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Longitudinal, transverse and ultrasound vibration for the prediction of stiffness using models incorporating features in *Pinus sylvestris* timber

Abstract

Non-destructive testing was used to predict the static modulus of elasticity (MOE_S) of Scots pine (*Pinus sylvestris*) timber from the northeast of Spain. Three vibration tests were performed, longitudinal, flatwise and edgewise, to obtain the dynamic modulus of elasticity (MOE_{dyn}) based on the fundamental resonant frequencies. The MOE_{dyn} was additionally obtained from ultrasound tests. Measurements of different features were performed of the various samples, which were also subjected to a bending test to find the MOE_S. Different types of models, simple linear regression (SLR), multiple linear regression (MLR) and artificial neural network (ANN), were generated to predict the MOE_S based on the study variables. The predictive capacity of the different models was analysed by comparing the root mean square error (RMSE) obtained using the 10-fold cross-validation method. The vibration techniques showed a better MOE_S prediction than the ultrasound techniques. The MOE_{dyn} obtained from the fundamental resonant frequency of the edgewise flexural vibration (MOE_{EV}) was the variable that best predicted the MOE_S. The error of the SLR with MOE_{EV} was not significantly improved by any other model, whether univariate or multivariate. The ANN-based models did not significantly improve the error of the MLR-based models.

1 Introduction

In recent years, the use of non-destructive testing (NDT) to determine the mechanical properties of wood has reached a high level of development (Arriaga et al. 2012), especially for techniques based on ultrasound (Sandoz 1989) and vibration (Brancheriau and Bailleres 2002). In some countries, technical standards have been established in reference to vibration tests (ASTM Standard E1876–15 2015) with the aim of determining the correlation between the dynamic modulus of elasticity (MOE_{dyn}), calculated using vibration or ultrasound techniques, and the static modulus of elasticity (MOE_S). Knowledge of this relationship can be useful to make simple and rapid estimations of the MOE_S.

Several authors (Arriaga et al. 2012; Hassan et al. 2013; Villasante et al. 2019) have carried out vibration tests with Scots pine timber (*Pinus sylvestris* L.). Scots pine is a very common species in mountainous areas in the north of Spain (Pardos et al. 1990) and is extensively used in timber structures throughout Europe. Other authors have carried out similar tests with other pine species, including *Pinus pinaster* (Pommier et al. 2013), *Pinus nigra* (Arriaga et al. 2012; Íñiguez González et al. 2007), *Pinus brutia* (Guntekin et al.

2013), *Pinus radiata* (Arriaga et al. 2012; García-Iruela et al. 2016; How et al. 2014) and southern pine (Wang et al. 2008). Tests have also commonly been performed to determine the MOE_{dyn} of the wood of Asian conifers (Cho 2007; Wang et al. 2008), American conifers (Barrett and Hong 2010; Wang et al. 2008) and European conifers (Hodousek et al. 2016; Larsson et al. 1998). Similar studies have also been published on temperate hardwood species (Cho 2007; Ilic 2001; Nocetti et al. 2016), and tropical hardwood species (Baar et al. 2015; Chauhan and Sethy 2016; Sales et al. 2011). Some of the studies involving pine combined vibration tests with ultrasound tests (García-Iruela et al. 2016; Hassan et al. 2013; Villasante et al. 2019).

Most of these studies establish the correlation through the coefficient of determination (R^2) of linear regressions. However, recent studies (Pommier et al. 2013; Villasante et al. 2019) have indicated that the root-mean-square error (RMSE) is a better reflection of the prediction error of the model.

Some authors have proposed the use of artificial neural network (ANN) to establish the MOE_S prediction models. Esteban et al. (2009) found that ANN improved the MOE_S prediction compared to MLR in *Abies pinsapo* timber. García-Iruela et al. (2016) observed the same tendency in *Pinus radiata*. However, Villasante et al. (2019) did not detect any statistically significant differences between the predictive capacity of ANN and MLR in *Pinus sylvestris*.

Although MOE_S prediction models have usually been developed without testing for the existence of significant differences between them and have been limited to a comparison of mean values, some studies have analysed the significant differences. Larsson et al. (1998) observed that the longitudinal vibration MOE (MOE_{LV}) value was significantly higher than that of the edgewise MOE (MOE_{EV}) in *Picea abies*. However, no comparisons were made between these MOE_{dyn} values and the MOE_S. Larsson et al. (1998) also observed that the MOE_S value in samples without pith was significantly higher than in those with pith, although this effect was not observed in all the sample types. Hodousek et al. (2016) obtained the MOE_{dyn} using the MTG Timber Grader and an accelerometer. For *Cupressus lusitanica*, they found statistically significant differences between both MOE_{dyn} values and the MOE_S. For *Populus canadiensis*, these differences disappeared. Villasante et al. (2019) analysed the capacity of different algorithms to predict the MOE_S based on NDT of *Pinus sylvestris* timber. They found that none of the algorithms significantly improved the MLR-obtained errors.

Some authors have tested the effect of including features of sawn timber in MOE_S prediction based on the MOE_{dyn}. However, Arriaga et al. (2014) and Villasante et al. (2019) found no improvement in the MOE_S prediction model when incorporating the concentrated knot diameter ratio (CKDR). Density showed a low

correlation with stiffness in studies carried out with both conifers (Larsson et al. 1998; Simic et al. 2019) and hardwoods (Baar et al. 2015; Chauhan and Sethy 2016; Faydi et al. 2017). Other works found that the annual ring width explained only a small proportion of the variability in stiffness (Guntekin et al. 2013; Larsson et al. 1998). Mania et al. (2020) found that in five temperate hardwood species the increment in the slope of grain produced a statistically significant decrease in MOE_S.

Whereas predictions were initially made using linear regressions of a single variable, some studies today are using multivariate models based on MLR or machine learning techniques. Complex models allow a more precise fit of the data of the tested samples, but there is a risk of losing predictive capacity when applied to an independent dataset - an effect known as overfitting. An overfitted model only responds to the particular case it has been trained for, and the bigger the fit the further it will be from the general behaviour prediction, especially in small datasets. As it uses a specific dataset for the training, an overfitted model even fits the noise of the sample, confusing the noise with the underlying structure of the model (Lever et al. 2016). In this way, overfitting will generate models that will provoke high errors when applied to datasets with noise different to that of the training set. The researcher may erroneously suppose that the model has a high predictive capacity, but this only occurs if it is applied to the samples that have been analysed, not with the rest.

Most of the studies consulted do not take into consideration the effect of overfitting on MOE_S prediction, and only a few authors have incorporated measures to avoid its occurrence. Esteban et al. (2009) and García-Iruela et al. (2016) used the so-called early-stopping method, dividing the set of samples into three groups: a training set (60% of the samples), a validation set (20%) and a testing set (20%). For small datasets the assumption that each set was representative of the full dataset might not be true and K-fold cross-validation is the most appropriate procedure (Lever et al. 2016). Villasante et al. (2019) used the 10-fold cross-validation method, randomly dividing the samples into 10 groups or folds and applying the training and validation process 10 times, once for each group. The cross-validation method avoids overfitting in complex predictive models like ANN (Tetko et al. 1995).

The aim of this work was to compare prediction models of the MOE_S of *Pinus sylvestris* wood based on features of sawn timber and the MOE_{dyn} obtained from vibration and ultrasound tests. Both univariate simple linear regression (SLR) models and multivariate MLR and ANN models are used for this purpose. The fit of the model was evaluated using the RMSE.

2 Materials and methods

2.1 Samples

Analyses were undertaken with samples of *Pinus sylvestris* from the same forest in the Pyrenees obtained from a local sawmill (Lérida, Spain) in two visits within one month. A total of 69 samples were obtained by random sampling of sawn timber stored at the sawmill. At the laboratory, twelve samples with bark pockets or rot were rejected, leaving a final total of 57 samples. Due to the sampling procedure and the small number of samples, the reported values are not necessarily representative of the resource. The average age of the trees was 60 years and the nominal sample size was 70 mm x 100 mm x 2000 mm. The samples were stored in the test laboratory. Initially, a periodic moisture testing was performed using the oven dry method (European Standard EN 13183-1 2002a) with 20 mm thick slices cut from the central part of the samples included in a moisture control group, until a moisture content (MC) below 14% was observed. The samples from this moisture control group were different from the 57 samples used for the analyses. Finally, testing was conducted when the 57 samples used for the analyses had reached a constant weight (± 0.1% in 6 hours), in accordance with European Standard 408:2010+A1 (2012).

2.2 Features and biological degradations

The dimensions of each sample were measured in accordance with European Standard 408+A1 (2012). The samples were also weighed to obtain the density (ρ). Subsequently, the following features and biological degradations were measured in accordance with the procedure outlined in European Standard 1309-3 (2018): slope of grain (SLG), rate of growth (RG), blue stain (BS), and wanes (WN). It was decided to include the numerical values of these features and biological degradation instead of using a visual classification of the samples, as the latter would offer few nominal values with less predictive potential. The influence of knots was studied using the knot area ratio (KAR), which is the proportion of the cross-section occupied by the knots (Walker 1993). The highest KAR value in the central third of the sample was the value used. Pre-test MC was measured in the central area of each sample using a wood moisture meter (Hydromette HB 30, Gann, Germany), in accordance with European Standard 13183-2 (2002b).

2.3 Ultrasounds

A Sylvatest Duo ultrasound device with a frequency of 22 kHz (CBS-CBT, Lausanne, Switzerland) was used, placing the transducers at opposite ends of the sample to obtain the velocity of ultrasound waves propagation (V_U) and the modulus of elasticity by ultrasound (MOE_U) provided by the device.

2.4 Vibration tests

The samples were subjected to a longitudinal vibration (LV) test and two transverse (or flexural) vibration tests: flatwise (FV) and edgewise (EV). Following the procedure set out in ASTM Standard E1876-15 (2015), the samples were suspended with elastic cords situated on the nodes of the fundamental transverse mode of vibration. In the transverse vibration with free ends, the two nodal points were located at a distance of 0.224 times the length (L) of the sample from each end (Fig. 1). This type of support allows isolation of the sample from external vibrations with no restriction of the desired vibration.

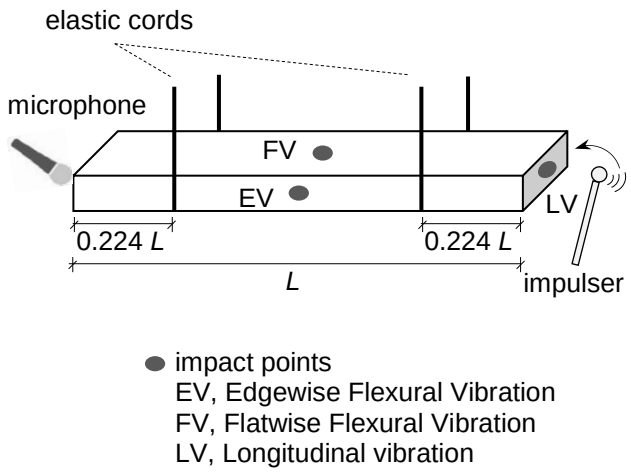

Fig. 1 Scheme of the vibration tests

To generate the vibration, the samples were tapped in the centre of the face and edge (transverse modes) and at one of the ends (longitudinal mode) with a special 22.7 g impulser consisting of a 230 mm long x 4 mm diameter wooden handle with a 26 mm diameter glass marble at the tip. The vibrations were recorded using a microphone with cardioid polar pattern and frequency range of 20 Hz to 20 kHz (Rode NT-USB, Rode Microphones, Australia). The microphone was placed at the opposite end to the end that was tapped in the longitudinal mode (Fig. 1). The signal picked by the microphone was recorded and analysed using the Audacity® software (Audacity Team 2015). A project sampling rate of 384 kHz and resolution of 24 bits were used for the recording in order to obtain a time domain with sufficient data for spectrum analysis.

The frequency spectrum analysis was performed with the Hann function. For each sample, the fundamental resonant frequency was obtained for each type of tested vibration: longitudinal (f_{LV}), flexural flatwise (f_{FV}) and flexural edgewise (f_{EV}). Based on the frequencies, the MOE_{dyn} was calculated for each sample in accordance with the following equations (Weaver et al. 1990):

$$\mathrm{MOE_{LV}} = 4 f_{\mathrm{LV}}^2 L^2 \rho \quad (1)$$

$$\mathrm{MOE_{FV}} = \frac{48\pi^2 \rho f_{\mathrm{FV}}^2 L^4}{4.73^4 b^2} \quad (2)$$

$$\mathrm{MOE_{EV}} = \frac{48\pi^2 \rho f_{\mathrm{EV}}^2 L^4}{4.73^4 h^2} \quad (3)$$

where f_{LV}, f_{FV} and f_{EV} are the fundamental resonant frequencies for each type of vibration, ρ is the density of the sample, and L, h and b are the actual length, width and thickness of each sample, respectively. The effect of shear was not taken into account because it had little influence, as the ratios L/b and L/h were equal to or greater than 20 (Arriaga et al. 2014).

2.5 Static bending test

To obtain the global MOE_S, the four point bending test in edgewise direction was performed using a 50-kN universal testing machine (Cohiner, Spain), in accordance with European Standard 408:2010+A1 (2012). Data acquisition was done with LabVIEW 7.1 (National Instruments, USA). The supports were placed at a distance equal to 18 times the width, and the two load points were placed at a distance from each support equal to 6 times the width. The position of the critical defect with respect to the load points was not considered. A displacement transducer was placed at the midpoint between the two supports. The MOE_S was derived using the stress-strain curve in the loading area between 10% and 40% of ultimate bending strength. The linear regression in this loading area presented an R^2 value above 0.99 for all the samples. After the bending test had been concluded, a 20 mm thick slice was cut as close as possible to the failure point to determine MC using the oven dry method (European Standard EN 13183-1 2002a). No adjustment of density and stiffness was made for MC, because all the samples had very close MC values. Destructive and non-destructive tests for every sample were carried out within one hour.

2.6 Statistical analyses

A prior analysis was performed to obtain the R^2 from the SLR between the MOE_S and all the study variables (MOE_U, MOE_{LV}, MOE_{FV}, MOE_{EV}). WEKA 3.6 software (Waikato University, Hamilton, New Zealand) was employed, using the simple linear regression algorithm, including all the data of the samples without

cross-validation, as is usually implicitly done in the studies that were consulted. This prior analysis was carried out to enable a comparison of the results obtained with those of other authors. In this first stage of the analysis, the comparison of errors was undertaken using the mean absolute error (MAE) as it is an intuitive measure and easy to interpret. The RMSE was not used during the first stage in order to avoid any potential confusion; it was reserved for carrying out the subsequent statistical analysis of the models.

After the comparison was made with other studies, the RMSE was obtained to evaluate the model fit of the MOE_S using SLR. Although R^2 is an adequate metric to describe the proportion of variation in the response that can be explained by the model, the RMSE provides better information about the goodness-of-fit of the model based on the difference between the values obtained by the prediction and the actual observed values. Alexander et al. (2015) observed that the value of a model depends on its overall accuracy and precision (RMSE) and not on how successfully it explains the variation in a particular data set (R^2). They recommended using RMSE because it is a more helpful indicator of a model's usefulness than is R^2.

Prediction models obtained from the whole dataset can cause overfitting, overestimating the goodness-of-fit. To avoid model overfitting, a 10-fold cross-validation method was used (Faydi et al. 2017; Hashim et al. 2016; Villasante et al. 2019). The samples were randomly split into ten groups or folds. Each fold was used to validate the model generated from the remaining 9 folds (Refaeilzadeh et al. 2009). In other words, this method allows ten validation values to be obtained. The 10-fold cross-validation method was repeated 5 times, randomly distributing the samples each time. In this way, 50 RMSE values were obtained for each of the models. This process was carried out with WEKA 3.6 software (Waikato University 2014, Hamilton, New Zealand).

The dataset with 50 RMSE values of each model was analysed with R 3.6.1 software (R Core Team 2019). The cross-validation method generated RMSE values that were not independent, and for this reason it was not possible to carry out an ANOVA or a paired t-test (Refaeilzadeh et al. 2009). Instead, the non-parametric Kruskal-Wallis test was used to compare the models. If statistically significant differences between the RMSE were found, post hoc analysis was carried out using Dunn's test with Bonferroni adjustment. In all cases, the level of significance was 0.05.

Firstly, the MOE_S prediction was analysed on the basis of simple variables: SLG, RG, BS, WN, KAR, V_U, density, f_{LV}, f_{FV} and f_{EV}. Subsequently, the MOE_S prediction was analysed on the basis of the four MOE_{dyn} (MOE_U, MOE_{LV}, MOE_{FV}, MOE_{EV}). This analysis was considered different to the previous analysis as the MOE_{dyn} is a compound variable which includes various simple variables (Eqs. 1, 2 and 3).

Finally, multivariate models were used. The analysis was first performed with MLR, generating a model which included all the study variables. Following this, a greedy selection using the Akaike information metric was used with WEKA 3.6 software (Waikato University, Hamilton, New Zealand) as a variable selection method to obtain the model with the lowest RMSE. This model was then simplified, eliminating one by one the variables which caused the least variation in the RMSE. A Kruskal-Wallis test was applied, using Dunn's test with Bonferroni adjustment, when necessary to verify whether there were any statistically significant differences between the RMSE of the models.

A prediction model was also generated using an ANN. A multilayer perceptron was used with sigmoid nodes and learning by backpropagation. The ANN parameters were adjusted in a prior test. The parameters were tested with a minimum of five values, corresponding to the default value proposed by WEKA 3.6 software (Waikato University, Hamilton, New Zealand), two values above and two values below. For each parameter, the value which offered the lowest RMSE was chosen. The values chosen were 0.1 for the learning rate, 500 for the training time and 0.1 for momentum applied to the weights. It was found that the models with a lower number of variables gave a lower error when using fewer neurons, the same that found Tetko et al. (1995). The best predictions were obtained with an ANN based on a single hidden layer of 3 to 5 neurons.

For each of the models obtained with MLR and ANN, 50 RMSE values were obtained using the 10-fold cross-validation method with five repetitions, with WEKA 3.6 software (Waikato University, Hamilton, New Zealand). The dataset with 50 RMSE values of each model was compared with the non-parametric Kruskal-Wallis test and Dunn's test with Bonferroni adjustment. The level of significance was 0.05.

3. Results and discussion

The values obtained for the different variables are shown in Table 1. In general, the MOE_S values were lower than those obtained in previous studies with *Pinus sylvestris* (Arriaga et al. 2012; Hassan et al. 2013; Ranta-Maunus et al. 2011) or with other species of pine, including *Pinus pinaster* (Pommier et al. 2013), *Pinus nigra* (Arriaga et al. 2012; Íñiguez González et al. 2007), *Pinus brutia* (Guntekin et al. 2013), *Pinus radiata* (Arriaga et al. 2012 2014; García-Iruela et al. 2016; How et al. 2014) and southern pine (Wang et al. 2008). The values are also lower than those obtained in previous studies with different conifer species, including *Picea abies* (Larsson et al. 1998; Spycher et al. 2008), *Cryptomeria japonica*, *Taiwania cryptomerioides* and *Pseudotsuga menziesii* (Wang et al. 2008). In all these studies, the MOE_{dyn} and MOE_S

Table 1. Summary of the study variables

Variable	units	Mean value	CV (%)
SLG	%	5.2	66.7
RG	mm	3.2	23.8
BS	%	10.4	147.0
WN	‰	1.2	282.8
KAR	$mm^2\ mm^{-2}$	0.25	70.1
MC	%	11.3	5.9
ρ	$kg\ m^{-3}$	549.5	7.1
V_U	$m\ s^{-1}$	4672	11.9
f_{LV}	Hz	999.9	13.0
f_{FV}	Hz	69.6	12.8
f_{EV}	Hz	99.0	11.6
MOE_U	MPa	7683	32.6
MOE_{LV}	MPa	8887	25.3
MOE_{FV}	MPa	8810	25.3
MOE_{EV}	MPa	8739	23.6
MOE_S	MPa	7701	23.9

values were between 8900 MPa and 12700 MPa, except for the study on southern pine (Wang et al. 2008) which gave values between 14900 MPa and 16200 MPa. However, other authors obtained values with conifer species lower than those obtained in the present study, including *Picea sitchensis* (Simic et al. 2019), *Abies pinsapo* (Esteban et al. 2009) and *Cupressus lusitanica* (Hodousek et al. 2016). In these cases, the MOE_{dyn} and MOE_S values were between 5800 MPa and 8000 MPa. The MOE_S values obtained were lower than the values found in most previous studies, though they cannot be considered atypical. The mean MOE_S value obtained (7701 MPa) lies within the range of values included in the European classification system (European Standard EN 338 2016).

The mean values of the different MOE_{dyn} were similar (MOE_U) or slightly higher (between 13% and 15% for MOE_{LV}, MOE_{FV} and MOE_{EV}) than the mean MOE_S values (Table 1). In general, the same trend was observed in studies by other authors, with the mean MOE_{dyn} value higher than that of the mean MOE_S. In some cases, the difference was smaller, between 3% and 5% (Arriaga et al. 2012; Guntekin et al. 2013; Íñiguez González et al. 2007). While Wang et al. (2008) found differences of up to 9%, those recorded in another group of studies were as high as 19% (Arriaga et al. 2014; Hassan et al. 2013; Larsson et al. 1998; Pommier et al. 2013; Simic et al. 2019). Only Hodousek et al. (2016) obtained a mean MOE_{dyn} value lower than that of the MOE_S (-11%).

The MOE_{EV} overestimated the MOE_S by 13.5%, the MOE_{FV} by 14.4% and the MOE_{LV} by 15.4%, a trend also observed in the studies consulted. Arriaga et al. (2014) found in *Pinus radiata* that both the MOE_{EV}

and the MOE_{LV} overestimated the MOE_S by 14%. Ilic (2001) also observed in *Eucalyptus delegatensis* that the MOE_{EV} and MOE_{LV} overestimated the MOE_S. Overestimation of the MOE_{LV} was higher than that of the MOE_{EV}. Cho (2007) found in five Asian species that the MOE_{EV} and MOE_{LV} overestimated the MOE_S, with overestimation of the MOE_{LV} (20%) higher in all cases than that of the MOE_{EV} (8%). Cheng and Hu (2011) found in *Populus tomentosa* that the MOE_{EV} overestimated the MOE_S by 9% and the MOE_{LV} by 12%. Hassan et al. (2013) found in *Pinus sylvestris* that the MOE_{EV} overestimated the MOE_S by 4%, the MOE_{LV} by 12% and the MOE_U by 19%. Baar et al. (2015) found in 5 African hardwood species that the MOE_{EV} overestimated the MOE_S by 13%, the MOE_{LV} by 24% and the MOE_U by 41%. Chauhan and Sethy (2016) found in 8 hardwood species that both the MOE_{EV} and MOE_{LV} overestimated the MOE_S. Hassan et al. (2013) explained the difference between the values of the MOE_{dyn} and the MOE_S as being due to the influence of shear deflection in the bending test. To calculate the MOE_S, they took into account this effect, significantly reducing the difference between the two MOE values. This correction was important because Hassan et al. (2013) performed the three point bending test. Ilic (2001) also performed the three point bending test and corrected the MOE_{EV} value taking into account shear deflection. In the present study, the four point bending test was carried out, in which the influence of shear deflection is lower. Another explanation for the difference between the MOE_S and MOE_{dyn} values is based on the viscoelastic behaviour of the timber. When forces with a short duration are applied, timber exhibits an elastic behaviour, whereas with a long duration, the behaviour is like that of a viscous liquid. As the vibration tests had a very short duration compared to the static bending tests, the timber exhibited different types of behaviour in the two tests and, in consequence, different results were observed (Cho 2007; Halabe et al. 1997).

The R^2 values that were obtained for the relationship of the MOE_S with the different MOE_{dyn} (Table 2) are similar to those found in previous studies with *Pinus sylvestris* (Arriaga et al. 2012; Hassan et al. 2013; Ranta-Maunus et al. 2011). Similar values are also found in studies with other pine species (Arriaga et al. 2012 2014; Guntekin et al. 2013; How et al. 2014; Íñiguez González et al. 2007), and with different conifer species, including Asian (Cho 2007; Wang et al. 2008), American (Barrett and Hong 2010; Wang et al. 2008) and European (Hodousek et al. 2016; Larsson et al. 1998) species. Likewise, studies made with different hardwood species have given similar values, for both temperate (Cho 2007; Ilic 2001; Nocetti et al. 2016), and tropical (Baar et al. 2015; Chauhan and Sethy 2016; Sales et al. 2011) species. The R^2 values were between 0.68 and 0.99 in the studies cited above. Only Liu et al. (2014) obtained noticeably lower R^2 values (of between 0.31 and 0.41) in tests performed with *Betula alleghaniensis* and *Acer saccharum*.

The highest coefficient of determination in the SLR between the MOE_S and MOE_{dyn} obtained by vibration was attained with the MOE_{EV} ($R^2 = 0.97$). In the case of the MOE_{FV} and the MOE_{LV}, the R^2 values worsened, decreasing by 4% and 6%, respectively (Table 2). Ilic (2001) found in *Eucalyptus delegatensis* that prediction of the MOE_S on the basis of the MOE_{EV} had an 8% higher R^2 value than prediction on the basis of the MOE_{LV}, similar to the increase in the present study. Faydi et al. (2017) found in oak that prediction of the MOE_S on the basis of the MOE_{EV} had a 9% higher R^2 value than prediction on the basis of the MOE_{LV} and a 12% higher value than with the MOE_{FV}. Hassan et al. (2013) found in *Pinus sylvestris* that prediction of the MOE_S on the basis of the MOE_{EV} had an 18% higher R^2 value than prediction on the basis of the MOE_{LV}. In contrast, other studies have found smaller differences, Baar et al. (2015), Chauan and Sethy (2016) and Larsson et al. (1998) found that prediction of the MOE_S on the basis of the MOE_{EV} and the MOE_{LV} had similar R^2 values, with differences of below 3%. Finally, Arriaga et al. (2014) found in *Pinus radiata* that prediction of the MOE_S on the basis of the MOE_{EV} had a similar R^2 value to that made on the basis of the MOE_{LV}.

Table 2. Simple linear regression to predict the MOE_S

Variable	Linear Regression Model (MPa)	R^2	RMSE (MPa)	RMSE increase with respect to the lowest value
SLG	$MOE_S = - 235.8\ SLG + 8930$	0.20	1632	390%
RG	$MOE_S = -1498\ RG + 12567$	0.40	1389	317%
BS	$MOE_S = 9.730\ BS + 7600$	0.01	1797	440%
WN	$MOE_S = 275.7\ WN + 7379$	0.25	1546	364%
KAR	$MOE_S = -4260.4\ KAR + 8753$	0.16	1649	395%
ρ	$MOE_S = 10.03\ \rho + 2192$	0.04	1788	437%
V_U	$MOE_S = 2.660\ V_U - 4731$	0.65	1051	216%
f_{LV}	$MOE_S = 12.54\ f_{LV} - 4834$	0.78	851	155%
f_{FV}	$MOE_S = 185.4\ f_{FV} - 5201$	0.81	795	139%
f_{EV}	$MOE_S = 147.4\ f_{EV} - 6897$	0.85	694	108%
MOE_U	$MOE_S = 0.563\ MOE_U + 3371$	0.59	1158 [c]	248%
MOE_{LV}	$MOE_S = 0.782\ MOE_{LV} + 757$	0.91	544 [b]	63%
MOE_{FV}	$MOE_S = 0.796\ MOE_{FV} + 693$	0.93	477 [b]	43%
MOE_{EV}	$MOE_S = 0.876\ MOE_{EV} + 45$	0.97	333 [a]	-

a, b, c = values matched by the same letter do not differ significantly (p = 0.05)

One of the advantages of knowing the MOE_{dyn} values is that they can be used for simple and rapid *in situ* prediction of the MOE_S. To obtain any of the MOE_{dyn}, a mean time of 1.5 minutes (data collection and calculations) was required, while the mean time for the MOE_S was 7 minutes. However, the results show

clear overestimation. Despite a very high correlation, the MOE_{dyn} values obtained with vibration (Eqs. 1, 2 and 3) overestimated the MOE_S value, with a MAE of above 1000 MPa (Table 3). This overestimation can easily be adjusted using a linear equation (Fig. 2 for MOE_{EV}). The values estimated in this way show a clear decrease in the prediction error of the MOE_S, with a noticeably lower MAE (75% for MOE_{EV}). If the estimated values are used rather than the corrected ones, the prediction errors that are made increase with the value of the MOE_S that is being predicted.

Table 3. Mean absolute error (MAE) of linear models to predict MOE_S (MPa)

Variable	MAE observed MOE	MAE adjusted MOE	MAE reduction
MOE_U	1390	906	35%
MOE_{LV}	1208	425	65%
MOE_{FV}	1110	387	65%
MOE_{EV}	1037	262	75%

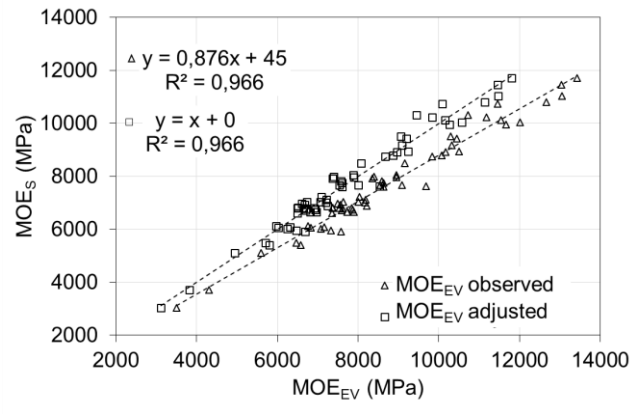

Fig. 2 Correlation of the MOE_S with the observed MOE_{EV} and with the adjusted MOE_{EV}

With respect to the ultrasound technique, the R^2 value for the V_U used to predict the MOE_S (0.65) was higher than the R^2 value for the MOE_U (0.59). That difference could have been an abnormal result, but the values in question were very similar and there were not statistically significant differences between them. The mean value of the MOE_U was similar to that of the MOE_S. However, as a consequence of the high variability of the values, the MAE of the MOE_U were 34% larger than that of the MOE_{EV} (Table 3). Variability of the MOE_U was higher than that of the MOE_{EV}, as can be seen in the 38% difference in R^2 values (Table 2). Hassan et al. (2013) found similar values in *Pinus sylvestris*, with the variability of MOE_S on the basis of the MOE_U presenting a 39% lower R^2 value than that of the prediction on the basis of the

MOE_{EV}. Other authors have found the same trend, though with smaller differences. Ranta-Maunus et al. (2011) found that in *Pinus sylvestris*, the MOE_S prediction based on the MOE_U had a 10% lower R^2 value than that of the prediction based on the MOE_{EV}. Wang et al. (2008) found in four conifer species that variability of the MOE_S on the basis of the MOE_U presented an 11% lower R^2 value than that of the prediction on the basis of the MOE_{EV}. Baar et al. (2015) found that variability of the MOE_S on the basis of the MOE_U presented a 7% lower R^2 value than that of the prediction on the basis of the MOE_{EV}. Sales et al. (2011) also found in *Goupia glabra* higher variability in the MOE_U than in the MOE_{EV} in the SLR to predict the MOE_S, although the difference between the R^2 values was very low (1%). A further consequence of this variability is that there is only a very slight reduction of the MAE with the corrected MOE_U.

A low correlation with the MOE_S was found in the present study for the features (SLG, RG, BS, WN, KAR) and the density, as can be seen in the R^2 values (Table 2). For this reason, it is unadvisable to use either the features or the density to predict the MOE_S using SLR. However, RG had a clearly higher R^2 value (0.40) than the rest, and could thus be useful in multivariate models. In the studies that have been consulted, the capacity of RG to predict the MOE_S is dubious. Guntekin et al. (2013) found that annual ring width had a significant impact on their model to predict the MOE_S in *Pinus brutia*. In contrast, Larsson et al. (1998) found in *Picea abies* that RG was not a good measure for stiffness. SLG showed a weak correlation with MOE_S (0.20); similar results were found to those reported by Mania et al. (2020) with slopes of grain between 0% and 9%. In the present study, a weak correlation (R^2 = 0.04) between density and the MOE_S was found. Similar results have been observed in other studies: in Faydi et al. (2017) with oak (R^2 = 0.09), Simic et al. (2019) with *Picea sitchensis* (R^2 = 0.18) and Baar et al. (2015) with five African hardwood species (R^2 = 0.23). Other studies have shown higher R^2 values, but always with weak correlations: in Ranta-Maunus et al. (2011) with *Pinus sylvestris* (R^2 = 0.50), in Larsson et al. (1998) with *Picea abies* (R^2 = 0.50) and in Chauhan and Sethy (2016) with eight hardwood species (R^2 = 0.45). In the present study, the correlation between density and the MOE_S was lower than in the other studies consulted. This may be due to the low variability in the density of the samples, with the lowest CV of all the study variables (7.1%). A low correlation was also found in the present study between the KAR and the MOE_S, (R^2 = 0.16), although it was similar to that reported in Ranta-Maunus et al. (2011) with *Pinus sylvestris* (R^2 = 0.25). This result is in agreement with Arriaga et al. (2014) who found for *Pinus radiata* that the addition of knottiness to the prediction model of the MOE_S on the basis of the MOE_{dyn} did not improve the R^2 value. Villasante et al. (2019) also observed that the inclusion of knottiness in the prediction model of the MOE_S

in *Pinus sylvestris* did not significantly decrease the RMSE.

The R^2 values were only used in the present study to allow a comparison with other studies made by different authors. We preferred to use the RMSE to assess the capacity of the different variables to predict the MOE_S. In addition, the 10-fold cross-validation method was used with 5 repetitions to avoid overfitting. Firstly, an analysis was made of the simple variables (V_U, f_{LV}, f_{FV}, f_{EV}). The results obtained (Table 2) showed statistically significant differences between their MOE_S predictive capacities. The V_U variable had the highest mean RMSE value, higher than any of the vibration frequencies, and was therefore the variable with the weakest prediction capacity. With respect to the frequencies, f_{EV} and f_{FV} had the lowest mean RMSE values and with no statistically significant differences between them.

As for the compound variables (MOE_U, MOE_{LV}, MOE_{FV}, MOE_{EV}), the results show statistically significant differences between some of them (Table 2). The MOE_U had a significantly higher RMSE mean value than any of the other compound variables. As in the case of the simple variables, the edgewise flexural vibration test was the most suitable for MOE_S prediction, as the MOE_{EV} variable had the significantly lowest RMSE mean value. The MOE_{LV} and the MOE_{FV}, had RMSE values somewhere in between (increase of 63% and 43% respectively with respect to the MOE_{EV}), with no statistically significant differences between them. Faydi et al. (2017) found a similar trend in oak, with the RMSE for the MOE_{LV} 24% higher than for the MOE_{EV}.

The MOE_{dyn} values obtained through the vibration tests (MOE_{EV}, MOE_{FV}, MOE_{LV}) predicted the MOE_S better than the resonance frequencies (f_{EV}, f_{FV}, f_{LV}). The RMSE values of any of the vibration MOE_{dyn} were significantly lower than the RMSE values of any of the frequencies. This is because the MOE_{dyn} are compound variables which include the resonance frequency and other variables of the sample (Eqs. 1, 2 and 3).

The multivariate analysis was performed using MLR and ANN. The analysis with MLR (Table 4) showed that the inclusion of different variables in the model did not improve the result obtained with the MOE_{EV}. The RMSE values obtained with the models that included MOE_{EV}, RG and SLG did not show statistically significant differences to those obtained only with MOE_{EV}. In contrast, when all the variables were used, the RMSE value was significantly worse. The results obtained are in agreement with Faydi et al. (2017), who found that the multivariate models slightly improved (2%) the RMSE of an SLR based on the MOE_{EV}. Although they did not analyse the existence of significant differences, they did not find utility for the use of multivariate models. Villasante et al. (2019) found that the MLR model with two variables

significantly improved the SLR model based on the longitudinal vibration velocity. The difference with the results of the present study may be due to the fact that the velocity offers less information than the MOE_{EV} and that only longitudinal vibration was considered, with lower predictive capacity than edgewise vibration. This difference can be seen in the RMSE values of the SLR models, 1206 MPa in Villasante et al. (2019) and 333 MPa in the present study. The analysis with ANN (Fig. 3) gave the same results, with no combination of variables offering an improvement over the RMSE value obtained with MOE_{EV}.

Table 4. Multiple linear regression to predict the MOE_S, mean value and standard deviation (in brackets) of the RMSE

Regression Model	RMSE (MPa)
all variables	396 [b] (85)
$-33.793 \cdot SLG - 134.7937 \cdot RG + 0.823 \cdot MOE_{EV} + 1123.6$	323 [a] (75)
$-141.1613 \cdot RG + 0.8441 \cdot MOE_{EV} + 783.4$	333 [a] (82)
$0.8761 \cdot MOE_{EV} + 45.8$	333 [a] (91)

a, b = values matched by the same letter do not differ significantly (p = 0.05)

Finally, it was verified that there were no statistically significant differences between the MLR and ANN results when using the same variables. Other authors have obtained a similar result. Villasante et al. (2019) found that the ANN-constructed model did not significantly improve the prediction of the MOE_S made with the MLR-based model in *Pinus sylvestris*. Tanaka et al. (1996) found that the ANN-constructed model did not contribute to improving the prediction of the MOR made through linear regression in *Cryptomeria japonica*. Other authors, in contrast, have found improvements in ANN-constructed models. Garcia-Iruela et al. (2016), working with ultrasound in *Pinus radiata*, found that the models made with ANN improved by 10% the R^2 of the SLR-based models, although they did not consider whether this difference was statistically significant. Esteban et al. (2009), working with ultrasound in *Abies pinsapo* found that ANN-based models notably improved the R^2 of the MLR-based models (from 0.12 to 0.75). Although the R^2 value of the ANN was similar to that of the present study, the R^2 value of the MLR was unusually low. Authors attributed this low value to the large amount of knots in the studied samples.

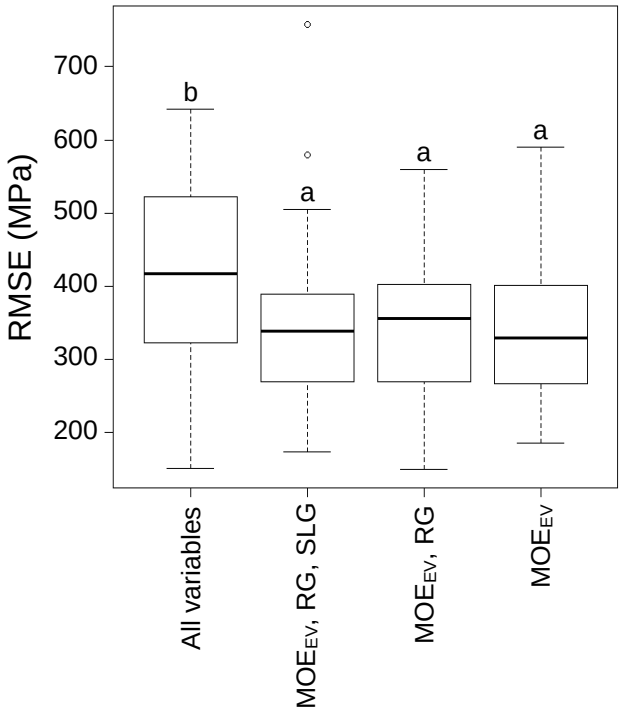

Fig. 3 RMSE of the artificial neural network. a, b = values matched by the same letter do not differ significantly (p = 0.05)

4 Conclusion

The results of the present study show the MOE_{dyn} obtained in the vibration tests (edgewise, flatwise and longitudinal) to be a good MOE_S predictor, better than the timber features (slope of grain, rate of growth, blue stain, wanes and knot area ratio), the density and the ultrasound technique, as seen in the R^2 and RMSE values with a low error and high fit of data. Although all the MOE_{dyn} obtained in the vibration tests overestimate the MOE_S value, this is easy to correct with a linear equation. The edgewise flexural vibration mode is a better MOE_S predictor than the flatwise and longitudinal modes. The MOE_{EV} variable had the significantly lowest RMSE in the MOE_S prediction. None of the multivariate models developed with MLR significantly reduced the RMSE obtained with the SLR model based on the MOE_{EV}. This model is the most suitable for its accuracy and simplicity.

The ANN-based models did not significantly improve the models generated using linear regressions.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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