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# Development of a segregation method to sort fast-grown *Eucalyptus nitens* (H. Deane & Maiden) Maiden plantation trees and logs for higher quality structural timber products

Michelle Balasso<sup>1,2\*</sup> , Mark Hunt<sup>1</sup>, Andrew Jacobs<sup>2</sup> and Julianne O'Reilly-Wapstra<sup>1</sup>

## Abstract

**Key message:** A method to segregate trees and logs of planted *Eucalyptus nitens* (H. Deane & Maiden) Maiden has been developed, showing that accounting for wood quality during the process of segregation and sorting of timber resources allows for the recovery of structural timber of the desired quality.

**Context:** Appropriate sorting of raw forest resources is necessary to allocate logs to different production streams, to ensure that the desired quality of timber is achieved. Acoustic wave velocity can be used to test the wood quality of trees and logs, and its use as a sorting tool needs to be investigated prior to the development of a segregation method to recover high-quality timber.

**Aims:** This study aimed to develop a segregation methodology for plantation *E. nitens* trees and logs to obtain high-quality structural boards.

**Methods:** Forty-nine logs of planted *E. nitens* were measured, assessed with acoustic wave velocity, and processed into 268 structural boards maintaining board, log, and tree identity. Board stiffness was determined via structural testing and boards were ranked in structural grades. Linear mixed effect models were used to predict board stiffness based on tree and log variables, and machine learning decision trees were used to create a segregation method for board grades. Different segregation options were compared through scenario simulation.

**Results:** The prediction of individual board stiffness with tree or log variables yielded low coefficients of variation due to large intra-log variability ( $R^2 = 0.22$  for tree variables and  $R^2 = 0.28$  for log variables). However, the decision tree identified acoustic wave velocity thresholds to segregate *E. nitens* trees and logs. When applied in scenario simulation, segregation based on log variables produced the best results, resulting in large shares of high-quality board grades, showing that a segregation method based on wood quality traits can yield larger higher recovery of higher quality timber, in respect to other scenarios.

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\* Correspondence: [Michelle.balasso@utas.edu.au](mailto:Michelle.balasso@utas.edu.au)

<sup>1</sup>School of Natural Sciences and ARC Training Centre for Forest Value, University of Tasmania, Hobart, Tasmania, Australia

<sup>2</sup>Forico Pty Limited, Launceston, Tasmania, Australia



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**Conclusion:** Acoustic wave velocity can be used to segregate trees and logs for structural boards from plantation *E. nitens*, and machine learning decision trees can support the development of a segregation method to determine operational thresholds to increase the recovery of high-quality timber.

**Keywords:** *Eucalyptus* plantations, Stiffness, Acoustic wave velocity, Non-destructive techniques, Segregation, Wood quality

## 1 Introduction

To increase the efficiency and value of the wood production supply chain, sorting and allocation of forest resources to the appropriate productive stream is needed. Such sorting can be performed on the basis of knowledge on tree and log wood quality traits relevant for different timber products (Murphy and Cown 2015). Important wood quality traits such as stiffness and density determine timber product grades, which in turn establish the value, use, and performance of the timber elements. These wood quality traits can be assessed on standing trees and logs and can then be used for the prediction of the quality of the timber products (Wang et al. 2007). Using this information on wood quality of trees and logs, segregation strategies for appropriate allocation of forest resources can then be developed and adapted for different productive systems.

*Eucalyptus* plantations offer a promising opportunity to explore forest resources segregation to obtain different products. The increasing interest in utilising plantation logs for timber products has moved the focus from the dominant production of fibre for the pulp and paper industry to other uses of plantation logs. Areas planted with species of this genus cover almost 26% of the total planted area across the globe (Binkley et al. 2017), and in Australia, 884,000 ha are planted with these hardwoods (ABARES 2019). Australian hardwood plantations are dominated by the Tasmanian blue gum (*Eucalyptus globulus* Labill.), covering 50% of the total estate, and shining gum (*Eucalyptus nitens* H. Deane & Maiden), occupying 26%, whilst a smaller percentage is planted with other eucalypt species. The demand for forest products to supply the construction market is rapidly increasing, especially for engineered wood products to substitute steel and concrete in buildings (Brandt et al. 2021). Plantation logs could be a source of structural timber to supply the increasing need of renewable materials in construction; however, knowledge on the quality of these fast-growing resources both in tree, logs, and timber products is needed prior to the production of final timber elements.

The prediction of quality and properties of timber from trees and logs has been the focus of decades of research on non-destructive testing techniques. Several methods have been proposed to assess wood properties such as density, stiffness, and strength before processing

logs into timber products (Moore et al. 2013; Merlo et al. 2014; Butler et al. 2017). Amongst those, the use of acoustic waves in standing trees and logs has been developed and used on several species to characterise wood quality (Wang 2013; Ross 2015) and even to predict important timber structural properties over large geographic areas (Caballé et al. 2020; Balasso et al. 2021). Acoustic tools measure the velocity of acoustic waves in trees and logs (acoustic wave velocity, AWW), from which the dynamic modulus of elasticity ( $MOE_{dyn}$ ), a measure of stiffness, can be calculated. Although the dynamic modulus of elasticity is an indirect measure of stiffness, it is closely related to the static modulus of elasticity ( $MOE_{stat}$ ) (Ilic 2001), which is usually estimated through mechanical testing of timber under bending. Such mechanical tests are regulated by national standards, which are used to determine the final grade of the timber (Standards Australia 2010a, b). Studies have correlated stiffness measured through AWW on trees and logs with that measured mechanically on timber products, and for *Eucalyptus* species, moderate correlations have been found. Dickson et al. (2003) have investigated stiffness in *E. dunnii* timber, finding a modest correlation between tree AWW and timber  $MOE_{stat}$  ( $R^2 = 0.16$ ) and a higher correlation with log AWW ( $R^2 = 0.52$ ). For 14-year-old *E. nitens*, similar log AWW-timber  $MOE_{stat}$  correlations have been found ( $R^2 = 0.47$ , Blackburn et al. 2010, and  $R^2 = 0.51$ , Farrell et al. 2012). However, these studies sampled one to two boards per tree (or log, as in Farrell et al. 2012), reducing the representativeness of the measurements. Similar correlations were found for numerous other species, and the use of non-destructive testing tools to sort raw forest resources has been frequently suggested (Tsehaye et al. 2000; Carter et al. 2006; Farrell et al. 2012).

Information on the variation in wood quality traits along the stems of trees can aid the sorting of logs for recovery of products of the desired quality. Studies on the variation in quality traits of *E. nitens* wood along the stem have shown that density increases longitudinally from the bottom to the top of the stems (Raymond and MacDonald 1998; Shelbourne et al. 2002), whilst stiffness has been shown to increase in the first part of the stems (Washusen et al. 2009; Hamilton et al. 2015). This information, coupled with knowledge on the external characteristics and internal properties of logs, such as stiffness estimated

through AWV, can be used to then develop segregation strategies to recover a diversified set of products from raw forest resources. To the best of our knowledge, no study has been undertaken to develop a segregation strategy on trees or logs on specific product types and grades of timber, in particular of *E. nitens* sawn timber.

In this study, we aimed to investigate how the relationships among tree and log characteristics and sawn-board structural grades can be used to develop a segregation methodology for plantation *E. nitens* timber. We used the results of our analysis to evaluate the potential of segregation choices in delivering two classes of wood products (pulplogs and sawlogs), developing and comparing different potential scenarios in terms of recovery of volume of pulplogs and of different sawn-board structural grades.

The approach presented in this study builds on the current knowledge on correlative relationships between tree and log stiffness and timber stiffness. We first present an investigation on the relationships between trees and log variables with timber stiffness, using mixed-linear models as the modelling method. We then introduce the use of machine learning algorithms to develop decision trees. This modelling choice allowed us to identify relevant tree and/or log classification variables and their thresholds to classify sawn boards into structural grades. These findings were then used to develop segregation strategies for *E. nitens* plantation timber and to evaluate the potential recovery under different segregation options through scenario simulation. The specific objectives of this study were to:

- (i) Investigate the longitudinal variation in basic density and dynamic modulus of elasticity of logs ( $MOE_{l,dyn}$ ) along the stems
- (ii) Investigate the correlative relationships between sawn-board stiffness (static modulus of elasticity,  $MOE_{b,stat}$ ) and log and tree traits and investigate the percentage of variability in  $MOE_{b,stat}$  due to the tree, log, or board strata
- (iii) Develop a descriptive mixed-linear model of sawn-board structural grades based on relevant tree and log traits
- (iv) Utilise machine learning techniques to develop decision trees and identify important classification variables to develop a segregation method based on statistically relevant tree or log variable thresholds
- (v) Develop different scenarios using the segregation strategies developed with the decision-tree analysis

## 2 Materials and methods

### 2.1 Timber material

The materials utilised for this study were structural boards from *E. nitens* trees harvested and sawn as a subset of a large sawing trial. The plantation was located in

southern Tasmania, Australia (at latitude 43° 03' S, longitude 146° 59' E). The area sits at 350 m above sea level, and receives an average annual rainfall of 750 mm. For this study, fifteen trees of 21 years of age were selected amongst the dominant and co-dominant classes to cover the range of diameters that would deliver acceptable sawlogs. All selections were over 30 cm diameter at breast height (DBH, cm), of appropriate straightness, free of excessive sweep, forking, and decay. Each standing tree was measured for DBH and total height (H, m), and slenderness of the stems was calculated as the ratio between tree height and diameter. The AWV of each tree was measured using the Director ST300 (Fibre-gen, New Zealand) on both sides of the stem, perpendicularly to the slope gradient to avoid areas with compression wood. The instrument uses two probes located approximately 1.2 m distance apart, with the bottom probe placed at 0.5 m from the ground level and the upper probe at 1.7 m. The bottom probe was hit eight times per reading, three readings per side were taken and final values averaged. Two 5-mm diameter and 7-cm-long outerwood cores were extracted on the two sides tested for the acoustic measurements using an increment borer (Haglöf Sweden®). Core samples were immediately labelled, stored in individual plastic bags in a cooler, and measured the same day for green density ( $\rho_g$ , g/cm<sup>3</sup>) and basic density ( $\rho_b$ , g/cm<sup>3</sup>) according to AS/NZS 1080.3:2000 (Standards Australia 2000) and volume measurements performed using the water displacement method (Smith 1954).

The trees were felled, delimbed and debarked during a commercial pulpwood harvesting operation, and bucked in log lengths of 5.5 m. Each tree was felled at 30 cm from the stump and cut to a small end diameter of 185 mm. Logs coming from the same tree were grouped together in cutting order, and at the top end of each log, a disk 2.5 cm thick was cut for laboratory density measurements. Disks were immediately wrapped to prevent loss of moisture and transported to the cooler until density measurements were performed, as described above. Green density and  $\rho_b$  of logs were calculated as an average of the  $\rho_g$  or  $\rho_b$  measurements of the bottom and top disks of the log. Each log was marked with tree number and log position in the stem as bottom log, middle logs (second or third), and top logs, to maintain their identity. The last harvested log was always kept as top log, whilst from the middle part of the stems, one or two logs were harvested, which were grouped in the analysis as middle logs. Logs were transported the following day to the sawmill and placed on bearers 50 cm far apart for assessment. Maximum and minimum diameters were measured at both log ends (large end diameter LED, small end diameter SED, mm), and log lengths ( $L$ , m) were measured. Log volume ( $V$ , m<sup>3</sup>) was calculated according to:

$$V = \left[ \frac{LED + SED}{2} \times \frac{1}{2} \right]^2 \times \pi \times L$$

The taper ( $T$ , cm/m) of each log was calculated according to:

$$T = \frac{LED - SED}{L}$$

Acoustic wave velocity of each log was tested with the acoustic resonance device Director HM200 (Fibre-gen, New Zealand). The test consists of tapping with a hammer one end of the log and reading the AWV value with the provided hand-held tool from the same end. Acoustic wave velocity and  $\rho_g$  measurements were used to calculate the  $MOE_{dyn}$  (GPa) of the trees and logs according to:

$$MOE_{dyn} = \rho_g \times AWV^2$$

where  $\rho_g$  represents the green density (g/cm<sup>3</sup>) of the sample and AWV its acoustic wave velocity (km/s). The dynamic modulus of elasticity of the trees ( $MOE_{t,dyn}$ , GPa) was calculated using the  $\rho_g$  measured on the cores and the AWV on the standing trees, whilst log  $MOE_{dyn}$  ( $MOE_{l,dyn}$ , GPa) was calculated through the  $\rho_g$  of the logs.

## 2.2 Sawing and board treatments

Forty-nine logs were recovered from the selected trees, and each log was individually identified with a colouring pattern to allow for tree, log, and board identification (Fig. 1). Logs were processed individually in a commercial sawmill with a back-sawing pattern chosen to maximise volume recovery. In total, 268 boards were sawn and stacked to be air-dried under cover for a period of 14 months and then reconditioned prior to final kiln drying. The kiln drying procedure followed the current drying schedule used for eucalypt timber, to a nominal moisture content (MC) of 12%. The dried boards were square dressed to final widths of 70, 90, 120, 140, and 165 mm, thickness of 35 mm, ; and average board length of 5.5 m, maintaining board identity.

Board volume was measured prior to dressing, and the nominal recovery rate, representing the volume of sawn boards recovered out of the volume of the logs sawn, was calculated as:

$$N_r = \frac{V_O}{V_L}$$

where  $N_r$  represents the nominal recovery rate of the boards (%),  $V_O$  represents the volume of the boards before dressing (m<sup>3</sup>), and  $V_L$  is the total volume of the harvested logs (m<sup>3</sup>). The dressed board static modulus of elasticity ( $MOE_{b,stat}$ , GPa) was tested through mechanical testing in edge-wise 4-point static bending test, according to the test procedures outlined in AS 4063.1 (Standards Australia 2010a), and calculated with:

$$MOE_{b,stat} = \frac{3al^2 - 4a^3}{4bd^3 \left( \frac{\phi_2 - \phi_1}{F_2 - F_1} \right)}$$

where  $b$  and  $d$  are the thickness and the width of the board (mm), respectively;  $l$  is the span length, which corresponds to 18 times the width of the board (mm);  $a$  is 6 times the board width (mm); and  $F_2$  and  $F_1$  are the loads at 40% and 10% of the maximum load, recorded at the failure point.  $\phi_2$  and  $\phi_1$  are the maximum displacement (mm) at  $F_2$  and  $F_1$  loads, respectively.

Basic density and MC assessment on boards was performed on samples of timber recovered from the top and bottom ends of each board. Samples were measured following the procedure described in AS 1080.3 and AS 1080.1 (Standards Australia 2000, 2012) using the following equations:

$$\text{Basic } \rho = \frac{m_1}{V} \times \frac{100}{(100 + MC)}$$

$$MC = \frac{m_1 - m_0}{m_0} \times 100$$

with  $m_1$  being the mass of the sample at the time of the testing (kg),  $V$  the volume of the sample before



**Fig. 1** Pattern used to maintain traceability from logs to sawn boards. Each log end was coloured with a unique colour combination



oven-drying ( $\text{m}^3$ ), and  $m_0$  the mass of the sample after oven-drying (kg). The MC and  $\rho_b$  of each board were calculated as an average of the samples at the bottom and top ends of each board. The  $\text{MOE}_{b,\text{stat}}$  values obtained were adjusted based on the MC of each board, according to AS 2878. The adjusted  $\text{MOE}_{b,\text{stat}}$  values were used to classify each board into structural grade equivalents, following AS 2082 and AS 1720.1 for *E. nitens* (Standards Australia 2006, 2010b). The minimum  $\text{MOE}_{b,\text{stat}}$  value per each structural grade is provided in Table 1, with the corresponding stress grade (F-grade).

### 2.3 Statistical analyses

Analyses were performed in R statistical software with R studio interface (RStudio Team 2016; R Core Team 2020).

The mean, standard deviation, and value ranges were calculated for each variable. To investigate the longitudinal variation in basic density and modulus of elasticity of logs ( $\text{MOE}_{l,\text{dyn}}$ ) along the stems, we employed one-way analysis of variance (ANOVA) for linear mixed models to test the effect of log position, accounted for as a categorical variable to identify bottom, middle, and top logs. Tree was used as a random factor to account for non-independence of logs within trees, and post hoc Tukey tests were conducted to compare basic density and  $\text{MOE}_{l,\text{dyn}}$  between bottom, middle, and top logs (significance level 0.001).

A random-effects model was developed to investigate the percentage of variability in  $\text{MOE}_{b,\text{stat}}$  due to the tree, log, or board strata, according to the model:

$$y_{ijk} = \mu + T_i + L_{j(i)} + e_{(kji)}$$

where  $y_{ijk}$  is the adjusted  $\text{MOE}_{b,\text{stat}}$  of a single board,  $\mu$  is the overall mean,  $T_i$  is the random effect of the  $i$ th tree [ $\sim N(0, \sigma_T^2)$ ],  $L_{j(i)}$  is the random effect of the  $j$ th log within the  $i$ th tree [ $\sim N(0, \sigma_L^2)$ ], and  $e_{(kji)}$  is the random effect of the  $k$ th board from the  $j$ th log [ $\sim N(0, \sigma_e^2)$ ].

**Table 1** Structural grades assigned to the sawn boards after mechanical testing according to AS 4063.1 (Standards Australia 2010a) and the corresponding static modulus of elasticity ( $\text{MOE}_{b,\text{stat}}$ ) outlined in AS 1720.1, Table H2.1 (Standards Australia 2010b)

Structural grade <sup>a</sup>	Stress grade (F-grade) <sup>a</sup>	Static board modulus of elasticity ( $\text{MOE}_{b,\text{stat}}$ GPa) <sup>b</sup>
Structural grade no. 1	F22	16
Structural grade no. 2	F17	14
Structural grade no. 3	F14	12
Structural grade no. 4	F11	10.5

<sup>a</sup>AS 2082 (Standards Australia 2006)

<sup>b</sup>AS 1720.1, Table H2.1 (Standards Australia 2010b)

Linear-mixed effect models were used to develop descriptive models of board  $\text{MOE}_{b,\text{stat}}$  with fixed variables being only tree, only log, and tree and log variables (complete model), including random effects for trees [ $\sim N(0, \sigma_T^2)$ ] and logs within trees [ $\sim N(0, \sigma_L^2)$ ]. The package ‘lme4’ (Bates et al. 2015) was used to compute the mixed effect models. The independent variables were chosen among those measured on trees (DBH, height, slenderness, AWW, density, and  $\text{MOE}_{t,\text{dyn}}$ ) and on logs (log position within the trees, small end diameter, log taper, AWW, density, and  $\text{MOE}_{l,\text{dyn}}$ ). Models were built inserting the independent variables in order of their correlation coefficient with the board  $\text{MOE}_{b,\text{stat}}$  and ensuring that tree or log variables with a Pearson correlation coefficient of more than 0.7 were not included in the same model. To evaluate the influence of log position in the stem on board  $\text{MOE}_{b,\text{stat}}$ , we used ANOVA for linear mixed models with tree and log as random factors to account for the non-independence of boards within logs and logs within trees. Each model was compared with the most simple one using the likelihood-ratio test (LRT) using the package ‘lmerTest’ (Zeileis and Hothorn 2002) and AIC values. The LRT procedure controls the insertion of new variables if they significantly improve the model’s performance at the threshold of  $P < 0.05$ . The models which performed best according to the LRT analysis were taken as the best descriptive tree, log, and complete models. The normal distribution of the residual of the models was evaluated through residual plots. Model bias and precision were evaluated with 10-fold cross-validation through the package ‘caret’ (Kuhn 2020). K-fold cross-validation (in our case  $k = 10$ ) trains the model in a subset of data ( $k-1$ ) and validates it on the left-over subset, hence evaluating model prediction accuracy. The splitting of the dataset is performed on sets of *folds* represented by the  $k$  parameter. At each validation, a prediction error is recorded and when all folds are run through the cross-validating procedure, the average prediction error is calculated. The metrics reported are the root mean squared error (RMSE), computed as the square root of the mean squared difference between predicted and observed response variable values, and the  $R$ -squared ( $R^2$ , coefficient of determination), representing the proportion of variance in the response variable explained by the model’s predictors.

The machine learning decision trees were applied to classify board structural grades as categorical variables (classification trees) using as predictors the same independent variables employed for the linear mixed effect models. Two mixed effect classification trees were developed, one model type considering all variables together (tree and log variables), and another with tree-only and log position variables, to provide an insight into a decision framework for harvesting operations which would have only tree-related variables available at the moment of harvest. We used the package ‘glmTree’ (Fokkema

et al. 2018) which allows for the presence of random effects in the models and grows classification trees with the variables provided. The decision tree classifiers were used to model the relationship with tree and log variables and board  $MOE_{b,stat}$ , accounting for the random effect of trees and logs, as in the mixed-model technique reported above. The tree structure is presented graphically and its potential as an aid to decision-making processes on tree and log segregation is discussed and presented in different segregation scenarios.

## 2.4 Segregation scenarios

The decision tree analysis allowed the identification of tree and log AWV thresholds (4.56 km/s for trees and 3.91 km/s for logs), as well as depicting log position as an important variable. These variables, were used to segregate trees and logs in categories of product recovery. The AWV thresholds were used to simulate product recovery under six different segregation scenarios presented below.

- (I) Scenario A, where no segregation is applied and all the logs are used as pulplogs for the production of woodchips for the pulp and paper industry.
- (II) Scenario B, where no segregation is applied and all the logs are used as sawlogs for the production of structural sawn boards.
- (III) Scenario C, where segregation is made only on a volumetric basis, using the first log as sawlog and all the other logs as pulplogs.
- (IV) Scenario D, where segregation is applied at the tree level only, utilising the AWV threshold of 4.56 km/s. All logs from trees with AWV above the threshold were used as sawlogs and all logs from trees with AWV below the threshold were used as pulplogs.
- (V) Scenario E, where segregation is applied at the tree level, plus log position is taken into account. This scenario follows scenario D with a AWV threshold of 4.56 km/s and in addition uses log position. All logs from trees above the AWV threshold and middle and top logs from trees below the AWV threshold were used as sawlogs, and the remaining logs from trees with AWV below 4.56 km/s and from the bottom of the tree were used as pulplogs.
- (VI) Scenario F, where segregation is applied at the log level. This last scenario presents the case in which only logs are segregated according to a AWV threshold of 3.91 km/s identified from the classification tree analysis. All logs above this AWV threshold were used as sawlogs and all logs below the AWV threshold were used as pulplogs.

Results are presented in cubic metre of recovered material, being either woodchips and/or volume of dried

board shared in grades (structural grade no. 1, 2, 3, 4). The nominal recovery rate for each scenario is presented, along with the amount of timber lost due to sawing, reported as sawdust.

## 3 Results

### 3.1 Trees and log traits

The characteristics of the *E. nitens* sampled trees are summarised in Table 2. There was moderate variation in tree size and wood properties, with tree basic density varying from 0.45 to 0.69 g/cm<sup>3</sup> and dynamic modulus of elasticity ranging from 15.5 to 25.5 GPa. In total, 18.5 m<sup>3</sup> of logs was harvested, with a single log volume ranging from 0.19 to 0.74 m<sup>3</sup>. Log wood properties also varied considerably, with a lower average and range in AWV in respect to the AWV values found on standing trees and a lower average of log modulus of elasticity (15.9 GPa) and range (11.5 to 19.9 GPa).

Basic density showed a longitudinal increase along stem height, with bottom logs presenting an average of 0.52 g/cm<sup>3</sup> (range 0.45–0.57 g/cm<sup>3</sup>), middle logs 0.53 g/cm<sup>3</sup> (range 0.45–0.59 g/cm<sup>3</sup>), and top logs 0.56 g/cm<sup>3</sup> (range 0.48–0.62 g/cm<sup>3</sup>). Top logs were significantly denser than bottom and middle logs ( $P < 0.001$ ). Dynamic modulus of elasticity significantly increased ( $P < 0.001$ ) from bottom (average of 14.4 GPa, range 11.5–18 GPa) to middle logs (average of 16.7 GPa, range 13.8–19.9 GPa) and then slightly decreased

**Table 2** Descriptive statistics of *E. nitens* selected trees ( $n = 15$ ) and logs ( $n = 49$ ). Mean, standard deviation presented in parenthesis (SD), and minimum and maximum values (min-max)

Variable	Mean and standard deviation	Min	Max
<b>Trees</b>			
DBH (cm)	39.9 (3.52)	35.0	46.5
<i>H</i> (m)	35.4 (3.10)	30.6	40.5
SL (m/m)	88.9 (6.22)	80.4	102.5
$AWV_{tree}$ (km/s)	4.15 (0.32)	3.76	4.69
$\rho_{g\ tree}$ (g/cm <sup>3</sup> )	1.14 (0.04)	1.05	1.21
$\rho_{b\ tree}$ (g/cm <sup>3</sup> )	0.59 (0.05)	0.45	0.69
$MOE_{t,dyn}$ (GPa)	19.8 (3.04)	15.5	25.5
<b>Logs</b>			
Log volume (m <sup>3</sup> )	0.38 (0.12)	0.19	0.74
Log taper (cm/m)	0.80 (0.31)	0.22	1.78
$AWV_{log}$ (km/s)	3.77 (0.22)	3.25	4.20
$\rho_{g\ log}$ (g/cm <sup>3</sup> )	1.11 (0.04)	1.02	1.19
$\rho_{b\ log}$ (g/cm <sup>3</sup> )	0.54 (0.40)	0.45	0.63
$MOE_{l,dyn}$ (GPa)	15.9 (1.94)	11.5	19.9

*DBH* diameter at breast height, *H* height, *SL* slenderness,  $AWV_{tree}$  tree acoustic wave velocity,  $\rho_{g\ tree}$  tree green density,  $\rho_{b\ tree}$  tree basic density,  $MOE_{t,dyn}$  tree dynamic modulus of elasticity,  $AWV_{log}$  log acoustic wave velocity,  $\rho_{g\ log}$  log green density,  $\rho_{b\ log}$  log basic density,  $MOE_{l,dyn}$  log dynamic modulus of elasticity

towards top logs (average 16.4 GPa, range 14.2–19.0 GPa).

### 3.2 Modelling

The results of the random-effects model show that of the overall variation in  $MOE_{b,stat}$  70% was attributable to differences between boards within a log, 2% was attributable to differences between logs in the same tree, and 28% was attributable to differences between trees. The cross-correlation analysis showed that the variables most correlated with  $MOE_{b,stat}$  were those related to the AWV and to dynamic MOE of logs and trees ( $AWV_{tree}$ ,  $AWV_{log}$ ,  $MOE_{t,dyn}$ ,  $MOE_{l,dyn}$ ). Moreover, we found a significant effect of log position, with significant differences in  $MOE_{b,stat}$  of boards coming from different positions in the stem; hence, the variable of log position was utilised in the models. Other variables did not display large or significant correlations with  $MOE_{b,stat}$  and were therefore excluded from the modelling.

The modelling of  $MOE_{b,stat}$  was performed through incremental insertion of variables into the simplest model, represented only by the acoustic wave velocity of the trees or of the logs (model 1) (Table 3). The likelihood-ratio test (LRT) analysis on the tree models shows that the addition of basic density to AWV improves the model performance (lower AIC value and higher log-likelihood), whilst further addition of the tree diameter does not improve the model. Model 2 was hence assumed to be the best, being also significantly different than model 1. When modelling  $MOE_{b,stat}$  with only log variables, the LRT analysis shows that the incremental addition of log density, log taper, and log position did not significantly improve the accuracy of the model ( $P = 0.67$  and  $P = 0.83$ ). Hence, the simplest model 4 was used in the cross-validation procedure.

In building the complete model, tree and log variables were considered together. Tree AWV was used again as the first and only fixed variable in the simplest model 1. With this model, the position of the log in the tree was added, yielding a model significantly different than the previous one ( $P < 0.001$ ). The further addition of the log AWV improved model 8 (lower log-likelihood and lower AIC and BIC) and was significantly different than model 7 ( $P < 0.05$ ). This last model was then chosen for the cross-validation procedure.

The tree model (model 2) of  $MOE_{b,stat}$  shows an increase of stiffness in the boards with increasing AWV of the trees and increasing basic density of the timber (Table 4). The cross-validation procedure of this model showed a RMSE of 2.01 GPa and an  $R^2$  of 0.22. The log model (model 4) considered the best in describing the  $MOE_{b,stat}$  shows a large positive effect of  $AWV_{log}$  in the boards' stiffness. The validation of this model yielded a RMSE of 1.93 GPa and a  $R^2$  of 0.28. When tree and log variables were used in the same model, those that most strongly influenced  $MOE_{b,stat}$  were AWV of the trees, with a moderate positive effect; the AWV of the logs, with a large and positive effect; and the position of the log in the tree. The cross-validation was applied to this model (9) yielding a RMSE of 1.94 GPa and a  $R^2$  of 0.26 (Table 4).

Whilst the log model performed slightly better than the tree model and the tree-and-log model, (showing a better fit and less RMSE) the variability explained was still moderate (less than 30% in all models). This is due to the large intra-log variability already demonstrated by the random-effects model and shown in the Fig. 2, in which each dot represents a board and dots stacked on the same vertical line belong to the same log. Although there is an increasing trend of average board stiffness ( $y$ -

**Table 3** Model comparison of  $MOE_{b,stat}$  modelled through tree-only, log-only, and tree- and log-related variables (AWV acoustic wave velocity,  $\rho_b$  basic density of trees or logs, DBH diameter at breast height)

Model		Df	AIC	BIC	logLik	Pr (> Chisq)
Tree level						
(1)	$AWV_{tree}$	5	1135.3	1153.5	− 562.7	
(2)	$AWV_{tree} + \rho_{b\ tree}$	6	1133.1	1154.7	− 560.6	*
(3)	$AWV_{tree} + \rho_{b\ tree} + DBH$	7	1135.1	1160.2	− 560.5	0.84
Log level						
(4)	$AWV_{log}$	5	1109.5	1127.4	− 549.73	
(5)	$AWV_{log} + \rho_{b\ log}$	6	1111.3	1132.8	− 549.64	0.67
(6)	$AWV_{log} + \rho_{b\ log} + taper$	7	1111.3	1138.4	− 549.61	0.83
Tree and log variables						
(1)	$AWV_{tree}$	5	1135.3	1153.5	− 562.7	
(7)	$AWV_{tree} + position$	7	1121.9	1147	− 553.9	***
(8)	$AWV_{tree} + position + AWV_{log}$	8	1114.3	1143	− 549.1	**

Significance levels: \* $< 0.05$ , \*\* $P 0.01$ , \*\*\* $P 0.001$

**Table 4** Model equations and statistics for the mixed-linear models of  $MOE_{b,stat}$  with tree-only, log-only, and tree and log variables (AWV acoustic wave velocity,  $\rho_b$  basic density)

Model	Equation and parameters	RMSE	$R^2$
(2) Tree	$MOE_{b,stat} = -1.41 + 2.31 AWV_{tree} + 9.18 \rho_{b, tree}$	2.01	0.22
(4) Log	$MOE_{b,stat} = -1.95 + 4.11 AWV_{log}$	1.93	0.28
(9) Tree-log	$MOE_{b,stat} = -3.5 + 0.86 AWV_{tree} + 3.57 AWV_{log} + \text{log position}$ (bottom = 0, middle = 0.12, top = 0.018)	1.94	0.26

axis, board MOE) with increasing stiffness of the logs ( $x$ -axis, log AWV), as shown in the log model (model 4), the variability in stiffness of boards sawn from the same log is appreciable. We investigated the standard deviation of  $MOE_{b,stat}$  per each log, and the range was from as little as 0.23 GPa up to 2.96 GPa in the log presenting the largest variation in board  $MOE_{b,stat}$ .

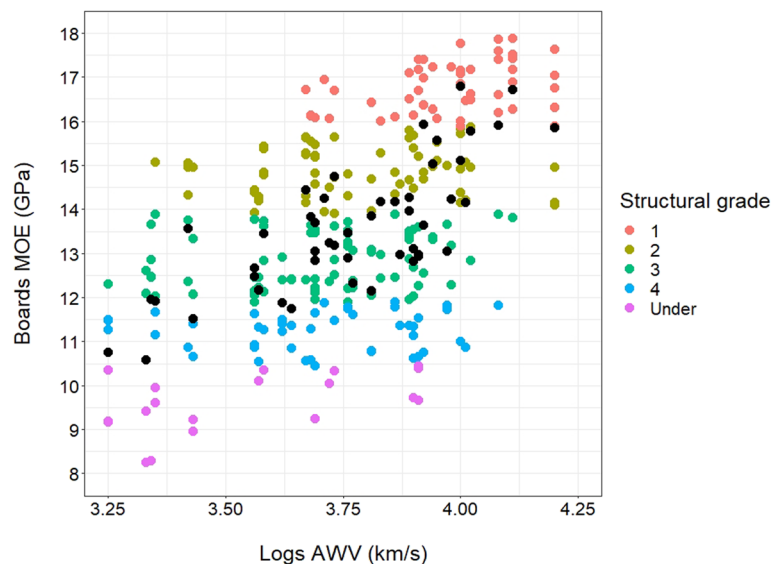
### 3.3 Classification tree analysis

The classification tree analysis allowed the determination of important variables on which to classify boards into structural grades, and results are reported below.

The classification trees (Figs. 3 and 4) show the proportion of boards obtained in the different grade classes when segregating only with tree variables or with both tree and log variables. When the mixed effect classification tree was developed with only tree and log position variables,  $AWV_{tree}$  and log position were found to be the most important variables (Fig. 3). Trees with AWV of 4.56 km/s or above yielded a significant ( $P < 0.001$ ) proportion of stiffer boards, of which more than 56% were of

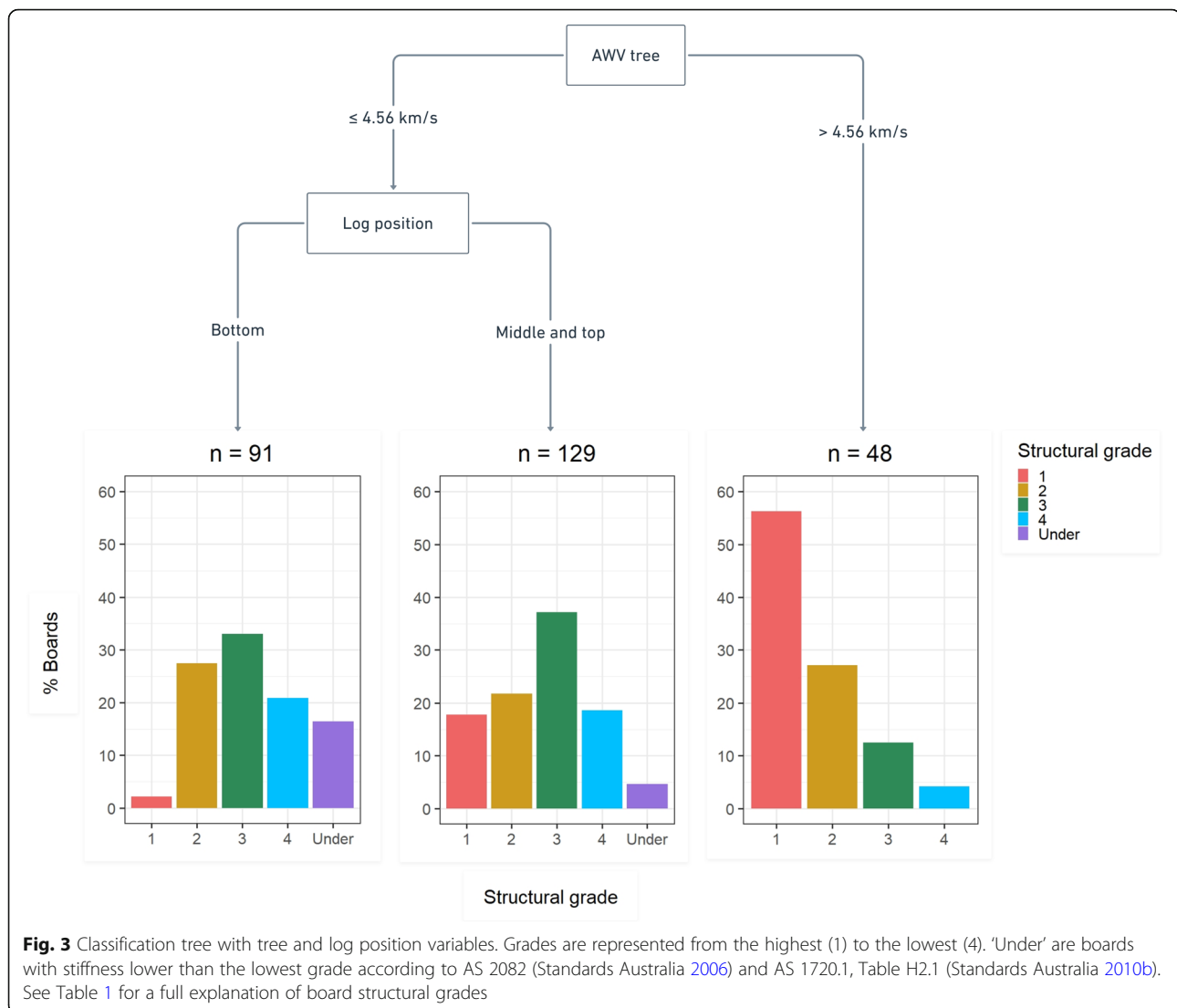
grade 1 and none were in the under-grade class (e.g. not reaching the minimum stiffness of 10.5 GPa). With trees of AWV less than 4.56 km/s, the next variable to significantly ( $P < 0.05$ ) categorise boards of higher classes was the position of the log in the tree, with middle and top logs yielding a homogeneous share of boards among grade classes and the majority (37%) of grade 3. Bottom logs of trees with AWV less than 4.56 km/s yielded a considerable proportion of boards of lower grades, among which 21% of grade 4 and 17% of under-grade boards.

When both tree and log variables were considered in the classification tree analysis,  $AWV_{log}$  was the only important classification variable (Fig. 4) to classify boards into structural grades. Logs with  $AWV_{log}$  over 3.91 km/s yielded a significant ( $P < 0.001$ ) proportion of stiffer boards, of which 46% were grade 1, and only 6% were under-grade. Logs with values of 3.91 km/s or less in  $AWV_{log}$  yielded a homogeneous proportion of boards in each grade, with the largest percentage (38%) being grade 3. The classification trees visually present the immediate results of splitting the population of trees or



**Fig. 2** MOE of boards in relation with the AWV of the logs. The structural grade corresponds to the categories reported in Table 1, where 1 is the highest structural grade and 'Under' refers to boards under-grade, with stiffness lower than acceptable. The black points show the average value of  $MOE_{b,stat}$  all the boards per each log



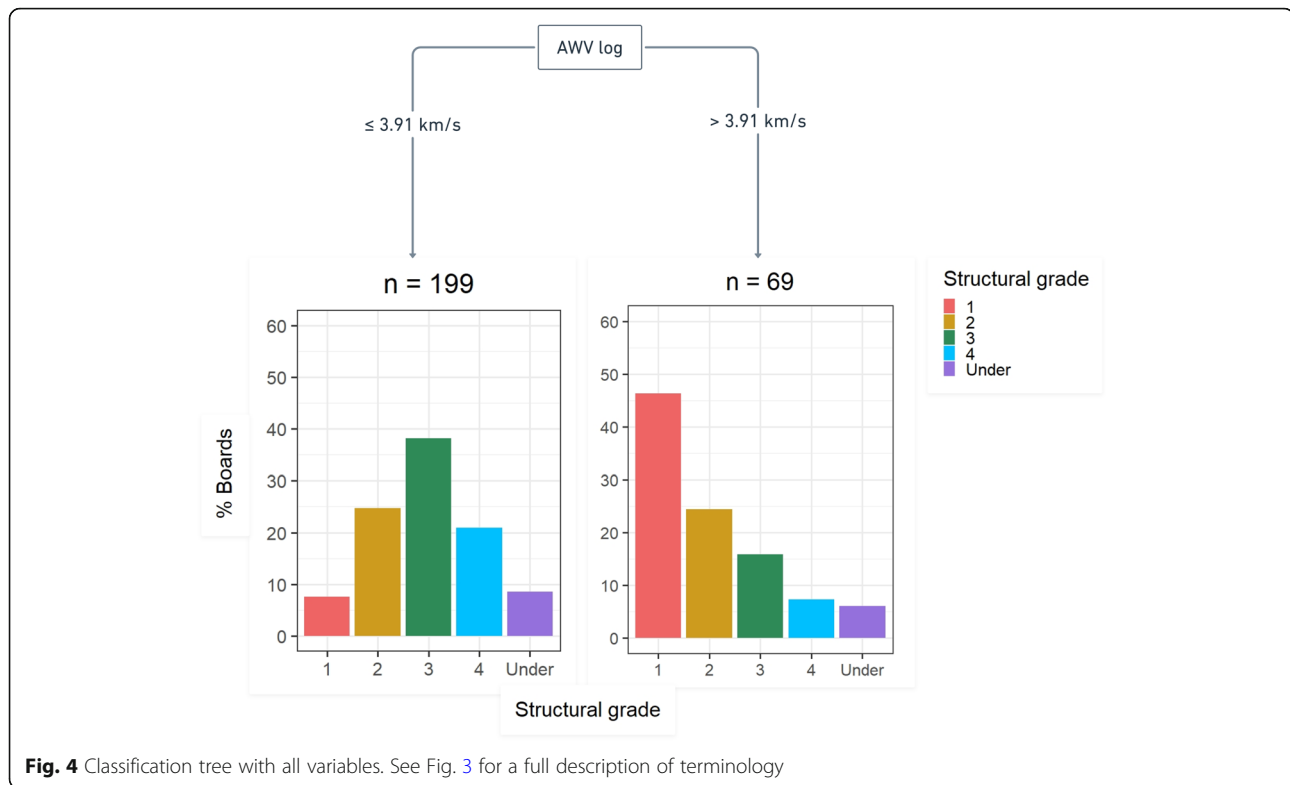


logs according to the variables most correlated with final board stiffness. This procedure can be easily translated into a segregation procedure, from which, according to the tree or log variables available, or those of interest, a prediction of the resulting board grades can be made.

### 3.4 Segregation scenarios

Utilising the thresholds identified from the classification tree analysis, we developed a range of segregation scenarios (section 2.4). In Table 5, the recovery of sawlogs or pulplogs is reported for each scenario. Different volumes of sawn boards were recovered from the sawlogs, and from each scenario, the nominal recovery rate was different, ranging from 37.4 to 44.6% (data not shown). The differences in recovery rates are due to the volume of logs sawn, their characteristics, and the milling process. For each scenario, the recovery of board grades varied, and the highest and more valuable grades

(structural grade no. 1 and 2) and lowest grades (structural grade no. 3 and 4 and under-grade boards) are tallied together for ease of presentation. Considering scenarios where segregation was applied, scenario D presents the largest amount of pulplogs (82.6%, 15.3 m<sup>3</sup>) and the lowest amount of logs sawn (17.4%, 3.21 m<sup>3</sup>) but presents the highest recovery of high board grades (81.4 % of str. grades 1–2), with no boards recorded in the under-grade class (Fig. 5). The second best scenario in terms of recovery of high grades is scenario F, where segregation is applied only to logs according to their stiffness. Although this scenario still presents a high proportion of logs destined for woodchips (69.3%, 12.8 m<sup>3</sup>) and only 5.66 m<sup>3</sup> of sawlogs, almost 70% of the boards recovered are high grades. In scenario E, half the boards are of high grades, although having the largest volume of sawlogs milled (76.5%, 14.1 m<sup>3</sup>), and this is due to the lowest recovery rate of boards after milling (37.4%). The



**Fig. 4** Classification tree with all variables. See Fig. 3 for a full description of terminology

scenarios where no segregation is applied (A, B) or where logs are segregated only by volume (bottom logs, scenario C) are the lowest in terms of recovery of high board grades.

The share of board grades recovered per scenario is graphically displayed in Fig. 5. From this figure, it is clear how the percentage of boards in higher grades (st. grades 1 and 2) rapidly increases when segregating trees or logs for stiffness values, as in scenarios D, E, and F. Scenario F appears to be very similar to D in terms of recovery of high board grades; however, it requires almost double the amount of logs to be sawn

(5.66 m<sup>3</sup> versus 3.21 m<sup>3</sup>). Scenario B, where no segregation is applied, delivers a variety of board grades, similar to scenario C, where logs are segregated only for their position, and E, where segregation is according to trees stiffness and log position. Scenarios B (no segregation) and E (tree and log segregation) require a large amount of logs to be sawn (18.5 m<sup>3</sup> and 14.1 m<sup>3</sup>), whilst returning both a homogeneous mixture of low-quality and high-quality boards. Scenario C has the lowest amount of high board grades, being developed on a volumetric segregation without considering the stiffness of trees or logs.

**Table 5** Volume (m<sup>3</sup>) of logs harvested and recovered as sawlogs or pulplogs under each scenario and volume (m<sup>3</sup>) and amount (%) of boards recovered divided in high and low grades

Scenario	Sawlogs		Pulplogs		Sawn boards (m <sup>3</sup> )	High grades (m <sup>3</sup> ) <sup>a</sup>		Low grades (m <sup>3</sup> ) <sup>b</sup>	
	(m <sup>3</sup> )	(%)*	(m <sup>3</sup> )	(%)*		(m <sup>3</sup> ) <sup>a</sup>	(%)**	(m <sup>3</sup> ) <sup>b</sup>	(%)**
A	0	0	18.5	100	0	0	0	0	0
B	18.5	100	0	0	8.05	3.41	42.4	4.64	57.6
C	7.54	40.8	10.9	59.2	3.21	1.13	35.2	2.08	64.8
D	3.21	17.4	15.3	82.6	1.42	1.16	81.4	0.26	18.6
E	14.1	76.5	4.33	23.5	5.28	2.65	50.2	2.63	49.8
F	5.66	30.7	12.8	69.3	2.53	1.75	69.4	0.77	30.6

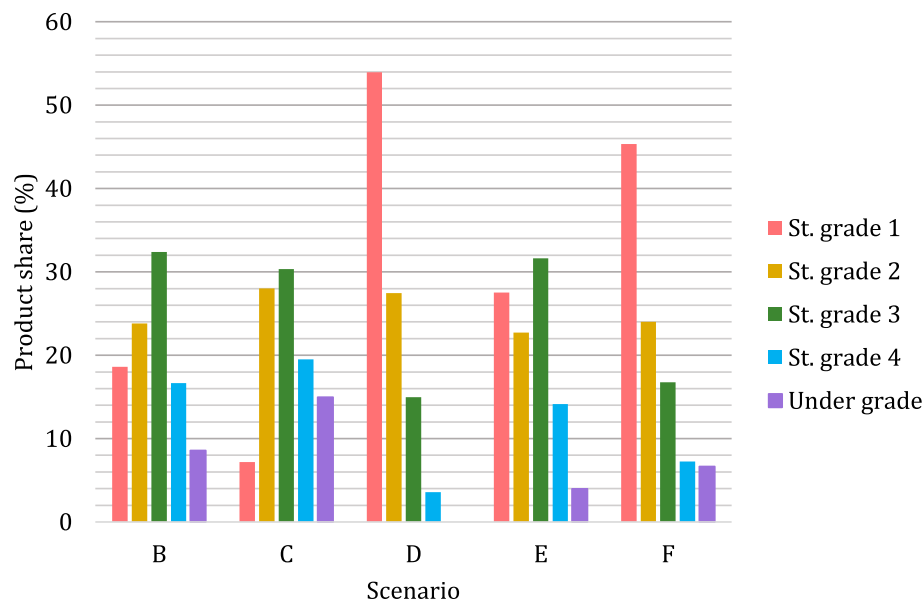
Ranking of scenario from best (scenario D) to least optimal for recovery of high-quality structural boards (scenarios E and F)

<sup>a</sup>High grades include Structural grade no. 1 and 2

<sup>b</sup>Low grades include Structural grade no. 3 and 4 and under-grade boards

\* (%) Percentages of logs are calculated as the volume of sawlogs/pulplogs over the total volume of harvested logs (18.5 m<sup>3</sup>)

\*\* (%) Grades are calculated as the volume of boards in that category over the total volume of boards sawn in that scenario



**Fig. 5** Structural grades (%) recovered in scenarios B–F

#### 4 Discussion

The results of our study show that a segregation method to obtain high-quality structural timber can be implemented on the basis of sound statistical methods which would use tree and log variables, delivering a higher proportion of material of higher structural properties when selecting trees and logs with quality above identified thresholds.

We found an increasing longitudinal pattern of density and log stiffness (measured as dynamic modulus of elasticity,  $MOE_{l,dyn}$ ) along the stems, which was reflected in the models of board stiffness, where log position was found to be a significant predictor of stiffness. We found similar correlations between trees and log AWW measurements,  $MOE_{l,dyn}$ , and board stiffness, showing that AWW can be used to test stiffness directly without the need to use MOE measurements, which involve the collection of density samples. Using only AWW, we developed models to describe the variation in stiffness of the boards with only-tree, only-log, and tree and log variables together. In all models, stiffness of the boards increased with increasing values of  $AWV_{tree}$  or  $AWV_{log}$ , but the validated models showed that none was able to explain more than 30% of average board stiffness. This low fit is due to the large within-log variability in log properties, as demonstrated by the random-effects model, where we found 70% of the overall variation in board stiffness was attributable to differences between boards within a log and only 2% was attributable to differences between logs in the same tree. These results are in line with research on other species used for production of structural timber (Moore et al. 2013; Merlo et al. 2014; Butler et al. 2017), where a large proportion of the

variability in board stiffness is found within a log, rather than between logs, and another considerable part of the variation is due to tree-to-tree differences. Our relatively low coefficients of determination differ from those found in previous studies on the same species (Blackburn et al. 2010; Farrell et al. 2012) and on *E. dunnii* (Dickson et al. 2003) for several reasons. In our study, we used all logs harvested from each tree, up to a small end diameter of 18.5 cm; this allowed us to capture a complete picture of the wood properties along the stems. However, this also reduced the strength in correlation between stiffness of boards derived from the top logs (placed at more than 15 m up the stem) and the AWW measured on the standing tree, which is evaluated at breast height (1.3 m). Furthermore, from each log, all sawn boards were used for mechanical testing, thus detecting the large radial variability in wood properties from pith to bark (Legg and Bradley 2016). In this study, a modelling approach different than the ones used in other studies was also employed, as mixed-linear models are more appropriate when dealing with clustered structures and random effects (Bolker et al. 2009); we took into consideration the fact that boards were derived from the same logs, which in turn have been harvested from the same tree. Along with a different model structure, we applied cross-validation of the models to increase the confidence in the predictive ability of the models, and the coefficient of determination and RMSE presented are from this cross-validation procedure, and not from the descriptive model developed on the training dataset only.

Utilising machine learning decision trees, we found that  $AWV_{tree}$ ,  $AWV_{log}$ , and log positions were the most

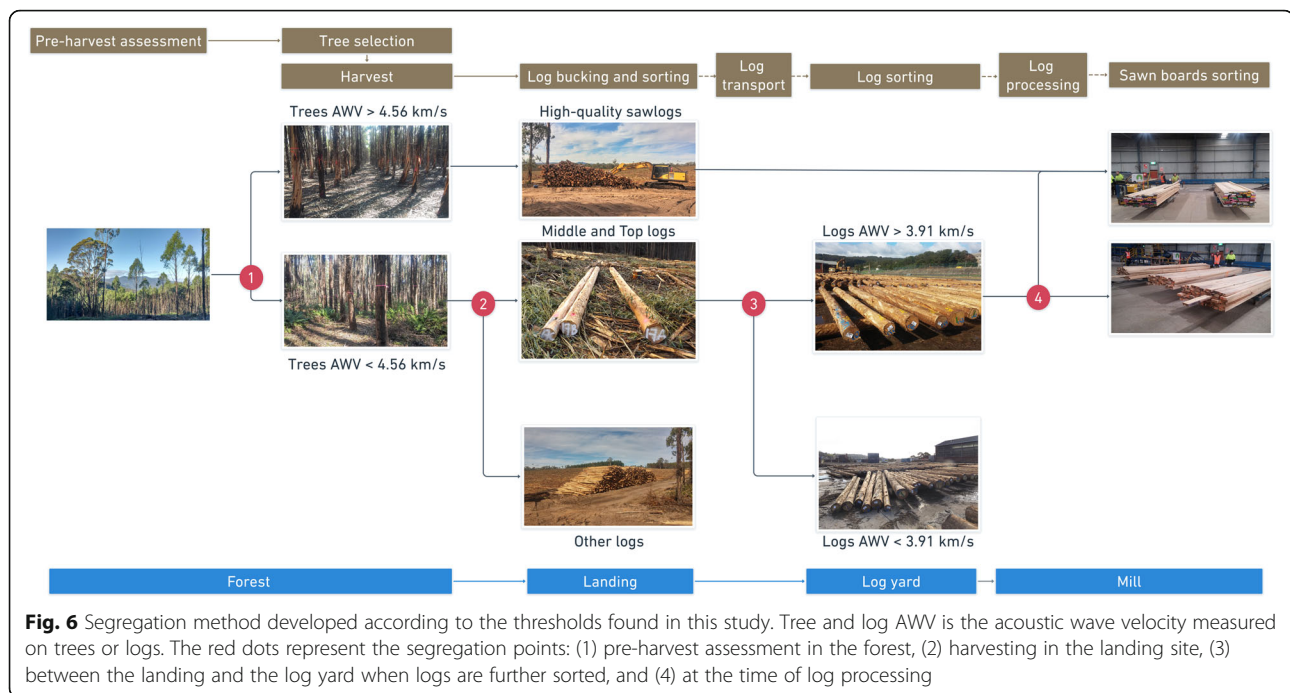
significant variables when classifying the population of boards into stiffness classes. This allowed for a clear and immediate understanding of the share in board grades after implementation of segregation through variable thresholds. To our knowledge, this is the first study using decision tree algorithms with clustered structure for timber material. These novel techniques can support forest growers and timber processors in understanding how much material of the desired quality would be achievable from their resource once the wood quality of trees and logs is known. We developed two different models, one which would better suit log processors and one for forest growers, and used those into different segregation scenarios, to understand the recovery in board grades for each segregation choice. Our approach can be employed for future large sawmilling trials involving a considerable number of sawn board samples. In this study, a limited number of trees was utilised, to maximise the number of sawn boards; however, the modelling methodology here presented could be scaled for larger samples.

In terms of optimal use of the resource which might satisfy different markets, we found that segregating for stiffness thresholds would yield both logs for woodchips and logs to be used for structural products. The model developed through classification for thresholds of  $AWV_{tree}$  and log position found that from trees with  $AWV$  of more than 4.56 km/s and logs from middle and top parts of the stem, larger recoveries of sawn timber of higher grades can be obtained. This model can lead to two different scenarios, namely, segregating only trees at the 4.56 km/s threshold (scenario D) or trees at this threshold, and then middle and top logs (scenario E). The first case achieves a large proportion of high-grade boards (81.4%), whilst being very restrictive on segregating only the best trees. This, however, leads to an overall low recovery of only 1.42 m<sup>3</sup> of sawn timber. In the second case (scenario E), more logs are accepted as sawlogs, yielding in total more sawn timber volume (2.65 m<sup>3</sup>) but an equal recovery of high-quality and low-quality boards. The model developed using only log variables found  $AWV_{log}$  to be the best classification variable, with a classification threshold of 3.91 km/s. Utilising this model, scenario F was developed, finding that whilst only a limited amount of logs was used as sawlogs (5.66 m<sup>3</sup>), almost 70% of boards are of high quality. These results hold considerable implications in the use of  $AWV$  as a sorting tool. With large percentages of sawn material being of the highest grades, the value recovered from these boards might compensate for the extra time that operators would need to test logs prior to milling. However, different segregation strategy models lead to scenarios which might largely differ in complexity, and the choice on the optimal segregation will be dependent on several factors.

Segregating logs will create both a physical and an operational challenge due to the increased amount of log sorts, which will require efforts from log harvesters and contractor companies to organise the sorting and to allocate space for different log stockpiles. Log transport will be of great impact, as different trucks will have to leave the harvesting site, directed to the processing facilities, and the structure of the supply chain will be a determinant factor in selecting how many log sorts can be created without disruption. At the processing facility, the number and type of logs will have to be handled, with processing costs increasing with the number of logs to be sawn and boards to be processed and stored. The timber resource market will be central in choosing one type of utilisation over another, considering that at times the market for structural products might be more demanding than the one for woodchips, and vice versa.

The large variation in board stiffness derived from the same tree and from the same log, as well as the increased complexity due to different segregation choices, proves that segregation might be more useful if considered as a multi-stage process (Fig. 6). If forest growers have the capability to implement wood quality testing to understand where trees of higher stiffness are located in their estates, plans for utilisation of the resource for different products can be developed far ahead of harvesting. Different plantations can be assigned to different uses according to their productivity, standing volume, and tree quality. In those areas where a mix of products (woodchips, sawlogs, and peeler logs) can be obtained, segregation might follow at the pre-harvesting assessment. During the pre-harvest assessment, the trees which will present larger volume and higher stiffness can be marked out for structural products (Segregation point n.1) (Wang 2013), and at harvest, the best trees would go directly into sawlogs, whilst logs from trees under the threshold would be further sorted (Segregation point n.2). During harvesting, the operators have the capability to perform a tree assessment according to the form of the stem, and before the cross-cutting, the harvesting machinery can optimise the cut according to the volume of timber available and the log sorts required. If tree selection is not feasible, this study has demonstrated that middle and top logs will deliver stiffer logs; hence, segregation can be applied for log position in the stem. Middle and top logs would be sorted as sawlogs, and bottom logs under the threshold would be destined for other uses (e.g. appearance products, veneers, fibre for pulp and paper). After this first sorting at the landing, a further segregation according to the stiffness of the logs might take place on the log yard (Segregation point n.3), where logs above the desired threshold would go directly to be processed for higher structural grades, and logs below the threshold can be processed





**Fig. 6** Segregation method developed according to the thresholds found in this study. Tree and log AWV is the acoustic wave velocity measured on trees or logs. The red dots represent the segregation points: (1) pre-harvest assessment in the forest, (2) harvesting in the landing site, (3) between the landing and the log yard when logs are further sorted, and (4) at the time of log processing

for lower grades or repurposed as other log types. The inner variability of wood properties in logs would need to be tackled with a further segregation on the sawing line (Segregation point n.4), to sort out boards of lower stiffness from those with higher values, thus improving the share of structural timber of higher grades. The segregation approach here presented might pose challenges due to the numerous stages of trees, log and timber testing, tracking, and sorting. For testing and sorting of logs and timber, separate production lines dedicated to different sorts could be employed. Other options include in-line wood quality testing before log sorting and after log breakdown, with individual sawn boards marked according to the appropriate stiffness class or timber grade.

To choose between the last three scenarios (D to F, segregation for stiffness), a detailed analysis of the recovery of the product is needed, after consideration of the operational constraints of increasing the amount of log sorts. When the market looks more favourable towards the production of woodchips, the choice can be made in selecting only the best material at the tree level, as presented in scenario D, where a large proportion of logs will be destined for fibre production and those streamed to sawn board production will deliver larger shares of higher board grades. In this case, the amount of logs to be sorted and transported is relatively low, as the segregation can be made by the harvester operator with as little as two stockpiles, one for woodchips and one for logs coming from high stiffness trees. The case presented in scenario E will render the segregation more complex, adding a step in selecting

only middle and top logs for trees of lower stiffness values, so increasing the number of log sorts and the number of logs to be sawn, delivering half boards of higher quality and half of lower quality. This scenario might be favoured when there are no specific requirements in terms of products from the market and the supply chain has been structured in a way to handle more log sorts. The last scenario (F) presents the case where a more straightforward selection can be applied. Operationally, log testing can be done at the harvest site, or through the use of specialised harvester heads (Walsh et al. 2014; Moore et al. 2016), and the creation of log stockpiles can ease the streaming of products to the best processing facility, where almost 70% of the material can be woodchips and out of the smaller number of log sawn almost 70% will satisfy higher grade requirements. This scenario will satisfy both forest growers, which would avoid tree selection and tree tracing, and log processors, which will have delivered smaller number of logs of quality high enough for recovery of the best grades.

## 5 Conclusions

The results of this study show that several tree and log variables are correlated with board stiffness, but only a limited number of these variables are useful for predicting final board grades. The classification trees developed for this study have found statistically relevant variables with which *E. nitens* trees and logs can be segregated to obtain sawn boards of desired stiffness and provide an understanding of the results that could be obtained

through different segregation procedures. We have shown that segregation can be applied according to trees or log variables and will influence operational choices and different recoveries of timber products. The optimal segregation strategy will depend on the number of log sorts that the supply chain can handle and from the market requirements; however, segregation on the basis of stiffness thresholds would in all cases yield larger recoveries of high-quality boards. The best case is represented by segregation at log level, where logs with acoustic wave velocity higher than 3.91 km/s are used as sawlogs, and the remaining material is used for wood-chips. This scenario may satisfy both forest growers interested in serving different markets and wood processors looking to achieve the best grades with minimal numbers of logs sawn. Other scenarios represent cases that can be chosen when there is more market flexibility towards more products or the opposite, higher demand for specific product types. The classification trees developed provide insights for forest growers and timber processors on the most important variables for structural products and appropriate thresholds, and the segregation methodology developed can serve as a support tool to understand when and how to segregate trees and logs to achieve the best recovery of high structural grades of sawn timber. This is the first work to analyse in-depth the process and consequences of segregation for eucalypt plantation resources, providing forest growers and timber processors with a greater understanding of the potential of their resource and with a scheme to operationally implement segregation strategies.

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#### Code availability

N/A

#### Authors' contributions

Conceptualization: M. Balasso, M. Hunt, A. Jacobs, and J. O'Reilly-Wapstra. Methodology: M. Balasso, M. Hunt, A. Jacobs, and J. O'Reilly-Wapstra. Investigation, formal analysis, data curation, validation, and visualisation: M. Balasso. Writing the original draft: M. Balasso. Writing, review, and editing: M. Balasso, M. Hunt, A. Jacobs, and J. O'Reilly-Wapstra. Supervision: M. Balasso and J. O'Reilly-Wapstra. Project administration: M. Balasso and J. O'Reilly-

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#### Availability of data and materials

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

#### Declarations

##### Ethics approval and consent to participate

N/A

##### Consent for publication

All authors gave their informed consent to this publication and its content.

##### Competing interests

The authors declare that they have no competing interests.

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