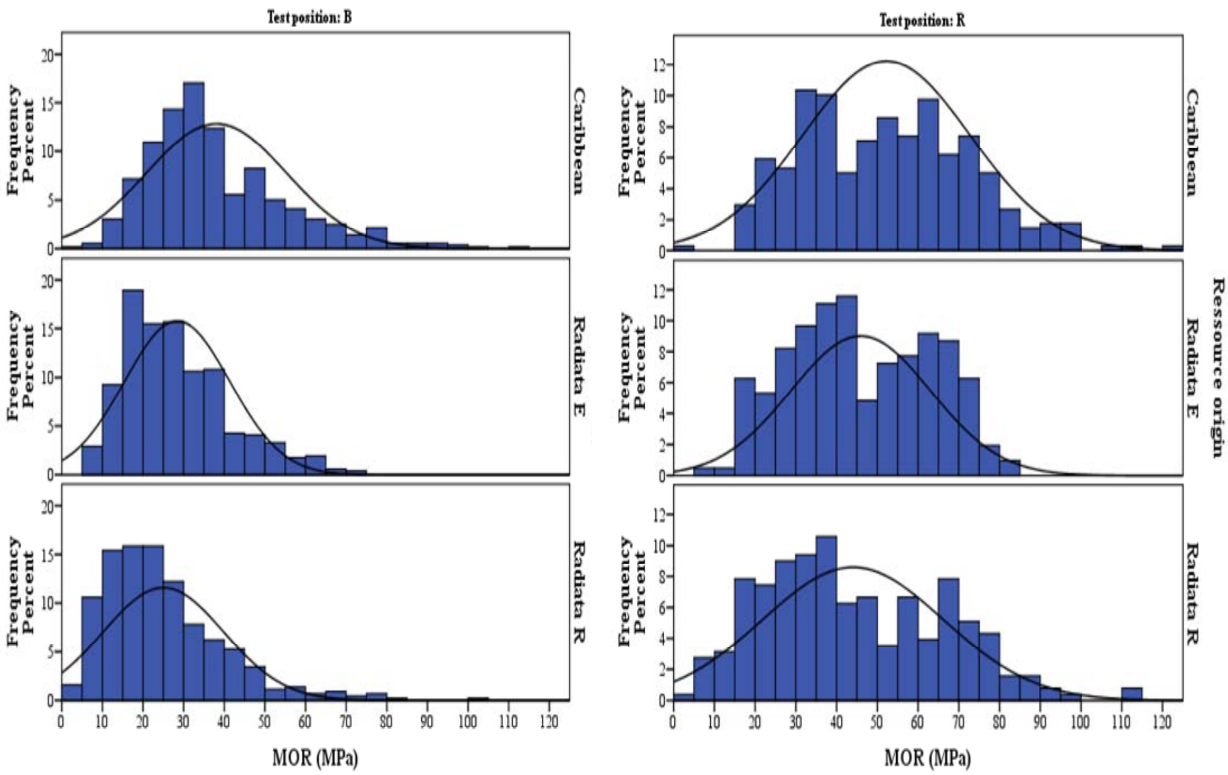

Figure 12. Histograms for biased sample MOR (left), and random position MOR (right), all resources.

The bivariate Pearson's correlation coefficients between density, MOE and MOR are displayed in Table 4 for biased and random tests separately. The correlations between MOE and MOR with density are always better on random due to a wider span of values across the density range. Correlations between MOE and MOR are similar on biased and random for Radiata E and R whereas Caribbean has better correlations on random.

Table 4. Bivariate Pearson's correlation coefficients between density, MOE and MOR, biased and random, all resources.

Test position	Resource		Dry density (kg/m^3)	MOE (MPa)
Biased	Radiata E	MOE (MPa)	0.68	
		MOR (MPa)	0.61	0.80
	Radiata R	MOE (MPa)	0.52	
		MOR (MPa)	0.34	0.74
	Caribbean	MOE (MPa)	0.31	
		MOR (MPa)	0.19	0.70
Random	Radiata E	MOE (MPa)	0.71	
		MOR (MPa)	0.59	0.81
	Radiata R	MOE (MPa)	0.65	
		MOR (MPa)	0.41	0.75
	Caribbean	MOE (MPa)	0.32	
		MOR (MPa)	0.24	0.78

All the correlations are significant at the 0.01 level (2-tailed).

The latter observation on Caribbean can be explained by a larger dispersion of MOR values for MOE values above 12000 MPa (see Figure 13 and Figure 14).

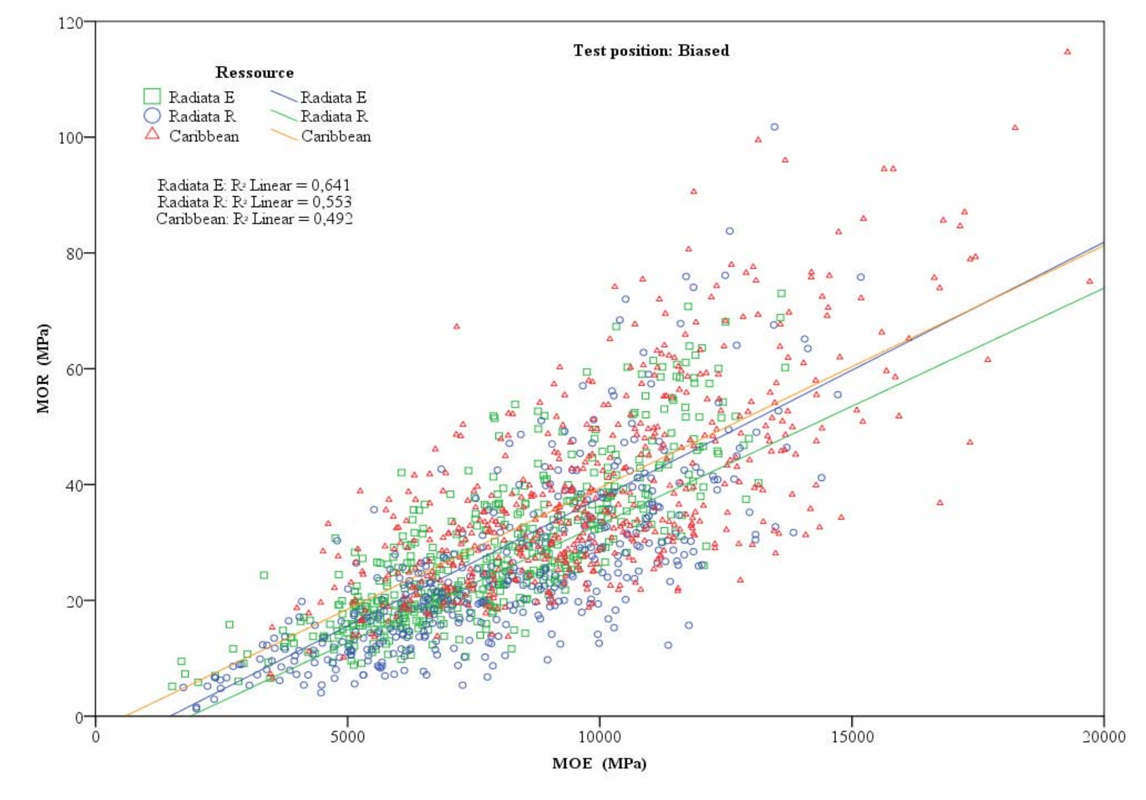

Figure 13. Biased test: MOE vs MOR, all resources.

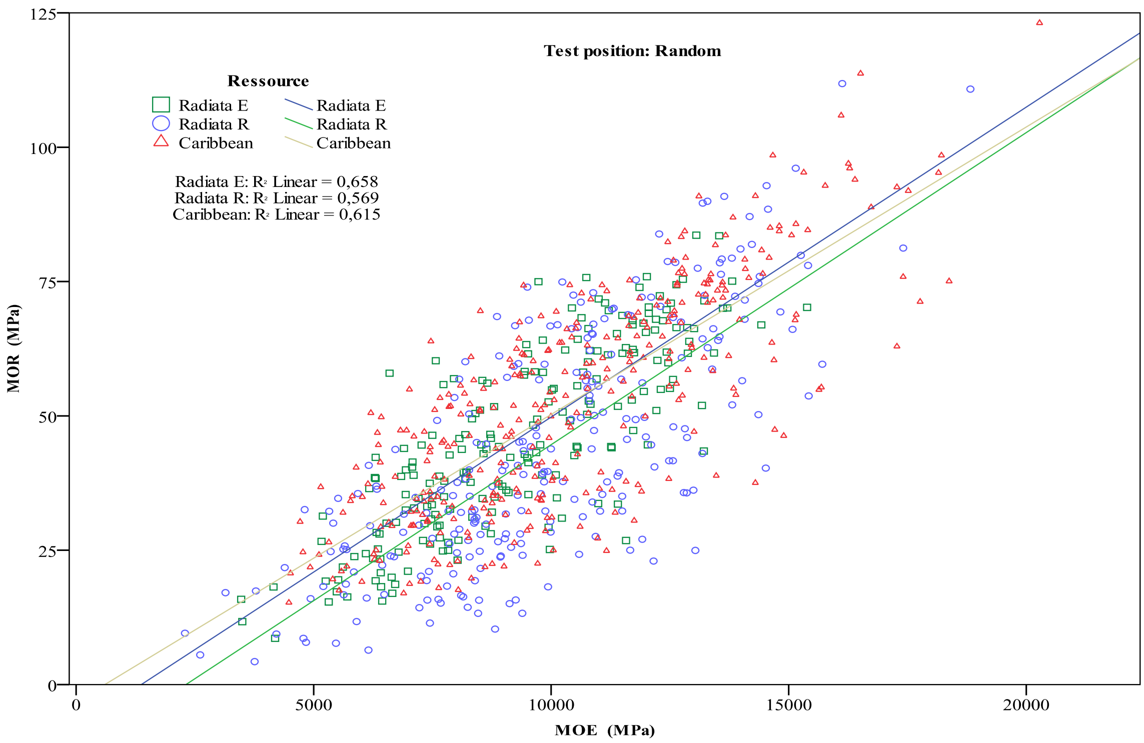

Figure 14. Random test: MOE vs MOR, all resources.

Biased vs Random

Figure 15, Figure 16 and Figure 17 display the correlations for each resource between MOR random and MOR biased tests performed on the same board at different locations. The red line represents the angle bisector of the graph. If selection of the weakest point on the board was perfect all the measurement points should be above this angle bisector line. For Radiata E resource the choice was generally good despite a few mistakes. In the case of Radiata R resource because some boards contained numerous large knots or defects it was sometimes difficult to nominate the weakest point unless without spending several minutes assessing each board. The result obtained for Caribbean is less easily explained because selection of the weakest point was apparently less difficult than Radiata R due to the proportion and sizes of the knots being somewhat smaller. Nevertheless it seems for some boards the nature or the type of the weakest knot or defect wasn't assessed correctly before testing.

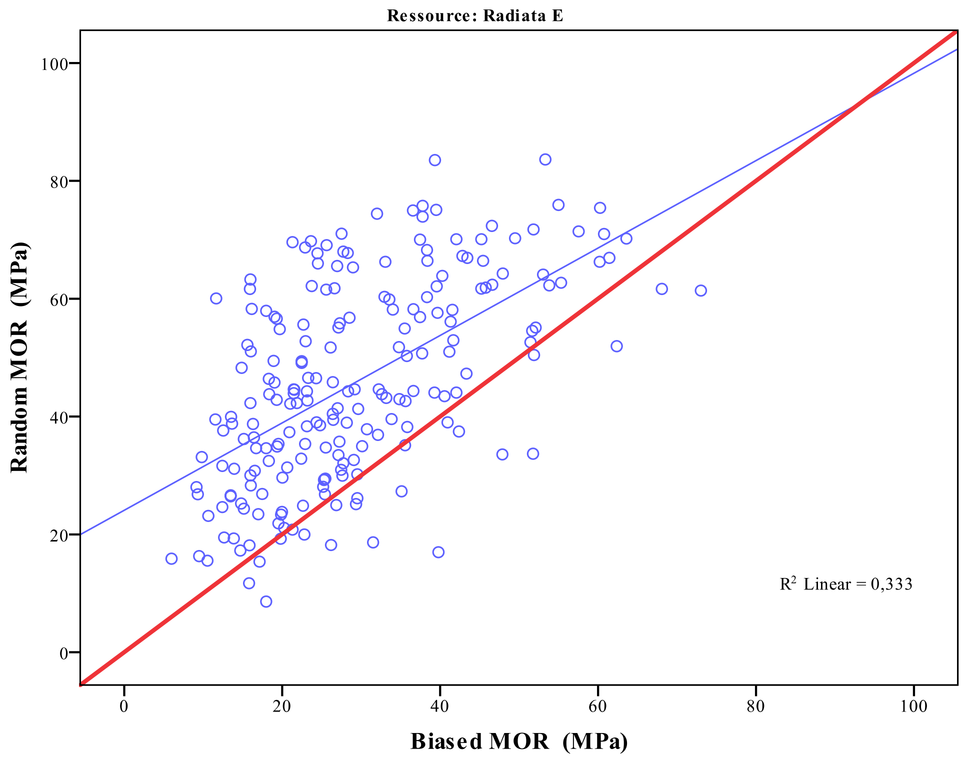

Figure 15. Stiffness limited radiata pine, random vs biased MOR.

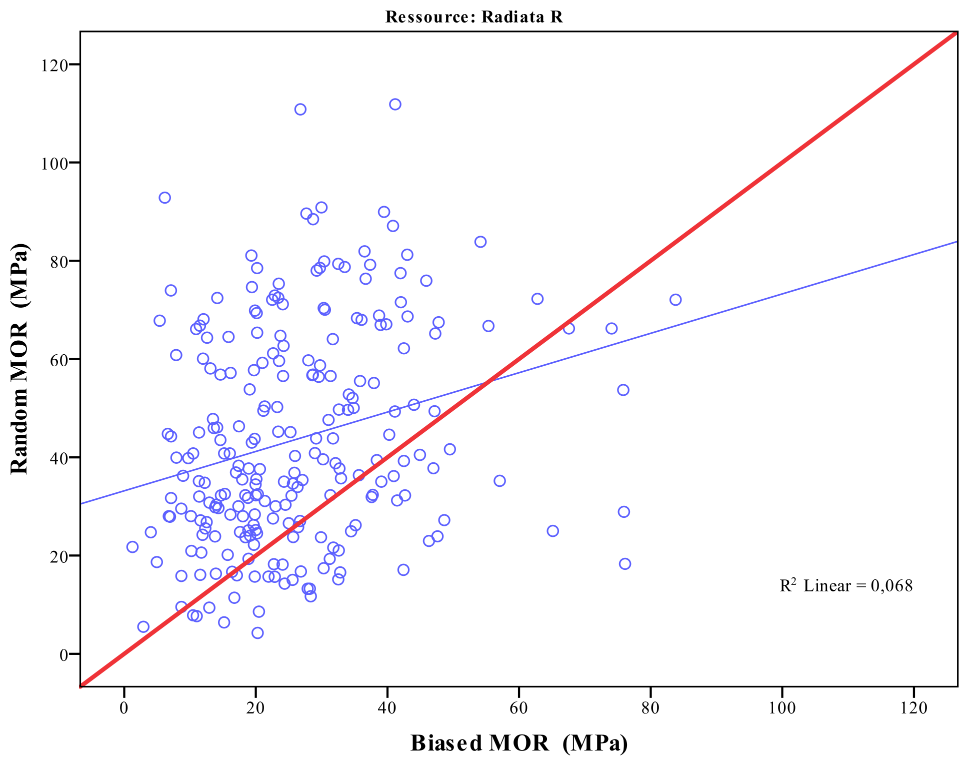

Figure 16. Strength limited radiata pine, random vs biased MOR.

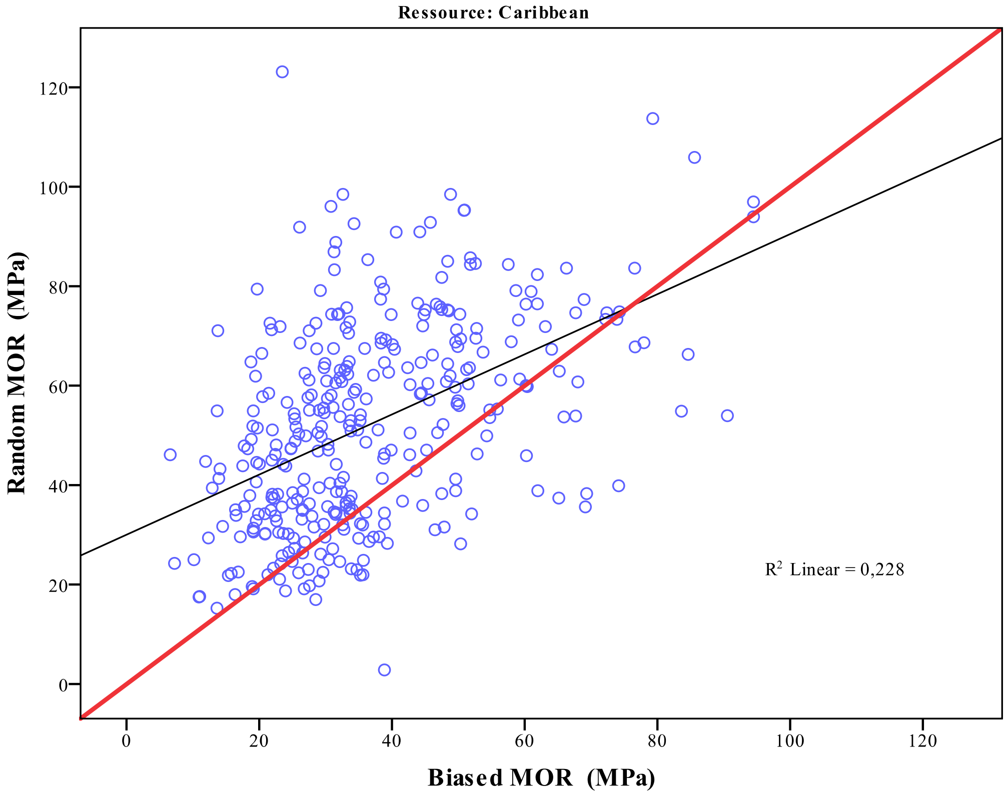

Figure 17. Caribbean pine, random vs biased MOR.

Position of the boards within the logs

For all three resources the position of the board determined by distance from the pith within the log had only a weak correlation with the MOE or the MOR of the board when considering biased and random all together (Table 5). Caribbean displays the best correlation followed by Radiata E then Radiata R.

Table 5. Distance from the pith vs static bending, all resources.

Resource / distance from the pith - R^2	*MOE*	*MOR*
Radiata E	0.13	0.08
Radiata R	0.09	0.04
Caribbean	0.21	0.11

Individual NDT predictors for static MOE and MOR biased evaluation

In the following section all the analyses presented are based on **biased boards** only according to the justification given in the earlier section **Biased versus random position** testing.

Correlation analyses between the individual NDT parameters and the destructively measured properties were carried out. In this way, the coefficient of determination (R^2) of each measured property in linear regression as a predictor for the destructively determined properties was obtained.

Our logic in presenting the results has been to start from the data collected chronologically as close as possible to the reference static bending i.e. the dry boards then present the results in reverse chronological order *viz* the green boards and finally for the logs.

At dry mill level

The R^2 values for each parameter are derived from the dried, dressed boards. The indicating properties obtained from the strength grading machines or equipment used are included as single parameters, even if some of them required more than one measurement.

Radiata E resource

Figure 18 and Figure 19 present the coefficient of determination obtained on Radiata E resource between the different individual predictors and the biased static bending MOE and MOR results.

The best predictors for static MOE were achieved through the resonance method. We remind the reader that the dynamic MOE is based on the measurement combination of the vibration signal and the density. The flexion mode provides the higher coefficient of determination (Figure 18). Bernoulli's model on the first resonance frequency and Timoshenko's model both gave similar results. The second or third resonance frequencies with Bernoulli's model gave a slightly lower level of correlation.

The vibration MOE in compression mode is very close or even equivalent to the vibration MOE in flexion. The average MOE Metriguard profile on the reference destructive static test span (local measurement) provides a correlation 0.05 lower than the flexion resonance method. If the average Metriguard MOE profile is calculated on the full length of the board, the coefficient of determination is 0.04 less than the vibration MOE in compression. The minima MOE Metriguard provides a similar level of correlation to the Metriguard MOE board profile. One would expect that the local measurement over the test span should be better than the global measurement (on the full length of the board), however this is not necessarily the case. It is possible that the flatwise, 3-point bending as utilised in the Metriguard process combined with the knotty attributes of the stiffness-limited resource, produces this discrepancy.

Interestingly the specific vibration MOE in compression as a predictor of static bending MOE provides an R^2 of 0.72 which is be acceptable to pre-sort the low stiffness boards with a very simple device able to measure only the board vibration. It may not be necessary to combine density as a parameter to achieve a satisfactory pre-grading result.

The best WoodEye® predictor for MOE is the KAR calculated with a triangular window (R^2=0.31).

Predictors	MOE (MPa)	MOR (MPa)
MOE (MPa)	**1.00**	**0.64**
Flex-Dry-MOET	0.85	0.53
Flex-Dry-MOE_1	0.85	0.53
Comp-Dry-MOE_1	0.83	0.50
Flex-Dry-MOE_2	0.82	0.50
Flex-Dry-MOE_3	0.82	0.50
Metri_avg Static Test	0.80	0.46
Comp-Dry-MOE_2	0.80	0.48
Flex-Dry-MOE_4	0.80	0.48
Metri_avg board	0.79	0.47
Comp-Dry-MOE_3	0.79	0.47
Metri_min Static Test	0.78	0.50
Metri_min board	0.77	0.52
Flex-Dry-MOE_1 /Density	0.75	0.41
Comp-Dry-MOE_1/Density	0.73	0.38
Comp-Dry-MOE_4	0.65	0.38
MOR (MPa)	**0.64**	**1.00**
Flex-Dry-SBandwidth	0.64	0.35
Flex-Dry-SCGravity	0.53	0.28
Comp-Dry-SBandwidth	0.47	0.24
Dry Density (kg/m3)	**0.46**	**0.37**
Comp-Dry-SSlope	0.32	0.19
WE_KAR_trgl_99	0.31	0.29
WE_KAR_ext_99	0.29	0.27
WE_KAR_ext_98	0.28	0.27
Comp-Dry-SCGravity	0.27	0.13
WE_CTR_trgl_AC_M	0.26	0.22
WE_KAR_trgl_M	0.26	0.24
WE_CTR_AC_M	0.26	0.22
WE_KAR_ext_M	0.26	0.23
WE_CTR_trgl_AC_3	0.24	0.24
WE_CTR_trgl_AC_5	0.23	0.23

Figure 18. R^2 of NDT measurements to destructively determined properties in bending for Radiata E resource on dry, dressed boards. Note: MOE R^2 sorted largest to smallest, lower limit = 0.2.

The best prediction of MOR comes from static bending MOE which is appreciably above the second best predictor which is vibration MOE in flexion (Figure 18). Indeed the resonance method, whatever the configuration, and Metriguard give similar levels of prediction, around 0.5. The MOEs calculated from higher resonance frequencies exhibit coefficient of determinations between 0.4 and 0.5. Because they are expressing the same physical property the levels of correlation with MOR are linked to those with static bending MOE. As a result, for simplification reasons, the Figure 18 displayed only the first resonance frequency MOEs in flexion and compression. Two signal descriptors, the spectral centre of gravity (R^2=0.28) and the spectral bandwidth (R^2=0.35), provide levels of prediction in the same range of the best optical scanner parameters.

Dry density has an R^2 equal to 0.37, which is above the level of prediction of even the best WoodEye® knot parameters which presents a coefficient of determination of 0.32. The fibre knot detection gives the best knot type prediction and the best mode of extraction is the maximum KAR.

Predictors	MOE (MPa)	MOR (MPa)
MOR (MPa)	**0.64**	**1.00**
MOE (MPa)	**1.00**	**0.64**
Flex-Dry-MOE_1	0.85	0.53
Metri_min board	0.77	0.52
Metri_min Static Test	0.78	0.50
Comp-Dry-MOE_1	0.83	0.50
Metri_avg board	0.79	0.47
Metri_avg Static Test	0.80	0.46
Dry Density (kg/m3)	**0.46**	**0.37**
Fk_KAR_trgl_99	0.33	0.32
Fk_KAR_ext_99	0.30	0.30
Fk_KAR_ext_98	0.30	0.30
WE_KAR_trgl_99	0.31	0.29
WE_KAR_ext_99	0.29	0.27
WE_KAR_ext_98	0.28	0.27
Fk_CTR_trgl_AC_3	0.26	0.27
Fk_CTR_trgl_AC_5	0.26	0.26
Fk_KAR_trgl_M	0.27	0.25
Fk_KAR_ext_M	0.26	0.25
Fk_CTR_trgl_AC_M	0.29	0.25
Fk_CTR_AC_M	0.29	0.25
WE_CTR_trgl_AC_3	0.24	0.24
WE_KAR_trgl_M	0.26	0.24
WE_CTR_trgl_AC_5	0.23	0.23
WE_KAR_ext_M	0.26	0.23
WE_CTR_trgl_AC_M	0.26	0.22
WE_CTR_AC_M	0.26	0.22

Figure 19. R^2 of NDT measurements to destructively determined properties in bending for Radiata E resource on dry, dressed boards. Only the first frequency vibration MOE for both compression and flexion are exhibited. Note: MOR R^2 sorted largest to smallest, lower limit = 0.2.

Figure 20 displays the high correlation between Metriguard average MOE on the board and vibration MOE in compression. The coefficients of determination are very high because the physical principles of measurement of these two methods are both established on strength of material principles and provide a direct measure of MOE. Nevertheless, they are based on different loading modes which explains the slight discrepancy observed through the linear regression equation (constant different from 0) and the residual error (dispersion around the regression line). Three factors can explain the observed difference of the experimental data:

- Metriguard measures a long-span flat-wise average MOE whereas the vibration compression MOE is measured through a uniform stress wave across the whole section.
- The tested span is shorter for Metriguard because the measurement span starts and finishes at 80 cm from both ends whereas the resonance method applies a stress on full length of the board.
- The longitudinal resonance method induces a compression-traction stress whereas Metriguard system induces a three point bending stress. The latter provokes a shear effect which should lead to a lower measured MOE. One should note that the constant of the regression equation is the same order of magnitude as the shear modulus of elasticity in the longitudinal-radial plane of the wood. Indeed Metriguard provides a higher MOE than vibration MOE in compression. There is no obvious explanation to this phenomenon.

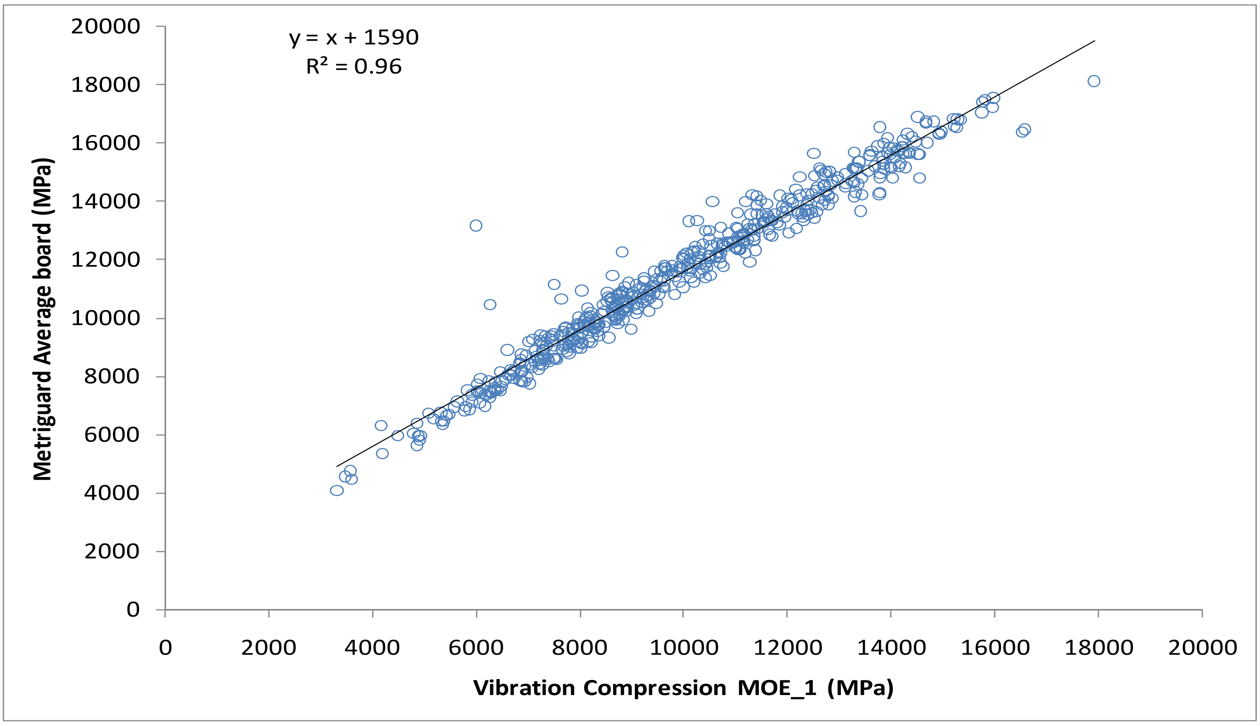

Figure 20. Linear regression between MOE measured by resonance method in compression and average MOE given by Metriguard for Radiata E resource on dry, dressed boards.

Radiata R resource

Figure 21 and Figure 23 present the coefficient of determination obtained on Radiata R resource between the different individual predictors and the biased static bending MOE and MOR results.

For this resource the X-ray scanner LHG was also included in the set of methods evaluated. The Metriguard HCLT provided the strongest correlation with static MOE, using the minimum MOE from the profile on the static bending test span (its local measurement).

The LHG predicted strength, which combines the previous parameter and X-ray knot descriptors, provided the second highest correlation as expected, due to the combination of Metriguard (minimum MOE from the profile on the static bending test span) and X-ray parameters. Vibration MOE in flexion, compression and flexion using Timoshenko's model, all deliver comparable quality of prediction. These predictors are closely followed by the average static test (local measurement). Surprisingly, this local parameter (matching the test span for the reference test) did not provide a stronger correlation than the global measurements.

Taken as a whole, the best predictors for the R limited resource have an average R^2 difference of 0.15 with Radiata E resource. This reflects the knotty nature of this resource which significantly impacts the results provided by individual or simple combined parameters. Specific knot information should be **qualitatively and quantitatively** added to a prediction model in order to improve the predictions.

As for Radiata E, the specific MOE correlation for the Radiata R was in the same magnitude of order to the best correlations, indicating that simple vibration systems may form the basis of an effective pre-grading tool.

For this resource, the R^2 for MOEs calculated using higher resonance frequencies were 0.05 lower than the first frequency. The Metriguard average MOE displays R^2 significantly lower than other Metriguard and vibration parameters. Despite the characteristic knottiness of the Radiata R resource, the knot parameters as measured by WoodEye® didn't provide as good indications for stiffness as for the Radiata E resource.

Predictors	MOE (MPa)	MOR (MPa)
MOE (MPa)	**1.00**	**0.56**
Metri_min Static Test	0.70	0.47
LHG predicted Strength	0.67	0.53
Flex-Dry-MOE_1	0.66	0.28
Comp-Dry-MOE_1	0.65	0.28
Flex-Dry-MOET	0.65	0.29
Metri_avg Static Test	0.64	0.28
Comp-Dry-MOE_1/Density	0.63	0.26
Metri_min board	0.61	0.37
Flex-Dry-MOE_2	0.61	0.26
Flex-Dry-MOE_3	0.61	0.26
Flex-Dry-MOE_5	0.60	0.24
Flex-Dry-MOE_4	0.59	0.23
Flex-Dry-MOE_1 /Density	0.59	0.26
Comp-Dry-MOE_2	0.57	0.25
Metri_avg board	0.57	0.22
MOR (MPa)	**0.56**	**1.00**
Comp-Dry-MOE_3	0.49	0.16
Comp-Dry-MOE_4	0.32	0.08
Comp-Dry-SBandwidth	0.32	0.16
Comp-Dry-SSlope	0.29	0.15
Dry Density	**0.28**	**0.12**
WE_KAR_trgl_M	0.27	0.30
WE_KAR_ext_M	0.27	0.30
WE_KAR_trgl_99	0.26	0.36
WE_KAR_ext_99	0.24	0.35
WE_KAR_ext_98	0.24	0.35
Comp-Dry-SCGravity	0.23	0.10
Flex-Dry-SCGravity	0.23	0.11
Flex-Dry-SBandwidth	0.23	0.12
LHG KAR	0.21	0.25
WE_CTR_trgl_AC_5	0.20	0.29

Figure 21. R^2 of NDT-measurements to destructively determined properties in bending for Radiata R resource on dry, dressed boards. Note: MOE R^2 sorted largest to smallest, lower limit = 0.2.

For MOR prediction, the MOEs calculated from higher resonance frequencies exhibit coefficient of determinations between 0.1 and 0.3. Because they are expressing the same physical property the levels of correlation with MOR are linked to those with static bending MOE. As a result, for simplification reasons, Figure 23 displays only the first resonance frequency MOEs in flexion and compression. Three signal descriptors, the spectral centre of gravity (R^2=0.1), the spectral slope (R^2=0.15) and the spectral bandwidth (R^2=0.16), provide a level of prediction significantly lower than the best optical scanner parameters (R^2 between 0.3 and 0.4).

LHG predicted strength provided R^2 of 0.53, the best result from all MOR predictors (Figure 23). As depicted in Figure 22 below, only the local measurements provided reasonable correlations for predictions, with Metriguard HCLT (minimum MOE) providing the best correlation to the static bending MOE. The test span information provides a significantly superior prediction of strength (R^2=0.47).

The R^2 for Metriguard minimum of the board was 0.1 lower than the Metriguard Static test span result (0.37 vs 0.47 respectively). This implies that the minimum for the board is not the best predictor from the Metriguard MOE profile for this resource. In the case of the Radiata E resource, these two parameters provided a similar level of correlation.

From the optical scanner information, WoodEye® KAR provided the best correlation with MOR, surpassing LHG X-ray by 0.1 (0.36 vs 0.25 respectively). The Metriguard minimum static test contains the majority of the information and combining with LHG only improves by a magnitude of 0.06.

Of the various knot types detected by WoodEye®, fibre knots provide the best correlation, with a similar level of correlation to the combined knot silhouette.

The Metriguard average and the vibration compression MOE both provide the same level of correlation.

Predictors	MOE (MPa)	MOR (MPa)
MOR (MPa)	**0.56**	**1.00**
MOE (MPa)	**1.00**	**0.56**
LHG predicted Strength	0.67	0.53
Metri_min Static Test	0.70	0.47
Metri_min board	0.61	0.37
WE_KAR_trgl_99	0.26	0.36
WE_KAR_ext_99	0.24	0.35
WE_KAR_ext_98	0.24	0.35
WE_KAR_trgl_99	0.25	0.34
Fk_KAR_trgl_99	0.23	0.34
Fk_KAR_ext_99	0.21	0.32
Fk_KAR_ext_98	0.21	0.32
WE_KAR_ext_M	0.27	0.30
WE_KAR_trgl_M	0.27	0.30
Fk_CTR_trgl_AC_3	0.21	0.30
Fk_CTR_trgl_AC_5	0.21	0.29
WE_CTR_trgl_AC_5	0.20	0.29
WE_CTR_trgl_AC_3	0.19	0.29
Fk_KAR_trgl_M	0.25	0.29
Fk_KAR_ext_M	0.24	0.28
Flex-Dry-MOE_1	0.66	0.28
Metri_avg Static Test	0.64	0.28
Comp-Dry-MOE_1	0.65	0.28
WE_KAR_trgl_M	0.26	0.26
LHG KAR	0.21	0.25
LHG weighted KAR	0.19	0.23
Metri_avg board	0.57	0.22
WE_KAR_int_99	0.16	0.21
WE_KAR_int_M	0.18	0.19
Fk_CTR_trgl_AC_M	0.18	0.19
Fk_CTR_AC_M	0.18	0.19
WE_CTR_trgl_AC_M	0.18	0.19
Fk_KAR_int_99	0.13	0.18
WE_CTR_AC_M	0.18	0.18
Fk_KAR_int_M	0.16	0.18
LHG I ratio	0.12	0.16

Figure 23. R^2 of individual NDT-measurements to destructively determined properties in bending for Radiata R resource on dried, dressed boards. Only the first frequency vibration MOE for both compression and flexion are exhibited. Note: MOR R^2 sorted largest to smallest, lower limit = LHG I ratio.

Again we found a very good correlation for Metriguard average MOE with vibration compression MOE ($R^2 = 0.90$). However, due to the knot characteristics of the strength limited resource and subsequent outliers, as seen in Figure 24 below, the correlation is lower than was achieved for the stiffness limited resource.

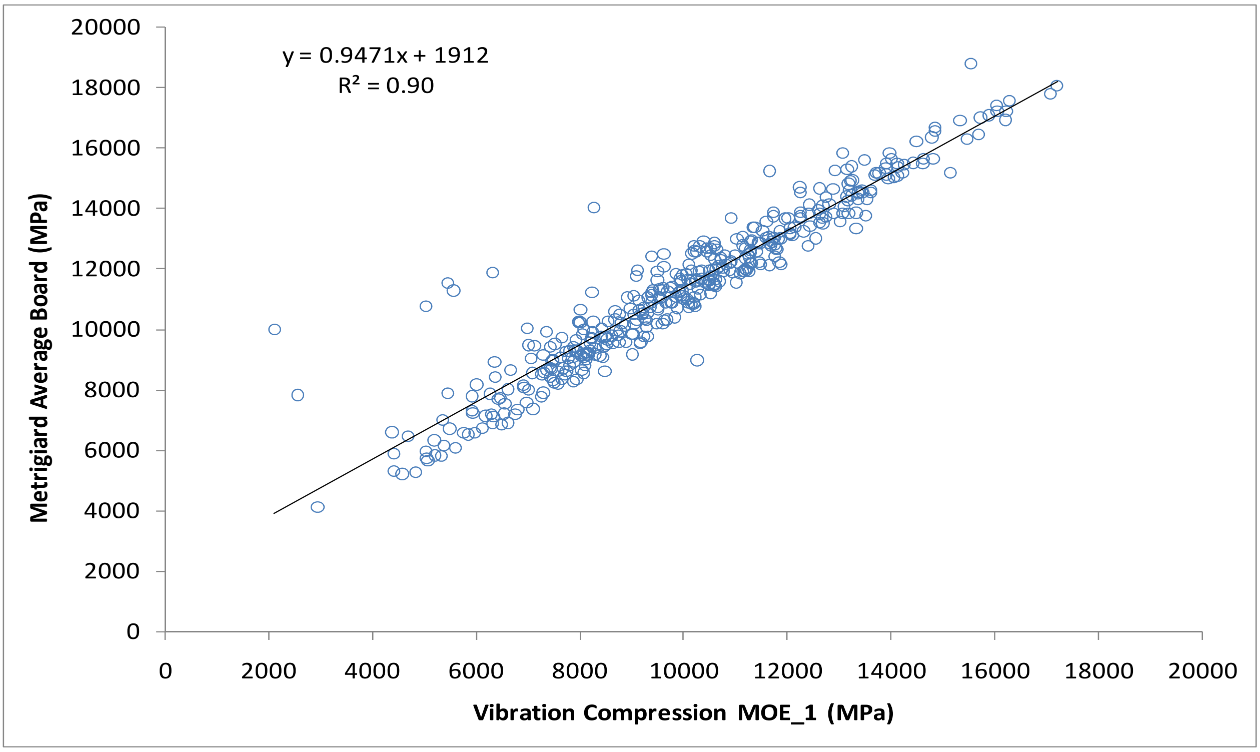

Figure 24. Linear regression between MOE measured by resonance method in compression and average MOE given by Metriguard for Radiata R resource on dried, dressed boards.

Caribbean resource

The levels of correlation observed for the Caribbean biased static bending MOE are slightly lower than achieved for Radiata E. For this resource the Metriguard provided the best prediction of MOE (R^2=0.84). As expected, the Metriguard average biased static test was better than the Metriguard average board result. In contrast to the Radiata E resource, the vibration MOE correlations were lower than for Metriguard.

Vibration MOE (compression) without combining density still achieved a reasonable correlation (R^2= 0.62). As for the other parameters, the vibration descriptors provided a range of R^2 from 0.30 to 0.40 for the best correlations.

Predictors	MOE (MPa)	MOR (MPa)
MOE (MPa)	**1.00**	**0.49**
Metri_avg Static Test	0.84	0.35
Metri_avg board	0.79	0.30
Flex-Dry-MOE_3	0.79	0.34
Flex-Dry-MOE_4	0.79	0.33
Comp-Dry-MOE_1	0.78	0.31
Metri_min Static Test	0.77	0.37
Flex-Dry-MOET	0.77	0.32
Flex-Dry-MOE_5	0.77	0.32
Flex-Dry-MOE_2	0.76	0.31
Comp-Dry-MOE_2	0.76	0.31
Comp-Dry-MOE_3	0.76	0.32
Flex-Dry-MOE_1	0.73	0.30
Metri_min board	0.69	0.31
Comp-Dry-MOE_1/Density	0.62	0.23
Comp-Dry-MOE_4	0.53	0.23
Flex-Dry-MOE_1 /Density	0.50	0.20
MOR (MPa)	**0.49**	**1.00**
Comp-Dry-SSlope	0.49	0.18
Flex-Dry-SBandwidth	0.46	0.18
Flex-Dry-SCGravity	0.43	0.16
Comp-Dry-SBandwidth	0.39	0.15
Comp-Dry-SCGravity	0.32	0.12
Comp-Dry-MSNrjRatio_4	0.24	0.09
Comp-Dry-MSRatioF_3	0.21	0.07
Comp-Dry-MSPowerF_4	0.20	0.10

Figure 25. R^2 of individual NDT-measurements to destructively determined properties in bending for Caribbean resource on dry, dressed boards. Note: MOE R^2 sorted largest to smallest, lower limit = 0.2.

For MOR prediction, the MOEs calculated from higher resonance frequencies exhibit coefficient of determinations between 0.2 and 0.3. Because they are expressing the same physical property the levels of correlation with MOR are linked to those with static bending MOE. As a result, for simplification reasons, Figure 25 displays only the first resonance frequency MOEs in flexion and compression. Three signal descriptors, the spectral centre of gravity, the spectral slope and the spectral bandwidth, provided coefficient of determinations between 0.1 and 0.2. They are slightly lower than the best optical scanner parameters (R^2 between 0.15 and 0.25).

As for the MOE prediction, the best predictor of MOR for the Caribbean resource was provided by the Metriguard, local parameters (R^2=0.37, Figure 26). This is significantly lower than for the Radiata E and Radiata R (both R^2 =0.53). Additionally, WoodEye® provides a lower level of prediction in the case of Caribbean pine (R^2= 0.24, best result for Caribbean compared to R^2= 0.36 for Radiata R and R^2=0.32 for Radiata E). The Caribbean pine knot attributes are generally captured by WoodEye® scanners as 'black knots', whereas this feature is less frequently detected for the radiata resources, whose knot attributes are mostly detected as fibre knots. This difference in knot attributes/descriptors may explain the low level of correlation for MOR. This may be due to the incidence of loose knots in the Caribbean material.

Predictors	MOE (MPa)	MOR (MPa)
MOR (MPa)	**0.49**	**1.00**
MOE (MPa)	**1.00**	**0.49**
Metri_min Static Test	0.77	0.37
Metri_avg Static Test	0.84	0.35
Comp-Dry-MOE_1	0.78	0.31
Metri_min board	0.69	0.31
Flex-Dry-MOE_1	0.73	0.30
Metri_avg board	0.79	0.30
WE_KAR_ext_99	0.04	0.24
WE_KAR_ext_98	0.04	0.24
WE_KAR_trgl_99	0.05	0.22
WE_CTR_trgl_AC_5	0.04	0.20
WE_CTR_trgl_AC_3	0.05	0.19
WE_KAR_ext_M	0.03	0.18
WE_CTR_AC_5	0.03	0.16
WE_KAR_trgl_M	0.03	0.16
Bk_CTR_trgl_AC_3	0.06	0.16
Fk_KAR_ext_99	0.01	0.15
Fk_KAR_ext_98	0.01	0.15
Bk_CTR_trgl_AC_5	0.05	0.15
Bk_CTR_AC_5	0.05	0.14
Fk_KAR_trgl_99	0.01	0.14
Fk_CTR_trgl_AC_5	0.02	0.13
Fk_CTR_trgl_AC_3	0.02	0.13
Bk_CTR_AC_M	0.05	0.12
Bk_CTR_trgl_AC_M	0.05	0.12
Fk_CTR_AC_5	0.01	0.12
Bk_KAR_trgl_99	0.02	0.11
Fk_KAR_ext_M	0.01	0.11
WE_CTR_trgl_AC_M	0.03	0.11

Figure 26. R^2 of individual NDT-measurements to destructively determined properties in bending for Caribbean resource on dry, dressed boards. Only the first frequency vibration MOE for both compression and flexion are exhibited. Note: MOR R^2 sorted largest to smallest, lower limit = 0.1.

As was found for the two radiata resources, a high correlation was found between the Metriguard average board MOE and vibration compression MOE (R^2=0.96, Figure 27).

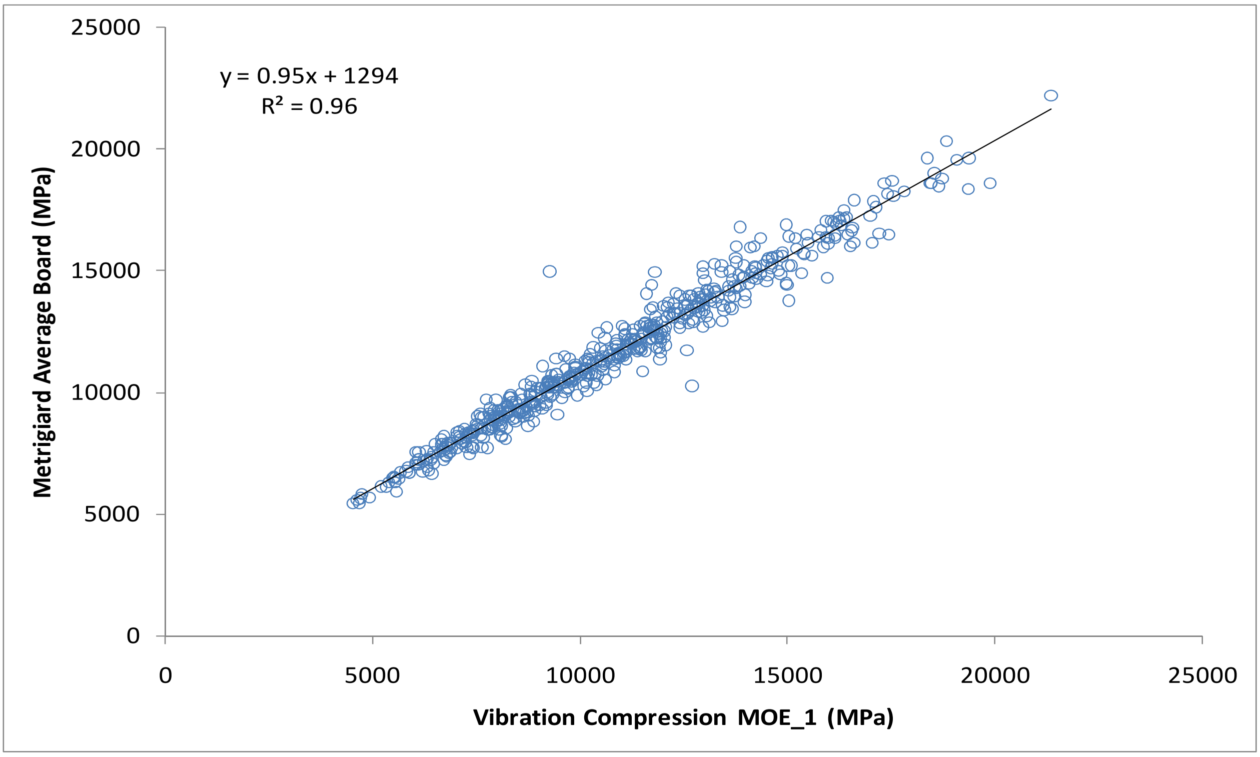

Figure 27. Linear regression between MOE measured by resonance method in compression and average MOE given by Metriguard for Caribbean resource on dry, dressed boards.

At green mill level

Radiata E resource

The vibration MOE in compression provides the best correlation with static bending MOE and MOR (R^2=0.77 and R^2=0.47 respectively) as depicted in Figure 28. MOE from flexion vibration displays a slightly lower level of correlation (R^2=0.75 and R^2=0.45 respectively).

The best predictor on dry dressed boards is from flexion vibration followed by compression vibration. They are calculated both from the first frequency with R^2=0.85 and R^2=0.83 for MOE and R^2=0.53 and R^2=0.50 for MOR respectively. These are better than the green board prediction by a magnitude of 0.05 to 0.08. The specific compression vibration MOE as a single predictor didn't provide a level of correlation suitable for sorting purposes.

Predictors	MOE (MPa)	MOR (MPa)
MOE (MPa)	**1.00**	**0.64**
Comp-Green-MOE_1	0.77	0.47
Comp-Green-MOE_3	0.76	0.45
Flex-Green-MOE_3	0.75	0.45
Flex-Green-MOET	0.74	0.45
Comp-Green-MOE_2	0.74	0.45
Flex-Green-MOE_2	0.74	0.44
Thumper_MOE (MPa)	0.74	0.44
Flex-Green-MOE_1	0.73	0.45
Flex-Green-MOE_4	0.72	0.44
Comp-Green-MOE_4	0.70	0.41
MOR (MPa)	**0.64**	**1.00**
Flex-Green-FacQ_4	0.36	0.23
Flex-Green-SSlope	0.29	0.17
Green Density	**0.27**	**0.19**
Flex-Green-MOE_1 /Density	0.26	0.13
Comp-Green-MOE_1/Density	0.25	0.12
Gamma_Density(Kg/m3)	0.23	0.17
Comp-Green-SSlope	0.22	0.13
Flex-Green-SBandwidth	0.20	0.11
Comp-Green-SBandwidth	0.17	0.08
Flex-Green-SCGravity	0.13	0.07
Flex-Green-R2T	0.12	0.10

Figure 28. R^2 of NDT measurements to destructively determined properties in bending for Radiata E resource on green sawn boards. Note: MOE R^2 sorted largest to smallest, lower limit = 0.1.

This difference between green board and dry board prediction is statistically significant but it is still probably low enough to consider a pre-grading system for sorting the low stiffness green boards. This was partially done in one mill with the Thumper system which provides a high level of prediction equivalent to the one obtained with Bing® system. Indeed these two systems should provide the same MOE values.

Figure 29 depicts the correlation between the green board compression MOE from the first frequency between *Bing*® and Thumper system. The correlation is not as high as expected and the residual error is quite significant. This discrepancy may be explained by the effect of uncontrolled drying on green density which occurred between the two set of measurements. *Bing*® measurements were performed three weeks after Thumper trial. The densities observed on the latter was on average 6% higher than the densities when the boards were measured for *Bing*® measurements with an important dispersion due to the position of the board in the stack (R^2=0.86 between green density measured by direct weighing and gamma ray system). Moreover the acoustic equipment can differ, i.e. settings (support effect, dimensions measurements etc.) and extraction algorithms (peak detection) which can lead to some small differences in the MOE calculation.

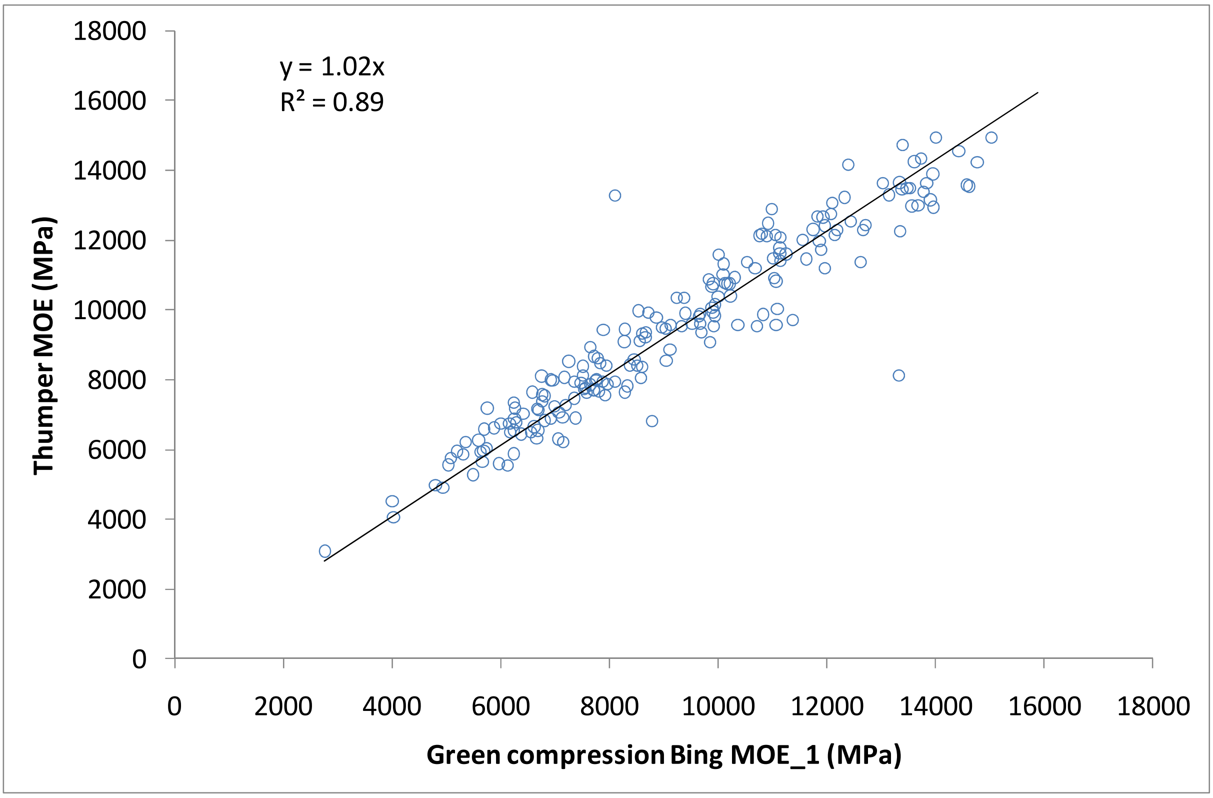

Figure 29. Linear regression between MOE from resonance method in compression measured by off line Bing® and by in-line Thumper systems, for **Radiata E** resource on green sawn boards.

Radiata R resource

Similarly to Radiata E resource, the vibration MOE in compression provides the best correlation with static bending MOE and MOR (R^2=0.58 and R^2=0.25 respectively) as depicted in Figure 30. MOE from flexion vibration displays a marginally lower level of correlation (R^2=0.57 and R^2=0.25 respectively).

For this resource the level of correlation of the best predictors is around 0.2 lower than Radiata E. This difference is higher than the difference observed on dry boards (around 0.15). The drying process certainly plays a role in this difference since the differential shrinkage from the knotty area may induce cracks and lack of adherence which may contribute to blurring the correlations between green and dry products.

Similar to Radiata E resource, the specific compression vibration MOE displays a very low prediction of static bending MOE and MOR.

Predictors	MOE (Mpa)	MOR (Mpa)
MOE (Mpa)	**1.00**	**0.56**
Comp-Green-MOE_1	0.58	0.25
Flex-Green-MOET	0.57	0.25
Flex-Green-MOE_1	0.57	0.24
MOR (Mpa)	**0.56**	**1.00**
Flex-Green-MOE_2	0.56	0.25
Flex-Green-MOE_3	0.54	0.22
Comp-Green-MOE_2	0.53	0.23
Comp-Green-MOE_3	0.53	0.23
Flex-Green-MOE_5	0.52	0.21
Flex-Green-MOE_4	0.51	0.21
Comp-Green-MOE_4	0.49	0.19
Flex-Green-MOE_1/Density	0.27	0.08
Comp-Green-MOE_1/Density	0.27	0.08
Flex-Green-R2T	0.27	0.15
Comp-Green-SSlope	0.19	0.09
Flex-Green-SCGravity	0.16	0.09
Comp-Green-SBandwidth	0.16	0.06
Flex-Green-SBandwidth	0.14	0.09
Flex-Green-MSPowerF_2	0.12	0.03
Flex-Green-MSPower_1	0.12	0.02
Flex-Green-SSlope	0.12	0.08
Flex-Green-Q_2	0.10	0.05
Flex-Green-MSPowerF_3	0.10	0.03
Flex-Green-MSPower_2	0.09	0.01
Comp-Green-Q_4	0.09	0.04
Green Density	**0.08**	**0.05**

Figure 30. R^2 of NDT measurements to destructively determined properties in bending for Radiata R resource on green sawn boards. Note: MOE R^2 sorted largest to smallest, lower limit given by the green density.

Caribbean resource

For the Caribbean resource, the best correlations are provided by flexion vibration which is marginally better than compression vibration. Contrasting with the other resources the best predictors are slightly improved from the use of higher resonance frequencies. The compression wood occurrence coupled together with high resin content may explain this observation already described in the static bending results paragraph above.

The vibration MOE in flexion provides the best correlation with static bending MOE and MOR (R^2=0.75 and R^2=0.31 respectively) as depicted in Figure 31. MOE from compression vibration displays a marginally lower level of correlation (R^2=0.74 and R^2=0.30 respectively).

Apart from the vibration MOE extracted parameters, the signal descriptors provide a higher static bending MOE prediction than the other resources but not for MOR prediction.

Predictors	MOE (MPa)	MOR (MPa)
MOE (MPa)	**1.00**	**0.49**
Flex-Green-MOE_4	0.75	0.31
Flex-Green-MOE_3	0.75	0.32
Flex-Green-MOE_2	0.74	0.32
Flex-Green-MOET	0.74	0.31
Comp-Green-MOE_3	0.74	0.30
Comp-Green-MOE_2	0.73	0.30
Comp-Green-MOE_1	0.73	0.30
Comp-Green-MOE_4	0.73	0.30
Flex-Green-MOE_5	0.73	0.30
Flex-Green-MOE_1	0.72	0.30
Comp-Green-MOE_1/Density	0.63	0.25
Flex-Green-MOE_1/Density	0.58	0.23
MOR (MPa)	**0.49**	**1.00**
Flex-Green-SBandwidth	0.48	0.18
Flex-Green-SSlope	0.43	0.17
Flex-Green-SCGravity	0.43	0.16
Comp-Green-SBandwidth	0.41	0.16
Comp-Green-SSlope	0.37	0.13
Comp-Green-SCGravity	0.31	0.13
Flex-Green-Q_2	0.29	0.16
Comp-Green-Alpha_1	0.27	0.09
Comp-Green-MSNrjRatio_3	0.26	0.09
Comp-Green-MSPower_3	0.25	0.10
Comp-Green-MSRatioF_3	0.25	0.10
Comp-Green-Q_2	0.25	0.10
Flex-Green-Alpha_2	0.23	0.09
Comp-Green-MSRatioF_4	0.23	0.11
Flex-Green-R2T	0.22	0.09
Comp-Green-MSNrjRatio_4	0.22	0.10
Green Density	**0.22**	**0.09**

Figure 31. R^2 of NDT measurements to destructively determined properties in bending for Caribbean resource on green sawn boards. Note: MOE R^2 sorted largest to smallest, lower limit given by the green density.

Combinations of NDT predictors for static MOE and MOR evaluation

We remind the reader that only the results from the biased static bending tests are analyzed.

The compression vibration system is more practical and easier to carry out in the mill than a flexion vibration because of the boundary conditions robustness and the fewer complementary data used. Moreover from the previous chapter we have noticed that the compression vibration and the flexion vibration provide comparable levels of prediction. For these reasons the following analysis will only focus on compression vibration data in combination with the other systems tested.

In this chapter, two statistical approaches are used: the Multiple Linear Regression (MLR) and the Partial Least Squares (PLS).

The variable selection for MLR was performed through a stepwise process: the selection process starts by adding the variable with the largest contribution to the model (the criterion used is Student's t statistic). If a second variable is such that the probability associated with its t is less than the "Probability for entry", it is added to the model. The same protocol applies for a third variable. After the third variable is added, the impact of removing each variable present in the model after it has been added is evaluated (still using the t statistic). If the probability is greater than the "Probability of removal", the variable is removed. The procedure continues until no more variables can be added or removed. The collinearity (or multicollinearity) problem was prevented by limiting the number of variables introduced in the model through a condition index threshold. Heteroscedasticity (non-homogeneous variance) was checked. If the model was subject to an heteroscedasticity problem an appropriate data transformation was applied. This was often the case for MOR prediction where a logarithm-transform was performed.

PLS attempts to find factors which both capture variance and achieve correlation. PLS attempts to maximize covariance and this is the explicit objective of the simple PLS (SIMPLS) algorithm used in this study. Two rules of thumb with regard to selecting the optimal number of factors were applied, namely:

- to only choose additional factors when the RMSEC improves by at least 2%, and
- to choose as few factors (called Latent Variables) as possible.

When developing the models an auto-scaling process was used (mean-centring followed by dividing variable by the standard) and no cross-validation performed. A log transformation was systematically applied on MOR values.

Radiata E resource

The coefficient of determination for predicting the static bending MOE from the best combinations of methods or parameters on dry boards ranges from 0.79 to 0.86 (Table 6). Using average MOE and minimum MOE together from Metriguard profiles in MLR doesn't improve the correlation. Only the profile average provides the best prediction from this equipment on Radiata E resource.

From the 35 variables extracted from each vibration spectrum only the first frequency vibration MOE was selected as a suitable explanatory variable in MLR. This fact is confirmed by the PLS model which displays the same level of prediction despite its complexity. The only advantage to use a PLS approach could be the robustness of the model since it uses several variables to perform the prediction.

Adding WoodEye® and/or Metriguard information to vibration measurement only improved the level of prediction by a maximum of 0.03. This observation indicates that the local information provided by WoodEye® or Metriguard marginally improves the static bending MOE prediction.

For the green boards, the static bending MOE prediction level is below that observed for dry boards by an average of only 0.06. If an optical or equivalent system can be used on green boards with the same quality of information as provided on dry boards, then there is a small improvement when combined with vibration using PLS on all parameters (+0.02).

Table 6. R^2 of combined NDT measurements to destructively determined properties in bending for Radiata E resource on green sawn boards. Note that the number listed beside PLS indicates the number of factors used in the models. Each colour corresponds to a different set of equipment or wood moisture content.

Methods	Reg.	Parameters	R^2 x 100 MOE	Parameters	R^2 x 100 MOR
Vibration GREEN	MLR/PLS 3	MOE_1	**77**	MOE_1	**48**
Vibration GREEN + WoodEye	PLS 3	all	**79**	all	**55**
Metriguard Board	MLR	Avg_Brd	**79**	Mini_Brd	**52**
Metriguard Test Span	MLR	Avg_Span	**80**	Mini_Span	**52**
Vibration	MLR	MOE_1	**83**	MOE_1 + MOE_1/density + Alpha_2	**53**
Vibration	PLS 4	all	**83**	all	**57**
Vibration + Metriguard	MLR	MOE_1 + Mini_Span	**85**	Mini_Span + MOE_1	**54**
Vibration + Metriguard	PLS 4	all	**85**	all	**61**
Vibration + WoodEye	MLR	MOE_1 + Fk_KAR-m	**84**	MOE_1 + KAR-Ext	**55**
Vibration + WoodEye	PLS 3	all	**84**	all	**62**
Vibration + WoodEye + Metriguard	MLR	MOE_1 + Mini-Span	**85**	Mini_Brd + Kar-Ext + MOE_1	**57**
Vibration + WoodEye + Metriguard	PLS 3	all	**86**	all (PLS 4)	**64**

When considering the MOR predictions, MLR provided an R^2 of 0.52 up to 0.57, with the best combination being the combination of three systems: vibration, WoodEye® and Metriguard. This level of prediction is achieved by using only the vibration methods in combination with a PLS model. In combination with Metriguard or WoodEye®, the prediction increases to 0.62. The best combination is achieved with the three systems combined where an R^2 of 0.64 resulted through PLS approach.

The first frequency vibration MOE alone provided an R^2 of 0.48 which wasn't improved by using MLR or PLS. Interestingly, using PLS on vibration parameters for green boards combined with an optical scanner achieved a prediction level as good as MLR on dry boards using a combination of vibration and Metriguard or WoodEye® (R^2=0.55).

Radiata R resource

On this resource, Metriguard only achieved an R^2 of 0.70 for static bending MOE prediction, which is 0.1 below the other two resources. The compression vibration system, whatever the statistical method, doesn't provide a better correlation; however, combining vibration measurements with local information obtained from WoodEye® or Metriguard, significantly improves the prediction (up to 0.77). As shown in Table 7 there is only marginal improvement by combining all three methods.

Combining LHG with vibration doesn't significantly improve the MOE prediction when compared to Metriguard alone. Metriguard combined with LHG provided an R^2 between Metriguard and vibration plus Metriguard or WoodEye®. The use of PLS method of regression doesn't improve MOE prediction compared to using MLR using 2 or 3 parameters.

On green boards when using PLS method, vibration alone indicates a level of correlation equivalent to the Metriguard average MOE profile on the board. If an optical or equivalent system can be used on green boards with the same quality of information as provided on dry boards, then there is a large improvement when combined with vibration using PLS on all parameters (approximately +0.1).

Contrary to Radiata E, these results prove that the characteristic knotty nature of his resource heavily impacts the MOE, since when local parameters are combined with global measurements the prediction improvement is substantial.

Table 7. R^2 of combined NDT measurements to destructively determined properties in bending for Radiata R resource on green sawn boards. Note that the number listed beside PLS indicates the number of factors used in the models. Each colour corresponds to a different set of equipment or wood moisture content.

Methods	**Reg.**	**Parameters**	**R^2 x 100 MOE**	**Parameters**	**R^2 x 100 MOR**
Vibration GREEN	MLR	MOE_1	**59**	MOE_1	**26**
Vibration GREEN	PLS 4	all	**62**	all	**33**
Vibration GREEN + WoodEye	PLS3	all	**71**	all	**55**
Metriguard Board	MLR	Avg_Brd	**63**	Mini_Brd	**27**
Metriguard Test span	MLR	Avg_Span	**70**	Mini_Span	**47**
Vibration	MLR	MOE_1 + Mspower	**67**	MOE_1 + MOE_1/density + Alpha_2	**31**
Vibration	PLS 4	all	**68**	all	**38**
Vibration + Metriguard	MLR	MOE_1 + Mini_Span	**77**	Mini_Span + MSpower2	**48**
Vibration + Metriguard	PLS 4	all	**77**	all	**49**
Vibration + WoodEye	MLR	MOE_1 + KAR_Ext	**75**	MOE_1 + KAR_Ext	**49**
Vibration + WoodEye	PLS 4	all	**76**	all	**59**
Vibration + WoodEye + Metriguard	MLR	MOE_1 + KAR_Ext + Mini_Span	**78**	MOE_1 + KAR_Ext + MSPower2	**57**
Vibration + WoodEye + Metriguard	PLS 4	all	**79**	all	**60**
Vibration + LHG (without Strength prediction)	MLR	MOE_1 + Weighted_KAR	**70**	MOE_1 + Weighted_KAR + MSpower2+ LHG I-ratio	**43**
LHG strength prediction	LR	Indicative property	**67**	Indicative property	**53**
Vibration + LHG (without Strength prediction)	PLS 4	all	**71**	all	**48**
Metriguard + LHG	MLR	Mini_Span + Avg_brd	**73**	Mini_Span + LHG I Ratio	**51**
Metriguard + LHG	PLS	not enough variables	**-**	not enough variables	**-**

The level of prediction for strength is rather low for most methods. The trend is the same as for MOE, in that when local information and global information are combined the prediction is significantly improved. Interestingly the PLS regression using data from vibration and WoodEye® systems provides one of the highest prediction of strength (R^2=0.59). The R^2 for LHG strength prediction is 0.53 which is the parameter currently used by the processor with this equipment. With additional optical equipment this may be improved significantly.

Caribbean resource

Similarly to Radiata E resource, the coefficient of determination for predicting the static bending MOE from the best combinations of methods or parameters on dry boards, ranges from 0.79 to 0.87 (Table 8). Using average MOE from Metriguard profiles from the static bending span test significantly improves the correlation compared to using the average of the board.

Vibration system alone provides a level of prediction equivalent to Metriguard from the average MOE on the board. These two systems combine together doesn't improve the static bending MOE. The average MOE from Metriguard profiles on static bending span remains the only reliable predictor since the MLR stepwise process selects only this parameter to perform the prediction.

Adding WoodEye® and/or Metriguard information to vibration measurement only improves the level of prediction by a maximum of 0.05. This observation indicates that the local information provided by WoodEye® or Metriguard improves the static bending MOE prediction. The best prediction (R^2=0.87) was achieved by using the WoodEye® (KAR outer third zone) and Metriguard (average MOE on test span) combined, without any measurable improvement by adding vibration to the combination. The best predictions are close to the maximum feasible level of correlation for MOE. Indeed the coefficient of determination reaches an asymptote thus it is very hard to improve the correlation as the measurement error is the main limiting factor.

For the green boards, the static bending MOE prediction level is below that observed for dry boards by an average of 0.08. If an optical or equivalent system can be used on green boards with the same quality of information as provided on dry boards, then there is a small improvement when combined with vibration using PLS on all parameters (+0.02).

Table 8. R^2 of combined NDT measurements to destructively determined properties in bending for Caribbean resource on green sawn boards. Note: MOE R^2 sorted largest to smallest, lower limit given by the green density. Note that the number listed beside PLS indicates the number of factors used in the models. Each colour corresponds to a different set of equipment or wood moisture content.

Methods	Reg.	Parameters	R^2 x 100 MOE	Parameters	R^2 x 100 MOR
Vibration GREEN	MLR	MOE_1	**73**	MOE_1	**31**
Vibration GREEN	PLS 3	all	**75**	all	**34**
Vibration GREEN + WoodEye	PLS 2	all	**77**	all (PLS 3)	**55**
Metriguard Board	MLR	Avg_Brd	**79**	Mini_Brd	**30**
Metriguard Test Span	MLR	Avg_Span	**84**	Mini_Span	**36**
Vibration	MLR	MOE_1 + FacQ1	**78**	MOE_1	**32**
Vibration	PLS 4	all	**79**	all	**33**
Vibration + Metriguard	MLR	Avg_Span	**84**	Mini_Span	**36**
Vibration + Metriguard	PLS 3	all	**82**	all	**36**
Vibration + WoodEye	MLR	MOE_1 + Fk_KAR-Ext	**79**	MOE_2 + KAR-Ext	**46**
Vibration + WoodEye	PLS 4	all	**84**	All (PLS 3)	**55**
Vibration + WoodEye + Metriguard	MLR	Avg_Span + KAR-Ext	**87**	Mini_Span+ Kar-Ext	**49**
Vibration + WoodEye + Metriguard	PLS 3	all	**83**	all	**56**

Despite the Caribbean resource having a similar range in the results for MOE prediction as for the Radiata E resource (R^2=0.79 to 0.87 and 0.79 to 0.86 respectively), the level of accuracy was not as strong for strength prediction ($R^{2=}$0.30 to 0.55 and 0.52 to 0.64). The poor level of strength prediction for Caribbean pine using current systems may be attributable to a feature of the knots in the resource tested, as discussed in the earlier section on individual NDT predictors.

The same level of strength prediction achieved on dry boards was achieved on green boards (R^2=0.55). This calculation was determined by the combined vibration (green boards) and WoodEye® (dry boards) data, and assumes that the optical data can be captured at the green stage with equivalent accuracy to that captured on dry boards. The use of PLS regression provides the best predictions.

Prediction of static bending MOE and MOR from logs

This section uses the average properties of all the boards from the log as the basis for the correlations. It does not use log property as a predictor of individual board properties. A summary of results is provided in Table 9.

Radiata E

The MOE velocity was calculated using Equation 1, combination of log density data and velocity (TOF) measurements in the longitudinal axes. When correlated with the average static MOE levels of prediction of R^2 of 0.64 for MOE and 0.33 for MOR were provided. Slightly better correlations were observed when using velocity alone (TOF and distance between sensors) to predict MOE and MOR. These are lower than the prediction provided by vibration analyses (R^2=0.70 and 0.45 respectively).

The MLR combining compression and flexion tests increases the coefficient of determination from 0.70 to 0.76 for MOE and 0.45 to 0.61 for MOR, significant improvements, especially in the case of MOR prediction. However, this combination of measurements would require additional systems to enable measurements in the two planes. When developing the stepwise MLR to combine compression and flexion parameters, the condition index was close to the threshold, indicating a potential collinearity problem. The quality of this prediction needs to be considered with care until a larger population of logs can be tested for verification.

Radiata R

The velocity MOE measurements provided an R^2 of 0.50 for static MOE and 0.34 for MOR. The MOE prediction from logs for this resource is quite significantly lower compared to the Radiata E prediction (-0.14). The MOR predictions were similar for both resources. Noticeably better correlations were observed when using velocity alone (TOF and distance between sensors) to predict MOE and MOR.

Vibration analysis provides better predictions compared to velocity measurements, with the best result using MLR with specific compression MOE (R^2=0.75). When predicting strength using the same parameter from the log tests, the R^2 achieved was 0.43. These results are interesting due to the fact that only the first frequency measurement was required and therefore the density data wasn't necessary to improve the result. This has positive implications for in-mill engineering and logistics in that weighing and log measuring systems may not be necessary for MOE prediction, but a larger log population should be tested to verify these results.

Caribbean

The velocity MOE measurements provided an R^2 of 0.56 for static MOE and 0.27 for MOR. The MOE prediction from logs for this resource is between the two radiata resources. The MOR prediction was significantly lower than the other material (-0.06). Conversely to the two other resources, markedly poorer correlations were observed when using velocity alone (TOF and distance between sensors) to predict MOE and MOR.

As with radiata pine, vibration analyses provided better predictions compared to velocity measurements.

Table 9. R^2 of combined NDT measurements to log **average,** destructively determined properties in bending for all resources. Note that the number listed beside PLS indicates the number of factors used in the models. Each colour corresponds to a different set of measurement.

Resource Biased + Random	**Methods**	**Reg. type**	**Parameters**	**R^2 x 100 MOE**	**Parameters**	**R^2 x 100 MOR**
	Velocity (TOF)	LR	Velocity	**65**	Velocity	**36**
Radiata E (n= 34)	MOE Velocity (TOF)	LR	Velocity_MOE	**64**	Velocity_MOE	**33**
	Specific MOE	LR	Comp-MOE_1 /density	**65**	Comp-MOE_1 /density	**43**
	Comp	LR	Comp_MOE_1	**70**	comp-SBandwidth	**45**
	Comp + Flex	MLR	Comp_MOE_1, Ratio (Comp/Flex)	**76**	comp-MOE_1, Flex-MSPower_0	**61**
	Velocity (TOF)	LR	Velocity	**65**	Velocity	**46**
Radiata R (n= 27)	MOE Velocity (TOF)	LR	Velocity_MOE	**50**	Velocity_MOE	**34**
	Specific MOE	LR	Comp-MOE_1 /density	**75**	Comp-MOE_1 /density	**43**
	Comp	MLR	Comp-MOE_1 /density	**75**	Comp-MOE_1 /density	**43**
	Velocity (TOF)	LR	Velocity	**48**	Velocity	**22**
Caribbean (n= 106)	MOE Velocity (TOF)	LR	Velocity_MOE	**56**	Velocity_MOE	**27**
	Specific MOE	LR	Comp-MOE_1 /density	**59**	Comp-MOE_1 /density	**27**
	Comp	MLR	Comp-MOE_4, Comp-Alpha_2	**75**	Comp-MOE_3, Comp-Alpha_2	**37**
	Comp	PLS 3	all	**78**	all	**44**

PLS analysis was able to be used on the Caribbean resource due to the higher number of logs in the study. As with green boards, the improvement for MOE prediction using the PLS method for Caribbean logs is slight, but for MOR it is a significant improvement.

The reader should note that when using the data for all the boards per log, instead of the average of all boards, for the predicted static bending MOE and MOR, the coefficient of determination decreases by approximately half.

Practical grading into MGP grades

Using best vibration prediction for logs

For each resource, the best prediction equation from the resonance method was used to simulate the MGP grade recoveries.

The removal of logs was based on a predicted threshold for MOE and MOR. The strategy was to target loss of no more than 5% of the potential MGP10 recovery through removal of logs.

Plots for the most promising logs in each resource are compared in Figure 32 below which displays the percentage loss for each MGP grade and non-structural material. Because the MGP10 losses are standardised between the three resources, there is little difference in the MGP10 recovery.

For Radiata E, 13.5% of the logs were removed using the 5% threshold for MGP10. Consequently, 32.1% of the non-structural material, 3.4% MGP10, and 0% for MGP12, were removed.

For Radiata R, 4.6% of the logs were removed using the 5% threshold for MGP10. Consequently, 8.7% of the non-structural material, 3.3% MGP10, and 0% for MGP12 and MGP15, were removed.

For Caribbean, 5.9% of the logs were removed using the 5% threshold for MGP10. Consequently, 13.3% of the non-structural material, 4.7% MGP10, 0% for MGP12, and 1.2% MGP15 were removed.

The MGP10 recovery of all three resources is similar as it was a key criterion for setting the threshold for rejection of logs.

For each plot, the non-structural (NS) had the lowest recovery in the remaining pieces. The implications derived from these results will vary between processors and resource characteristics.

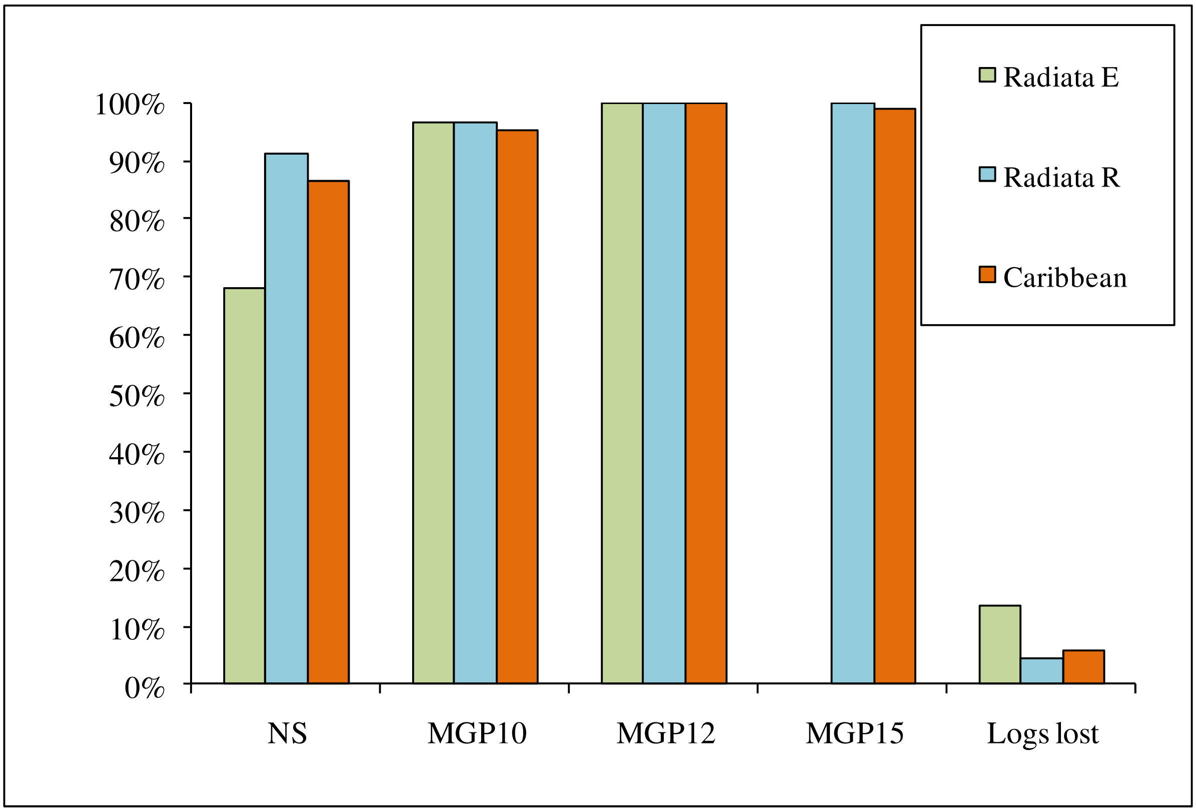

Figure 32. Histogram of recovery based on random data by MGP grade when no more than 5% of the potential MGP10 is lost through removal of poor logs.

The differences are in the percentage of logs removed and the recovery into NS in the remnant material. Radiata E had the best results with the largest reduction in NS after drying and planing. Radiata R had the worst results with the lowest reduction in NS. This may be linked to the good growing conditions for Radiata R, where bigger logs contain a large core of large knots, juvenile wood but a large proportion of the periphery contains good quality wood. The size of the log facilitates a high recovery of this part. With such good growth conditions the “mature” wood is proportionally higher than in the case of tree growing on poorer sites where the trees display a slower speed of growth when ageing, leading to smaller log where the good part is more difficult to recover. The size of the log is the key: the bigger the log, the more variety of wood there is in the log, so rejecting a whole log inevitably also rejects some good timber.

Pre-sorting the cants (including the juvenile core) rather than whole logs, could be a better option for the resource, as the wing boards are likely to contain suitable material for structural grade products.

Using best prediction for dry boards NDT technologies

We have restricted the recovery simulations on dry boards to two different combinations of equipment:

- compression vibration plus WoodEye® (WE Comp Vib);
- compression vibration plus WoodEye® plus Metriguard (WE Comp Vib Metriguard).

PLS was used with the above combinations of grading technologies to develop predictions for the biased test MOR from the grading parameters of each board tested. A separate PLS study developed predictions of the biased test MOE for the same combinations of grading technology. Each of these predictions was then used to assign a grade to the whole board based on a threshold. The thresholds were evaluated by trying a number of different thresholds with the random position test data, until the pieces that fell into each grade gave characteristic values that exceeded the design characteristic value for all grades simultaneously. These thresholds could then be used to sort either the biased position test data or the random position test data into stress grades.

Additionally, a composite grading was used in which each of the combinations used both the MOE prediction and the MOR prediction, with the requirement that the predictions for any board had to exceed both the MOE threshold and the MOR threshold for the grade to be admitted to the stress grade. The thresholds were set using the random position test data as indicated above.

Figure 33 and Figure 34 display the correlations between the best grade parameter above and MOE (Figure 32) a MOR (Figure 33) for the three resources when applied on biased test data. The main observation is the similarity between the correlations on these three different resources. This is expressed by a low difference on R^2 associated with a tiny difference on both slope and constant of the associated linear equation.

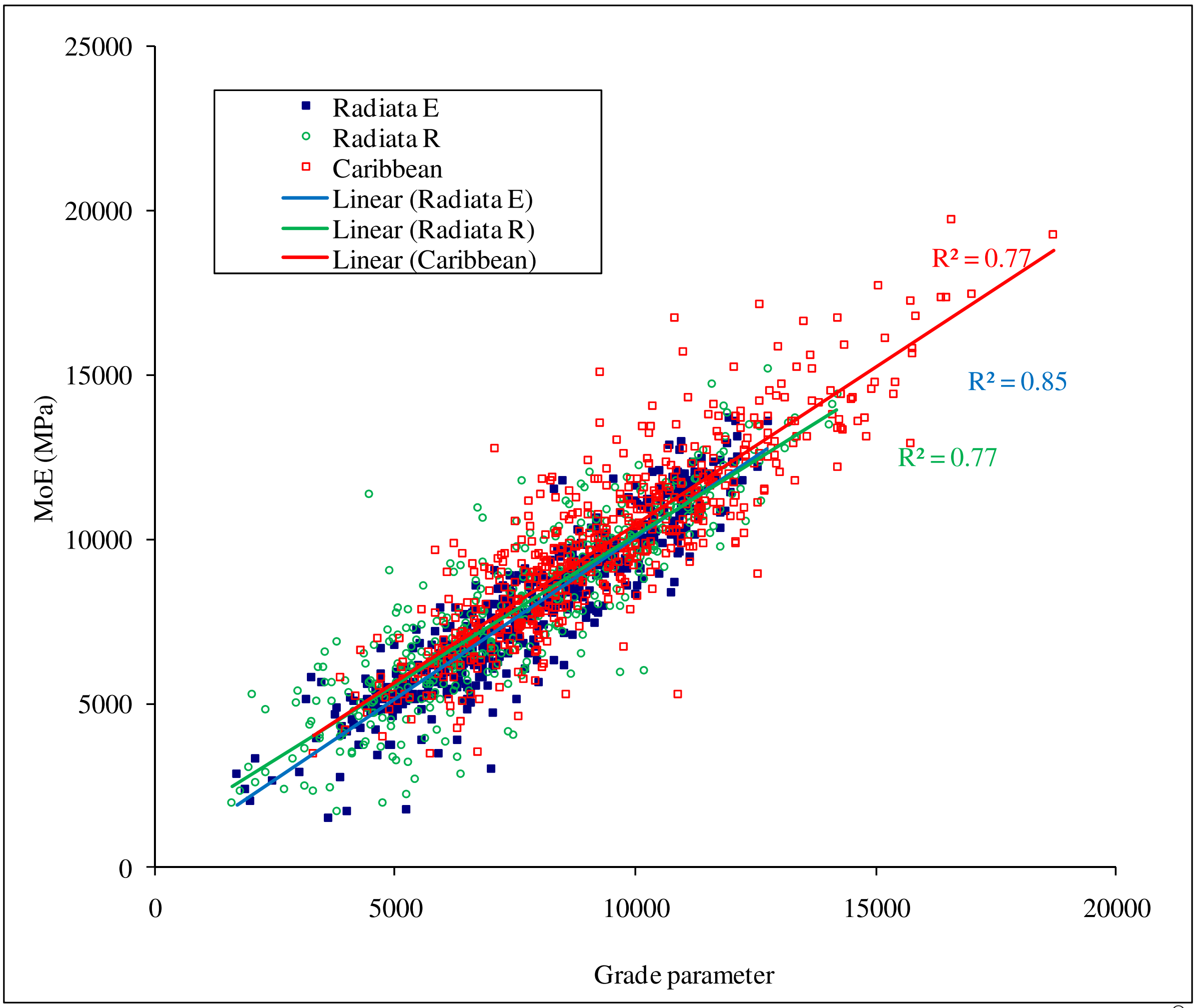

Figure 33. Correlation between MOE and grade parameter from the best combinations of WoodEye®, compression vibration and Metriguard predictors. Biased MOE and MOR threshold combination was applied.

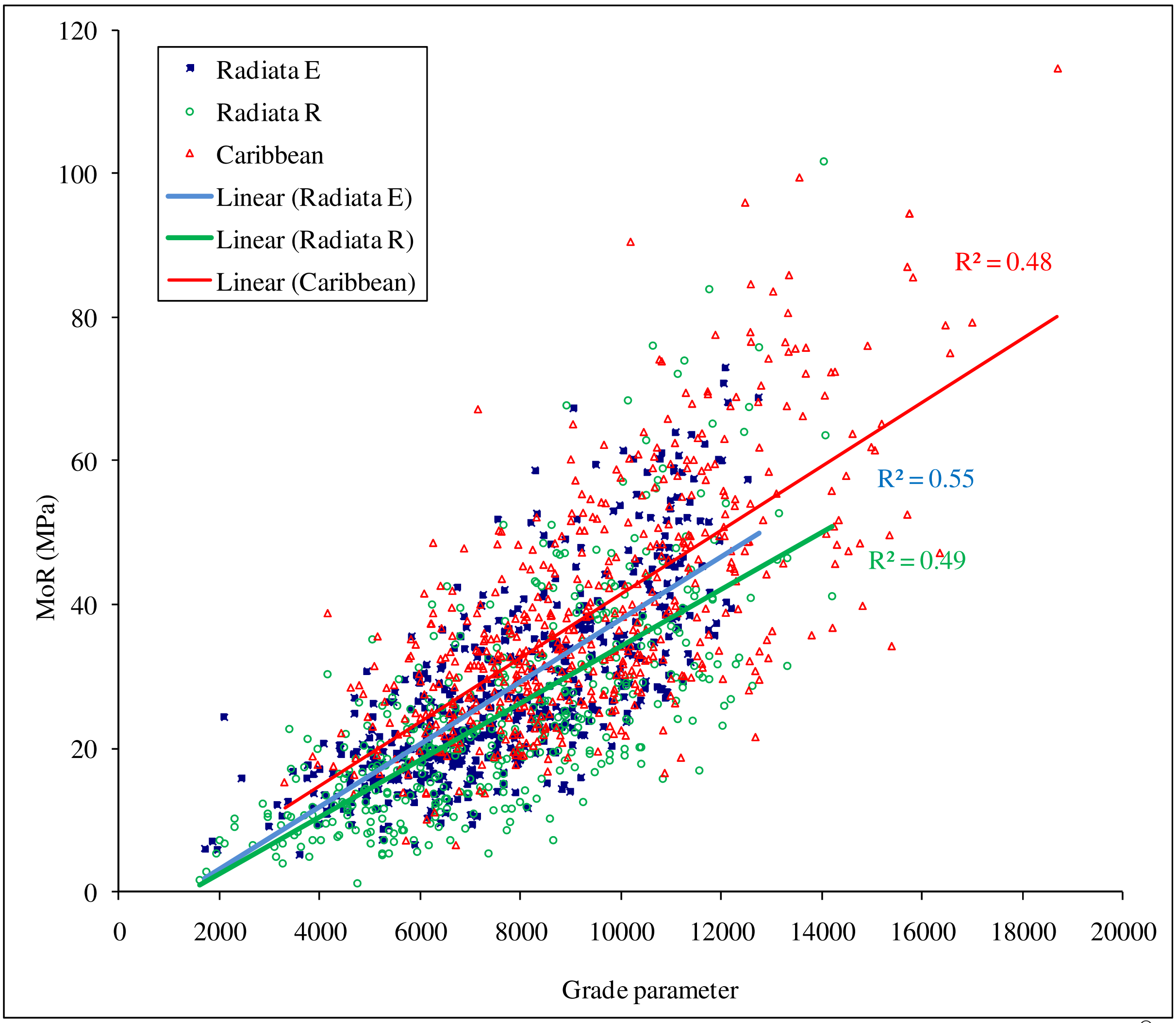

Figure 34. Correlation between MOR and grade parameter from the best combinations of WoodEye®, compression vibration and Metriguard predictors. Biased MOE and MOR threshold combination was applied.

Figure 35, Figure 36, and Figure 37 display the coefficient of determination and the coefficient of variation for each resource. For a base-line comparison, two combinations and Metriguard grading parameters applied to the biased position test data are presented.

For the Radiata E resource, Figure 35, shows that the R^2 for all grading methods and MOE are close to the range of 80% to 90% which is expected to be the maximum attainable within the bounds of experimental error. For this resource, most MOE based grading methods were demonstrated to perform effectively. There was little difference between the correlations of any of the combinations and the Metriguard grading.

However, Figure 35 also shows that the R^2 for all of the combinations and MOR was better than that for the Metriguard grading. As this resource is primarily limited by its MOE properties, there may be a large number of MOE measurement devices (including the Metriguard) that could return grading as effective as the best of the combination systems. It also shows that there is little difference in the COV of bending strength of each of the commercial grades and hence all of the plotted grading methods return comparable reliability of graded product.

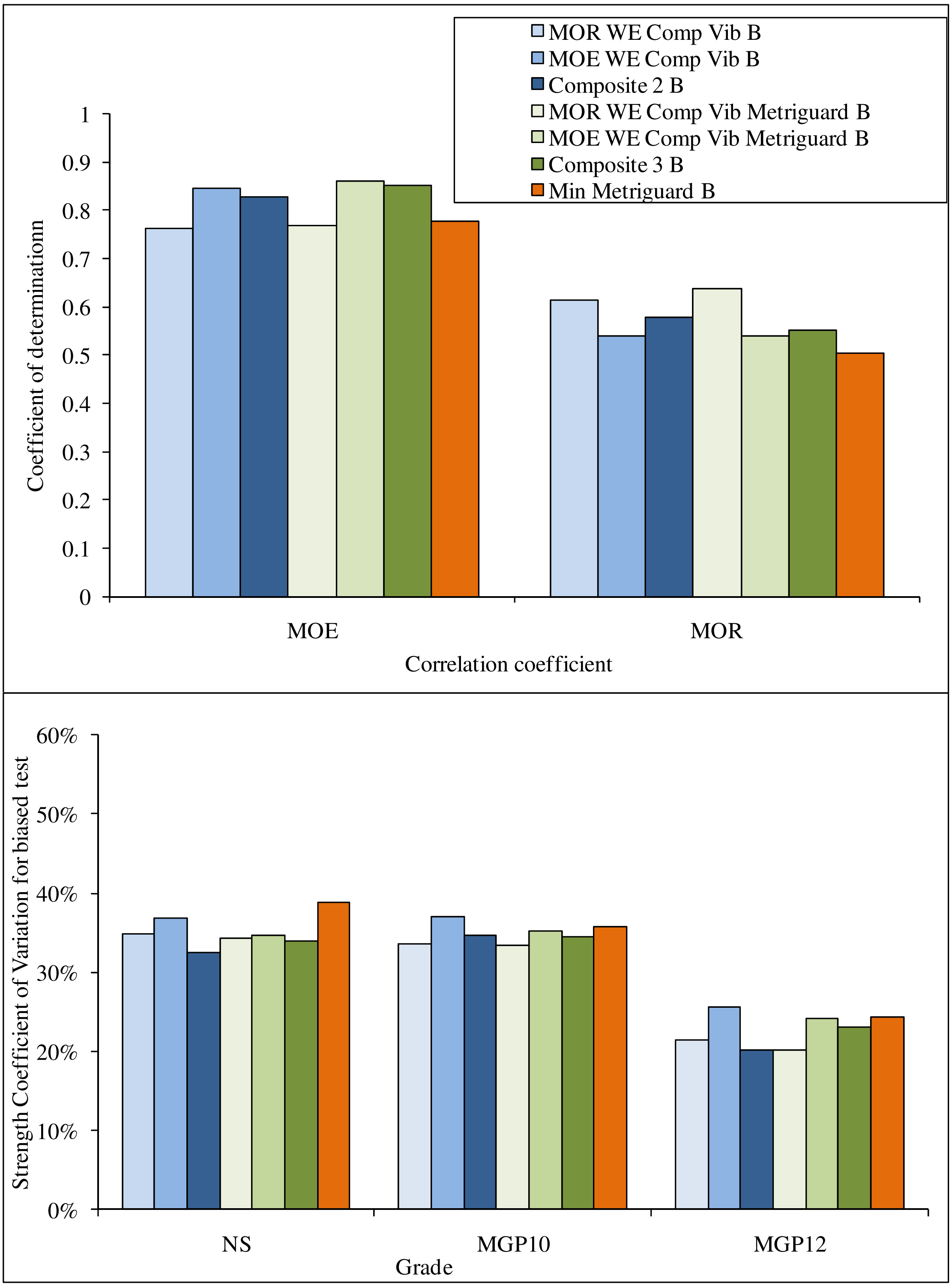

Figure 35. Radiata E resource, coefficient of determination and coefficient of variation for strength when grading with the best combinations of WoodEye®, compression vibration and Metriguard. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

For Radiata R resource, Figure 36 below shows there is a minor improvement in R^2 with MOE using the MOE predictions or the Composite for both combinations. There is a similar improvement in R^2 with MOR using the MOR predictions or the Composite for both combinations. There was little variation in the COV of MOR for graded material between the grading methods with comparable reliability of graded product for all of these grading methods.

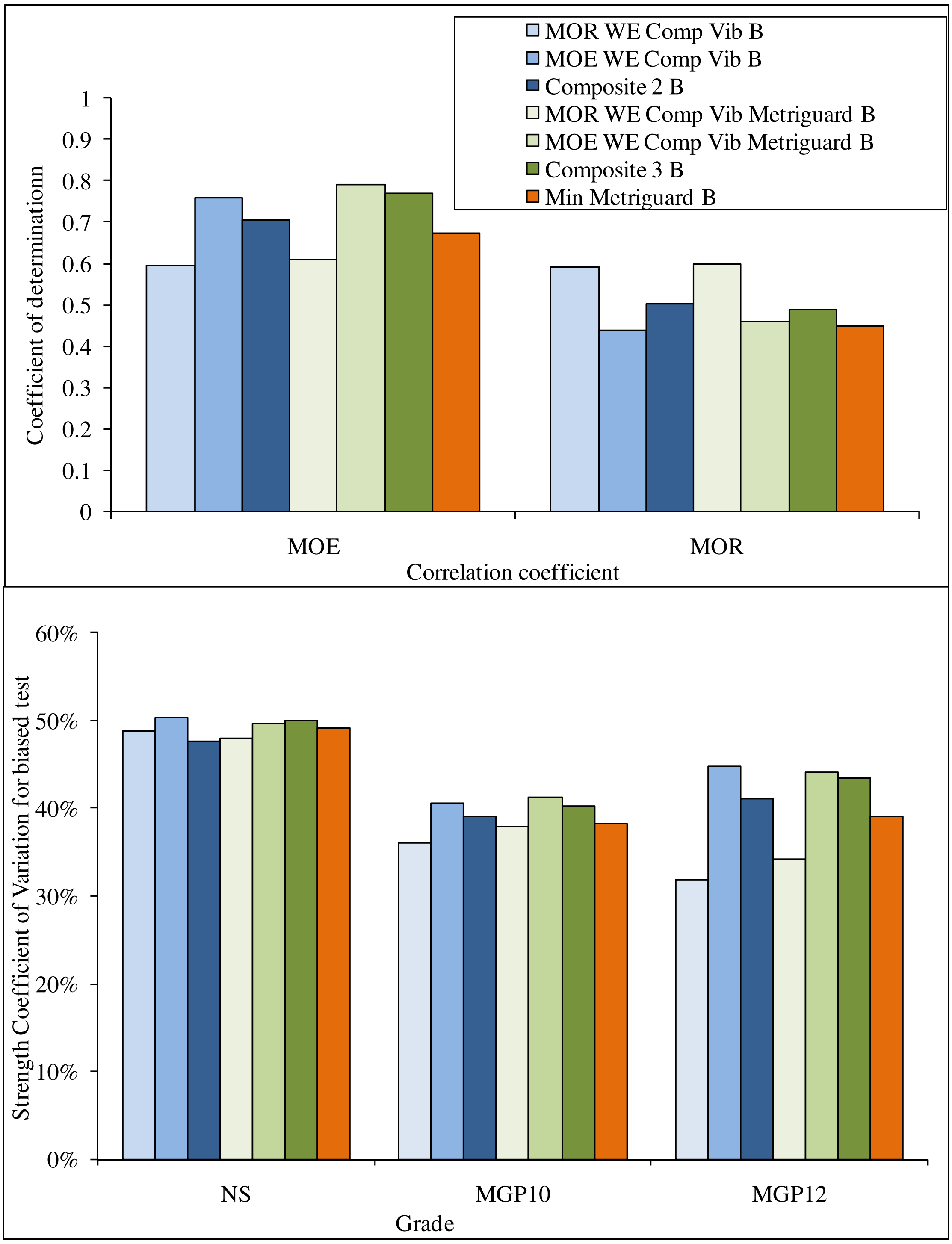

Figure 36. Radiata R resource, coefficient of determination and coefficient of variation for strength when grading with the best combinations of WoodEye®, compression vibration and Metriguard. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

For Caribbean resource the use of a combination of grading equipment or predictors significantly increased the R^2 of both MOE and MOR. The R^2 with MOE was increased most using the MOE prediction and the R^2 with MOR was increased most using the MOR prediction. These and the composite grading returned higher R^2 than the base-line Metriguard grading for both MOE and MOR as shown in Figure 37.

The COV of the MOR for each of the MGP12 and MGP15 grades, also shown in Figure 37, showed a significant reduction below its Metriguard base-line value with the application of new technology. This resource offered the most potential for improvement of grading using a combination of grading technologies.

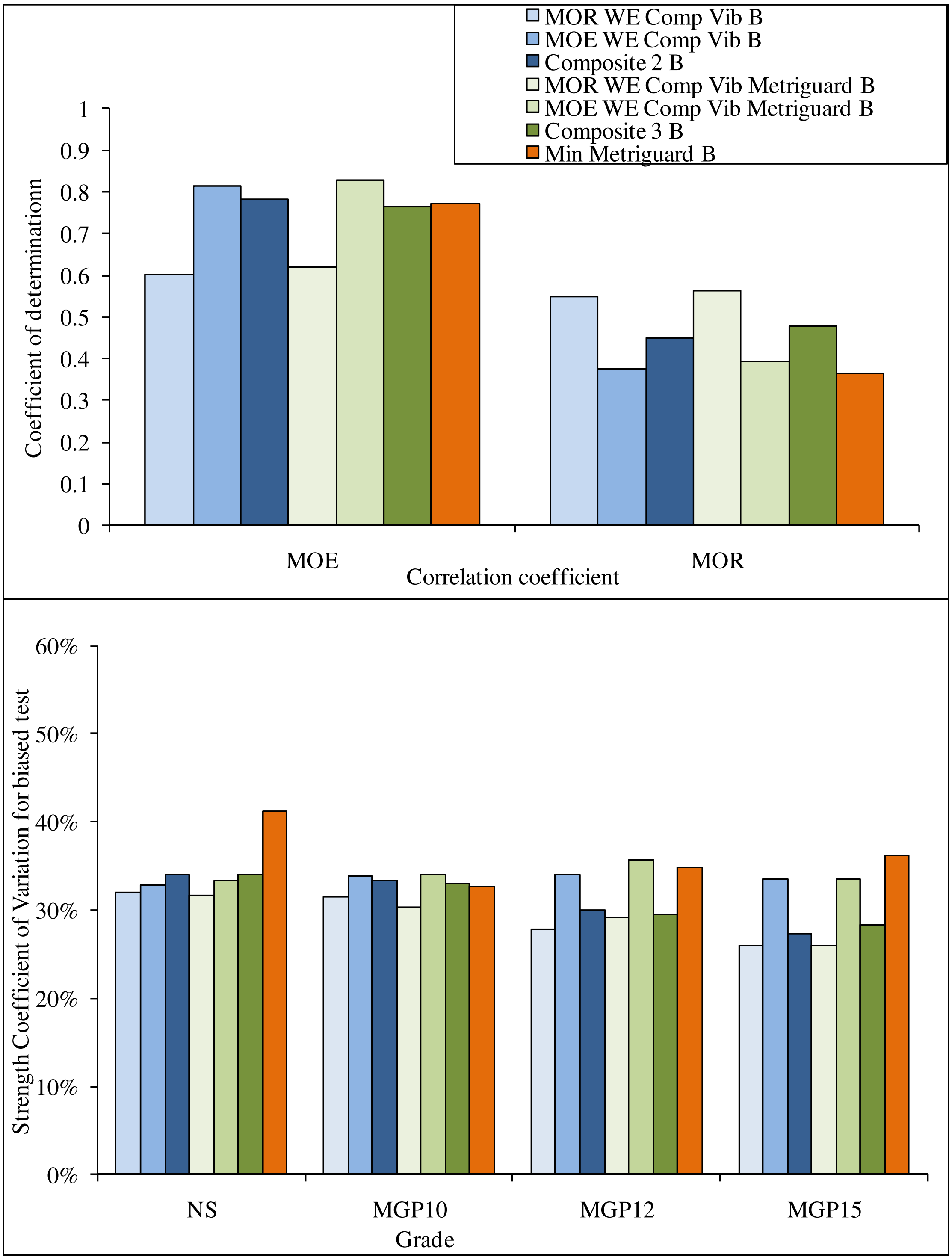

Figure 37. Caribbean resource, coefficient of determination and coefficient of variation for strength when grading with the best combinations of WoodEye®, compression vibration and Metriguard. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

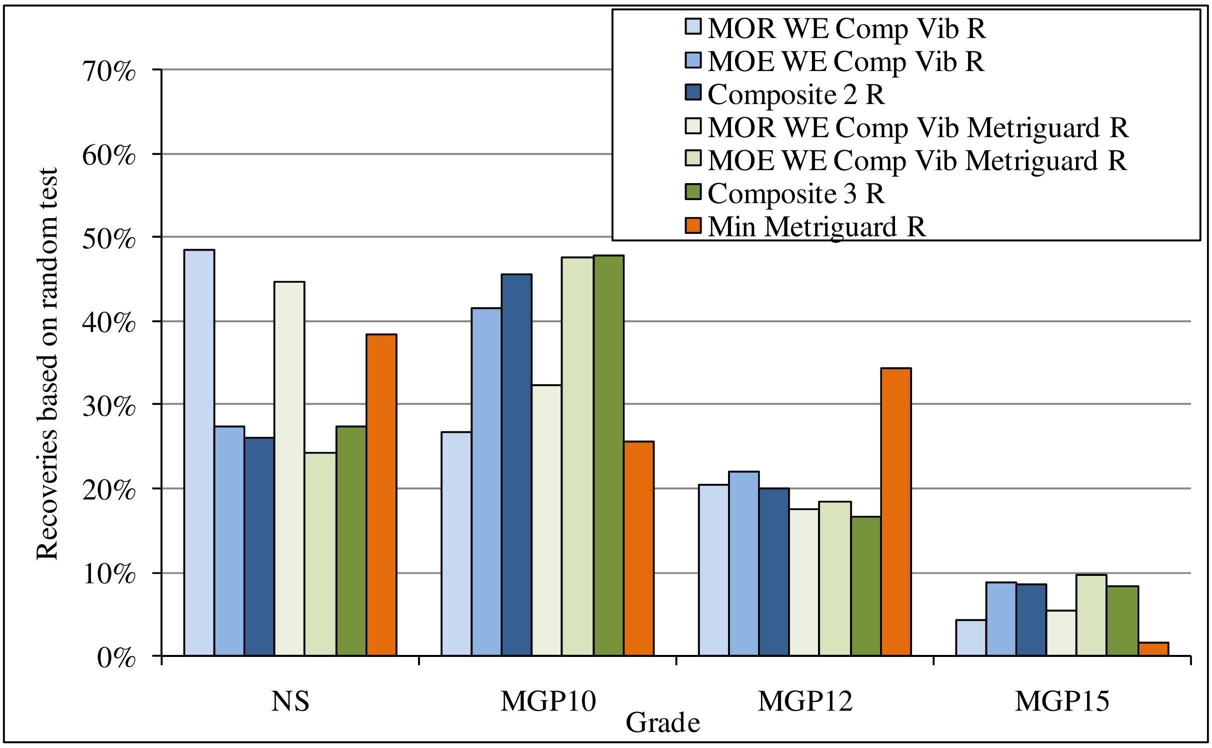

Figure 40 display the recoveries from the application of the same grade thresholds illustrated above to the full suite of boards represented by the random data.

The important thing to focus on in these graphs is the recovery to non-structural (NS). We want to minimise this as this is timber that loses money for the mill. The tendencies observed on the quality regression indicators when applying the best predictions on biased test data are confirmed on the recoveries while applying on random test data, namely:

- Radiata E resource: there is no improvement observed when using the best combinations of WoodEye®, compression vibration and Metriguard compared to the use of Metriguard alone.
- Radiata R resource: the recovery increase observed on MGP10 grade is somewhat offset by an increase of non structural products and a recovery decrease in MGP 12 grade.
- Caribbean resource: a significant recovery increase on MGP10 and MGP15 grades associated with an important decrease of non structural products. Despite an absolute decrease of 15% on MGP12 recovery, the 10% absolute decrease of non structural products associated with a 20% absolute increase on MGP10 recovery represents certainly a key advantage for this resource.

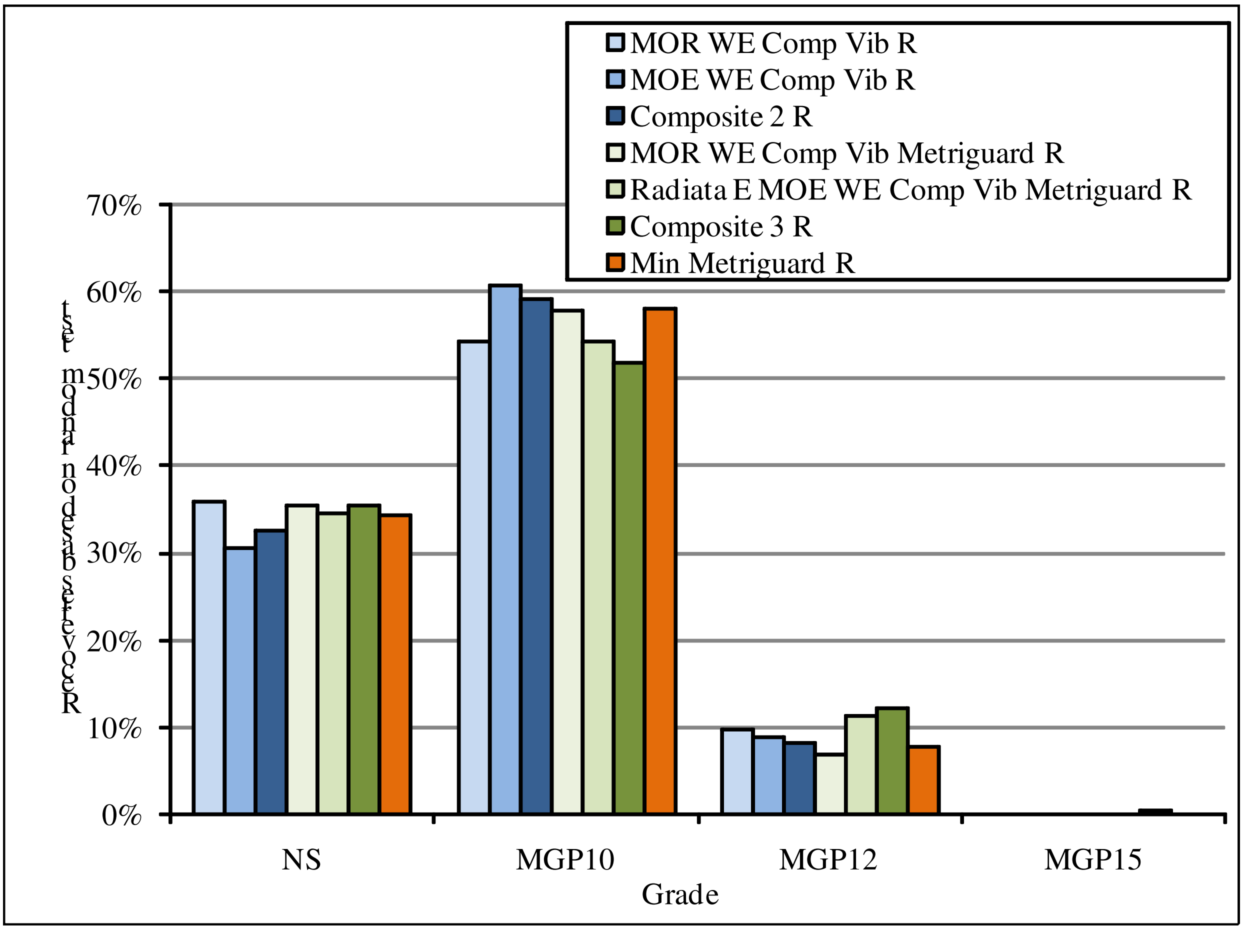

Figure 38. Radiata E recoveries from calibrations developed with biased test data for each resource and for different grading parameters when using static bending random data. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

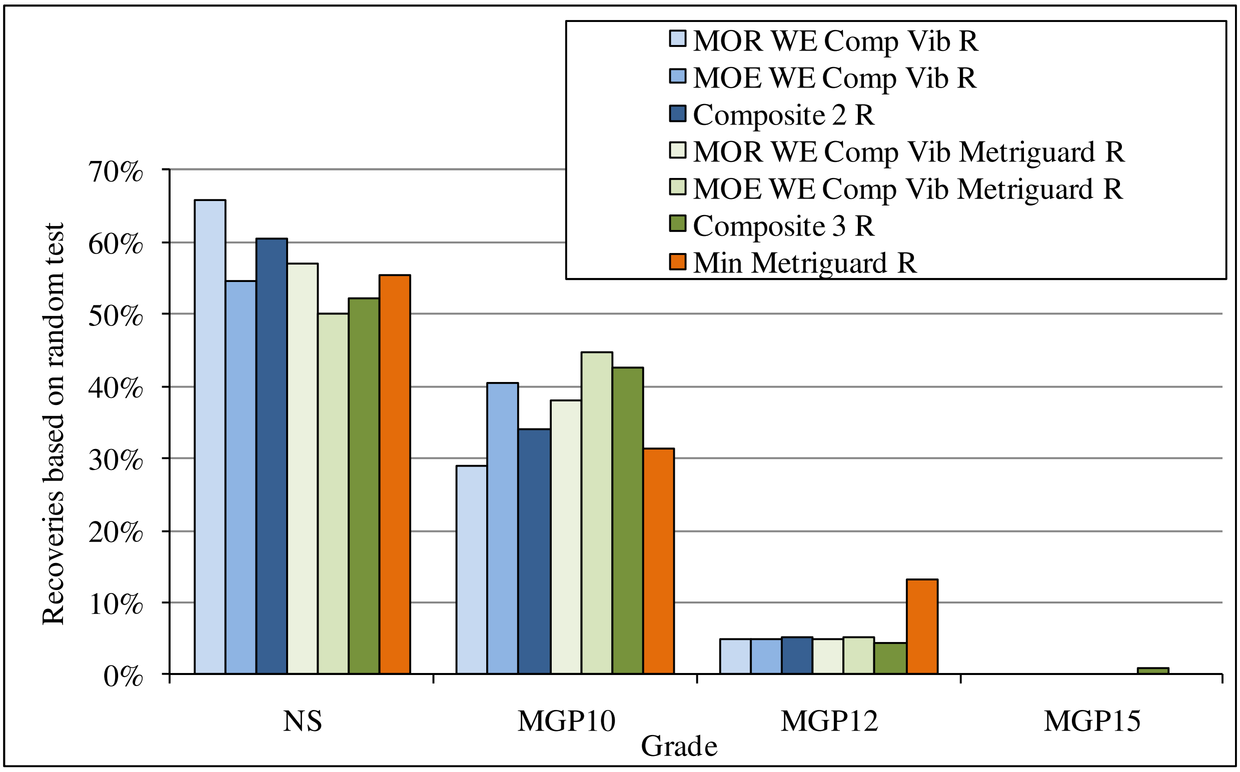

Figure 39. Radiata R recoveries from calibrations developed with biased test data for each resource and for different grading parameters when using static bending random data. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

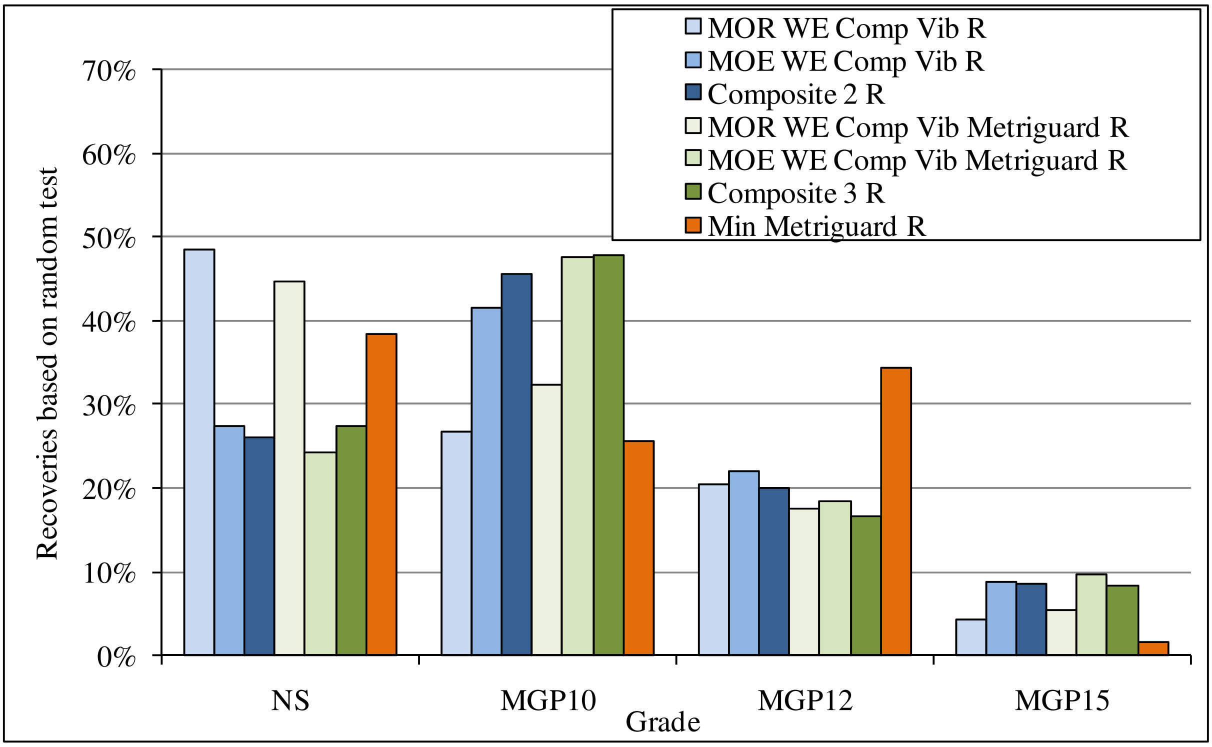

Figure 40. Caribbean recoveries from calibrations developed with biased test data for each resource and for different grading parameters when using static bending random data. Biased MOE, MOR or combination (composite) of both thresholds was applied. Note: WE Comp Vib = 2 and WE Comp Vib Metriguard = 3.

Discussion and conclusions

The capability of a grading system to predict accurately and reliably the reference parameters of a product, namely the board's actual stiffness and strength, depends mainly on how well the prediction agrees with:

- the reference parameters (indicated by R^2, the coefficient of determination);
- the measurement error of the predictor parameter(s) (indicated by COV, the coefficient of variation); and
- the capability of the system to accommodate resource variability (indicated by its prediction robustness and the level of recovery compared to the actual grading based on destructive tests).

If the regression analysis is based on measurements made in the same conditions and the same apparatus that is used in grading machines, the effect of the measurement error and COV is already included in the R^2 value directly. This was the case for the in-line equipment tested. For the resonance methods made in laboratory conditions with the *Bing*® equipment, the effect of measurement error should be considered separately, when evaluating its effectiveness. However resonance methods have proven to be very robust and accurate due to their metrological[1] simplicity and fundamental principles. There is a large quantity of publications based on theoretical mechanics work and experimental results which demonstrate the capability to predict stiffness and strength parameters of wood and other materials. In this study the comparison of results obtained between in-line equipment (Thumper and Metriguard) and a laboratory system (*Bing*®) demonstrated the high degree of closeness between in-line and laboratory measurements on one hand, and the quality of the prediction of the reference static bending MOE and MOR on the other hand. Theoretical, flexion should provide the best results due to the parallels to static bending, that is the configuration implied flexure stress. However, due to metrological constraints, low frequencies and signal duration, plus boundary conditions, compression and flexion vibration provide the same level of prediction.

The sample size for each resource (approximately five hundred boards per resource) was large enough to make the results reliable. The measurements of the various parameters of this study were performed at different times and sometimes under dissimilar conditions. Despite the effort to keep these conditions as homogenous as possible some variations may persist. As a consequence, the results presented here should not be used as definitive when the difference between the R^2 is typically less than 0.02.

As was found in the European Combigrade projects' (Hanhijärvi *et al.* 2008 and 2005) results for dry boards, this study demonstrates that the best single parameter predictors of MOE and MOR are the stiffness related measurements derived by either direct mechanical test (Metriguard) or vibration method. These two approaches offer a similar level of prediction which the R^2 ranges from 0.66 to 0.85 for MOE and 0.35 to 0.53 for MOR, depending on the resource. Importantly because the Metriguard provides both average and local board measurements it shows better performance on strength limited or defect affected resources. On clearly stiffness-limited resource, vibration seems to provide a slightly better prediction than Metriguard. On this type of resource combining stiffness parameters with local measurements, knot or local stiffness, does not improve the prediction significantly.

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[1] relating to metrology. Metrology is the scientific study of measurement.

Reference static bending parameters prediction for strength limited, or defect affected resources, can be notably improved by combining stiffness parameters with local information and an R^2 improvement magnitude up to 0.1 for MOE and 0.2 for MOR can be expected.

The choice of the statistical approach to achieve these improvements is determinant. The application of classical MLR on several predictors proved to be effective, in particular for MOR predictions. However the usage of a modern statistics approach (chemometrics tools) such as PLS proves to be more efficient for improving the level of prediction. This is due to the problem of multi-collinearity in MLR which impaired the efficient exploitation of the information contained in all the predictors available for a given combination of grading systems. As the development of robust calibration is based on training samples (samples specifically selected to develop the prediction equation) and application of complex mathematics, the robustness and accuracy of the prediction requires a sound knowledge and a disciplined approach.

Obviously statistical analysis alone is only a criterion, even if decisive, when considering the fitness of a grading system to a certain application. The price of the system, its maintenance cost, its production line adaptation, versatility, reliability, simplicity, etc. are all important factors.

Moreover, the reference method accuracy is not perfect. The impact of the experimental error on the reference's actual parameters leads to a maximum attainable level of prediction within the bounds of error. When the quality of the prediction comes closer to this threshold, any improvement requires much more effort and consequently investment. The balance between grade selection accuracy and investment depend on each processor's strategy.

The consequence of the application of combined grading systems on grade recoveries has to be analysed carefully since it is clearly resource dependent. The trend observed shows that there is no advantage to using combined grading systems for a stiffness-limited resource. The advantage for a strength limited resource has to be weighed with other processing impacts. The Caribbean resource offers the most promising improvement potential using a combination of new technologies.

The use of resonance method for MOE and MOR prediction on green boards provides slightly less successful results when compared to dry boards. Nevertheless, the R^2 decrease is only 0.1 to 0.15 depending on the resource. This result is a real opportunity for processors to try to apply an early detection of the weakest boards in order to relieve the cost of non-value added further processing. Moreover the potential use of optical scanners or equivalent equipment allowing the detection of grain deviation and knot characteristics on green boards promises to increase quite significantly the MOR prediction. It represents an avenue to improve the efficiency of the mill.

Log segregation through vibration method (compression) is also resource dependent. From the results of this study, it is clear that the stiffness-limited resource should have the highest gain in recovery, through removal of the lowest stiffness logs. Therefore, significant cost savings could be achieved by processing these into non-structural products, with minimal impact on final graded product recovery. The value gain from log stiffness sorting is less for Caribbean pine and requires further assessment. For strength limited resources, the consequences on recovery are insignificant.

Recommendations

All the results obtained from this study should be validated with full in-mill simulations. This could be achieved using calibrations developed during this project and applied to independent samples in sufficient numbers of replicates covering the range of variability of material handled by each processor.

There is room for improvement on each system used, for example the use of an optical system could be tuned for the resource's grade limiting features. The WoodEye® system used in this study was tuned for appearance grading of hoop pine and it was outside the scope of the project to re-tune the equipment for structural grading purposes. Moreover, the raw data variables extracted from WoodEye® weren't refined to provide the most appropriate characterization of the material tested. Further discussion with qualified optical scanning system engineers should provide optimized extraction for structural grading purposes. This will involve the development of clear definitions of the optical characteristics that impact MOE and MOR for each resource.

Vibration method can be improved through:

- installation of devices at strategic locations in the mill (i.e. cants);
- refining data extracted, e.g. using current dataset, further analysis to improve algorithm extraction;
- using flexure with different boundary conditions, e.g. testing local span within boards.

At green board level, an optical scanning system coupled with a vibration system, has proved to be nearly as efficient as the same combination on dry boards. Depending on the processor's strategy, further investigation may provide an avenue for efficient green mill grading technologies.

A larger sample of logs should be tested to verify the potential for effective log segregation.

An error analysis on the reference method for MOE/MOR measurement should be performed in order to assess the maximal level of prediction achievable.

Locating vibration devices at strategic locations in the mill may provide a cost-effective alternative to investment in higher cost capital items installed near to the end of the process line.

A further project could be designed to continue mining the existing dataset. For example, testing the consequence of grading at stages through the flow of the boards.

References

Baradit, E., Aedo R. and Correa J. (2006). *Knots detection in wood using microwaves*, Wood Science and Technology 40 (pp118-123).

Bendtsen B.A. (1978) Properties of wood from improved and intensively managed trees.

Bootle K.R., (2005). WOOD IN AUSTRALIA. TYPES, PROPERTIES AND USES. 2nd Ed. McGraw-Hill Book Company, Sydney, Australia.

Brancheriau, L. (2002). Expertise mécanique des sciages par analyses des vibrations dans le domaine acoustique, Université de la méditerranée - Aix Marseille II, Université de la méditerranée - Aix Marseille II, Marseille (p 278).

Brancheriau, L. (2007). WISIS - Wood In Situ Inspection- Instructions for use Version 1.0. CIRAD.

Brancheriau, L. and Bailleres, H. (2002). *Natural vibration analysis of clear wooden beams: a theoretical review*. Wood Science and Technology 36 (pp 346-365). Springer-Verlag.

Brancheriau, L. and Bailleres, H. (2003). *Use of Partial Least Squares Method with Acoustic Vibration Spectra as a New grading Technique for Structural Timber*. Holzforschung Vol. 57, No. 6 (pp 644-652).

Bucur, V. (2003). NONDESTRUCTIVE CHARACTERIZATION AND IMAGING OF WOOD. Springer-Verlag, Berlin, Germany.

Duff, G. (2005). Technology for delivering high quality graded softwood product- practical applications. Gottstein Fellowship report.

Grabianowski, M., B. Manley, and J.C.F. Walker. 2006. Acoustic measurements on standing trees, logs and green lumber. Wood Sci. Technol. 40(3):205-216.

Halabe, U.B., Bidigalu G.M., GangaRao H.V.S. and Ross R.J. (1995). *Nondestructive Evaluation of Green Wood Using Stress Wave and Transverse Vibration Techniques*. Vol. 55, No. 9.

Hanhijärvi, A. and Ranta-Maunus, A (2008). Development of strength grading of timber using combined measurement techniques. Report of the Combigrade project – phase 2. VTT Publications 686.

Hanhijärvi, A., Ranta-Maunus, A and Turk, G. (2005). Potential of strength grading of timber with combined measurement techniques. Report of the Combigrade project – phase 1. VTT Publications 568.

Harris J.M. (1991). PROPERTIES AND USES OF NEW ZEALAND RADIATA PINE. Volume one - wood properties, Forest Research Institute, Rotorua, New Zealand.

Hopewell, G. (Ed.) 2006. CONSTRUCTION TIMBERS IN QUEENSLAND: PROPERTIES AND SPECIFICATIONS FOR SATISFACTORY PERFORMANCE OF CONSTRUCTION

TIMBERS IN QUEENSLAND, CLASS 1 AND CLASS 10 BUILDINGS (BOOKS 1 AND 2). Department of Primary Industries and Fisheries, Brisbane.

Ilic, J., Northway, R. and Pongracic, S. (2003). Juvenile Wood Characteristics, Effects and Identification. Literature Review. FWPRDC Project No. PN02.1907.

Kininmonth, J.A., Whitehouse, L.J. (1991). Properties and Uses of New Zealand Radiata Pine, Vol. 1. Forest Research Institute, Rotorua, New Zealand,

Krautkrämer, J. K.H. (1986). Werkstoffprüfung mit Ultraschall, Springer Verlag, Berlin.

Krzosek, S. (2003). Machine stress-grading of timber: current status and prospects of development, Festigkeitssortierung des Bauholzes mit Maschinen - Ist-Stand und Entwicklungsperspektiven.

Lamb A.F.A., (1973). *Pinus caribaea* FAST GROWING TREES OF THE LOWLAND TROPICS Volume 1. N°6. University of Oxford, England (254 pp).

Leicester, R.H. (2004). Grading for structural timber. *Progress in Structural engineering and Materials.* Vol. 6 (pp 69-78).

Leicester, R.H., Breitinger, H.O. and Fordham, H.F. (1996). Equivalence of in-grade testing standards. CIB/W18A- Timber Structures, Paper 29-6-2, Bordeaux, France.

Ross, R.J. and Pellerin, R.F. (1994). Non-destructive testing for assessing wood members in structures- a review. (40 pp). Rev. Ed. Forest Products Laboratory USDA Forest Service, Madison USA.

Ross, R.J., Brashaw B.K. and Wang X.P. (2006). *Structural condition assessment of in-service wood*. Forest Products Journal 56, 4.

Ross, R.J., Zerbe, J.I., Wang, X.P., Green D.W. and Pellerin R.F. (2005). *Stress wave nondestructive evaluation of Douglas-fir peeler cores*. Forest Products Journal 55 (pp 90-94).

Sandoz, J.L. (1989). *Grading of construction timber by ultrasound*. Wood Science and Technology 23 (pp 95-108).

Schimleck, L.R., Evans, R., Ilic, J. and Matheson A.C. (2002). *Estimation of wood stiffness of increment cores by near-infrared spectroscopy*. Canadian Journal of Forest Research 32 (pp 129-135).

Siemon, G. (1981). Effect of CCA-preservative treatment on bending strength of small clear specimens of high-temperature dried and air-dried Caribbean pine. Technical Paper No. 27. (4 pp). Department of Forestry, Queensland.

Smith, R.G.B., Palmer, G. Davies, M. And Muneri, A (2003). *A method enabling the reconstruction of internal features of logs from sawn lumber: the log end template*. Forest Products Journal Volume 53 No. 11/12 (pp 95-98).

Steiger, R. (1996). Mechanische Eigenschaften von Schweizer Fichten-Bauholz bei Biege-, Zug-, Druck- und kombinierter M/N-Belastung Sortierung von Rund- und Schnittholz mittels

Ultraschall, VII, 168S. Institut für Baustatik und Konstruktion (IBK), Eidgenössische Technische Hochschule Zürich (ETH), Zürich.

Tsehaye, A.., Buchanan, A.H. and Walker, J.C.F. (2000). *Sorting of logs using acoustics*. Wood Science and Technology 34 (pp 337-344).

Tsuchikawa, S. (2007). *A Review of Recent Near Infrared Research for Wood and Paper*. Applied Spectroscopy Reviews 42 (1) (pp 43–71).

Wang, X.P., Ross, R.J., Green, D.W., Brasha, B., Englund, K. and Wolcott, M. (2003). *Stress wave sorting of red maple logs for structural quality*. Wood Science and Technology 37 (pp 531-537).

Yeh, T.F., Chang, H.M. and Kadla, J.F. (2004). *Rapid prediction of solid wood lignin content using transmittance near-infrared spectroscopy*. Journal of Agricultural and Food Chemistry 52 (pp 1435-1439).

Zobel, B.J. and Buijtenen J.P.V (1989). WOOD VARIATION: ITS CAUSES AND CONTROL. Springer-Verlag, Berlin, Germany.

Internet references

Web 1. http://www.weeds.org.au/cgi-bin/weedident.cgi?tpl=plant.tpl&ibra=all&card=E41#
Visited in April 2007

Web 2. http://www.statsoft.com/textbook
Visited 31.07.09

Web 3. http://www2.dpi.qld.gov.au/hardwoodsqld/13322.html
Visited in August 2008.

Web 4. http://www.metriguard.com/
Visited in August 2008

Web 5. http://www.newnes-mcgehee.com/splash.htm
Visited in August 2008

Standards

AS/NZS 1748:2003 - *Timber-Stress-graded-product requirements for mechanically stress-graded timber.*

EN 408 (1995). European Standard 408, *Timber structures- Structural timber and glued laminated timber- Determination of some physical and mechanical properties.* Brussels.

EN 14081-1 (2003). European Standard E. *Timber structures- Strength graded structural timber with rectangular cross section- Part 1: General requirements.* Brussels.

AS 1720.1 (1997) Australian Standard. *Timber structures, Part 1: Design methods*.

AS/NZS 4063 (1992). Australian/New Zealand Standard 4063. *Timber–Stress-graded–In-grade–strength and stiffness evaluation.*

Personal communication

Boughton, G. (2009). pers. comm. Director, TimberED, Bunbury Western Australia.

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Researcher’s Disclaimer

Appendix 1. Resonance method extracted signal descriptors

SCGravity

Spectral centre of gravity divided by the fundamental frequency (f1) in %:

$$SCG = \frac{\sum_{p=1}^{p=N} A_p . f_p}{\sum_{p=1}^{p=N} A_p} \text{ with } f(N) = \text{Fmax range}$$

SCGf1 = SCG ./ f1 .* 100;

SBandwidth

Spectral extent divided the fundamental frequency (f1) in %:

$$Sband = \sqrt{\frac{\sum_{p=1}^{p=N} A_p . (f_p - SCG)^2}{\sum_{p=1}^{p=N} A_p}}$$

Sbandf1 = Sband ./ f1 .* 100;

SSlope

Spectral slope divided the fundamental frequency (f1) in %:

$$Sslope = \sqrt[3]{\frac{\sum_{p=1}^{p=N} A_p . (f_p - SCG)^3}{\sum_{p=1}^{p=N} A_p}}$$

Sslopef1 = Sslope ./ f1 .* 100;

IF

Inharmonicity factor:

$$IF - \frac{f_2 . f_3}{{f_1}^2} x100$$

ME

Average of the first three dynamic MOE

MOE_n

Dynamic MOE associated with fn

FacQ_n

Quality factor (inverse internal damping or friction) associated with fn:

$$FacQ1 = \frac{\pi . f_1}{\alpha_1} \text{ such as } s(t) = \sum_{p=1}^{p=\infty} \beta_p e^{-\alpha_p t} \sin(2\pi f_p t + \phi_p)$$

Pow_n

Mean power in frequency sub-band (between 0 and f1; f1 and f2...):

$$Pow1 = \frac{1}{f_1 - f_0} \int_{f_0}^{f_1} A(f)^2 \mathrm{df}$$

MSNrjRatioF_n

Sub-band energy ratio (between the resonance frequencies) :

$$NrjRat1 = \frac{\int_{f_0}^{f_1} A(f)^2 \mathrm{df}}{\int_{f_0}^{f_{Max}} A(f)^2 \mathrm{df}} = \text{Sub-band energy / Total range energy}$$

PowF_n

Mean power of the sub-band (resonance shoulder defined by a pass band of -20dB) :

$$PowF1 = \frac{1}{f_{BandMax} - f_{BandMin}} \int_{f_{BandMin}}^{f_{BandMax}} A(f)^2 \mathrm{df}$$

MSRatioF_n

Sub-band energy ratio (resonance shoulder defined by a pass band of -20dB)

$$RatF1 = \frac{\int_{f_{BandMin}}^{f_{BandMax}} A(f)^2 \mathrm{df}}{\int_{f_0}^{f_{Max}} A(f)^2 \mathrm{df}} = \text{sub-band energy / total range energy}$$

Appendix 2. WoodEye profile descriptions.

CTR	Material inertia ratio = calculated inertia / beam inertia (b.h³/12) The inertia is calculated from the sum of inertias according to Parallel Axis Theorem (also known as Huygens-Steiner theorem) Profile is calculated between the external loading points Profile is weighted by the bending moment (unit maximum moment) Profile is equal to the product of the profiles from the 4 beam sides.
CTR_AC_M	Sides A&C, rectangular window, mean value
CTR_AC_5	Sides A&C, rectangular window, 5% fractile (equivalent to a minimum)
CTR_BD_5	Ratio defect surface/total surface; B&D edges, rectangular window, 5% fractile
CTR_trgl_BD_5	B&D edges, triangular window, 5% fractile
CTR_trgl_AC_M	Sides A&C, triangular window, mean value
CTR_trgl_AC_3	Sides A&C, triangular window, 3% fractile
CTR_trgl_AC_5	Sides A&C, triangular window, 5% fractile
KAR	Perimeter ratio = calculated perimeter / beam perimeter (2.b.h) The perimeter is associated to defect height (sum of the heights) Profile is calculated between the external loading points Profile is equal to the sum of the profiles from the 4 beam sides.
KAR_ext_M	A&B&C&D, 1/3 external height for A&C), rectangular window, mean value
KAR_ext_99	99% fractile (equivalent to a maximum)
KAR_ext_98	98% fractile
KAR_int_M	A&B&C&D, 1/3 internal height for A&C), rectangular window, mean value
KAR_int_99	99% fractile
KAR_trgl_M	A&B&C&D, triangular window, mean value
KAR_trgl_99	99% fractile

Notes: A and C are the faces and B and D are the board edges.

Appendix 3. Biased and random testing protocol.

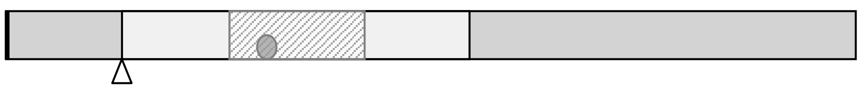
Radiata E resource

- Identify the limiting feature (that is, the largest strength limiting defect) to provide the biased sample location.
- Mark the 1.8 m length so that this point lies within the middle third of the specimen.
- Using a random number calculator, provide the distance from the board end for random sample datum point.
- If this position is situated so that a second 1.8 m long test piece can be created without overlapping the biased specimen, it is marked ‘true random’.
- Otherwise a sample is cut directly next to the biased one and marked ‘false random’.
- When the biased and the random samples are situated so that both conditions were satisfied, the specimen is marked with ‘biased and random’.
- The specimens called true and false random are both considered as random samples.
- The results obtained from the ‘biased and random’ samples are taken into account in random as well as biased analyses.

This sampling methodology, whereby the biased sampling had priority and a random sample was only available if located outside the biased sample region, provided a random sample set of approximately 40% of the whole sub-sample.

Radiata R and Caribbean resources

- Using a random number calculator, provide the distance from the numbered board end for the random sample datum point.
- A 1800 mm test specimen template with the centre third demarcated is placed at this datum to locate random specimen location.
- Check to see if the maximum strength reducing defect is located in the centre third of the possible test specimen.
- If yes then mark the test specimen for docking and retain the board number on the specimen with the letters “rb” for “random and biased”.

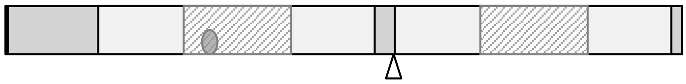


△ Random length measured from the end with the full board identification code

| End with the full board identification code

● Maximum strength reducing defect

- If no then locate the maximum strength reducing defect in the board and position the test specimen template so that the defect is in the middle third of the test span.
- Mark the test specimen ends for docking and retain the board number on the test specimen with the letters “b” after the sample number (“b” indicates a biased sample).
- If the random sample doesn’t overlap the biased sample, two samples can be cut.



Δ Random length measured from the end with the full board identification code

| End with the full board identification code

● Maximum strength reducing defect

- If the biased and random samples overlap slightly, the combined length is docked and the biased test section tested first, followed by the random section length.

Δ Random length measured from the end with the full board identification code

| End with the full board identification code

● Maximum strength reducing defect

- If the overlap is too large only one test can be done the piece with the priority has to be selected (random or biased). In this case only one specimen will result.

Δ Random length measured from the end with the full board identification code

| End with the full board identification code

● Maximum strength reducing defect

This protocol would ensure that for approximately 60% of boards, both random and biased test specimens will be available.