Crown characteristics slightly improve lumber mechanical property models for black spruce (*Picea mariana* (Mill.) BSP)

by Hugues Power[1], Tony Franceschini[2], Robert Schneider[2], Isabelle Duchesne[3] and Frank Berninger[4]

ABSTRACT

Most models of modulus of elasticity (MOE) and modulus of rupture (MOR) use classical dendrometric variables and do not use crown characteristics that are known to influence wood formation and properties. The objective of this study was to evaluate the benefit of including crown variables in black spruce MOE and MOR models. Values of MOE and MOR were measured on 99 boards from 21 black spruce trees located in nine stands in the Lac-Saint-Jean region of Québec (Canada). Site, tree and crown variables (crown surface area, crown length, branch basal area) were measured. Stand age and basal area were found to be positively related to MOE and MOR. Stem DBH and crown length were negatively related to MOE and MOR. When including crown variables, Akaike's Information Criterion was stable while the R^2 increased slightly (+ 2.7% for MOE and + 1% for MOR). The small benefit in model performance associated with the inclusion of crown variables in MOE and MOR models suggests that models without crown variables could be used for industrial purposes without much loss in performance.

Key words: modulus of elasticity, modulus of rupture, crown characteristics, black spruce

RÉSUMÉ

La plupart des modèles de module d'élasticité (MOE) et de module de rupture (MOR) utilisent des variables dendrométriques standards, mais pas les caractéristiques du houppier reconnues pour influencer la formation du bois et ses propriétés. Cette étude avait pour but d'évaluer l'intérêt d'utiliser les variables de houppier dans les modèles de MOE et de MOR pour l'épinette noire. Les valeurs du MOE et du MOR ont été mesurées sur 99 pièces de bois obtenues de 21 tiges d'épinette noire provenant de l'épinette noire réparties dans neuf peuplements de la région du Lac-Saint-Jean, au Québec (Canada). Les mesures ont porté sur les variables de la station, des arbres ainsi que des cimes (superficie de la cime, longueur de la cime, surface terrière). On a observé que l'âge du peuplement et la surface terrière étaient corrélées de façon positive avec le MOE et le MOR. Le dhp des tiges et la longueur des cimes montraient une corrélation négative avec le MOR et le MOE. En incluant les variables des cimes, le critère d'information d'Akaike s'avère stable tandis que le R2 s'accroît légèrement (+ 2,7 % pour le MOE et + 1 % pour le MOR). Le peu de gain dans la performance du modèle lié à l'inclusion des variables de la cime dans les modèles du MOE et du MOR indique que les modèles sans les variables de la cime pourraient être utilisés à des fins industrielles sans diminution importante au niveau de la performance.

Mots clés : module d'élasticité, module de rupture, caractéristiques de la cime, épinette noire

Introduction

Black spruce is one of the most important commercial tree species in the Canadian boreal forest (Burns and Honkala 1990), an ecosystem that covers more than 310 million hectares and represents 30% of Canada's total land (Canadian Forest Service 2005). Assessing wood properties of standing black spruce trees is thus an important issue for the Canadian forest industry (Bustos *et al.* 2003). To allocate wood to structural and non-structural uses properly, forest managers need tools to quickly assess final product characteristics from a given tree to ensure its optimal processing (Duchesne 2006). Understanding the sources of variation and particularly the effect of growth conditions on wood properties is therefore of greatest interest (Zobel and vanBuijtenen 1989).

The modulus of elasticity (MOE) and the modulus of rupture (MOR) are two common metrics of wood properties. The MOE (also termed stiffness) is the ability of wood to sustain a certain load without permanent plastic deformation while the MOR (also termed strength) is the maximum loading that a wood piece can support in bending condition just before breaking (Green *et al.* 1999). It is widely known that a strong positive relationship exists between MOE and MOR (Lei *et al.* 2005). However, both variables are useful, even if MOE is considered as a proxy for MOR (Moore *et al.* 2013). MOE is used in machine stress-rated (MSR) classification of lumber products in order to classify wood pieces non-destructively for structural uses (NLGA 1997) while MOR is a destructive measure of wood strength.

Wood mechanical properties have long been known to vary between trees (Larson 1969) as a consequence of differences in genetics (Zhang 1998) or in growth conditions (Liu *et al.* 2007). Recently, some work has been done to better

[1]Corresponding author: Direction de la recherche forestière, Ministère des Forêts, de la Faune et des Parcs, Québec, QC, G1P 3W8; E-mail : hugues.power@mffp.gouv.qc.ca.
[2]Département de biologie, Université du Québec à Rimouski, Rimouski, QC, H3C 3P8
[3]Centre canadien sur la fibre de bois, Ressources naturelles Canada, Québec, QC, G1V 4C7
[4]Department of Forest Sciences, University of Helsinki, P.O. Box 27, 00014, Helsinki, Finland.

understand and quantify the influences of the growing conditions on black spruce lumber strength and stiffness. Stand density has been found to be positively correlated to black spruce MOE (Reid *et al.* 2009). Moreover, pre-commercial thinnings in plantations have been reported to negatively affect lumber MOE and MOR (Tong *et al.* 2009). In contrast, commercial thinning in fire-origin natural stands was not found to influence black spruce MOE (Vincent *et al.* 2011).

Several studies have considered that the effects of tree competition on wood mechanical properties can in part be explained by changes between mature and juvenile wood proportions. Many definitions of juvenile wood exist in the scientific literature (Zobel and van Buijtenen 1989). For this study, we considered juvenile wood as the wood produced inside the living crown (Wellwood and Smith 1962). The link between juvenile wood and live crown can be explained by the higher concentration of auxins in the crown that stimulate cambial activity (Zobel and van Buijtenen 1989). Juvenile wood is known to have lower MOE and MOR when compared with mature wood (Alteyrac *et al.* 2006). Moreover, fast-growing trees are often found to have higher juvenile wood proportion (Alteyrac *et al.* 2006) and larger crowns, which have been negatively correlated with the mechanical properties (Kuprevicius *et al.* 2013). The lower properties of juvenile wood have been attributed to the microfibril angle in the secondary wall of wood fibres that is larger in juvenile wood (Burdon *et al.* 2004). In addition, crown characteristics are also an indicator of tree vitality (Dobbertin 2005), which directly influence wood properties (Lenz *et al.* 2012). Finally, crown dimensions are strongly related to knot size, which in turn influence both MOE and MOR (Aubry *et al.* 1998) by locally deviating fibres in relation to the stem axis, creating mechanically weak areas (Tong *et al.* 2013).

It remains to be determined if crown characteristics, which are rarely measured in forest inventories, improve the performance of statistical models used to predict wood mechanical properties. The general objective of this paper is to establish the importance of log, tree, stand and crown variables in the variations of both MOE and MOR for black spruce lumber. Specifically, we aim to produce models to estimate black spruce MOE and MOR and to test which stand, tree or crown variables provide the best fit for explaining these properties. We hypothesized that the use of crown variables would result in a better model of MOE and MOR than models that do not include crown variables.

Table 1. Summary statistics for plot, tree, lumber and branch level variables

Variable	Minimum	Mean	Maximum	Standard deviation
Mean annual temperature (°C)	–	2.7	–	–
Mean annual precipitation (mm)	–	887	–	–
Modulus of elasticity (MPa), **MOE**	7164	12087	16961	1848
Modulus of rupture (MPa), **MOR**	19.04	61.93	89.57	12.80
Moisture content (%)	11.0	12.8	17.1	1.0
Log variables				
Distance to crown base (m), **DCB**	0.60	4.73	11.38	2.51
Log identifiant, **LID**	Binary variable			
Tree variables				
Diameter at breast height (cm), **DBH**	10.9	17.5	25.6	4.5
Total tree height (m), **TH**	11.0	16.0	20.8	2.8
Stand variables				
Stand age (age at 1 m height), **SA**	45	80	119	24
Dominant height (m), **DH**	12.7	17.5	18.8	1.9
Quadratic mean DBH (cm), **QDBH**	8.3	13.6	17.8	3.3
Site index (m), **SI**	12.6	15.4	16.9	1.2
Competition variables				
Stand basal area (m^2/ha), **SBA**	23	32.9	45	8.3
Stand density (stems ha^{-1}), **SD**	921	2890	7203	1957
Tree competition index (unitless), **TCI**	0.802	1.411	2.072	0.337
Crown variables				
Branch basal area (m^2), **BBA**	0.007	0.020	0.044	0.012
Crown surface area (m^2), **CSA**	18.1	53.8	150.3	37
Crown length (m), **CL**	4.0	8.0	14.5	3.0

Material and Methods

Data

A total of 21 black spruce trees located in nine monospecific, naturally regenerated, even-aged, unmanaged stands were felled in the summer of 2009. The stands were located in the north of the Lac-St-Jean administrative region in the Province of Quebec, Canada (48 ° 45′ N to 49 ° 01′ N, 72 ° 45′ W to 73 ° 19′ W) and were selected from the forest cover map in order to cover different age, stand density and site indices (Table 1). In each stand, a variable radius sample plot with a basal area factor of 1 $m^2.ha^{-1}$ was established and the diameter at breast height (DBH, measured 1.3 m above ground) of every living tree with a DBH larger than 1.0 cm was measured with a diameter tape to the nearest millimeter. In each plot, trees were assigned to one of three DBH groups (small, medium and large) so that each group included the same number of trees. Total height of a subsample of trees from each DBH group was measured to the nearest decimeter with a hypsometer (Vertex[tm]). Thereafter, one tree per DBH group was randomly selected as a sample tree and felled.

Stand basal area (SBA) and stand mean quadratic diameter (QDBH) were derived from the measurement of the DBH of the variable radius sample plots. A plot-specific tree height model was parameterized to estimate unmeasured tree heights (details are provided in Power *et al.* 2012). Once all unmeasured heights were imputed, the dominant height (DH) of each plot was calculated by averaging the height of the 100 largest trees per hectare. With stand age obtained from increment cores collected on three dominant trees of the stand at 1 m height, dominant height was used to estimate site index with Pothier and Savard's (1998) equations. A tree competition index (TCI) was computed by dividing the diameter of the considered sample tree by the stand quadratic mean diameter.

After felling, total sample tree height and height to live crown were measured to the nearest centimeter. Height to live crown was considered as the height of the lowest branch that presented green foliage and above which all the whorls included at least one living branch. Basal diameter and height of all living branches were measured. Crown surface area of trees was then calculated according to the method described in Power *et al.* (2012).

Two 2.25 m logs were then collected between the stump height (established at 0.25 m) and 5.75 m. However, logs were only collected when the top end diameter of the log was larger than 8 cm. This implies that for some sample trees, only one or even no log was collected. A total of 39 logs (with a possibility of 54) were sampled in order to perform MOE and MOR measurements. The butt-end diameter of the sampled logs varied from 9.9 cm to 25.0 cm and from 8.3 cm to 21.2 cm at the top end.

Logs were transported to FPInnovations (Québec City) where they were sawn using a portable sawmill. Each of the 39 logs produced between one and five boards for a total of 99 pieces of lumber with a nominal size 38 mm x 64 mm. The lumber was kiln dried using a standard industrial drying schedule and dressed before mechanical testing.

Lumber pieces were stored in a conditioning chamber (20 °C and 75% relative humidity) until they reached approximately 15% equilibrium moisture content (MC). Prior to each static bending test, MC was estimated for each piece using a handheld resistance-type moisture meter (Delmhorst Instrument Co.). Lumber MOE and MOR were tested edgewise with third-point loading in accordance with ASTM D 4761-05 American Standard Test Methods (ASTM) for Mechanical Properties of Lumber and Wood-Base Structural Material (ASTM International 2009). All bending tests were carried out using a Metriguard 312 testing machine with a span-to-depth ratio of 17.5 to 1. The type of fracture was recorded on each piece of lumber. Following the ASTM D-1900-00 (2002) (ASTM International 2009), MOE and MOR values were normalized to 15% MC. Two small 4-cm wood sections were also cut to determine moisture content (ASTM D 4442-07, ASTM International 2009) and wood basic density (ASTM D 2395-07, ASTM International 2009).

Statistical analysis

Pearson's correlation coefficients were computed between each modulus (i.e., MOE or MOR) and all the possible explanatory variables. This yielded a first estimate of the links between log, tree, stand and crown variables and MOE and MOR. The effect of log position (bottom or top log) was first verified with a t-test. The mean values of MOE and MOR of the two types of log were compared to test if these values were higher for the bottom log.

The variations in MOE and MOR were examined as a function of a wide variety of variables that were classified in five groups to account for the different sources of variation that can affect wood mechanical properties. The 'Log' variables (group **i**) accounted for the within-tree variation consisted of the position of the log in the tree encoded as a binary variable (1 if bottom log, 0 if top log) and the distance to crown base of the top of the log. The 'Tree' variables (group **ii**) accounted for the variation between trees of the same stand included DBH and total height of tree. 'Stand' variables (group **iii**), excluding the variables directly related to inter-tree competition, accounted for the development stage and fertility of the stand and included stand age, dominant height, mean quadratic diameter and site index (height in m at 50 years). The 'Competition' variables (group **iv**) included stand basal area, stand density and the tree competition index (TCI). Finally, 'Crown' variables (group **v**) included the total basal area of living branches in the tree, the crown surface area of the tree, and the crown length of the tree. As the data were hierarchical, linear mixed-effect models were used. All models were fitted using the "lme" function of the "nlme" package (Pinheiro *et al.* 2007) of the statistical software R 3.1.1 (R Core Team 2014).

As a first step, the importance of the hierarchical levels was determined by comparing various random effect structures with intercept-only models. Models were thus fitted using the restricted maximum likelihood (REML) method. Three nested hierarchical levels were considered: the stand, tree nested in the stand and the log nested in the tree nested in the stand. The model with the lowest AIC was then chosen.

Secondly, all possible models were fitted by considering all the variable combinations from one of the five previously defined groups using the maximum likelihood (ML) method. Consequently, the models had between one and five covariates, depending on the number of groups considered in the model. A total of 719 models were thus fit. In order to avoid spurious correlation between variables, the variance inflation factors (VIF) were computed for each variable of the multiple linear models corresponding to the tested combinations. If a VIF value was superior to five, the corresponding model was discarded. VIFs were computed using the "vif" function from the "car" package of the statistical software R (Fox *et al.* 2014). Because VIF values larger than 10 are generally considered to affect the value of the estimates of the parameters of the regression (Besley *et al.* 1980), the chosen threshold of five can be considered as a conservative approach. Model selection was based on AIC comparisons and on likelihood ratio tests (LRT) for nested models, when applicable. In addition, all parameters of the selected models had to be significant (p-value < 0.1). The selected model residuals were checked for homoscedasticity and normality. Using these criteria, we selected the best model with a variable from the "crown" group and the best model without a variable from this group. This led to two models being selected for MOE and two for MOR: one with and one without crown variables.

Model with crown variable:
Modulus = f(Log, Tree, Stand, Competition, Crown)

Model without crown variable:
Modulus = f(Log, Tree, Stand, Competition)

In order to visualize and illustrate the effects of each variable on MOE and MOR, the partial regressions between MOE and MOR and each variable of the selected models were plotted (Quinn and Keough 2002). Partial regression plots consist in plotting two sets of residuals. First, the Y-axis is the residuals of the linear model of MOE or MOR as a function of all variables except the one of interest. Second, the X-axis is the residuals of the linear model of the variable of interest as a function of all other variables. The slope of the residuals is thus equal to the slope obtained from the multiple regressions.

Table 2. Correlations between variables and both MOE and MOR

Variable	MOE	MOR
Log variables		
Distance to crown base (m), **DCB**	0.404^{***}	0.361^{***}
Log identifiant, **LID †**	301 º	5.21^{*}
Tree variables		
Diameter at breast height (cm), **DBH**	-0.378^{***}	-0.291^{**}
Total tree height (m), **HT**	-0.205^{*}	-0.169^{+}
Stand variables		
Stand age (age at 1 m height), **SA**	0.040^{+}	0.016^{+}
Dominant height (m), **DH**	-0.129^{+}	-0.039^{+}
Quadratic mean DBH (cm), **QDBH**	-0.039^{+}	-0.045^{+}
Site index (m), **SI**	0.020^{+}	0.112^{+}
Competition variables		
Stand basal area (m^2/ha), **SBA**	0.229^{*}	0.250^{*}
Stand density (stems ha^{-1}), **SD**	0.155^{+}	0.126^{+}
Tree competition index (unitless), **TCI**	0.285^{**}	-0.202^{*}
Crown variables		
Branch basal area (m^2), **BBA**	-0.375^{***}	-0.307^{***}
Crown surface area (m^2), **CSA**	-0.406^{***}	-0.293^{**}
Crown length (m), **CL**	-0.429^{***}	-0.316^{**}

*** p-value <0.001; ** p-value < 0.01; * p-value < 0.05; + p-value < 0.1
†The variable Log identifiant is factorial; therefore we reported here the difference in MOE and MOR between the two LIDs.

Results

Selected stands varied in age between 45 and 119 years, their dominant height between 12 and 19 m and their site index between 13 and 17 m. Moreover, MOE and MOR of the sampled logs varied respectively from 7 164 to 16 961 MPa and from 19.04 to 89.57 MPa (Table 1). The DBH was found to be strongly negatively correlated to both wood stiffness and strength while total tree height was only poorly negatively correlated with these two variables (Table 2, Fig. 1 and Fig. 2). Competition variables were moderately positively correlated with MOE and MOR, the TCI was the most correlated with MOE (Pearson's correlation = 0.285) while MOR had the highest correlation with stand basal area (Pearson's correlation = 0.250). All crown variables showed correlations lower than -0.25 with both MOE and MOR. When considering log level variables, distance to crown base of the log was strongly correlated to both MOE and MOR. The correlation between crown variables and wood mechanical properties justified the search for a relationship between these variables. Even considering the large range of growing conditions sampled, stand variables were only poorly correlated with both MOE and MOR (Table 2).

Only small differences were found for strength and stiffness according to their position in the tree. The average MOE value for the lumber of the lower log was 301 MPa higher than that for the top log. The difference was however non-significant (p-value = 0.42). Similarly, the MOR decreased with increasing height in the tree (Fig. 3), the difference between the two logs being 5.21 MPa and was thus statistically different (p-value = 0.047).

Model for MOE

The first step of the modeling process was to identify the hierarchical levels to consider in the analysis. When comparing models with different hierarchical structures, the best model was obtained by integrating a tree and a log nested in a tree random effects (Model MOE.r2 in Table 3). This model leads to the lowest AIC (1741 points) while the model integrating only a log random effect (MOE.r3, 1744 points) or an additional plot random effect (MOE.r1, 1743 points) leads to higher AICs.

The second step of the process was to select the best model among all possible combinations of variables from each defined group using the ML convergence method. The selected model with crown variables was model MOE.2 (AIC = 1745, Table 4) which included the following variables: stand age (SA), stand basal area (SBA) and crown length (CL).

MOE.2:

$$MOE_{ijkl} = a_1 + a_2 \cdot SA_i + a_3 \cdot SBA_i + a_4 \cdot CL_{ij} + \alpha_{ik} + \alpha_j + \varepsilon_{ijkl}$$

With (a_1, a_2, a_3, a_4) the estimated fixed effect parameters of the model, α_{jk} the log nested in tree random effect, α_j the tree random effect and ε_{ijkl} the random error for the observation *l* from log *k* nested in tree *j* nested in stand *i*.

When discarding crown variables, the selected model MOE.3 had only a slightly higher AIC (AIC = 1746, Table 4).

MOE.3:

$$MOE_{ijkl} = b_1 + b_2 \cdot SA_i + b_3 \cdot SBA_i + b_4 \cdot DBH_{ij} + \beta_{jk} + \beta_j + \varepsilon_{ijkl}$$

With (b_1, b_2, b_3, b_4) the estimated fixed effect parameters of the model, β_{jk} the log nested in tree random effect, β_j the tree random effect and ε_{ijkl} the random error for the observation *l* from log *k* nested in tree *j* nested in stand *i*.

Both models show that MOE is proportional to stand age and basal area (Table 4). In addition, MOE was found to be inversely proportional to crown length (model MOE.2) and DBH (model MOE.3). The coefficient of determination of the fixed effects decreased from 0.290 to 0.263 while the residual standard error increased from 1708 MPa to 1776 MPa, for the models with and without crown variables, respectively.

Model for MOR

When considering the MOR, the best hierarchical structure was obtained by integrating only a log random effect (model MOR.r3, AIC = 779 points, Table 5). Specifically, the integration of a plot random effect (model MOR.r1, AIC = 783 points) and a tree random effect (model MOR.r2, AIC = 781) led to a slightly higher AIC.

Among all combinations of variables possible from each defined group, the model (MOR.2) with SBA, SA, crown length (CL) and log location (LogID) was the best model based on the AIC (AIC = 773.4, Table 6).

MOR.2:

$$MOR_{ijkl} = c_1 + c_2 \cdot SA_i + c_3 \cdot SBA_i + c_4 \cdot CL_{ij} + c_5 \cdot LogID_{ijk} + \gamma_k + \varepsilon_{ijkl}$$

With (c_1, c_2, c_3, c_4, c_5) the estimated fixed effect parameters of the model, γ_k the log random effect and ε_{ijkl} the random error for the observation *l* from log *k* nested in tree *j* nested in stand *i*.

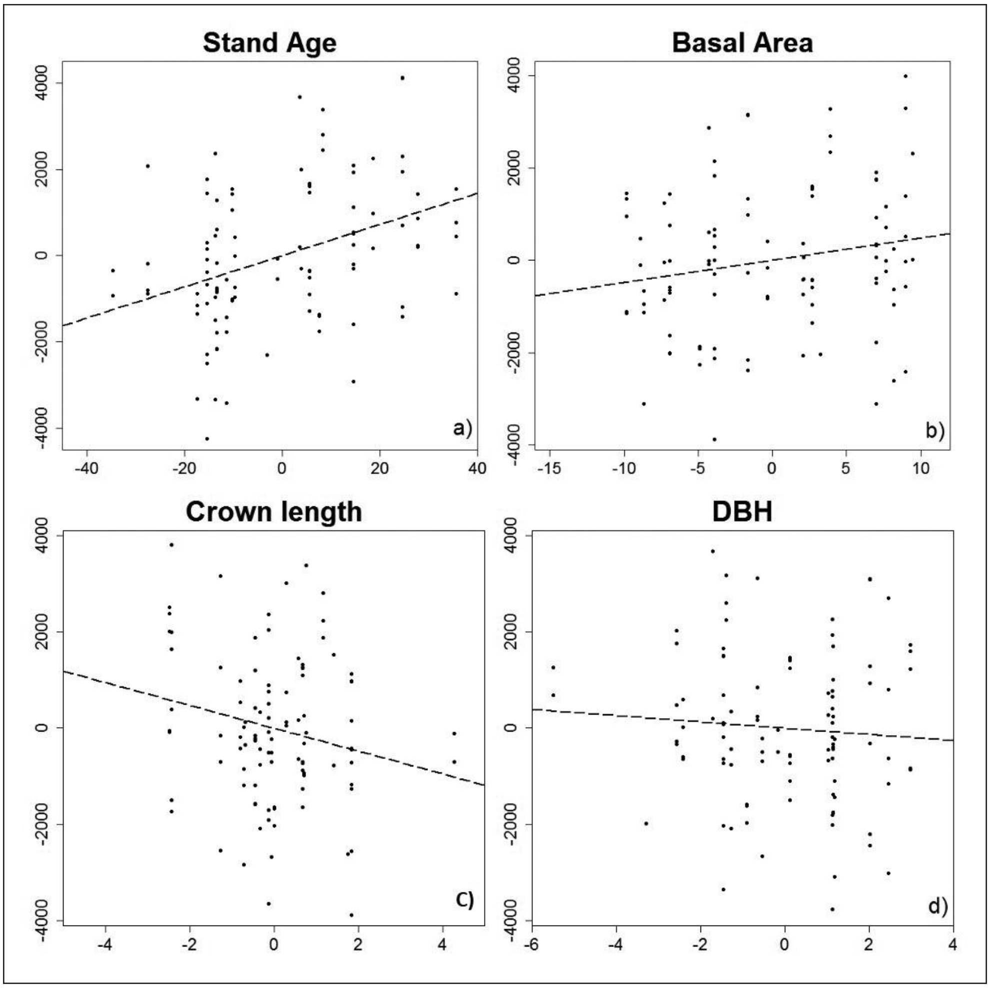

Fig. 1. Partial regression plots for the variations of the MOE as a function of **a)** stand age, **b)** stand basal area, **c)** crown length and **d)** DBH. The Y-axis is the residuals from the regression of MOE against all variables except the one labelled. The X-axis is the residuals of the regression of the labelled variable against all other predictors.

When crown variables were discarded, the selected model (MOR.3) had a slightly higher AIC (AIC = 773.7, Table 3) and included SBA, SA, diameter at breast height (DBH) and the log identifiant (LogID).

MOR.3:

$$MOR_{ijkl} = d_1 + d_2 \cdot SA_i + d_3 \cdot SBA_i + d_4 \cdot DBH_{ij} + d_5 \cdot LogID_{ijk} + \delta_k + \varepsilon_{ijkl}$$

With (d_1, d_2, d_3, d_4) the estimated fixed effect parameters of the model, δ_{1k} the log random effect and ε_{ijkl} the random error for the observation *l* from log *k* nested in tree *j* nested in stand *i*.

In both models, MOR is proportional to stand basal area (Table 6). MOR is also proportional to stand age (MOR.2) and to the distance of the log to crown base (MOR.3). In contrast, MOR is inversely proportional to crown length. Furthermore, the fixed effects coefficient of determination followed the same trends as with the AIC, with the R^2 of MOR.2 (0.196) being slightly higher than the MOR.3 R^2 (0.190), while the residuals standard error was similar for both models at 10.3 MPa.

Discussion

With our dataset, efforts were made to improve the understanding and the predicting capacity of bending stiffness and strength by considering traditional forest survey data (DBH, tree height, age, stand density) as well as detailed crown and branch measurements. The fit statistics (i.e., AIC, coefficient of determination and standard error of the residuals) of models with crown characteristics are only slightly better than those without crown attributes, with differences in AIC of 1 point for MOE and 0.3 point for MOR. Differences in AIC smaller than 2 points can indicate that two models are equally plausible (Burnham and Anderson 2002), and thus the models with crown variables cannot be differentiated from the models without crown variables. The similarities of fit statistics of models with and without crown characteristics could be partly attributed to the large within-tree variation of MOE and MOR found in this study. For MOE, this variation was described by the random effect associated with the log. A high variability of MOE was previously found at both the inter-individual (Vincent *et al.* 2011) and intra-individual levels (Alteyrac *et al.* 2006). Another explanation of the small improvement made by the addition of crown variables is the strong relationship between crown length and DBH (correlation = 0.907, p-value < 10^{-16}). In both MOE and MOR models, crown length was replaced by DBH without losing much prediction power. However, even if it is often the case in destructive studies, the small number of sampled logs could also explain why no significant differences were found between models with and without crown variables.

The within-stem MOR variation was quantified by both a random effect associated with the log and by the fixed effect associated with the position of the log within the tree. Specifically, the MOR was larger for lumber pieces found in the lower log than in the upper log in accordance with previous studies (Duchesne 2006). Another study also found a slight but non-significant increase of MOE with height along stem, particularly for mature trees (Sattler *et al.* 2013). Lumber taken from higher up in the tree closer to the living crown, contains a higher proportion of juvenile wood which has shorter fibres, lower wood density, higher microfibril angles and thus lower mechanical bending properties (Tong *et al.* 2009). In contrast with other species like jack pine, crowns in black spruce are characterized by a large number of small branches (Duchateau *et al.* 2013). Small knots are known to have less impact on lumber strength than large knots, and NLGA (National Lumber Grades Authority) visual grades specifically aim to capture the effects of knots on lumber performance. In this study, branches may have had little effect on mechanical properties because of the particular morphology of the black spruce crown, which is relatively narrow (Power *et al.* 2012) and includes numerous small branches.

Studies on the influence of the crown on wood properties would benefit from having historic or dynamic information on crown characteristics during the whole lifetime of trees (instead of having only one static crown measurement). This would allow for having tree information when the sampled logs were located inside the living crown. However, such repeated measurements are unusual although promising new techniques such as terrestrial and aerial LiDAR may provide large-scale crown metrics (Dassot *et al.* 2011).

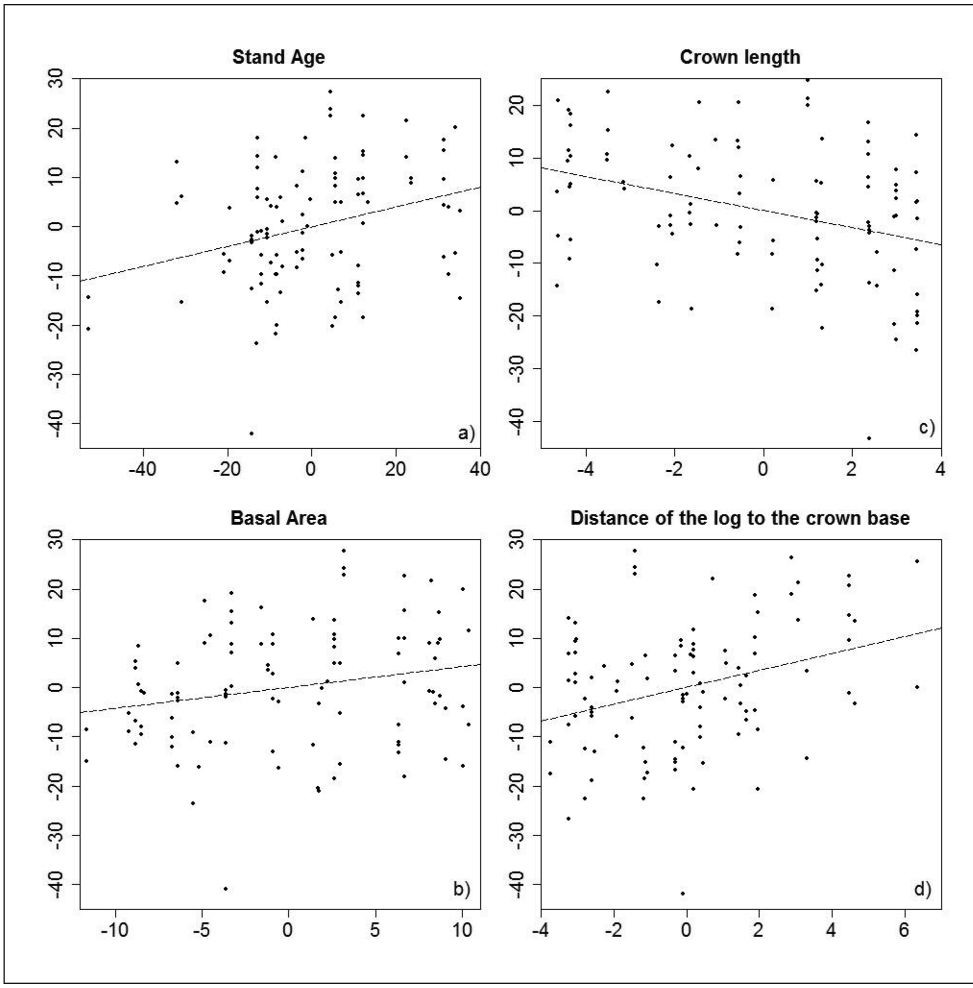

Fig. 2. Partial regression plots for the variations of the MOR as a function of **a)** stand age, **b)** stand basal area, **c)** crown length and **d)** distance of the log to crown base. The Y-axis is the residuals from the regression of MOR against all variables except the one labelled. The X-axis is the residuals of the regression of the labelled variables against all other predictors. This figure also shows **e)** the variations of MOR as a function of the position of the log in the tree (1 = base of the stem, 2 = top of the stem).

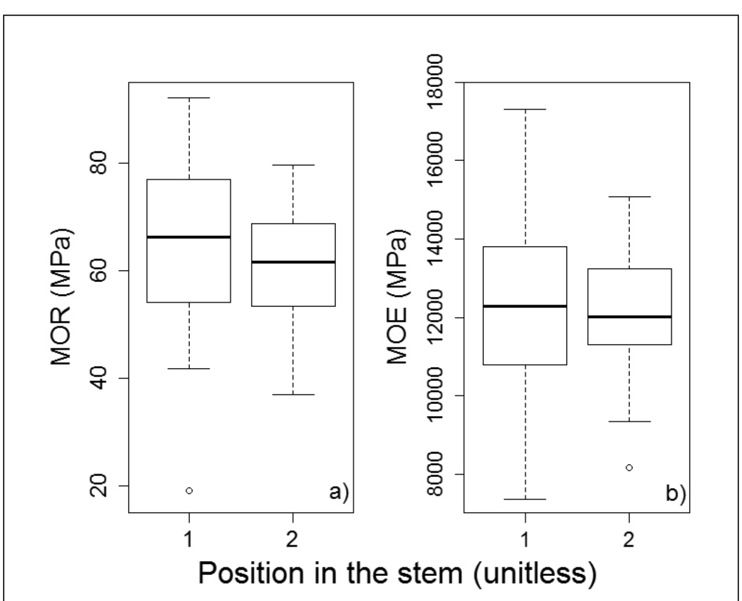

Fig. 3. Variations of the MOR and MOE as a function of the position of the log in the tree (1 = base of the stem, 2 = top of the stem).

An important aspect of the impact of crown characteristics on wood mechanical properties is that trees developing narrow crowns (in dense stands) will have smaller branches due to early crown recession and natural pruning of the lower bole (Mäkinen *et al.* 2003). Lumber sawn from these trees will have smaller knots and potentially more clear wood. It is well known that increasing knot size and number negatively affects lumber mechanical properties (Aubry *et al.* 1998). Thus, the smaller the knots and grain deviation around the knots, the stronger the wood will be. The negative effect of crown length on both MOE and

Table 3. Model statistics for MOE models fitted with the REML method with different hierarchical structure. σ_k: log random effect standard deviation, σ_{jk}: tree random effect standard deviation, σ_{ijk}: plot random effect standard deviation. Numbers in brackets are standard deviation of parameter estimates. LRT were performed between the model with the lowest AIC against the others.

	MOE.r1	MOE.r2	MOE.r3
Intercept	12 300*** (321)	12 300*** (302)	12 300*** (247)
σ_{ijk}	679	681	1210
σ_{jk}	1010	1070	–
σ_k	384	–	–
ε_{ijkl}	1358	1358	1378
AIC	1743	1741	1744
df	5	4	3
p-value LRT	0.1009	–	0.0343

*** p-value <0.001

Table 4. Model statistics for models of MOE fitted with the ML method. Numbers in brackets are standard deviation of parameter estimates

MOE.1			MOE.2		MOE.3	
variable		parameter	variable	parameter	variable	parameter
Intercept		12 300 *** (296)	Intercept	10 400 *** (1650)	Intercept	10 800 *** (1760)
		–	SA	32.0 ** (10.4)	SA	35.2 *** (11.2)
		–	SBA	47.3 + (29.5)	SBA	65.9 * (29.6)
		–	CL	-302 *** (72.5)	DBH	-210 *** (54.7)
σ_k		1028	–	0.201	–	0.585
σ_{jk}		683	–	708	–	776
ε_{ijkl}		1358	–	1376	–	1363
AIC		1754	–	1745	–	1746
R^2	fixed part	–	–	0.290	–	0.263
	random part	–	–	0.232	–	0.277
	BLUP	–	–	0.522	–	0.540

*** p-value <0.001; ** p-value < 0.01; * p-value < 0.05; + p-value <0.1;

MOR found in this study is in agreement with this explanation. Along with lower juvenile wood proportion, smaller knots in narrow crowns also help explain the positive relationship between basal area and MOE and MOR observed in this study. In fact, knots are one of the major classification criteria (or downgrading defects) used by the NLGA to visually grade lumber products to ensure uniform quality of Canadian lumber products (NLGA 2008).

In this study, both the MOE and MOR were found to be proportional to the stand age and basal area, and inversely proportional to tree size. As trees age, the proportion of juvenile wood in the stem decreases (Larson 1969), thus leading to higher flexural strength. However, all things being equal (age and site index), trees growing faster in the same stand will have proportionally larger juvenile wood cores (Macdonald and Hubert 2002), and an increased probability of sawing in that specific area and obtain lower-strength lumber. In addition, it is also known that highly dense stands produce trees with lower juvenile wood proportion (Kennedy 1995).

With the recent applications of LiDAR to forestry, studies were conducted to estimate wood properties from variables that can be derived from airborne LiDAR (e.g., Hiker *et al.* 2013). Airborne LiDAR measurements can rapidly be obtained for large areas and can give access to a large amount of data. It can therefore be used in combination with or in replacement of traditional forest surveys (Wulder *et al.* 2012). Tree crown characteristics, total height and stand density are among the variables that can be obtained from airborne LiDAR data. Our models that used crown variables also used stand age and stand basal area, variables that can hardly be obtained without ground-level forest surveys. Consequently, we may expect a loss of precision if we build models for MOE and MOR using only data from airborne LiDAR. However the precision loss of the model may be compensated for by the decrease in sampling error due to a larger number of measurements (Hilker *et al.* 2013).

With only 21 trees from nine different sites, the assumption of linearity between the dependent and explanatory variables could not be tested, although previous studies used linear models (Liu *et al.* 2007). In the near future, stronger relationships between crown attributes and mechanical properties may possibly be found thanks to the rising accessibility and use of airborne and terrestrial LiDAR technologies, which associated with traditional forest surveys will allow the user to collect more data on a larger number of trees per stand. These tools also offer the possibility to carry out repeated crown characteristics measurements through time, which so far has been too labour intensive using manual techniques.

Conclusion

The present study demonstrated that crown characteristics help us to understand how MOE and MOR vary within and between black spruce stems. Particularly, we were able to relate variables such as crown length to changes in MOE and MOR. These tree characteristics can be associated with juvenile wood proportion within the stem. However, it was shown that the consideration of crown characteristics only slightly improves the performance of MOE and MOR models without giving clear indications that one model was better than another. Therefore, when considering current applications in forest management or wood processing, the results suggest that models of MOE and MOR could probably consider only traditional dendrometric variables without crown metrics. In coming applications, where remote sensing technologies will generate large-scale high-resolution crown metrics at a reasonable cost, the inclusion of crown variables may turn out to strengthen wood mechanical property models. However, more research is needed in this emerging field as well as results from other studies performed in other areas of black spruce distribution in order to strengthen the results obtained in this study.

Acknowledgements

The authors would like to thank ForValueNet for funding the study and Mrs. Pamela Cheers for reviewing the manuscript. They also want to thank the two anonymous reviewers for their comments on the manuscript.

Table 6. Model statistics for models of MOR fitted with the ML method. Numbers in brackets are standard deviation of parameter estimates

MOR.1			MOR.2		MOR.3	
variable		parameter	variable	parameter	variable	parameter
Intercept		64.2 *** (1.82)	Intercept	46.1 *** (12.0)	Intercept	48.2 *** (12.5)
		–	SA	0.176 * (0.0755)	SA	0.192 ** (0.0791)
		–	SBA	0.455 * (0.215)	SBA	0.534 * (0.210)
		–	CL	-1.35 * (0.526)	DBH	-0.962 ** (0.388)
		–	LID	-5.43 * (2.76)	LID	-5.02 + (2.78)
σ_i		8.67	–	4.88	–	4.96
ε_{ijkl}		10.5	–	10.3	–	10.3
AIC		790	–	773.4	–	773.7
R^2	fixed part	–	–	0.196	–	0.190
	random part	–	–	0.238	–	0.246
	BLUP	–	–	0.434	–	0.436

*** p-value <0.001; ** p-value < 0.01; * p-value < 0.05; + p-value <0.1;

Table 5. Model statistics for MOR models fitted with the REML method with different hierarchical structures. σ_k: log random effect standard deviation, σ_{jk}: tree random effect standard deviation, σ_{ijk}: plot random effect standard deviation. Figures in brackets are standard deviation of parameter estimates. LRT were performed between the model with the lowest AIC against the others.

	MOR.r1	MOR.r2	MOR.r3
Intercept	62.7 *** (1.97)	62.7 *** (1.80)	62.5 *** (1.67)
σ_{ijk}	6.37	6.47	7.50
σ_{jk}	3.24	4.08	–
σ_k	2.77	–	–
ε_{ijkl}	10.5	10.5	10.5
AIC	783	781	779
df	5	4	3
p-value LRT	0.8008	0.6752	–

*** p-value <0.001

References

Alteyrac, J., A. Cloutier and S.Y. Zhang. 2006. Characterization of juvenile wood to mature wood transition age in black spruce (*Picea mariana* (Mill.) B.S.P.) at different stand densities and sampling heights. Wood Sci. Technol. 40: 124–138. doi: 10.1007/s00226-005-0047-4

ASTM International. 2009. Annual Book of ASTM Standards. ASTM, Philadelphia, PA.

Aubry, C.A., W.T. Adams and T.D. Fahey. 1998. Determination of relative economic weights for multitrait selection in coastal Douglas-fir. Can. J. Fort. Res. 28: 1164–1170. doi: 10.1139/x98-084

Besley, D.A., E. Kuh and R.E. Welsh. 1980. Regression diagnostics. New York, John Wiley and Sons.

Burdon, R.D., R.P. Kibblewhite, J.C.F. Walker, R.A. Megraw, R. Evans and D.J. Cown. 2004. Juvenile versus mature wood: A new concept, orthogonal to corewood versus outerwood, with special reference to *Pinus radiata* and *P. taeda*. For. Sci. 50: 399–415.

Burnham, K.P. and D.R. Anderson. 2002. Model selection and multimodel inference: A practical information-theoretic approach, second edition. Springer-Verlag, New York.

Burns, R.M. and B.H. Honkala. 1990. Silvics of North America. Volume 1. Conifers.

Bustos, C., R. Beauregard, M. Mohammad and R.E. Hernandez. 2003. Structural performance of finger-jointed black spruce lumber with different joint configurations. For. Prod. J. 53: 72–76.

Canadian Forest Service. 2005. The State of Canada's Forests 2004-2005: The boreal forest.

Dassot, M., T. Constant and M. Fournier. 2011. The use of terrestrial LiDAR technology in forest science: application fields, benefits and challenges. Ann. For. Sci. 68: 959–974. doi: 10.1007/s13595-011-0102-2

Dobbertin, M. 2005. Tree growth as indicator of tree vitality and of tree reaction to environmental stress: a review. Eur. J. For. Res. 124: 319–333. doi: 10.1007/s10342-005-0085-3

Duchateau, E., F. Longuetaud, F. Mothe, C. Ung, D. Auty and A. Achim. 2013. Modelling knot morphology as a function of external tree and branch attributes. Can. J. For. Res. 43: 266–277.

Duchesne, I. 2006. Effect of rotation age on lumber grade yield, bending strength and stiffness in jack pine (*Pinus banksiana* Lamb.) natural stands. Wood Fiber Sci. 38: 84–94.

Fox, J. *et al.* (2014) car: Companion to Applied Regression.

Green, D.W., J.E. Winandy and D.E. Kretschmann. 1999 Mechanical properties of wood. In Wood Handbook: Wood as an engineering material. General technical report 113. pp. 4.1-4.45. USDA Forest Service, Madison, WI.

Hilker, T., G.W. Frazer, N.C. Coops, M.A. Wulder, G.J. Newnham, J.D. Stewart, M.v. Leeuwen and D.S. Culvenor. 2013. Prediction of wood fiber attributes from LiDAR-derived forest canopy indicators. For. Sci. 59: 231–242.

Kennedy, R.W. 1995. Coniferous wood quality in the future: concerns and strategies. Wood Sci. Technol. 29: 321–338. doi: 10.1007/BF00202581

Kuprevicius, A., D. Auty, A. Achim and J.P. Caspersen. 2013. Quantifying the influence of live crown ratio on the mechanical properties of clear wood. Forestry 86: 361–369. doi: 10.1093/forestry/cpt006

Larson, P.R. 1969. Wood formation and the concept of wood quality. Yale Univ. Sch. For. Bulletin No. 74.

Lei, Y.C., S.Y. Zhang and Z. Jiang. 2005. Models for predicting lumber bending MOR and MOE based on tree and stand characteristics in black spruce. Wood Sci. Technol. 39: 37–47. doi: 10.1007/s00226-004-0269-x

Lenz, P., M. Bernier-Cardou, J. MacKay and J. Beaulieu. 2012. Can wood properties be predicted from the morphological traits of a tree? A canonical correlation study of plantation-grown white spruce. Can. J. For. Res. 42: 1518–1529. doi: 10.1139/x2012-087

Liu, C., S.Y. Zhang, A. Cloutier and T. Rycabel. 2007. Modeling lumber bending stiffness and strength in natural black spruce stands using stand and tree characteristics. Forest Ecol. Manage. 242: 648–655. doi:10.1016/j.foreco.2007.01.077

Macdonald, E. and J. Hubert. 2002. A review of the effects of silviculture on timber quality of Sitka spruce. Forestry 75: 107–138. doi: 10.1093/forestry/75.2.107

Mäkinen, H., R. Ojansuu, P. Sairanen and H. Yli‐Kojola. 2003. Predicting branch characteristics of Norway spruce (*Picea abies* (L.) Karst.) from simple stand and tree measurements. Forestry 76: 525–546. doi: 10.1093/forestry/76.5.525

Moore, J.R. *et al.* 2013. Within- and between-stand variation in selected properties of Sitka spruce sawn timber in the UK: implications for segregation and grade recovery. Ann. For. Sci. 70: 403–415. doi: 10.1007/s13595-013-0275-y

NLGA (1997). SPS 2-97. Norme de produits spéciaux NLGA pour le bois classé par machine, Commission nationale de la classification des sciages.

NLGA (2008). Standard grading rules for Canadian lumber. National Lumber Grades Authority. Vancouver, BC.

Pinheiro, J., D. Bates and S. DebRoy. 2007. Linear and nonlinear mixed effects models. R Package Version 3.57.

Pothier, D. and F. Savard. 1998. Actualisation des tables de production pour les principales espèces forestières du Québec. Ministère des Ressources naturelles et de la Faune du Québec. 183 p.

Power, H., V. LeMay F. Berninger, D. Kneeshaw and D.F. Sattler. 2012. Differences in crown characteristics between black (*Picea mariana*) and white spruce (*Picea glauca*). Can. J. For. Res. 42: 1733–1743. doi: 10.1139/x2012-106

Quinn, G.P. and M.J. Keough. 2002. Experimental design and data analysis for biologists. Cambridge University Press. 553 p.

R Core Team (2014). R: A Language and Environment for Statistical Computing.

Reid, D.E.B., S. Young, Q. Tong, S.Y. Zhang and D.M. Morris. 2009. Lumber grade yield, and value of plantation-grown black spruce from 3 stands in northwestern Ontario. Forest. Chron. 85: 609–617. doi: 10.5558/tfc85609-4

Sattler, D.F., P.G. Comeau and A. Achim. 2013. Within-tree patterns of wood stiffness for white spruce (*Picea glauca*) and trembling aspen (*Populus tremuloides*). Can. J. For. Res. 44: 162–171. doi: 10.1139/cjfr-2013-0150

Tong, Q.J., R. Fleming, F. Tanguay and S.Y. Zhang. 2009. Wood and lumber properties from unthinned and precommercially thinned black spruce plantations. Wood Fiber Sci. 41: 168–179.

Tong, Q.J., I. Duchesne, D. Belley, M. Beaudoin and E. Swift. 2013. Characterization of knots in plantation white spruce. Wood Fiber Sci. 45: 84-97.

Vincent, M., C. Krause and A. Koubaa. 2011. Variation in black spruce (*Picea mariana* (Mill.) BSP) wood quality after thinning. Ann. For. Sci. 68: 1115–1125. doi: 10.1007/s13595-011-0127-6

Wellwood, R.W. and J.H.G. Smith. 1962. Variation in some important qualities of wood from young Douglas-fir and hemlock trees. The University of British Columbia, Faculty of Forestry. Vancouver, B.C. Research Paper 50.

Wulder, M.A., J.C. White, R.F. Nelson, E. Naesset, H.O. Orka, N.C. Coops, T. Hilker, C.W. Bater and T. Gobakken. 2012. Lidar sampling for large-area forest characterization: A review. Remote Sensing Environ. 121: 196–209.

Zhang, S.Y. 1998. Effect of age on the variation, correlations and inheritance of selected wood characteristics in black spruce (*Picea mariana*). Wood. Sci. Technol. 32: 197–204. doi: 10.1007/BF00704842

Zobel, B.J. and J.P. van Buijtenen. 1989. Wood variation: its causes and control. Springer-Verlag, Berlin, Heidelberg. 363 p.