The prediction of the flexural lumber properties from standing South African-grown *Pinus patula* trees

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Abstract

Pinus patula is the most intensively planted conifer in the tropics and sub-tropics. The increased proportion of corewood that results when rotation ages of pine plantations are shortened has become a wood quality factor of growing concern worldwide. The purpose of this study was to develop empirically based models for predicting the flexural properties of the wood produced from relatively young *Pinus patula* trees. Models were based on the properties of standing trees and their effectiveness was evaluated at board, tree and compartment levels. Sample material was obtained from 170 *Pinus patula* trees, 16-20 years old, established in 17 compartments on the Mpumalanga escarpment of South Africa. Multiple regression models were developed which managed to explain 68%, 60% and 95% of the variation in the dynamic modulus of elasticity (MOE) on individual boards, trees and compartments levels respectively. At compartment level, 80% of the variation in the 5th percentile MOR value could be explained by the model. Sensitivity analyses showed that site index at base age of 10 years, acoustic time-of-flight, wood density and ring width were influential variables in the MOE models. The models indicated that tree slenderness during early growth seems to play a major role in determining the dynamic MOE and MOR of lumber. This is in agreement with Euler's buckling theory and the bending stress theory. The results from this study indicated that the MOE_{dyn} and MOR of lumber can be accurately predicted on especially a compartment level. The predictive models developed can be used as management tools to improve operational decisions around tree breeding, silvicultural practices and rotation ages.

Keywords: MOE, MOR, *Pinus patula,* modelling wood properties, site influence

1. Introduction

Planted forests are rapidly expanding on a global scale at about 5 million ha per year and currently account for about 7% of the total afforested area worldwide (FAO 2013). In 1980 there were 18 million ha of planted forests, compared to 187 million ha in 1990 and 264 million ha in 2012 (Carle et al 2002, FAO 2013). Carle and Holmgren (2008) estimated that in 2005, globally, about two thirds of the industrial timber originated from commercial plantations.

Pinus patula is the most intensively planted conifer in the tropics and sub-tropics. It is estimated that more than one million hectares are planted with this species; about half of that in Africa (Wright 1994). *Pinus patula* is also planted in the Andean countries of South America with potential to increase the area under this species in the high altitude areas in Brazil (Hodge and Dvorak 2012). In

South Africa it is the most important commercial plantation softwood resource with a total of 338 923 ha planted with *Pinus patula* trees (DAFF 2009). The Mpumalanga escarpment is the largest saw log growing area in South Africa with *Pinus patula* the main species being planted.

South Africa was one of the first countries to establish plantation forestry on a large scale, starting in the late nineteenth century. By 1960 the forestry area had increased to about 1 million ha (Owen and Van der Zel 2000). Due to a shortage of suitable land available for afforestation, as well as competition from agriculture and water catchment, the area under forest plantations in South Africa has since stabilised. To meet the country's growing needs for wood this resulted in increased emphases in the forestry and wood processing industries on higher volume production per unit area through improved silvicultural practices and genetic improvement, as well as improved wood product yield and quality.

However, the increased size of the corewood zone, and the bigger proportion of corewood that results when rotation ages are shortened to reap the financial benefits of the faster growth, has become a wood quality factor of growing concern worldwide (Zobel and Sprague 1998, Cown 2006, Malan 2010). Cown (2006) states that "researchers around the world have confirmed that aggressive silvicultural regimes have caused a significant reduction in mechanical properties" of plantation grown pines.

Studies in South Africa have shown sharp reductions in some of the mechanical properties of pine lumber processed from material harvested at a younger age, as trees reach merchantable size much earlier due to faster growth rates (Burdzik 2004, Dowse and Wessels 2013, Wessels et al 2011a). Studies by Dowse and Wessels (2013) have shown that the mean modulus of elasticity (MOE) of plantation-grown softwood lumber harvested before the age of 20 years can be more than 25% below the requirement of the lowest structural lumber grade in South Africa, which will have a significant effect on revenue. While the financial importance of increased volume production of plantations is undisputed, it is increasingly important that forest managers and researchers take into consideration the adverse effects of their actions on end-product quality.

More than 70% of the solid sawn lumber produced in SA is sold as structural or building timber (Crickmay and Associates 2011), a wood product category which has to comply to very strict strength and stiffness requirements   Given the challenges caused by an increasing proportion of juvenile wood in the timber resource, there is a growing need for non-destructive methods, capable of accurately predicting the mechanical properties of the lumber from standing trees.

Models to accurately predict mechanical properties can serve a useful role in managing the challenges of fast growing softwood plantations and shorter rotation ages. Tree-level predictions can assist tree breeders to screen and select for superior breeding material (Launay et al 2002, Lindström et al 2002, Ivković et al 2009), while at sawn board and compartment levels, predictions can be used to assist in decisions related to the allocation of trees to different processing facilities, especially where structural lumber is an option (Matheson et al 2002, Cown 2006, Wang et al 2007). Models can also be used to assist in processing production planning (Uusitalo 1997, Wessels et al 2006) and to study the effects of site and silviculture factors on the mechanical properties of wood (Wang et al 2000, Grabianowski et al 2004, Wang et al 2005).

The purpose of this study was to develop empirically based prediction models for the flexural lumber properties from standing *Pinus patula* selected from a number of diverse forestry sites on the Mpumalanga escarpment in South Africa. The intention was to evaluate various input variables in these models from data that could be obtained non-destructively from standing trees. This study is, to the authors' best knowledge, the first one of this nature performed on *Pinus patula* and the only one for any species where suitable compartment level models were developed to predict the MOE and MOR of lumber.

2. Background

Structural engineers and other designers of timber constructions use six different strengths and a stiffness value in the design of a structure. Since a piece of lumber can only be destructively tested in one strength mode, the question arises, which of the strength properties are the most important in terms of end-use requirements. In a study by Peterson and Wessels (2011) it has been found that bending strength or modulus of rupture (MOR) and stiffness or modulus of elasticity (MOE) were the two most important design properties for residential roof truss construction in South Africa. Since more than half of all South Africa's sawn lumber is utilized in roof constructions (pers. comm. Roy Southey, Sawmilling South Africa, Feb 2013), the most appropriate evaluation method for lumber destined for structural use will therefore be the bending test from which both the MOE and MOR can be derived.

The characteristic strength and stiffness values used in designing timber structures are determined by testing large numbers of full-sized structural grade lumber members – a process referred to as in-grade testing. In the past these properties have been determined on small defect-free wood specimens but it has been shown that the fracture behaviour in clear wood compared to defect-containing lumber is very different (Madsen 1992). Although clear-wood testing is more convenient with fewer sources of variation, it seldom gives a realistic indication of the strength and stiffness characteristics of full-sized, defect-containing lumber.

The MOE of wood is a well-researched topic and is known to depend on a number of basic wood properties. Evans and Ilic (2001) found that density alone accounted for 70% of the variation in the MOE of clear *Eucalyptus delegatensis* wood samples while microfibril angle alone accounted for 86%

of the variation indicating a combined effect, which accounted for 96% of variation in MOE. Megraw et al (1999) found that density and microfibril angle together explained 93% of variation of MOE in small clear wood samples of *Pinus taeda*. There is also a strong relationship between the acoustic velocity in the longitudinal direction and the microfibril angle of clear wood. Both Wang et al (2007) and Evans and Ilic (2001) reported a coefficient of determination (R^2) of 0.86 for *P. radiata*. For full sized specimens, which contained defects such as knots and reaction wood these relationships were much weaker. For instance, Dowse (2010) found that the density of full-sized *Pinus patula* lumber only explained 30% of the variation in MOE and when knot properties were added, the percentage increased to 36%. Acoustic or vibrational methods performed much better with full sized lumber. Pellerin and Ross (2002) reported a number of studies on various species where the MOE of boards could be predicted with a coefficient of determination of more than 90%.

Table 1. The range of coefficient of determination values between MOR and other lumber properties on individual boards from various studies (compiled from Johansson 2003, and Glos 2004).

Properties	**Coefficient of determination range (R^2)**
Density	0.16 – 0.40
Knot properties	0.15 – 0.35
Annual ring width	0.20 – 0.44
MOE	0.40 – 0.72
Acoustic or vibrational properties	0.30 – 0.55
Knots and density combined	0.38 – 0.60
MOE and knots combined	0.58 – 0.73
Acoustic, knots and density combined	0.55 – 0.80

The bending strength or MOR of lumber, as with MOE, depends on several wood properties. The results of a number of studies on full-sized lumber have been summarised based on results of Johansson (2003) and Glos (2004) in Table 1. From the fairly low R^2 values it is clear that MOR is a complex property that cannot be predicted easily. Although failures are almost always associated with grain distortion caused by knots, the measurable knot properties such as knot size and distribution did not explain variation in MOR very well. MOE has been found to be the best single property for explaining the variation in MOR. A combination of acoustic, density and knot properties explained up to 80% of the variation in MOR.

Many methods have been developed in the past to determine some of the properties listed above from standing trees using non-destructive methods. These methods have been extensively reviewed by Wessels et al (2011b).

An important aspect to keep in mind when trying to predict the mechanical properties of structural lumber is that the characteristic strength of a grade is determined by the 5th percentile strength value (Figure 1), in other words by results representing the weak portion of the strength distribution curve (Madsen 1992). It is therefore essential that any property and method used in a predictive study has to be an accurate predictor of the weak portion of the strength distribution curve. For stiffness, however, design codes often use the mean MOE values, necessitating predictions of the full stiffness distribution (i.e. SANS 10163-1 2003 and CSA O86-01 2001).

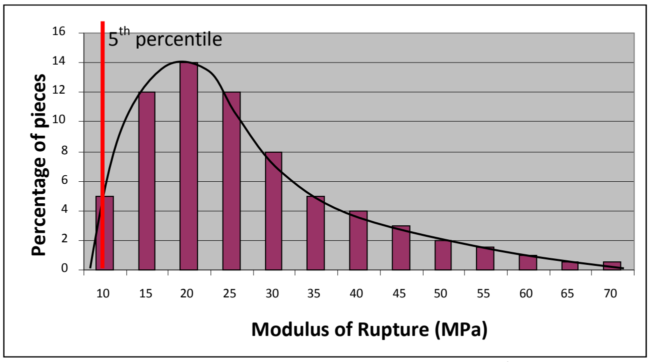

Fig. 1. A typical histogram of the MOR of lumber with the 5th percentile value indicated

In South Africa the mean age of pine plantations grown for sawlog production has reduced from 14.1 years in 1983 to 11.3 years in 2003 (Crickmay and Associates 2004). This suggests a reduction in mean harvesting age from about 28 years in 1983 to about 23 years in 2003 resulting in increased proportions of juvenile wood (or corewood) when harvested.

3. Materials and methods

3.1 Description of the study area and sample compartments

The study area is located along the Mpumalanga escarpment, South Africa, stretching from 23°48'S to 25°49'S and from 30°02'E to 30°59'E. The area is geologically complex with large variation in soil characteristics, altitude, precipitation and temperature. A total of 17 sample compartments were selected across the area. The sample compartments varied in age from 16 to 20 years, situated at altitudes varying from 810 m to 1930 m above sea level, mean annual precipitations varying from 840 mm to 1299 mm and mean annual temperatures which ranged from 13.7 °C to 19.4 °C. Site indices at base age 10 years (SI10) ranged from 9.6 to 19.6 (Table 2). The compartments received the normal commercial management treatments of weeding, thinning and pruning.

Table 2. General data for each sample compartment, the mean diameter at breast height (DBH) and the mean height of the ten sample trees.

Sample compartment	Plantation	Age (yrs)	Mean DBH (cm)	Mean height (m)	Site Index at age 10 (m)	Mean annual precipitation (mm)	Mean annual temperature (°C)
A (E66)	Nelshoogte	17	36	20.9	14.3	1061	16.0
B (E28a)	Nelshoogte	19	33.8	21.8	14.5	1036	16.1
C (G21)	Nelshoogte	16	26.2	18.4	15.5	1057	16.1
D (D1)	Uitsoek	17	32.7	22.3	15.7	944	17.4
E (D88)	Uitsoek	17	30.2	18.4	15.3	942	17.3
F (E55a)	Uitsoek	20	32.3	20.1	14.6	1151	13.7
G (E36c)	Uitsoek	19	31.9	23.0	16.8	902	14.0
H (E22)	Uitsoek	17	27.6	20.8	16.5	840	14.2
I (E5)	Berlin	19	36.5	23.8	16.7	1284	16.1
J (E15)	Berlin	19	37.4	23.8	17.6	1082	15.9
K (E35)	Berlin	16	29.1	18.0	16.5	1006	17.2
L (C22)	Blyde	20	34	27.0	18.5	1156	16.1
M (E3)	Morgenzon	17	31.4	20.6	13.5	1015	14.3
N (D74)	Morgenzon	19	26.9	16.4	9.6	997	16.2
O (A1a)	Morgenzon	16	27.8	19.0	13.6	862	15.1
P (D11)	Wilgeboom	18	29.4	22.8	19.6	1242	19.4
R (J20)	Wilgeboom	19	33.4	24.0	16.8	1299	18.5
Mean		**18**	**31.6**	**21.2**	**15.6**	**1052**	**16.1**

The work described in this paper is one of several studies performed on the same experimental material. Previous studies include those reported by Louw and Scholes (2002, 2003 and 2006) on the influence of site factors on nitrogen mineralization in forest soils of the Mpumalanga escarpment area, the development of a method to predict the knotty defect core (Munalula 2010) and a study which evaluated the structural grading parameters for this particular resource (Dowse and Wessels 2013). Some results from the mentioned studies were used as inputs in the research described in this paper. A comprehensive description of the environmental variables, geology, soil and productivity of the sites can be viewed in Louw and Scholes (2002, 2003 and 2006).

A total of 126 environmental, soil, leaf nutrient analysis, and productivity variables were measured or calculated for each compartment. These variables were also considered for the development of predictive models described in this study. For brevity's sake only variables that were found to contribute significantly to the models are described in the Results section.

3.2 Tree measurements

In each of the 17 sample compartments, a stratified sampling procedure based on tree diameter was followed so that the sample trees represented the productive timber volume available from each compartment. One tree was randomly selected in each compartment from the first quartile (small diameter), two trees from the second quartile, three trees from the third quartile and four trees from the fourth quartile (large diameters), giving a total of ten sample trees per plot, thus 170 trees for the entire investigation.

The Fakopp TreeSonic® microsecond timer was used to calculate the speed of an acoustic longitudinal stress wave at breast height of each of the standing sample trees. This device measured the time-of-flight of a stress wave induced by a hammer tap between two probes, hammered into the outer 10 to 15 mm of the stem one meter apart around breast height. Sound velocity is often used in studies as an indirect indicator of the stiffness of the outer wood in trees. The use of acoustic technology in wood studies has been extensively reviewed by Wang and Ross (2002) and Wang (2013).

After felling, the height of each tree and the height to the first branch whorl were measured. As all trees had been pruned, branches generally only started at a height of 7m above ground. The number of branch whorls, maximum branch diameter and the branch angle of one randomly selected branch were measured for every two-meter section of the trunk up to a height of 19 meters (Figure 2).

A disc was removed from the stem at the breast height location and later used to perform ring width measurements on the cross-section in order to determine the annual growth rate of each tree. Available pruning records were used to determine the maximum knotty or defect core size of all the logs originating from the pruned section of each tree (Figure 2). For comparative purposes the maximum defect core size of each log was expressed as a percentage of the log diameter.

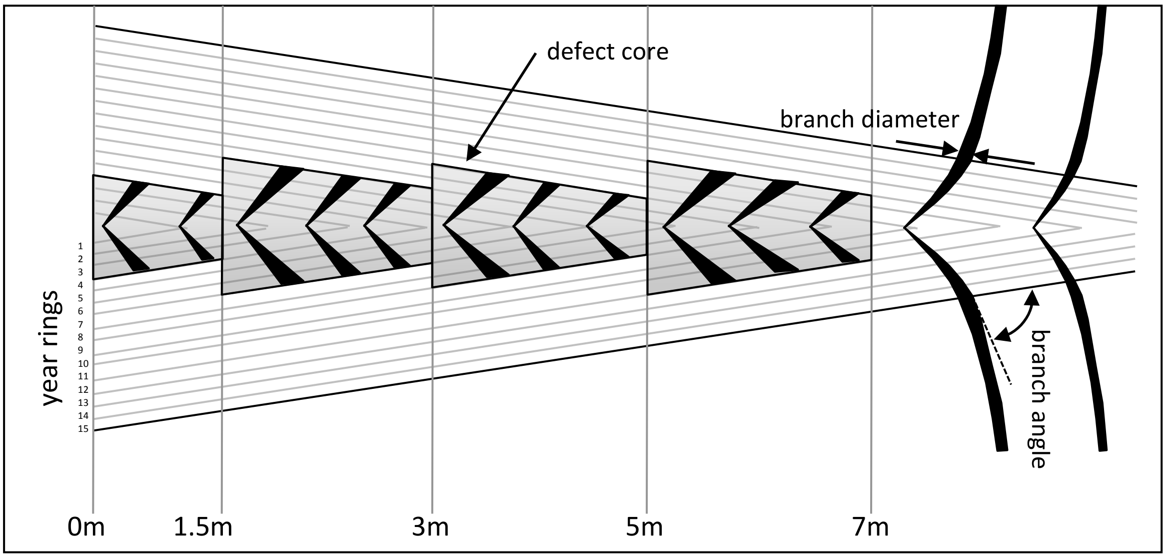

Fig. 2. Defect core reconstruction using ring width data and pruning records. Branch properties measured are also shown (adapted from Munalula 2010).

Two 2.1m long logs were removed from each tree; one from the pruned section of the stem at 2.3m height and one from the unpruned section at 7m height (Figure 3), which yielded 340 sawlogs.

3.3 Board measurements

The logs were processed at a local sawmill into boards of cross-sectional dimensions of 40 x 120 mm, using frame-saws and a cant sawing pattern (Figure 3). Only boards processed from the cant were used for this study since these boards represented the full diameter of each log. As the secondary breakdown saw was fitted with a curve-sawing device, the grain direction of the boards was predominantly parallel to the longitudinal axis of the log. A total of 1402 boards were produced. The boards were kiln dried to a target moisture content of 12% using a medium temperature schedule.

Boards were numbered based on their position from the pith. Boards containing pith tissue were marked 0, the two boards on the outer side of the pith boards were numbered 1, the next two boards were numbered 2, and so on. Sometimes there was only one pith-containing board in a log and sometimes two pith-containing boards (Figure 3).

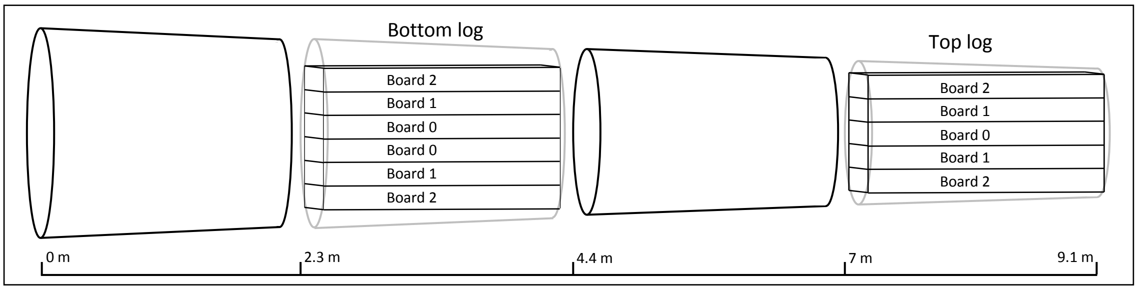

Fig. 3. Position of logs and the numbering of boards processed from the cants.

After drying board densities were calculated from the mass and dimensional data of each board and corrected for moisture content when necessary. Moisture content was measured with a resistance moisture meter.

The ends of the boards were sanded to improve the visibility of the annual rings. The number of annual rings on each board was counted and numbered from the pith outwards. This data was used to estimate the cambial ages (mean, maximum and minimum) of the wood which comprised each board. The cambial age was based on ring counts from the pith.

Ring widths were measured perpendicularly to the growth ring boundaries from the pith to the bark, using a digital calliper. Measurements were rounded to the nearest 0.1 mm. For each board the minimum, maximum and mean ring widths were calculated.

The acoustic resonance frequency of each board was measured using the A-Grader Portable software from Falcon Engineering. The dynamic MOE was determined from the frequency and the density using the following relationship:

$MOE_{dyn} = \rho \cdot (2 \cdot l \cdot f)^2$ ……………………………………………………………………………………………….Equation 1

where:

MOE_{dyn}	=	Dynamic modulus of elasticity (MPa),
P	=	Density (kg/m^3),
l	=	Length of the test specimen (m),
f	=	Frequency of the test specimen (Hz).

The sample material was divided into two groups based on board position and a random allocation function. The random function was used to allocate the boards from the same position in a log (i.e. the two number 1 boards) into the two different groups. One group was tested in bending and the other in tension. Tension test results will not be discussed in this paper as most boards failed at the grips which might cause unreliable results. A total of 57 boards had to be discarded due to breakages which occurred during processing as well as due to numbering errors, which reduced the number of boards available for destructive strength testing to 1345.

Bending tests were performed in compliance with South African Bureau of Standards specification SANS 6122 (2008). Of the 699 boards that were subjected to bending tests 674 yielded useful results. Sixteen could not be tested successfully due to excessive warp, while the test results of nine boards had to be discarded due to numbering errors. The MOR and MOE for each board were calculated from the bending tests. The stiffness calculated from this test is referred to as the MOE_{static} as opposed to MOE_{dyn}, which was determined from acoustic measurements.

MOE_{dyn} was taken as the dependent variable in developing predictive models for wood stiffness rather than the static MOE_{static}. MOE_{dyn} was expected to give a better measure of the mean stiffness of a piece of lumber as it reflects the stiffness of the entire board mass, whereas MOE_{static} at best gives a measurement of the local stiffness of the material at the highly stressed areas of a specific test setup. Contrary to $MOE_{static,}$, which was determined on a sub-sample of boards, MOE_{dyn} assessments were performed on all available boards, which made it possible to study the extent and patterns of variation in stiffness among logs, trees and compartments in far more detail.

It should be noted that a number of properties were measured on both boards and/or from discs from the trees. In this study it was deemed preferable to remove the log processing step as a source of error and rather use, where possible, measurements conducted on the boards. For instance, tree ring widths were measured on both discs from trees and on the individual boards after sawmill processing. In this case the tree ring widths measured on the boards were used in developing predictive models. By using measurables from boards, inaccuracies in relating tree properties at specific positions to board properties are avoided.

Although variables such as density and ring width were measured on boards, in practice to obtain these measurements non-destructively from standing trees, increment cores will have to be used.

3.4 Statistical analysis

Three different sample levels were used in this study viz. individual boards (n=1345), trees (n=170), and compartments (n=17). Some variables were measured on boards, some on trees and some for compartments. Where variables were measured on individual boards, the mean value of a specific variable for all the boards from a tree was used as the tree-level value. Similarly, the mean value of a variable for all the trees in a compartment was used as the compartment-level value.

To gain an overview about relations, Pearson correlations were performed between all 143 variables. Most of the variables considered were environmental, soil, leaf nutrient analysis, and productivity variables as described in Louw and Scholes (2002, 2003, and 2006). To reduce the number of variables to consider in the multiple regression analysis, a factor analysis was performed and together with the results of the correlation analysis, some variables were removed from the dataset used in the regression analysis. Multiple regression analysis was performed using the best subsets in Statistica (Statsoft 2013) to develop predictive models. Mallow's Cp value was used as the criterion for choosing the best subset of predictor effects. This measure of the quality of fit addresses the issue of overfitting. It tends to be less dependent than the R^2 value on the number of effects in the model, and hence, it tends to find the best subset that includes only the important predictors of the respective dependent variable and thus helps establishing parsimonious models. Ordinary multiple regression was preferred above other methods such as mixed models due to the techniques available to select independent variables from a large number of possibilities. Predictive models were developed for the MOE_{dyn} and MOR of individual boards, trees and compartments. For individual boards the MOE_{dyn} and MOR were used as dependent variables. For trees the mean MOE_{dyn} and mean MOR value of the boards from a tree were used as the dependent variables. For compartments the mean MOE_{dyn} and the 5th percentile MOR value (MOR_{5perc}) of the boards from a compartment were used as the dependent variables.

Sensitivity analyses were performed on the models to determine the influence of varying independent variables, one at a time, on the dependent variables (Pannel, 1997).

4. Results

4.1 Correlation analyses

The variables that appear in the correlation matrix and in some of the predictive models developed (see section 4.2) can be seen in Table 3.

Results of Pearson correlation analyses for selected variables are shown in Table 4. Only variables which entered the regression models were included in the table. Correlation coefficients with regard to all three sampling levels, where applicable, are presented in each cell. The values in the first row are the correlation coefficients where boards were the statistical (experimental) unit, the correlation coefficients in the second row are based on tree values and those in the last row are based on compartments. For variables measured at the board level, the mean value for all the boards from a tree was used for tree-level correlations and models. Similarly, for variables measured at the tree level, the mean value for all the trees from a compartment was used for compartment-level correlations and models.

4.2 Predictive models for MOE_{dyn} and MOR

Multiple regression models were developed to predict the MOE_{dyn} and MOR for individual boards, trees and compartments. The number of input variables was very large (143 variables) and by inspecting the Pearson correlation coefficients and doing a factor analysis, variables which were considered less influential were excluded from the regression analyses.

Table 3. Measured and derived variables used in predictive models.

Level	Variable	Unit	Description
Board	MOE_{dyn}	MPa	the dynamic modulus of elasticity for a board
	MOR	MPa	the modulus of rupture for a board
	LogPos	m	the midpoint log height in the tree from which a board was processed
	BoardPos		the radial position of a board with 0 being a pith board (see Figure 3)
	RingWidth	mm	the mean tree ring width in a board
	Density	kg/m^3	the density of a board at 12% moisture content
Tree	*DBH*	cm	the diameter at 1.3m height of a tree
	TOF	µs	the acoustic Fakopp time-of-flight reading for a tree between two probes 1m apart
	BranchDia	mm	the maximum branch diameter in the bottom two meters of the unpruned section of the stem of a tree
	BranchAngle	degrees	the angle between the branch and stem of a randomly selected branch in the bottom two meters of the unpruned section of the stem of a tree
	BranchSpacing		the number of branch whorls in the bottom two meters of the unpruned part of the stem of a tree
	DefCor		the ratio of the maximum defect core diameter to log diameter for a tree
Compartment	MOR_{5perc}	MPa	the 5^{th} percentile MOR value for all boards from a compartment
	Topheight	m	the mean height of the four largest diameter trees sampled per compartment
	Age	years	the age of trees in a compartment
	SI10	m	the site index or dominant height at index age 10 of a compartment
	MAP	mm	the mean annual precipitation for a compartment
	MayP	mm	the mean precipitation during May for a compartment
	MAT	degrees C	the mean annual temperature for a compartment
	JulMinT	degrees C	the minimum temperature during July for a compartment
	NK		the ratio of N:K for a compartment determined from a leaf analysis 8 years prior to felling for this study

Table 4. Pearson correlation coefficients between selected board, tree, and compartment variables. The top value in each cell is the board correlation value, the second value tree correlations, and the bottom value compartment correlations. Statistically significant correlations at 0.1, 0.05 and 0.01 probability levels are indicated by the symbols *, ** and *** respectively.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. MOE$_{dyn}$	1 1 1																	
2. MOR	,76*** ,68*** ,89***	1 1 1																
3. MOR$_{5perc}$ (comp)	,74***	,77***	1															
4. LogPos (board)	,13***	,21***		1														
5. BoardPos (board)	,55***	,37***		,13***	1													
6. RingWidth	-,62*** -,42*** -,71***	-,43*** -,39*** -,57**	-,70***		-,47***	1 1 1												
7. Density	,67*** ,65*** ,87***	,48*** ,36*** ,80***	,55**	,14***	,30***	-,46*** -,40*** -,56**	1 1 1											
8. Topheight		 ,16*		-,06*	,08**	,11*** ,23*** ,52**	-,09***	1 1 1										
9. Age	,11*** ,24***	,11** ,28***			,10***		,09***	,59*** ,52*** ,54**	1 1 1									
10. SI10		,13***				,08**		,70***	,22***	1								

		,24***				,17*		,72*** ,71***	,15*	1 1								
11. DBH		-,08* -,16*			,30***	,23*** ,49*** ,49**	-,09*** -,15*	,35*** ,32*** ,62***	,29*** ,21** ,45*	,19*** ,20**	1 1 1							
12. TOF	-,18*** -,32*** -,52**	-,20*** -,24*** -,49**					-,19*** -,27*** -,45*	-,19*** -,22** -,47*	-,12***	-,16*** -,19**	,28*** ,30***	1 1 1						
13. BranchSpacing						-,08*** -,17** -,51**		-,40*** -,40*** -,76***	-,16***	-,32*** -,31*** -,54**	-,21*** -,19** -,43*		1 1 1					
14. BranchDia	-,09*** -,19**	-,18*** -,38***			,09***			-,23*** -,25*** -,47*	-,14*** -,16*	-,23*** -,23*** -,43*	,24*** ,24***	,20*** ,22*** ,45*	,06* ,42*	1 1 1				
15. BranchAngle	,06* ,14*				,07**		,11*** ,15*	,18*** ,17** ,46*	,25*** ,24*** ,48**		,21*** ,23***	-,16***		-,25*** -,23*** -,63***	1 1 1			
16. DefCor	-,07**				-,12***	-,08**		-,22*** -,18**	-,19*** -,15*	,06*	-,37*** -,31***	-,11***	,30*** ,34*** ,46*	-,11***		1 1 1		
17. MAP	,14*** ,28***	,16*** ,27***			,08**		,22*** ,28***	,43*** ,41***	,53*** ,52***	,41*** ,40***	,31*** ,26***	-,17*** -,15*	-,22*** -,21**		,06*	-,49*** -	1 1	

	,49**	,55**					,63***	,41*	,52**		,46*					,47*** -,47*	1	
18. MayP	,15*** ,30*** ,53**	,17*** ,28*** ,56**			,07**		,23*** ,30*** ,61***	,41*** ,38***	,56*** ,56*** ,58**	,38*** ,35***	,23*** ,18**	-,19*** -,17**	-,26*** -,25*** -,42*			-,51*** -,49*** -,50**	,95*** ,94*** ,95***	1 1 1
19. MAT		,08*				,12*** ,23***	,09***	,09***	-,07**	,38*** ,34***		-,23*** -,26*** -,45*		,09***	-,18*** -,18**	-,09***	,50*** ,49*** ,47*	,42*** ,40***
20. JulMinT	,06*	,09**				,11*** ,19**	,12*** ,15*		-,1***	,29*** ,24***		-,19*** -,18**	-,06*			-,20*** -,19**	,57*** ,55*** ,55**	,43*** ,40*** ,42*
21. NK	,19*** ,30*** ,62***	,14*** ,23*** ,45*	,57**			-,20*** -,42*** -,79***	,20*** ,26***	-,38*** -,45***	,336*** ,351***	-,36*** -,45*** -,42*	-,14*** -,17**		,21*** ,25*** ,42*	-,14***	,18*** ,16*	,19*** ,20**		,06*

As mentioned previously, the 5th percentile MOR value of a board grade is used in the design of structures. Since there were not enough boards from individual trees to determine a 5th percentile value the mean MOR value for each tree was used instead. Trees that yielded fewer than 5 boards in total, or fewer than 2 boards per log suitable for testing, were discarded. As a result the data of only 142 trees out of 170 trees could be considered for the tree level analysis.

For each compartment the mean MOE_{dyn} values for all the boards from that compartment were calculated and used as the dependent variable in the predictive model. The 5th percentile MOR value of all the boards from a compartment was used as the other dependent variable (MOR_{5perc}). Due to the limited number of compartments (n=17) a maximum of five independent variables were allowed for the compartment level models to avoid over-parameterisation.

The coefficient of determination (R^2) and the parameters for the models developed are presented in Table 5. Figures 4 to 7 show the predicted vs. observed values for the MOE_{dyn} and MOR_{5perc} models.

4.3 Sensitivity analyses

Table 6 shows the results of sensitivity analyses performed on the models developed for MOE_{dyn} and *MOR*. For the board and tree-level models each independent variable in the models was varied from the 5th percentile observed value to the 95th percentile observed value. For the compartment-level models the independent variables were varied from the minimum value to the maximum value. The effect of these changes on the dependent variable was expressed as the independent variable's influence (%). The influence is the relative effect that the change in the individual variable has, compared to the total range in MOE_{dyn} and *MOR* values. For example, when *RingWidth* in the board level MOE_{dyn} model was changed from the 5th percentile observed value to the 95th percentile

Table 5. Parameters and coefficients of determination (R^2) of the predictive models developed for MOE_{dyn} and MOR on individual board, tree and compartment levels. All models were significant at the 0.001 probability level. Parameters marked with *, **, *** were significant at the 0.1, 0.05 and 0.001 probability levels, respectively.

	Board		**Tree**		**Compartment**	
	MOE_{dyn}	***MOR***	***MOE_{dyn}***	***MOR***	***MOE_{dyn}***	***MOR_{5perc}***
Coefficient of determination (R^2)	0.682	0.402	0.600	0.421	0.952	0.798
Parameters:						
Intercept	1870.6	5.08	-290.9	8.16	6296.0*	
LogPos		0.72***				
BoardPos	803.4***	2.83***				
RingWidth	-152.4***	-0.69***	-90.2**	-1.04**	-315.4***	-1.69***
Density	24.4***	0.08***	21.4***	0.05**	18.2***	
SI10	145.3***	1.89***	150.3***	1.03***	43.2*	0.64**
TOF	-11.5***	-0.07**	-11.0**		-18.3**	
BranchDia	-12.6***	-0.13***	-11.5**	0.15***		
BranchAngle	-15.1***					0.28***
BranchSpacing						0.90**
DefCor	-2679.5***	-13.26**	-3544.7***	-9.09**		
MayP	-104.8***	-0.49**	-91.5**			
MAT	77.0**		282.2**			
JulMinT			-249.5**			
NK	734.2***		895.1***	2.98**		
Topheight (m)		-1.34***				
Age (years)		1.66**			81.2**	

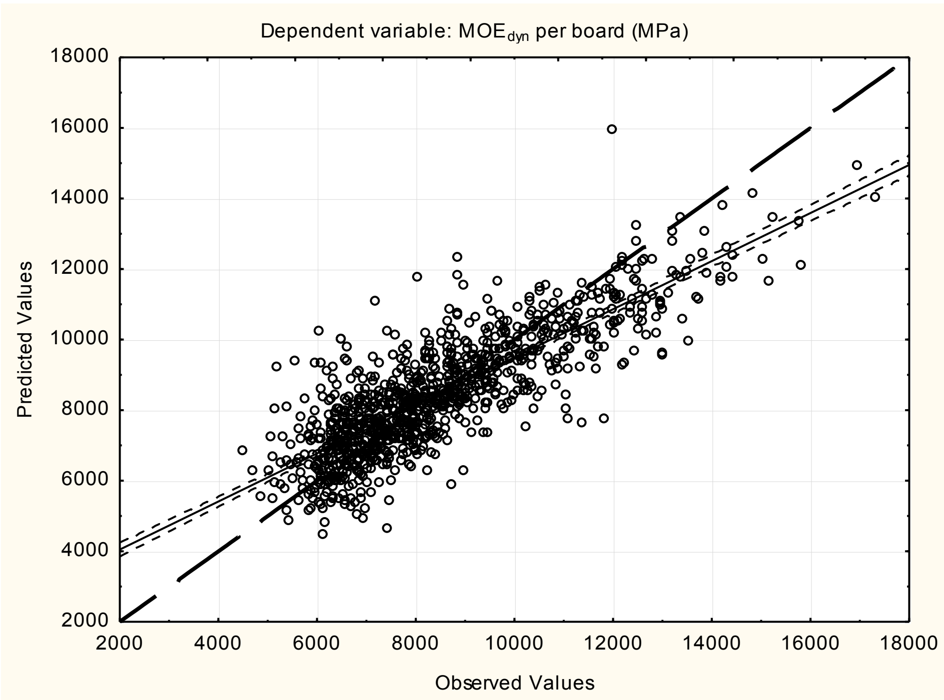

Fig. 4. The predicted vs. observed values for the board-level MOE_{dyn}. The model, 95% confidence limits and 1:1 relationship are indicated (see model parameters in Table 5).

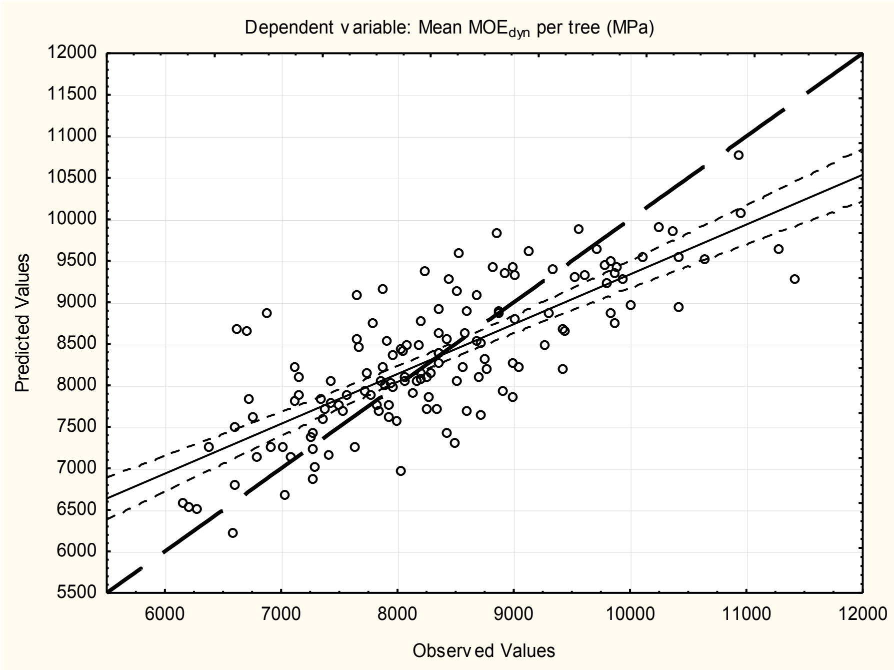

Fig. 5. The predicted vs. observed values for the tree-level MOE_{dyn}. The model, 95% confidence limits and 1:1 relationship are indicated (see model parameters in Table 5).

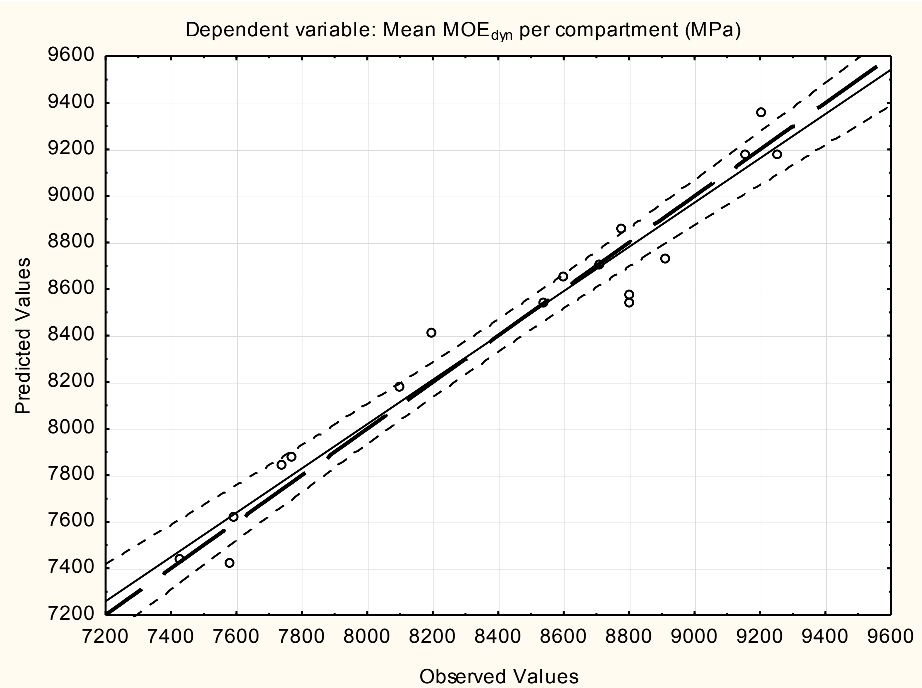

Fig. 6. The predicted vs. observed values for the compartment-level MOE_{dyn}. The model, 95% confidence limits and 1:1 relationship are indicated (see model parameters in Table 5).

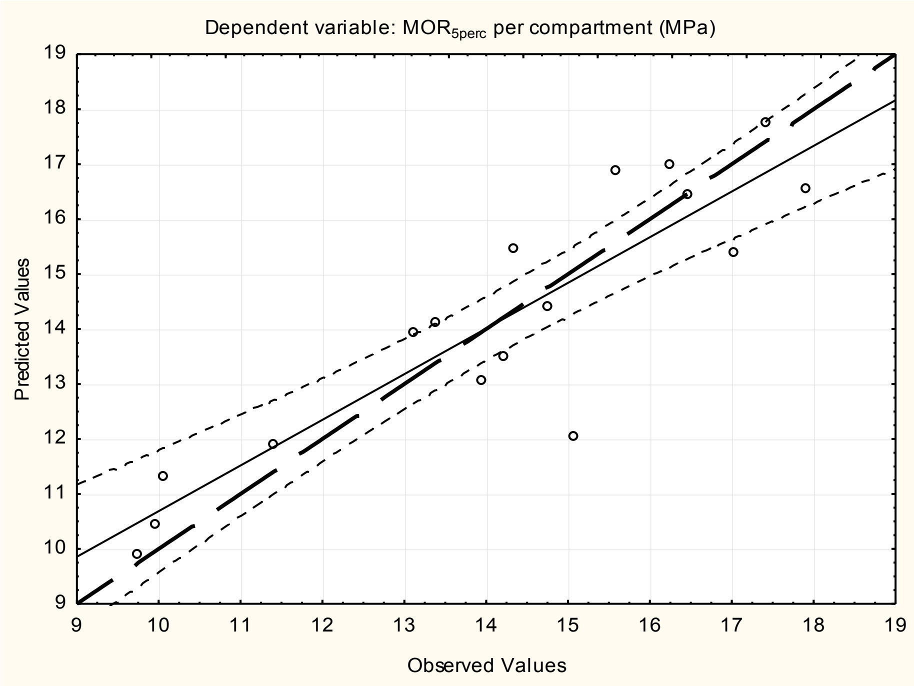

Fig. 7. The predicted vs. observed values for the compartment-level MOR_{5perc}. The model, 95% confidence limits and 1:1 relationship are indicated (see model parameters in Table 5).

Table 6. Results of sensitivity analyses on the predictive models from Table 5. Independent variables of tree and board level models were changed from the 5^{th} to the 95^{th} percentile observed value and for compartment-level models it was changed from the minimum to maximum observed values. The influence (%) is the relative effect that the change in the individual variable has compared to the range in MOE_{dyn} and MOR.

Independent variables	**Influence (%)**					
	Board		**Tree**		**Compartment**	
	MOE$_{dyn}$	***MOR***	***MOE$_{dyn}$***	***MOR***	***MOE$_{dyn}$***	***MOR$_{5perc}$***
LogPos		4.3%				
BoardPos	12.4%	7.1%				
RingWidth	13.7%	10.2%	4.5%	20.2%	32.2%	28.2%
Density	22.0%	12.2%	15.0%	14.5%	30.0%	
SI10	6.8%	14.5%	12.3%	32.7%	12.5%	30.6%
TOF	4.4%	4.6%	4.6%		15.9%	
BranchDia	4.2%	7.1%	4.1%	21.5%		
BranchAngle	4.1%					20.2%
BranchSpacing						20.9%
DefCor	8.6%	7.0%	12.3%	12.2%		
MayP	8.7%	6.6%	8.0%			
MAT	3.4%		13.0%			
JulMinT			11.2%			
NK	11.7%		14.8%	19.1%		
Topheight		18.1%				
Age		8.4%			9.4%	

observed value, and all the other parameters were kept constant at their mean observed values, the change in MOE_{dyn} was 13.7% of the total change in MOE_{dyn} possible (Table 6).

5. Discussion

The predictive models developed for MOE_{dyn} had moderate coefficients of determination at sawn board as well as tree level (R^2 = 0.682 and R^2 =0.600 respectively, see Table 5) but a high coefficient of determination at compartment level (R^2 =0.952). Compared to other studies where the modulus of elasticity of lumber at board-level was predicted from standing trees, the R^2–value found in this study was relatively high. For instance, Ikeda and Arima (2000) found an R^2-value of 0.410 in the case of mature Sugi trees, Wagner et al (2003) and Chestnut (2009) found R^2-values of 0.591 and 0.174 respectively in studies on Douglas fir trees and Bier (1985) found an R^2-value of 0.480 on radiata pine trees (all these were board-level predictions).

Tree-level models for predicting MOE and MOR developed by Liu et al (2007) for 90-100 year-old black spruce trees, using both stand and tree characteristics as inputs, showed R^2-values of 0.65 and 0.68 for MOE and MOR respectively. Huang (2000) developed a tree-level model for loblolly pine and obtained an R^2-value of 0.51 and Launay et al (2000) found an R^2-value of 0.29 for Douglas fir and larch trees. Most of the studies on lumber did not consider the MOR of the lumber. Bier (1985) obtained R^2-values of between 0.30 and 0.37 predicting the mean and minimum MOR of lumber from *P. radiata* trees. The authors are not aware of studies where MOE or MOR models for lumber were developed at a compartment level.

The high coefficient of determination for the compartment level model for MOE_{dyn} (R^2 = 0.952) was surprising when compared to the board- and tree level models of this and other studies, where the R^2-values were generally lower than 0.7. As this was the first compartment level study of this type of which we are aware of, we cannot compare it with other results. The high R^2-value was probably due to the within-tree and within-compartment variability in properties that get averaged for all the boards from a compartment. Similarly, individual processing decisions which influenced, for instance, the position of knots within a board will also largely be cancelled at a compartment level due to this averaging effect.

Although a significant correlation exists for both the board and tree level MOE_{dyn} regression models, it deviates substantially from the 1:1 relationship (Figures 4 and 5). This is an indication of a strong tendency to over-predict and under-predict at low and high MOE_{dyn} values respectively.

In the multiple regression models for MOE_{dyn}, the independent variables *Density*, *RingWidth*, *SI10*, and *TOF* appear in the models at all three sampling levels (Table 5). *Density* was the best single independent variable for predicting MOE_{dyn} with a Pearson correlation of r = 0.67 for boards, r = 0.65 for trees and r = 0.87 for compartments (Table 4). For boards, the correlation value corresponds roughly to those found in various structural grading studies reviewed extensively by Johansson (2003). The sensitivity analysis of the MOE_{dyn} models showed that *Density* was the most influential parameter at board -and tree level and the second most influential at the compartment level (Table 6).

Density has long been considered as one of the most important wood properties, if not the most important, in terms of its effect on the quality of solid wood products. For instance, in their extensive review Zobel and Van Buijtenen (1989) concluded “therefore, specific gravity largely determines the value and utility of wood and overshadows the importance of other wood properties”. This view has later been challenged by many authors i.e. Cherry et al (2008) who questioned whether tree breeders should select solely for wood density because (i) the time-of-flight or acoustic velocity is a better predictor of stiffness than density, (ii) wood density has a negative correlation with growth, and (iii) density is expensive to measure on increment cores. Cave and Walker (1994) argued that only microfibril angle, and not density, can explain the large increase of stiffness over the first 30 years of growth of fast-grown plantation softwoods. Since microfibril angle was not measured in this study it was not possible to assess its influence on wood stiffness (or MOE) relative to that of density.

In the case of all three model levels, acoustic assessments (*TOF*) carried out on the outerwood of the standing trees were much less influential than *Density*. This is largely due to the fact that velocity assessments on standing trees only serve as a measure of the outerwood stiffness of the tree stem. The lesser influence of *TOF* was confirmed by the results of the sensitivity analyses on the MOE_{dyn} models, which showed that the influence of *TOF* was very small at the board and tree level (<5%) and only moderately influential at compartment level (Table 6).

RingWidth showed an inverse relationship with MOE_{dyn} with correlations of -0.62 at board level, -0.42 at tree level and -0.71 at compartment level (Table 4), suggesting that MOE_{dyn} decreases with increasing growth rate. At compartment level *RingWidth* was the most influential variable (Table 6), followed by *Density*. At tree level the influence of *RingWidth* in the model was noticeably lower. As with *Density, RingWidth* can be measured on increment cores from standing trees. It is correlated to the *DBH* of trees, although it was slightly surprising to see the moderate to low correlation of 0.49 between *RingWidth* and *DBH* at a tree level. The sum of all tree ring widths at a particular height level in a stem will in fact be the underbark radius of the stem at that point. The poor correlation might be due to the fact that some tree rings occur in up to three boards from a log while others, such as the outer rings, might not be present in any of the boards. *RingWidth* will thus be biased towards the younger year rings present in several boards. Other causes for the weak correlation might include the fact that the compartments were of slightly different ages and also that boards were recovered from logs from two different heights in a tree.

There were moderate and significant negative correlations between *Density* and *RingWidth* at all three levels (Table 4). In conifers large ring widths are often associated with smaller latewood percentage and subsequently a lower density (Seifert et al 2006). However, since *RingWidth* and *Density* both appear in the models it clearly suggests that the effect of ring width on MOE_{dyn} is not purely due to its effect on density. It also needs to be emphasized that smaller ring widths ensure that older, more mature rings will be present in boards cut at or close to the pith. For example, if you have two pith-boards of the same dimensions, one containing wide year rings from ring 0 (pith) to ring 3 and another containing narrow year rings from ring 0 to ring 10, it is obvious that the second board will in most cases have better mechanical properties simply due to the higher age of the rings present in that board. The ring width was also related to tree shape, which may affect mechanical properties. The role of tree shape is discussed later.

The site index at year 10 (*SI10*) consistently appears as a variable in all the models for both MOE_{dyn} and MOR. This suggests an indirect effect of tree height on MOE and MOR, which can be explained in terms of the resistance of trees to buckling and bending failure, as illustrated in Figure 8.

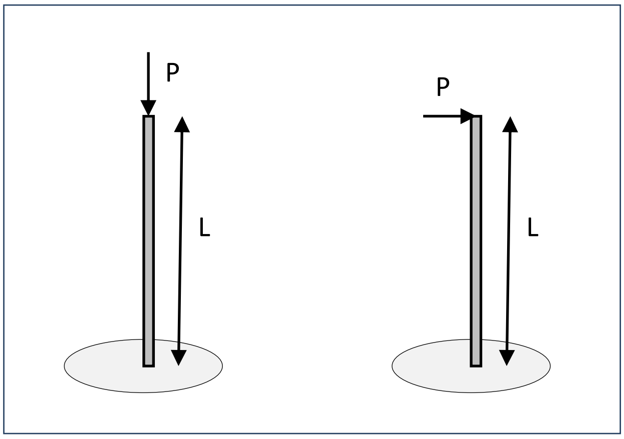

Fig. 8. Basic models for a tree loaded by self-weight (left) and wind-load (right).

A tree loaded by its own mass behaves in a similar way as a rod, fixed at one end, under compressive loading (Figure 8). Using the Euler formula for buckling of a rod fixed at one end, the MOE required to withstand buckling failure yields Equation 2 (derived from Euler formula, Hibbeler, 2005):

$MOE = (16L^2P)/(\pi^3r^4)$……………………………………………………………………………………………….Equation 2

where L is the length of the rod (m), P is the compressive load on the rod (N), and r is the radius of the rod (m).

A tree under wind loading can be modelled as a cantilevered rod subjected to a point load (Figure 8). Basic statics theory using the bending stress formula shows that the rod requires the following bending strength or MOR to avoid a bending failure (derived from bending stress formula, Hibbeler, 2005):

$MOR = (4PL)/(\pi r^3)$……………………………………………………………………………..Equation 3

From the Euler formula it is clear that the ratio L^2/r^4 determines the MOE required for buckling resistance. The bending stress formula shows that the L/r^3-ratio determines the MOR required to withstand wind load. Trees with a high slenderness (i.e. trees that are tall in relation to their diameter) therefore require wood that's higher in MOE and MOR in order to increase their resistance to buckling under its own weight or breakage due to excessive wind loads. The radius or diameter, which is to the power four and three respectively in the two formulas, is also relatively more influential than the height of the tree. A positive correlation between tree slenderness and MOE has been found in several studies on other species (i.e. Lasserre et al 2005, Watt et al 2006, Roth et al 2007, Lasserre et al 2009).

In this study stem slenderness at felling age was very weakly correlated with MOE_{dyn}, and was therefore not included in any of the models. However, both *RingWidth*, which is related to the diameter of a tree and *SI10*, which is related to tree height, appear in all the models for MOE_{dyn} and MOR. In fact, these variables are the only two that appear in all models, stressing the important influence they both have on wood strength and stiffness. As *RingWidth* has a negative parameter value in the models and *SI10* positive parameters, these two variables will (combined) function similar to a slenderness ratio in the models. The big difference with the slenderness ratio at felling age is the fact that *SI10* was the dominant height at age 10, while *RingWidth* is weighted towards growth during the earlier years. It appears as if the inclusion and influence of *RingWidth* and *SI10* in the models for MOE_{dyn} and MOR might, at least partially, due to its effect on stem form or slenderness during earlier growth in the trees. As one would expect from the Euler formula and the bending stress formula (Equations 2 and 3), *RingWidth*, which is related to radius, was more influential in the models than *SI10*, which is related to length (Table 6).

Johansson (2003) has found in destructive bending and tension tests that failure was almost exclusively caused by knots. In this study failure was also usually initiated around knots. In spite of the marked influence of knots on MOR, the correlations between MOR and MOR_{5perc} with branching variables such as *BranchDia, BranchAngle, BranchSpacing* and *DefCor* were either not statistically significant or weakly significant (Table 4). However, branch variables nevertheless appeared in a number of models. *DefCor* was present in all the board and tree-level models. *BranchAngle* and *BranchSpacing* were present in the compartment level MOR_{5perc} model where the sensitivity study shows that together it accounts for about 41% influence in the model (Table 6). It was somewhat surprising that *BranchDia* was not included in the latter model as it appeared in all the other MOR models and will obviously be related to knot size. At a compartment level it means that the visible branch diameters at the bottom 2m of the crown did not add to the MOR_{5perc} model where *BranchAngle* and *BranchSpacing* were already included.

There are a number of possible reasons why branch characteristics were less prominent in the board and tree-level models than expected. In the first place the influence of a knot on the bending strength of a board is strongly dependent on the location of the knot. For instance, the effect of knots situated at or near high-stressed areas, such as at the bottom edge and close to the centre (lengthwise) of a board, is known to be far more pronounced on the bending strength of a board than knots situated elsewhere in the board. As knot location was a random variable it might dilute the effect of the measured branch characteristics. Since the bottom sections of the trees were pruned, measurement of branching characteristics could only be performed on the second logs which represented the 7-9m height section of the trees. The branching characteristics of the bottom log were therefore not directly reflected by any of the variables except for *DefCor*.

As expected, branching characteristics were not very influential in the MOE_{dyn} models where knots play a relatively less important role.

The ratio of nitrogen to potassium (NK), which was determined for each stand by leaf analysis eight years prior to sampling for this study, appears in a number of models, and has a moderate influence on MOE_{dyn} and MOR as suggested by the outcome of the sensitivity analysis. This variable was also found to correlate positively with MOE_{dyn} and MOR at board, tree and compartment levels (Table 4). Nitrogen and potassium content were also determined individually but did not correlate as well with MOE_{dyn} and MOR as the NK ratio.

Nitrogen is required for tree growth as it is a constituent of proteins, nucleic acids and several other important substances, while potassium is essential for cell division and development. It is very mobile and soluble, principally being used in young tissues (Ache et al 2010, Barrelet et al 2006). The fact that the *NK* parameter was positive in all the models may suggest that trees grown in compartments characterised by a combination of high nitrogen and low potassium levels tend to produce wood which has higher MOE_{dyn} and MOR.

Louw and Scholes (2003), in a study using the same foliar data, concluded that too little N might be a growth limiting nutrient on these sites and age classes for *Pinus patula.* They observed large variation in the different foliar element concentrations between seasons. Higher concentrations of N were found in the needles during the active growth season, while higher concentrations of K were observed during the dormant season.

Barrelet et al (2006), analysing seasonal profiles of K in Norway spruce wood, found that K seems to accumulate mainly in the latewood, in other words, mainly during dormant seasonal growth. Ache et al (2010), in a review of the effect of potassium on wood formation in poplar, concluded that potassium peaks in the cambial region during the active growth period of trees where it is essential for cell division and elongation.

In this study, it can be argued that if the effect of *NK* on wood formation was purely a function of the rate of growth, it would not have added to the MOE_{dyn} and MOR models where *RingWidth* was already included. Due to the strong seasonal variation that exists for especially K in different parts of trees, it can be hypothesized, that the *NK* ratio might be related to the earlywood to latewood formation switch in the wood. This effect possibly explains why both *NK* and *RingWidth* significantly contributed to the models. Earlywood and latewood were not assessed quantitatively in this study but a visual inspection/assessment and comparison of discs from the compartment with the highest *NK* ratio versus the compartment with the lowest *NK* ratio was done. The annual rings of the discs taken from the compartment characterised by a high *NK* ratio (compartment F) clearly exhibited larger latewood percentages than those from the low *NK* compartment (compartment L). Given that latewood has higher stiffness than earlywood (Watt et al 2006), the effect would be a higher overall stiffness of the wood, which would support our hypothesis. A more detailed study would be required to thoroughly test this hypothesis.

Apart from the insight gained by developing models for the flexural properties of *Pinus patula* grown in South Africa, the models itself have practical significance. The tree-level models might be useful in tree improvement programmes for selecting trees with improved strength and stiffness. Experience in industry, supported by recent studies by Dowse and Wessels (2013), have shown that low MOE of sawn lumber is becoming more and more problematic in South African structural timber. The high predictive power shown by the compartment level model, which explained 95% of variability in MOE_{dyn}, proved that this model could be extremely useful in practice, as it would enable the identification of compartments that are expected to yield a significant proportion of structural grade lumber in their outputs prior to harvesting. Compartments that do not fall into this category can be earmarked either for other purposes, such as industrial or appearance grade lumber, where strength and stiffness are of less importance, or the decision can be made to allow the compartments to grow older in order to increase the proportion of lumber suitable for structural purposes at final harvest.

The relatively strong influence of tree slenderness during early growth might provide an ideal opportunity to improve wood stiffness during juvenile growth through silviculture of the current genetically advanced pines. For instance, planting at closer spacing will result in the development of more slender and less exposed trees, producing wood that might be of higher stiffness. This tendency has already been confirmed by studies on other species (Lasserre et al 2005, Watt et al 2006, Roth et al 2007, Lasserre et al 2009).

Further studies involving samples taken from suitable spacing trials, are therefore strongly recommended, as positive results will provide a relatively simple, easy-to-apply, silvicultural regime, capable of enhancing the formation of corewood with increased stiffness. Finding a short-term solution towards increased corewood stiffness is of utmost importance, as selective breeding for increased corewood stiffness in saw-timber, which is currently actively pursued in many breeding programmes in South Africa, has quite a more long-term horizon.

6. Conclusions

It was possible to develop multiple regression models to predict MOE_{dyn} and MOR of defect-containing lumber at a board, tree and compartment level for plantation-grown *Pinus patula* from the Mpumalanga escarpment, South Africa. The models developed were capable of explaining 68%, 60% and 95% of the variability in MOE_{dyn} at individual board, tree and compartment level respectively. The best models developed explained 40% and 42% of variability in MOR at a board and tree level respectively. At compartment level the best model explained 80% of the variability in MOR_{5perc}.

Results of sensitivity analyses showed that site index at base age of 10 years, acoustic time-of-flight, wood density and ring width were influential variables in the MOE_{dyn} models. In the MOR_{5perc} model at compartment level site index at base age 10 years, branch angle, branch spacing and ring width were influential variables.

The models developed also suggest that tree slenderness during early growth may play an important role in determining the MOE_{dyn} and MOR of boards originating from the corewood zone, which is consistent with the Euler buckling and the bending stress theories.

Improved intensive silvicultural practices and tree breeding have resulted in marked increases in the rate of growth of plantation species worldwide leading to reduced rotation ages, increased proportions of corewood and consequently a reduction in mechanical properties of products. The results from this study indicated that the MOE_{dyn} and MOR of lumber can be accurately predicted on especially a compartment level. The predictive models developed can be used as management tools to improve operational decisions around tree breeding, silvicultural practices and rotation ages.

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References

Ache P, Fromm J, Hedrich R (2010) Potassium-dependent wood formation in poplar: seasonal aspects and environmental limitations. Plant Biology 12: 259-267.

Barrelet T, Ulrich A, Rennenberg H, Krähenbühl U (2006) Seasonal profiles of sulphur, phosphorus, and potassium in Norway spruce wood. Plant Biology 8: 462-469.

Bier H (1985) Bending properties of structural timber from a 28-year-old stand of New Zealand *Pinus radiata*. New Zealand J. of For Sci. 15(2):233-50.

Burdzik W (2004) Grade verification of SA pine. S. Afr. Forestry J 202: 21-27.

Carle J, Holmgren P (2008) Wood from planted forests. A global outlook 2005-2030. Forest Prod. J. 58(12):6-18.

Carle J, Vuorinen P, Del Lungo A (2002) Status and trends in global forest plantation development. Forest Prod. J. 52 (7): 2-13.

Cave ID, Walker JCF (1994) Stiffness of wood in fast-grown plantation softwoods: the influence of microfibril angle. Forest Prod. J. 44(5):43-49.

Cherry ML, Vikram V, Briggs D, Cress DW, Howe GT (2008) Genetic variation in direct and indirect measures of wood stiffness in coastal Douglas-fir. Can. J. of Forest Res. 38(9): 2476-2486.

Chestnut IM (2009) Nondestructive assessment of standing Douglas fir trees and logs to estimate lumber quality. MSc thesis, University of Idaho.

Cown DJ (2006) Wood quality in standing timber – evolution of assessment methods in plantations. In: Kurjatko, S., Kúdela, J. and R. Lagaňa (eds.) 2006. Proceedings of the 5th IUFRO Symposium "Wood Structure and Properties '06", September 3-6, Sliač – Sielnica, Slovakia. Organised jointly by the Faculty of Wood Sciences and Technology of the Technical University of Zvolen and the IUFRO Division 5 Forest Products 5.01.00.

Crickmay and Associates (2004) Supply and demand study of softwood saw log and saw timber in South Africa. Copy obtainable from mandy@crickmay.co.za.

Crickmay and Associates (2011) South African Lumber Index for October 2011. Copy obtainable from mandy@crickmay.co.za.

CSA O86-01 (2001) Engineering Design in Wood: Canadian Standards Association.

DAFF (2009) Report on commercial timber resources and primary roundwood processing in South Africa 2008/9. Department of Agriculture, Forestry and Fisheries, RSA.

Dowse GP (2010) Selected mechanical properties and the structural grading of young *Pinus patula* sawn timber. MScFor thesis. Department of Forest and Wood Science, Stellenbosch University.

Dowse GP, Wessels CB (2013) The structural grading of young South African grown *Pinus patula* sawn timber. Southern Forests 75 (1): 7–17.

Evans R, Ilic J (2001) Rapid prediction of wood stiffness from microfibril angle and density. Forest Prod. J. 51(3):53-57.

FAO (2013) Planted forests. http://www.fao.org/forestry/plantedforests/en/ . Accessed 26/06/2013.

Glos P (2004) New grading methods. Proceedings of COST E29 Symposioum, Florence October 27-29. CNR-Ivalsa, San Michele all'Adige, Italy, p 1-8.

Grabianowski M, Manley B, Walker JCF (2004) Impact of stocking and exposure on outerwood acoustic properties of *Pinus Radiata* in Eyrewell Forest. NZ J. Forestry, August 2004.

Hibbeler RC (2005) Mechanics of materials. SI second edition. Pearson Prentice Hall. 871pp.

Hodge GR, Dvorak WS (2012) Growth potential and genetic parameters of four Mesoamerican pines planted in the Southern Hemisphere. Southern Forests 74(1): 27-49.

Huang C-H (2000) Predicting lumber stiffness of standing trees. In: Divos, F. (ed). 2000. Proceedings of 12th International symposium on nondestructive testing of wood. September 13-15. University of Western Hungary, Sopron, Hungary: 173-180.

Ikeda K, Arima T (2000) Quality evaluation of standing trees by stress wave propagation method and its application II: Evaluation of sugi stands and application to production of sugi (*Cryptomeria japonica* D. Don) structural squared sawn timber. Journal of the Japan Wood Research Society 46(3): 189-196.

Ivković M, Gapare WG, Abarquez A, Ilic J, Powell MB, Wu HX (2009) Prediction of wood stiffness, strength, and shrinkage in juvenile wood of radiata pine. Wood Sci. Technol. 43: 237-257.

Johansson C-J, (2003) Grading of timber with respect to mechanical properties. In Thelandersson, S., and J.L. Larsen. (eds). 2003. Timber Engineering. John Wiley and Sons Ltd. 446 pp.

Lasserre J-P, Mason EG, Watt MS (2005) The effects of genotype and spacing on *Pinus radiata D. Don* corewood stiffness in an 11-year old experiment. Forest Ecol. Manag. 205: 375-383.

Lasserre J-P, Mason EG, Watt MS, Moore JR (2009) Influence of initial planting spacing and genotype on microfibril angle, wood density, fibre properties and modulus of elasticity in *Pinus radiata D. Don* corewood. Forest Ecol. Manag. 258: 1924-1931.

Launay J, Rozenberg P, Paques L, Dewitte J-M (2000) A new experimental device for rapid measurement of the trunk equivalent modulus of elasticity on standing trees. Ann. For. Sci. 57: 351-359.

Launay J, Ivkovich M, Paques L, Bastien C, Higelin P, Rozenberg P (2002) Rapid measurement of trunk MOE on standing trees using Rigidimeter. Ann. For. Sci. 59: 465-469.

Lindström H, Harris P, Nakada R (2002) Methods for measuring stiffness of young trees. Holz als Roh Werkst. 60:165-174.

Liu C, Zhang SY, Cloutier A, Rycabel T (2007) Modeling lumber bending stiffness and strength in natural black spruce stand using stand and tree characteristics. Forest Ecol. Manag. 242: 648-655.

Louw JH, Scholes M (2002) The influence of site factors on nitrogen mineralization in forest soils of the Mpumalanga escarpment area: South Africa. South African For. J. 193: 47-63

Louw JH, Scholes M (2003) Foliar nutrient levels as indicators of site quality for *Pinus patula* in the Mpumalanga escarpment area. South African For. J. 193: 47-63

Louw JH, Scholes M (2006) Site index functions using site descriptors for *Pinus patula* plantations in South Africa. Forest Ecol. Manag. 225: 94-103.

Madsen B (1992) Structural behaviour of timber. Timber Engineering Ltd, North Vancouver, Canada. 405pp.

Malan FS (2010) Corewood in South African pine: necessity and opportunities for improvement. Southern Forests 72(2): 99-105.

Matheson AC, Dickson RL, Spencer DJ, Joe B, Ilic J (2002) Acoustic segregation of *Pinus radiata* logs according to stiffness. Ann. For. Sci. 59:471–477.

Megraw R, Bremer D, Leaf G, Roers J (1999) Stiffness in Loblolly pine as a function of ring position and height, and its relationship to microfibril angle and specific gravity. In Third Workshop, Connection between silviculture and wood quality through modelling approaches and simulation software, IUFRO WP S5.01-04, La Londe-Les-Maures, France, Sept 5-12, (1999.

Munalula F, (2010) A method for the non-destructive determination of the knotty core sizes of standing *Pinus patula* trees, based on ring width assessments at breast height and the pruning history. MSc (Wood Products Science) thesis. Department of Forest and Wood Science, Stellenbosch University.

Owen DL, Van der Zel DW (2000) Trees, forests and plantations in Southern Africa. In: Van der Zel, D.L. (ed). South African Forestry Handbook. Southern African Institute of Forestry.

Pannell DJ (1997) Sensitivity analysis of normative economic models: Theoretical framework and practical strategies, Agricultural Economics 16: 139-152.

Pellerin RF, Ross RJ (2002) Transverse vibration and longitudinal stress wave non-destructive evaluation methods. In: Pellerin, R.F., and R.J. Ross (eds.). 2002. Nondestructive evaluation of wood. Forest Products Society, Madison. 210 pp

Petersen N-O, Wessels CB (2011) Timber properties and roof truss design. Report to Sawmilling South Africa. Copy obtainable from Roy Southey at southeys@iafrica.com.

Roth BE, Li X, Huber DA, Peter GF (2007) Effects of management intensity, genetics, and planting density on wood stiffness in a plantation of juvenile loblolly pine in the southeastern USA. Forest Ecol. Manag. 246: 155-162.

SANS 10163-1 (2003) South African National Standard. The structural use of timber – Part 1: Limit-states design. Edition 2.3.

SANS 6122 (2008) Qualification testing of solid structural timber and laminated structural timber (glulam) for verifying timber grading systems in accordance to a given standard. Edition 2.1.

Seifert T, Schuck J, Block J, Pretzsch H (2006) Simulation von Biomasse- und Nährstoffgehalt von Waldbäumen mit dem Waldwachstumssimulator SILVA. Tagungsband der Jahrestagung der Sektion Ertragskunde im Deutschen Verband Forstlicher Forschungsanstalten, 208 – 223.

StatSoft (2013) Electronic Statistics Textbook. Available at http://www.statsoft.com/textbook/. Accessed 7 February 2014.

Uusitalo J (1997) Pre-harvest measurement of pine stands for sawing production planning. Acta Forestalia Fennica 259. p 56.

Wagner FG, Gorman TM, Wu S-Y (2003) Assessment of intensive stress-wave scanning of Douglas-fir trees for predicting lumber MOE. Forest Prod. J. 53(3):36-39.

Wang S-Y, Lin C-J, Chiu C-M (2005) Evaluation of wood quality of Taiwania trees grown with different thinning and pruning treatments using ultrasonic wave testing. Wood Fiber Sci. 37(2): 192–200.

Wang X, Ross RJ, McClellan M (2000) Strength and stiffness assessment of standing trees using a nondestructive stress wave technique. Research paper FPL-RP-600. U.S. Department of Agriculture, Forest Products Laboratory, Madison, WI. 9p.

Wang X, Ross RJ (2002) Nondestructive evaluation of green materials – recent research and development activities. In: Pellerin, R.F., and R.J. Ross (*eds*.). 2002. Nondestructive evaluation of wood. Forest Products Society, Madison. 210pp.

Wang X, Carter P, Ross RJ, Brashaw BK (2007) Acoustic assessment of wood quality of raw forest materials–a path to increased profitability. Forest Prod. J. 57(5):6–14

Wang X (2013) Acoustic measurements on trees and logs: A review and analysis. Wood Science and Technology 47(5): 965-975.

Watt MS, Moore JR, Façon JP, Downes GM, Clinton PW, Coker G, Davis MR, Simcock R, Parfitt RL, Dando J, Mason EG, Bown HE (2006) Modelling the influence of stand structural, edaphic and climatic influences on juvenile *Pinus radiata* dynamic modulus of elasticity. Forest Ecol. Manag. 229 (1‑3): 136‑144.

Wright JA (1994) Utilization of *Pinus patula*: An annotated bibliography. Oxford Forestry Institute Occasional Paper no. 45.

Wessels CB, Dowse GP, Smit HC (2011a) The flexural properties of young *Pinus elliottii x Pinus caribaea var. hondurensis* timber from the Southern Cape, and their prediction from acoustic measurements. Southern Forests 73(3&4): 137–147.

Wessels CB, Malan FS, Rypstra T (2011b) A review of measurement methods used on standing trees for the prediction of some mechanical properties of timber. Eur. J. Forest Res. 130(6): 881-893.

Wessels CB, Price CS, Turner P, Dell MP (2006) Integrating harvesting and sawmill operations using an optimized sawmill production planning system. In: Ackerman, P.A., Langin, D.W., Antonides, M.C.

(eds) Proceedings of the International Precision Forestry Symposium, Stellenbosch University, South Africa, 5–10 March 2006. ISBN 0-7972-1121-7

Zobel BJ, Sprague JR (1998. Juvenile wood in forest trees. Springer Verlag Berlin Heidelberg, 300pp.

Zobel BJ, Van Buijtenen JP (1989) Wood variation. Its causes and control. Springer, Berlin Heidelberg New York. 363p.