Predicting Strength of Norway Spruce and Scots Pine Sawn Timber Using Discrete X-ray Log Scanning, Optical Board Scanning, Traceability, and Partial Least Squares Regression

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Recently developed technology in sawmills such as advanced log scanning and traceability concepts enable new ways of grading logs and boards. When it comes to strength grading, this is often done on sawn boards using automatic scanning systems. However, if board scanners were to be augmented with data from log scanners by using traceability, more information on the wood properties is available. In this study, the main objective was to compare the strength prediction capability of board scanning alone, to board scanning augmented with X-ray and 3D data from log scanning, for Norway spruce (*Picea abies* L. Karst.) and Scots pine (*Pinus sylvestris* L.). In that case, data from three different scanning systems was combined, two for logs and one for boards. A further objective was to investigate whether pre-sorting logs for strength grading can be done using either 3D log data alone, or 3D log data augmented with X-ray data. The results show an improved strength prediction when adding log data to board data, and that 3D log data alone is not enough to pre-sort logs for strength, while adding X-ray log data makes it possible. Strength prediction on Scots pine performed somewhat better than prediction on Norway spruce.

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Keywords: 3D scanning; Board scanning; Log scanning; Norway spruce; Sawmills; Scots pine; Strength grading; Traceability, X-ray scanning

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INTRODUCTION

Using wood as a construction material requires that it is classified and graded regarding strength. The reason for this is to avoid failures of the construction and ensure proper dimensioning. Traditionally in the Nordic countries, strength grading has been done on mainly Norway spruce (*Picea abies* L. Karst.) using either visual grading on features that can be seen on the surface, or by mechanical testing. Grading can be done manually or automatically, and in Europe, the harmonized standard EN 14081 (2019) is used for structural timber.

Scanning systems used for industrial automatic strength grading of sawn timber can be based on visual light, often complemented with a laser line or laser dots, or X-ray scanning. Many times, different technologies are used in combination, or together with mechanical test methods such as dynamic stiffness measurement (Olsson *et al.* 2012).

The sawmill process is a non-continuous process, meaning that material is re-sorted, stored, and transported between production stations, not necessarily arriving in the same order as it left the previous station. This is often a practical necessity, for instance in the case of kiln drying. This also means that it is difficult to retain information on individual pieces of material (logs and boards). Each new production station then requires new measurements, without any knowledge of what happened in previous steps. Therefore, strength grading of wood is normally based on measurements on the sawn timber alone.

Developments in measurement technology and data handling and analysis in sawmills mean possibilities to improve industrial strength grading of wood, as more information on the wood material is available than before. One example is computed tomography X-ray scanning of logs (Fredriksson *et al.* 2017). Implementation of such technology is creating opportunities to measure and classify logs at an early stage of the sawmill process, using detailed information on internal features of the logs. Other existing log scanning technologies used for grading and sorting include discrete X-ray scanners (Grundberg 1999; Skog and Oja 2009), optical 3D scanners using laser triangulation (Jäppinen 2000), and simpler shadow scanners (Mongeau *et al.* 1993; Skatter *et al.* 1998). Discrete X-ray scanners give density information on the log and some internal information such as knot whorl positions and size, while the different 3D scanners give information on the log shape, measuring *e.g.*, taper, ovality, diameter, length, *etc*. These technologies have been in use for several decades but are constantly improving. Studies have been made on the performance of X-ray log scanning for strength grading (Brännström *et al.* 2007; Brännström 2009), but since then the scanning technology has improved and other advances have been made. Johansson *et al.* (2016) made strength prediction based on various scanning technologies with good results, but on a small number of logs and possible overfitting of their models.

One example of such recent development is fingerprint traceability in the sawmill process, meaning that individual sawn boards can be traced back to their log of origin, and more importantly, measurements made on the log can be connected to measurements on the sawn board (Skog *et al.* 2017). The working principle of the method is that the lengthwise position of knot clusters detected in X-ray images of logs are matched with knot positions detected using camera measurements on sawn boards. Logs and sawn boards are therefore matched even though their process order might have changed between *e.g.*, a log yard and a drying and trimming plant. This also means that data from log scanners can be used to complement and strengthen board measurements, creating synergy effects and improved control. For instance, many board scanner systems lack X-ray capabilities, but X-ray scanning of logs is becoming more and more common. If X-ray log data could complement strength grading done by board scanners, then a lot more information on *e.g.*, wood density would be available when grading.

Both improved log scanning using more modern X-ray scanners, as well as traceability methods to aggregate data and thus increase the amount of information available at a certain point in the sawmill process, mean possibilities to improve the decisions taken – strength grading being one important example.

Most previous studies on strength grading of softwood species used in northern Europe have focused on Norway spruce, since this is the species traditionally used for construction purposes. However, a large amount of Scots pine (*Pinus sylvestris* L.) is also grown in *e.g.*, the Nordic countries, so there is a potential to use this species for construction purposes. Therefore, it is of interest to develop prediction models for strength of Scots pine timber as well.

The objective of this study was therefore to compare the strength prediction capability of board scanning alone, to board scanning augmented with X-ray and 3D data from log scanning. This was achieved using partial least squares regression models predicting bending strength, stiffness, and density of Scots pine and Norway spruce boards based on measurement data from log and board scanning technologies, both separate and combined. The latter case corresponds to a situation where log data is available at the board scanning stage, using real-time fingerprint traceability within the sawmill. A further objective was to investigate whether pre-sorting logs for strength grading can be done using either 3D data alone, or 3D data augmented with X-ray data, for both wood species.

EXPERIMENTAL

Material and Data Collection

A total of 600 logs were used, from two different species, Scots pine and Norway spruce. They were collected at the log yard of a sawmill in northern Sweden, from the sawmill's normal storage of logs for production. The logs were categorized as butt logs, middle logs, and top logs, using visual assessment by an expert grader, and 100 logs from each log type and species were sampled. The top diameter ranges were 155 to 172 mm for Scots pine and 169 to 175 mm for Norway spruce. Apart from this, no other selection was made. All logs were marked with color and a number at the butt end to ensure full traceability, as shown in Fig. 1. The color and number were visible also on the sawn timber after sawing.

Fig. 1. Half of the logs tested (Scots pine), colored and ID marked to ensure full traceability through the saw line.

The logs were transported to another sawmill around 230 km away, for scanning. They were scanned using a log 3D scanner (Sawco ProScan, Nyköping, Sweden), measuring the outer shape of the log, and a log X-ray scanner (RemaSawco RS-Xray, Linköping, Sweden) measuring inner properties of the log using two fixed X-ray directions. The measurements were used to calculate log properties such as length, various diameters along the log, taper, sweep, ovality, volume, knot volume, heartwood content, density, and quality grades of each log. This was done using automatic image processing algorithms built into the commercial scanning programs (3D and X-ray, respectively).

The logs were sawn into boards, with two centerpieces produced from each log, at a nominal size of 50 × 100 mm thickness and width. Sideboards were not used in this study. The centerboards were dried to a nominal moisture content of 12%. They were transported to a third sawmill in southern Sweden where they were scanned using a board scanner (RemaSawco RS-BoardScannerQ, Linköping, Sweden) with RGB cameras and laser triangulation to measure shape and visual features on the board surfaces. Features such as knots, cracks, rot, wane, bark, resin wood, pitch pockets and pith were detected and measured using automatic image processing algorithms built into the board scanning system. Due to drying time, transportation, and various tests being made, the time between log scanning and board scanning was approximately two months.

Finally, destructive testing was made in edgewise bending according to the standard EN 408 (2012). The average oven-dry moisture content was 11.3% for the Scots pine samples and 11.5% for the Norway spruce samples. No sample had below 10.0% or above 14.0% moisture content. Bending strength (f_m) and global modulus of elasticity MOE ($E_{m,g}$) were derived for each board according to the standard EN 384 (2018). Density was measured by removing a cross section sample as close to the failure as possible. The sample was oven dried to zero moisture content and the density at testing time and nominal density at 12% moisture content were calculated for each board.

Because each log was sawn into two centerpieces, and due to breakages and other lost material during transportation and handling, 286 pine boards from 141 logs and 297 spruce boards from 148 logs were used. Note that in some cases only one board of the two from an individual log was lost.

Data Processing and Modelling

Multivariate partial least squares (PLS) statistical models (Wold *et al.* 2001) were developed with the aim of testing three different grading scenarios: log grading, board grading, and integrated grading, using both log and board data. Log grading was tested using two different setups of equipment: solely data from the 3D optical scanner; and 3D data combined with data from the X-ray log scanner. The reason for not investigating X-ray alone was that it is seldom used alone in sawmill log sorting stations. Thus, in total four grading scenarios were investigated, as shown in Table 1. These were based on in total three scanning systems, of which all three are combined in the BS3DX scenario. The BS scenario represents how grading is done today.

Table 1. Grading Scenarios

Scenario	Data from System(s)	Prediction on	Grading type
3D	3D	Logs (average strength)	Log
3DX	3D + X-ray	Logs (average strength)	Log
BS	BoardScanner	Boards	Board
BS3DX	3D + X-ray + BoardScanner	Boards	Integrated
3D = log grading using only 3D data of logs, 3DX = log grading using 3D and X-ray data of logs, BS = board grading using data from a camera-based board scanning system, BS3DX = combining all systems together using traceability.			

The aim of each model was to predict the bending strength (dependent variable) using the available log and/or board measurement data (predictor variables). The features forming the basis of predictor variables are described in brief form in Table 2.

Table 2. Example Log and Board Features Forming Predictor Variables in the Models

Scenario	Example Features
3D	Taper, ovality, diameter, length, sweep
3DX	3D combined with density, log type, knot volume, quality
BS	Knots, cracks, wane, holes, pith
BS3DX	BS + 3DX combined

Because several thousands of variables were used, they cannot be described in their full form here. Calculations of variables are further described in the coming sections. Before developing the models, the data was pre-processed in different ways.

Pre-processing of BoardScanner data

Data received from the board scanning system was processed to anonymize it and separate it from the data used commercially – the aim of this study was not to analyze the performance of the commercial system but to investigate how an augmentation with log scanner data can improve board scanner data. From the board scanner, defect information was exported, containing a description of the type of defect, position on the board face (lengthwise and crosswise from one corner), width, and length, for all defects detected by the camera system. In other words, the defect size was described using a rectangular bounding box of a certain width and length. Using this information, descriptive variables were calculated and used as predictor variables in the PLS models. This was done as follows:

- The board was divided into six zones (Fig. 2) separated on
  - Flat face or edge face, with both flat faces and both edge faces treated as the same "face".
  - Butt, middle or top zone, each representing one third of the board length.
- Defects were then sorted into groups based on their type and which zone they were in.
- An area of each defect was calculated, as *width* × *length*.
- A *diagonal* of each defect was calculated, as $\sqrt{width^2 + length^2}$, *i.e.*, a corner-to-corner diagonal measurement of the defect bounding box.
- For each defect group on each board, the following aggregated variables were calculated:
  - Number of defects
  - 20^{th} percentile of diagonal, length, and width, respectively
  - 80^{th} percentile of diagonal, length, and width, respectively
  - Median of diagonal, length, and width, respectively
  - Average of diagonal, length, and width, respectively
  - Maximum diagonal, length and width, respectively
  - Minimum diagonal, length and width, respectively
  - Standard deviation of diagonal, length and width, respectively
  - Total area
  - Total area on the 25 cm board length containing the largest defect area, *i.e.*, a "worst 25 cm"

This resulted in a total of 6 × 24 = 144 variables per defect type, for 37 different defect types. Also included were length, width, and thickness, as well as a so-called indicating property (Lukacevic *et al.* 2015) calculated by the scanner software.

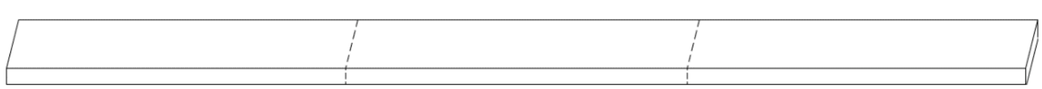

Fig. 2. Division of board into six zones based on flat/edge face, and butt/middle/top third

Overall, the number of predictor variables were 50 from the X-ray log scanner, 33 from the 3D log scanner, and 5332 from the board scanner.

Pre-processing of bending test data

Since the X-ray scanner used was two directional and not a computed tomography scanner, features were measured on the log level rather than for individual boards or parts of the log cross-section. Therefore, the average value of the bending strength was used for all models predicting on the log level. For the models making predictions on the board level, strength values for individual boards were used.

PLS models

The models were developed using SIMCA 14 (Sartorius 2023). Variables were scaled and centered before training the models, by subtracting the mean and dividing by the standard deviation. Separate training sets containing a randomized set with 90% of the observations were used. The models were evaluated using a test set containing the remaining 10% of observations. This was repeated ten times, ensuring that all observations were part of the test set exactly once, thus forming part of the training set the other nine times.

SIMCA's automatic functionality for finding a suitable number of principal components was used, *i.e.*, adding one principal component at a time until the calculated Q^2 (cross-validated coefficient of determination R^2, Eriksson *et al.* 2013) value begins to recede. All models were evaluated on average, median and standard deviation of the coefficient of determination R^2 and root-mean-square error (RMSE) respectively.

Each model was created in a hierarchical way, in three steps. First, a model predicting the density of the board (or average in the case of prediction on logs) was created. Secondly, a model predicting the MOE was created, including the predicted density from the first model as a predictor variable together with all others. Thirdly, a model predicting bending strength was created using both predicted density and MOE as predictor variables with all others.

For all models, a variable reduction step was made, in which the thirty most important predictor variables were retained. The selection was made by creating a basic model in SIMCA, then sorting the variables on their influence on projection (VIP, Eriksson *et al.* 2013) value and retaining the top thirty. For the 3D scenario, this number was reduced to ten variables since the amount of available predictor variables were just 32.

For each prediction model, R^2 was calculated on the test set according to Eq. 1,

$$1-\frac{SS_{res}}{SS_{tot}} \tag{1}$$

where SS_{res} is the residual sum of squares and SS_{tot} is the total sum of squares. The RMSE was calculated according to Eq. 2,

$$\sqrt{\frac{\sum_1^n(\bar{y}-y_i)^2}{n}} \tag{2}$$

where n is the number of observations, $\bar{y}$ is the observed average of the dependent variable, and y_i is the predicted dependent variable for observation i.

Average, median, and standard deviation of R^2 and RMSE was calculated for the ten model permutations, for each of the four scenarios in Table 1.

RESULTS AND DISCUSSION

The prediction strength of each of the developed models is summarized in Table 3 for Norway spruce and Table 4 for Scots pine. Note that the models created on the log level (3D, 3DX) predict the average strength of the boards produced from the log, while the models on the board level (BS, BS3DX) predict individual strength of boards. There was an increase of the average R^2 values by 0.04 to 0.19 when augmenting board scanner data with X-ray and 3D log data, and a decrease of the average RMSE of the bending strength by 0.28 to 1.09 MPa. Doing a two-sample t-test showed that the null hypotheses of equal average R^2 and RMSE values between BS and BS3DX could both be rejected at a confidence level of 95% for spruce, but not for pine. Stating a null hypothesis of no difference between the species for all average R^2 and RMSE values and performing a t-test does not support a rejection of the null hypothesis, except possibly in the BS scenario. Care should be taken when interpreting p-values however (Colquhoun 2014), and in all the investigated cases the addition of log 3D and X-ray data to board data resulted in an improvement of the strength prediction.

Table 3. Prediction Results for Norway Spruce

	R^2			RMSE (MPa)		
Scenario	Average	Median	SD	Average	Median	SD
3D	0.028	-0.025	0.32	8.3	7.8	1.9
3DX	0.34	0.50	0.36	6.7	6.1	1.9
BS	0.33	0.33	0.16	7.7	7.9	0.90
BS3DX	0.50	0.52	0.16	6.6	6.9	1.1

RMSE = root mean square error. SD = standard deviation. The numbers were calculated for ten permutations of different training- and test sets.

Table 4. Prediction Results for Scots Pine

	R^2			RMSE (MPa)		
Scenario	Average	Median	SD	Average	Median	SD
3D	-0.10	0.23	0.58	9.6	9.9	1.4
3DX	0.55	0.60	0.27	6.2	6.5	0.78
BS	0.55	0.57	0.12	7.4	7.5	0.74
BS3DX	0.59	0.63	0.093	7.1	7.2	1.1

RMSE = root mean square error. SD = standard deviation. The numbers were calculated for ten permutations of different training- and test sets.

Individual observations of strength and the model predicted values for boards and logs are presented in Figs. 3 and 4. A *t*-test was performed for the slope coefficient of the least squares linear regression performed on each of the plots, with the null hypothesis of the slope being zero, *i.e.*, no significant trend between observed and predicted value. The largest p value found was 3×10^{-8}, for the *3D* plot for Scots pine. The results indicate that augmenting board scanner data with log scanner data by using traceability can improve the results for strength prediction. R^2 values are higher for the BS3DX scenario than the BS scenario, and RMSE values are lower. Specifically, this type of board scanner lacked sensing technology to detect the wood density – adding X-ray data for the log meant that density information was available. Furthermore, certain log features that are difficult to detect at the board level improved the results, such as log type, heartwood content, distance between knot whorls and so on. This effect was stronger for Norway spruce than for Scots pine, possibly indicating a larger influence of individual knots in Scots pine – a feature that is possible to detect using board scanners. For prediction of strength based on log data alone, a 3D-X-ray combination performed well enough to potentially be used for log pre-sorting, while a 3D scanner alone was not enough.

There were differences between the two species in this study, when it comes to the model prediction performance. Scots pine models generally performed better than the corresponding Norway spruce models. The only larger difference between the species was when only using board scanner data, however. There are several possible explanations for the differences. One is the collected data; the spread of the measured strength was higher in pine than spruce, with no spruce board falling below 20 MPa bending strength for instance. This made training of a linear model more difficult. One other possible explanation is that Scots pine has been found to have larger knots than Norway spruce (Nylinder 1959; Charpentier *et al.* 2013), so knots will be easier to detect and could hypothetically have a larger effect on the bending strength in Scots pine than Norway spruce. It was possible to observe higher average measured knot sizes in the material for Scots pine than for Norway spruce, but given the limited sample size, generalizations are difficult to make.

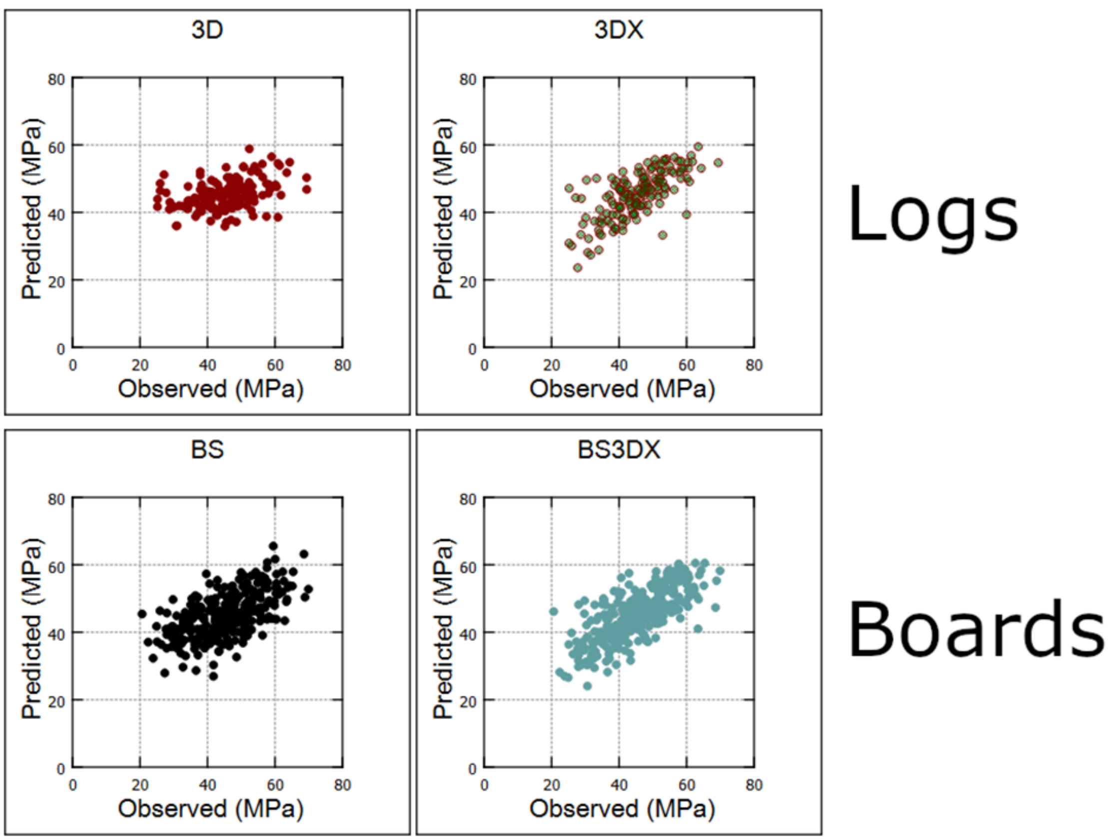

Fig. 3. Scatter plots of observed and predicted values of bending strength of Norway spruce boards, for the ten model permutations used. The top row shows data for logs which means that average strength values for the two sawn center boards have been used, while the bottom row shows individual board data. The title of each plot describes the scenario *i.e.*, which data source or combination of data sources that was used. *RMSE* for the plots are for *3D* 8.4, *3DX* 6.9, *BS* 7.8 and *BS3DX* 6.7.

The limited amount of data used for training in this study mean that the model prediction strength is potentially lower than would be the case if training was done on a larger set, which would probably be the case if this was to be done for an industrial application. However, comparisons between the different methods and scanning technologies are still valid and any models based on more data can be expected to perform equally well or better. There was a large difference between the median and average R^2 for the spruce prediction results using log data, indicating that there was a small number of repetitions with a very low prediction strength compared to the others, which possibly can be attributed to a few individual logs that contain features not included in the prediction set. This is also indicated by the higher standard deviation for the R^2 compared to other models, and a couple of outliers can be seen in the Fig. 3 3DX plot. With a larger training set, this situation could hypothetically be avoided.

The fact that logs were taken from a specific diameter interval can affect the results, since the variation in size is lower than if a completely random set of logs were used. Larger logs in many cases mean butt logs with a different structure than for instance top logs, which are smaller on average. However, it is entirely possible to use different models for different log classes also in practice.

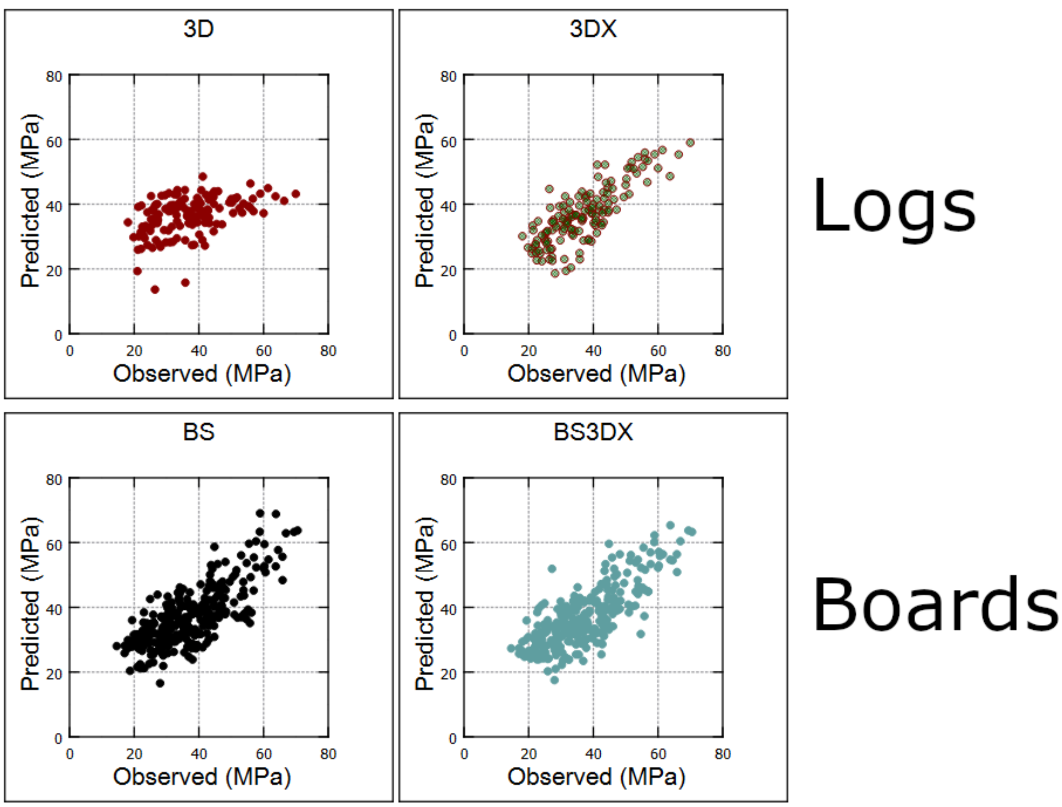

Fig. 4. Scatter plots of observed and predicted values of bending strength of Scots pine boards, for the ten model permutations used. The top row shows data for logs which means that average strength values for the two sawn center boards has been used, while the bottom row shows individual board data. The title of each plot describes the scenario *i.e.*, which data source or combination of data sources that was used. *RMSE* for the plots are for *3D* 9.6, *3DX* 6.2, *BS* 7.4 and *BS3DX* 7.2.

For the variable reduction, the choice of doing a flat reduction down to thirty or ten predictor variables can be discussed. Given the time constraints of the project, software limitations, number of variables, and the need to develop several different prediction models, this strategy was selected to be able to finalize the models on time. It is entirely possible to do a manual variable reduction based on maximizing the Q^2 value, such as in Johansson *et al.* (2016), which might produce better results in the end but be more time consuming.

The results presented by Johansson *et al.* (2016) are better than in the present study when it comes to strength prediction based on discrete X-ray scanning, but as those authors point out, they are wary of the small data set and the risk of overfitting, since they did not test their models on an external test set. Other studies include Brännström *et al.* (2007), where the results are in a similar range as those presented here for X-ray data and spruce, with a better R^2 and a worse RMSE. In their study, only one iteration of prediction set – test set was made. Those studies were only made on Norway spruce and did not include Scots pine.

CONCLUSIONS

1. Traceability within sawmills, connecting log data to measurements of sawn and dried boards, improves prediction models for bending strength, compared to using only board data. The effect is considerable for Norway spruce and smaller for Scots pine. This is shown in a comparison between the "3D + X-ray + BoardScanner" (BS3DX) and the sole reliance on the BoardScanner (BS) scenarios in this study, in terms of root mean square error (RMSE) and coefficient of determination (R^2).
2. Strength prediction of Scots pine performed equally well or better than the same predictions on Norway spruce. This is reflected in the quantitative evaluations of the prediction models, be it RMSE or R^2.
3. Discrete X-ray scanners in combination with three-dimensional (3D) scanners can be used for strength sorting of Scots pine and Norway spruce logs.
4. Optical 3D scanners of this type do not provide enough information for strength sorting of logs.

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