Alvaro Fernandez-Serrano* (corresponding author)
alvaro.fernandezserrano@udl.cat
tel. +34 973702860
https://orcid.org/0000-0002-5171-5044

Antonio Villasante*
antonio.villasante@udl.cat
https://orcid.org/0000-0002-7549-7424

*University of Lleida
Department of Agricultural and Forest Engineering
Av. Rovira Roure, 191
25198 Lleida
Spain
Abstract

Non-destructive testing was used to predict the static modulus of elasticity (MOE\textsubscript{S}) of Scots pine (\textit{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\textsubscript{dyn}) based on the fundamental resonant frequencies. The MOE\textsubscript{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\textsubscript{S}. Different types of models, simple linear regression (SLR), multiple linear regression (MLR) and artificial neural network (ANN), were generated to predict the MOE\textsubscript{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\textsubscript{S} prediction than the ultrasound techniques. The MOE\textsubscript{dyn} obtained from the fundamental resonant frequency of the edgewise flexural vibration (MOE\textsubscript{EV}) was the variable that best predicted the MOE\textsubscript{S}. The error of the SLR with MOE\textsubscript{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\textsubscript{dyn}), calculated using vibration or ultrasound techniques, and the static modulus of elasticity (MOE\textsubscript{S}). Knowledge of this relationship can be useful to make simple and rapid estimations of the MOE\textsubscript{S}.

Several authors (Arriaga et al. 2012; Hassan et al. 2013; Villasante et al. 2019) have carried out vibration tests with Scots pine timber (\textit{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 \textit{Pinus pinaster} (Pommier et al. 2013), \textit{Pinus nigra} (Arriaga et al. 2012; Íñiguez González et al. 2007), \textit{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\textsubscript{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\textsuperscript{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\textsubscript{S} prediction models. Esteban et al. (2009) found that ANN improved the MOE\textsubscript{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\textsubscript{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\textsubscript{LV}) value was significantly higher than that of the edgewise MOE (MOE\textsubscript{EV}) in *Picea abies*. However, no comparisons were made between these MOE\textsubscript{dyn} values and the MOE\textsubscript{S}. Larsson et al. (1998) also observed that the MOE\textsubscript{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\textsubscript{dyn} using the MTG Timber Grader and an accelerometer. For *Cupressus lusitanica*, they found statistically significant differences between both MOE\textsubscript{dyn} values and the MOE\textsubscript{S}. For *Populus canadiensis*, these differences disappeared. Villasante et al. (2019) analysed the capacity of different algorithms to predict the MOE\textsubscript{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\textsubscript{S} prediction based on the MOE\textsubscript{dyn}. However, Arriaga et al. (2014) and Villasante et al. (2019) found no improvement in the MOE\textsubscript{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 MOEs.

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 MOEs 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 MOEₜ of *Pinus sylvestris* wood based on features of sawn timber and the MOEₜ₀₀₀ 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 \( \text{MOE}_U \) 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.

![Scheme of the vibration tests](image)

**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 $\text{MOE}_{\text{dyn}}$ was calculated for each sample in accordance with the following equations (Weaver et al. 1990):

$$\text{MOE}_{LV} = 4f_{LV}^2 L^2 \rho$$  \hspace{1cm} (1)

$$\text{MOE}_{FV} = \frac{48\pi^2 \rho f_{FV}^4}{4.73^4 b^4}$$  \hspace{1cm} (2)

$$\text{MOE}_{EV} = \frac{48\pi^2 \rho f_{EV}^4}{4.73^4 h^4}$$  \hspace{1cm} (3)

where $f_{LV}, f_{FV}$ and $f_{EV}$ are the fundamental resonant frequencies for each type of vibration, $\rho$ 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 $\text{MOE}_S$, 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 $\text{MOE}_S$ 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 $\text{MOE}_S$ and all the study variables ($\text{MOE}_{U}, \text{MOE}_{LV}, \text{MOE}_{FV}, \text{MOE}_{EV}$). 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 MOE₅ using SLR. Although R² 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 (R²). They recommended using RMSE because it is a more helpful indicator of a model's usefulness than is R².

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 MOE₅ prediction was analysed on the basis of simple variables: SLG, RG, BS, WN, KAR, Vₑ, density, fₑV, fₑV and fₑV. Subsequently, the MOE₅ prediction was analysed on the basis of the four MOEₜₙ (MOEₑₑ, MOEₑₑ, MOEₑₑ, MOEₑₑ). This analysis was considered different to the previous analysis as the MOEₜₙ 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 pinea* (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    |
| $\rho$   | 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; Gunтекin 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*. 

11
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$_{EV}$ 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$_{LV}$.

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

| 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%                                        |
| $\rho$   | 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%                                        |
| $f_{EV}$ | MOE$_S$ = 185.4 $f_{EV}$ - 5201 | 0.81  | 795        | 139%                                        |
| $f_{EV}$ | MOE$_S$ = 147.4 $f_{EV}$ - 6897 | 0.85  | 694        | 108%                                        |
| MOE$_{LV}$ | MOE$_S$ = 0.563 MOE$_{LV}$ + 3371 | 0.59  | 1158 $^c$ | 248%                                        |
| MOE$_{LV}$ | MOE$_S$ = 0.782 MOE$_{LV}$ + 757 | 0.91  | 544 $^b$  | 63%                                         |
| MOE$_{EV}$ | MOE$_S$ = 0.796 MOE$_{EV}$ + 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 ($p = 0.05$)
clear overestimation. Despite a very high correlation, the MOE\textsubscript{dyn} values obtained with vibration (Eqs. 1, 2 and 3) overestimated the MOE\textsubscript{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\textsubscript{EV}). The values estimated in this way show a clear decrease in the prediction error of the MOE\textsubscript{S}, with a noticeably lower MAE (75% for MOE\textsubscript{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\textsubscript{S} that is being predicted.

![Fig. 2 Correlation of the MOE\textsubscript{S} with the observed MOE\textsubscript{EV} and with the adjusted MOE\textsubscript{EV}](image)

| Variable | MAE observed MOE | MAE adjusted MOE | MAE reduction |
|----------|------------------|------------------|---------------|
| MOE\textsubscript{U} | 1390 | 906 | 35% |
| MOE\textsubscript{LV} | 1208 | 425 | 65% |
| MOE\textsubscript{FV} | 1110 | 387 | 65% |
| MOE\textsubscript{EV} | 1037 | 262 | 75% |

With respect to the ultrasound technique, the R\textsuperscript{2} value for the V\textsubscript{U} used to predict the MOE\textsubscript{S} (0.65) was higher than the R\textsuperscript{2} value for the MOE\textsubscript{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\textsubscript{U} was similar to that of the MOE\textsubscript{S}. However, as a consequence of the high variability of the values, the MAE of the MOE\textsubscript{U} were 34% larger than that of the MOE\textsubscript{EV} (Table 3). Variability of the MOE\textsubscript{U} was higher than that of the MOE\textsubscript{EV}, as can be seen in the 38% difference in R\textsuperscript{2} values (Table 2). Hassan et al. (2013) found similar values in Pinus sylvestris, with the variability of MOE\textsubscript{S} on the basis of the MOE\textsubscript{U} presenting a 39% lower R\textsuperscript{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 MOEs. 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 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 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 MOEs 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 $\text{MOE}_{\text{EV}}$ 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 $\text{MOE}_{\text{EV}}$.

| Regression Model | RMSE (MPa) |
|------------------|------------|
| all variables    | 396 $^b$ (85) |
| -33.793·SLG - 134.7937·RG + 0.823·$\text{MOE}_{\text{EV}}$ + 1123.6 | 323 $^a$ (75) |
| -141.1613·RG + 0.8441·$\text{MOE}_{\text{EV}}$ + 783.4 | 333 $^a$ (82) |
| 0.8761·$\text{MOE}_{\text{EV}}$ + 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.
References

Alexander DLJ, Tropsha A, Winkler DA (2015) Beware of R²: Simple, Unambiguous Assessment of the Prediction Accuracy of QSAR and QSRR Models. J. Chem. Inf. Model. 55:1316–1322

Arriaga F, Iniguez-Gonzalez G, Esteban M, Divos F (2012) Vibration method for grading of large cross-section coniferous timber species. Holzfortschung 66:381–387

Arriaga F, Monton J, Segues E, Iniguez-Gonzalez G (2014) Determination of the mechanical properties of radiata pine timber by means of longitudinal and transverse vibration methods. Holzfortschung 68:299–305

ASTM Standard (2015) E1876–15 Standard Test Method for Dynamic Young’s Modulus, Shear Modulus, and Poisson’s Ratio by Impulse Excitation of Vibration. ASTM, West Conshohocken, PA

Audacity Team (2015) Audacity®. Version 2.1.12. Audio editor and recorder. Retrieved from http://audacityteam.org/

Baar J, Tippner J, Rademacher P (2015) Prediction of mechanical properties - modulus of rupture and modulus of elasticity - of five tropical species by nondestructive methods. Maderas-Cienc. Tecnol. 17:239–252

Barrett JD, Hong IP (2010) Moisture content adjustments for dynamic modulus of elasticity of wood members. Wood Sci. Technol. 44:485–495

Brancheriau L, Bailleres H (2002) Natural vibration analysis of clear wooden beams: A theoretical review. Wood Sci. Technol. 36:347–365

Chauhan S, Sethy A (2016) Differences in dynamic modulus of elasticity determined by three vibration methods and their relationship with static modulus of elasticity. Maderas-Cienc. Tecnol. 18:373–382

Cheng F, Hu Y (2011) Reliability analysis of timber structure design of poplar lumber with nondestructive testing methods. Bioresources 6:3188–3198

Cho CL (2007) Comparison of three methods for determining Young’s modulus of wood. Taiwan Journal of Forest Science 22:297–306

Esteban LG, Fernández FG, De Palacios P (2009) MOE prediction in Abies pinsapo Boiss. timber: Application of an artificial neural network using non-destructive testing. Comput. Struct. 87:1360–1365

European Standard (2002a) EN 13183-1. Moisture content of a piece of sawn timber. Part 1: Determination by oven dry method. European Committee for Standardization (CEN), Brussels, Belgium

European Standard (2002b) EN 13183-2 Moisture content of a piece of sawn timber - Part 2: Estimation by electrical resistance method. European Committee for Standardization (CEN), Brussels, Belgium

European Standard (2012) EN 408:2010+A1:2012. Timber structures. Structural timber and glued laminated timber. Determination of some physical and mechanical properties. European Committee for Standardization (CEN), Brussels, Belgium

European Standard (2016) EN 338:2016. Structural timber. Strength classes. European Committee for Standardization (CEN), Brussels, Belgium

European Standard (2018) EN 1309-3:2018. Round and sawn timber - Methods of measurements - Part 3: Features and biological degradations. European Committee for Standardization (CEN), Brussels, Belgium

Faydi Y, Brancheriau L, Pot G, Collet R (2017) Prediction of oak wood mechanical properties based on the statistical exploitation of vibrational response. Bioresources 12:5913–5927

García-Iruela A, Fernández FG, Esteban LG, De Palacios P, Simón C, Arriaga F (2016) Comparison of modelling using regression techniques and an artificial neural network for obtaining the static modulus of elasticity of Pinus radiata D. Don. timber by ultrasound. Compos. Part B-Eng. 96:112–118

Guntekin E, Emiroglu Z, Yilmaz T (2013) Prediction of Bending properties for Turkish Red Pine (Pinus brutia Ten.) Lumber using stress wave method. Bioresources 8:231–237
Halabe UB, Bidigalu GM, GangaRao HVS, Ross RJ (1997) Nondestructive evaluation of green wood using stress wave and transverse vibration techniques. Mater. Eval. 55:1013–1018

Hashim UR, Hashim SZM, Muda AK (2016) Performance evaluation of multivariate texture descriptor for classification of timber defect. Optik 127:6071–6080

Hassan KTS, Horacek P, Tippera J (2013) Evaluation of stiffness and strength of scots pine wood using resonance frequency and ultrasonic techniques. Bioresources 8:1634–1645

Hodousek M, Dias M, Martins C, Marques A, Böhm M (2016) Comparison of non-destructive methods based on natural frequency for determining the modulus of elasticity of Cupressus lusitanica and Populus x canadiensis. Bioresources 12:270–282

How SS, Williamson CJ, Carradine D, Tan YE, Cambridge J, Pang S (2014) Predicting the young’s modulus of defect free radiata pine shooks in finger-jointing using resonance frequency. Madera Cienc. Tecnol. 16:435–444

Ilic J (2001) Relationship among the dynamic and static elastic properties of air-dry Eucalyptus delegatensis R. Baker. Holz Roh Werkst. 59:169–175

Íñiguez González G, Arriaga Martitegui F, Esteban Herrero M, Argüelles Álvarez R (2007) Los métodos de vibración como herramienta no destructiva para la estimación de las propiedades resistentes de la madera aserrada estructural [Vibration methods as non-destructive tool for structural properties assessment of sawn timber]. Inf. Constr. 59:97–105

Larsson D, Ohlsson S, Perstorpher M, Brundin J (1998) Mechanical properties of sawn timber from Norway spruce. Holz Roh Werkst. 56:331–338

Lever J, Krzywinski M, Altman N (2016) Model selection and overfitting. Nat Methods. 13:703–704

Liu Y, Gong M, Li L, Chui YH (2014) Width effect on the modulus of elasticity of hardwood lumber measured by non-destructive evaluation techniques. Constr. Build. Mater. 50:276–280

Mania P, Siuda F, Roszyk E (2020) Effect of slope grain on mechanical properties of different wood species. Materials 13:1503

Nocetti M, Brunetti M, Bacher M (2016) Efficiency of the machine grading of chestnut structural timber: prediction of strength classes by dry and wet measurements. Mater. Struct. 49:4439–4450

Pardos JA, Werner L, Günter W (1990) Morphological and Chemical Aspects of Pinus sylvestris L. from Spain. Holzforschung 44:143–146

Pommier R, Breysse D, Dumail JF (2013) Non-destructive grading of green Maritime pine using the vibration method. Eur. J. Wood Prod. 71:663–673

R Core Team (2019) R: A language and environment for statistical computing. Version 3.6.1. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from http://www.R-project.org/

Ranta-Maunus A, Denzler JK, Stapel P (2011) Strength of European timber. Part 2. Properties of spruce and pine tested in Gradewood project. VTT Technical Research Centre of Finland. VTT Working Papers, No. 179 Retrieved from http://www.vtt.fi/inf/pdf/workingpapers/2011/W179.pdf

Refaeilzadeh P, Tang L, Liu H (2009) Cross-Validation. In Liu L and Özsü MT (Eds.), Encyclopedia of Database Systems, Springer US, Boston, MA. pp. 532–538

Sales A, Candian M, De Salles Cardin V (2011) Evaluation of the mechanical properties of Brazilian lumber (Goupiá glabra) by nondestructive techniques. Constr. Build. Mater. 25:1450–1454

Sandoz JL (1989) Grading of construction timber by ultrasound. Wood Sci. Technol. 23:95–108

Simic K, Gendvilas V, O’Reilly C, Harte AM (2019) Predicting structural timber grade-determining properties using acoustic and density measurements on young Sitka spruce trees and logs. Holzforschung 73:139–149

Spycher M, Schwarze FW, Steiger R (2008) Assessment of resonance wood quality by comparing its physical and histological properties. Wood Sci. Technol. 42:325–342

Tanaka T, Tanaka T, Nagao H, Kato H (1996) A preliminary investigation on evaluation of strength of soft wood timbers by neural network. Proceeding of the 10th International Symposium on Nondestructive Testing of Wood, Lausanne. pp. 323–329
Tetko IV, Livingstone DJ, Luik AI (1995) Neural Network Studies. 1. Comparison of Overfitting and Overtraining. J. Chem. Inf. Comput. Sci. 35:826–833

Villasante A, Iniguez-Gonzalez G, Puigdomenech L (2019) Comparison of various multivariate models to estimate structural properties by means of non-destructive techniques (NDTs) in Pinus sylvestris L. timber. Holzforschung 73:331–338

Waikato University (2014) WEKA software. Version 3.6.12. Waikato University, Hamilton, New Zealand. Retrieved from https://www.cs.waikato.ac.nz/ml/weka/

Walker J (1993) Primary Wood Processing: Principles and Practice. Chapman & Hall, London, pp. 348–352

Wang SY, Chen JH, Tsai MJ, Lin CJ, Yang TH (2008) Grading of softwood lumber using non-destructive techniques. J. Mater. Process. Tech. 208:149–158

Weaver W, Timoshenko S, Young DH (1990) Vibration problems in engineering. Wiley, New York