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Modeling wood fiber attributes using forest inventory and environmental data for Newfoundland's boreal forest

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ABSTRACT

We explore the possibility of predicting wood fiber attributes across Newfoundland for two commercial species: black spruce (*Picea mariana* (Mill.) B.S.P.) and balsam fir (*Abies balsamea* (L.) Mill.). Estimates of key fiber attributes (including wood density, coarseness, fiber length, and modulus of elasticity) were derived from measurements of wood cores taken from sample plots representing a wide structural gradient of forest stands. Candidate models for predicting fiber attributes at plot and landscape scales were developed using an information-theoretical approach and compared based on Akaike's information criterion. The most influential variables were stand age and the presence of precommercial thinning. Other significant explanatory variables included those that characterize vegetation structure (mean diameter at breast height, dominant height), climate (annual precipitation, mean temperature of the growing season), and geography (elevation, latitude) depending on the species and fiber attribute being modeled. At the plot level, model inference gave root mean square errors of 5.3–11.9% for all attributes. At the landscape level, prediction errors were similar (5.4–12.1%), with the added benefit of being suitable for mapping fiber attributes across the landscape. The results obtained demonstrate the potential for predicting and mapping fiber attributes over a large region of boreal forest in Newfoundland, Canada.

1. Introduction

There is a lack of information regarding the variation of wood fiber attributes across geographic locations for different species. However, this information is fundamental to optimize fiber use and improve competitiveness in the forest industry (MacKenzie and Bruemmer, 2009; Pitt and Pineau, 2009). Wood fiber attributes provide indicators of wood quality that are linked to product potential and performance (i.e., pulp yield, strength and stiffness of lumber) (Kennedy, 1995; MacDonald and Hubert, 2002; Zhang et al., 2002). For example, knowledge of fiber attributes while planning forest operations can lead to improved fiber input to the paper mill, leading to optimized industrial processes. Moreover, knowledge about fiber attributes may lead to the development of new products that require unique attributes. Obtaining information on fiber attributes is costly because direct measurement typically requires the extraction of core samples from trees. Thus, models are needed to predict fiber attributes from forest stand and environmental factors, which can be measured and mapped more easily over large areas.

Wood fiber can be described through a large array of attributes, and the most cited attributes describing wood fiber also correspond to those considered to be the most important for forest industry: wood density, coarseness, fiber length, and modulus of elasticity (Bergqvist et al., 2000; Schimleck et al., 2002; van Leeuwen et al., 2011; Watson and Bradley, 2009; Watt et al., 2008a). Many studies emphasize wood density as a key variable because it is a good indicator of wood strength and stiffness. Wood density also plays a role in biomass and carbon storage estimation (van Leeuwen et al., 2011; Zobel and van Buijtenen, 1989).

Studies on wood fiber attributes in boreal forests have focused on conifer species, such as white spruce (*Picea glauca* (Moench) Voss) (Lenz et al., 2012), black spruce (*Picea mariana* (Mill.) B.S.P.) (Liu et al., 2007), Scots pine (*Pinus sylvestris* L.) (Kilpeläinen et al., 2005), and Sitka spruce (*Picea sitchensis* (Bong.) Carrière) (MacDonald and Hubert, 2002). The relationships between wood fiber attributes and stand variables have been studied mainly in plantations of softwood species (Lei et al., 2005; Watt et al., 2008b), and only a few studies investigated those relationships in natural stands (Wilhelmsson et al., 2002; Liu et al., 2007). Previous arguments support the idea that environmental factors (climate and forest inventory variables) influence wood fiber attributes and provide promising avenues to develop predictive models both

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in managed and natural stands. To our knowledge, no predictive models using typical forest inventory data are currently available to inform decisions at the landscape scale.

Climate and site play an important role in tree growth, and many studies have reported correlations between fiber attributes and climatic variables. For example, temperature and precipitation influence wood density (Kilpeläinen et al., 2005; Swenson and Enquist, 2007; Watt et al., 2008b; Wimmer et al., 2002). Wood fiber attributes have also been linked to forest stand and tree variables, such as precommercial thinning (MacDonald and Hubert, 2002), age (Wilhelmsson et al., 2002), diameter at breast height (DBH, in cm measured at 1.3 m), height (Liu et al., 2007; van Leeuwen et al., 2011), competition, stand density (van Leeuwen et al., 2011), elevation (Swenson and Enquist, 2007), aspect and slope (Stage, 1976). Most of these relationships were quantified through various statistical techniques, such as analysis of variance, generalized linear models, linear mixed effects models, ordinary least squares regression, path analysis, or stepwise regression (Bergqvist et al., 2000; Bouriaud et al., 2004; Lei et al., 2005; Liu et al., 2007; Watt et al., 2008b; Wimmer et al., 2002). Akaike's information criterion (AIC) (Burnham and Anderson, 2002, 2004; Mazerolle, 2006) is another approach that is well designed for exploring the effect of multiple predictor variables and for identifying the most parsimonious models predicting wood fiber attributes in complex natural environments (Burnham and Anderson, 2002, 2004; Johnson and Omland, 2004; Mazerolle, 2006).

The overall goal of the study was to model and map wood fiber attributes across the merchantable forest area of Newfoundland. Our working hypothesis was that wood fiber attributes of black spruce and balsam fir (*Abies balsamea* (L.) Mill.) stands are related to environmental variables and forest variables measured in existing inventory plots or available from stand-level maps. Three key research questions were identified: (1) what are the relationships between fiber attributes and available forest inventory and environmental data? (2) to what extent can the relationships be used to predict and map fiber attributes across Newfoundland? and (3) what models can be used with the available spatial data to produce maps of fiber attributes for Newfoundland? Specific objectives were to:

(i) Identify environmental and forest inventory variables that can be used to predict wood fiber attributes.
(ii) Develop predictive models at the plot level for estimating fiber attributes from an extensive database of wood fiber attributes measured *in situ* at plot locations.
(iii) Develop predictive models at the landscape level for mapping fiber attributes for the island of Newfoundland using available spatial databases.

2. Methods

2.1. Study site

The study was conducted on the island of Newfoundland (111,390 km^2), located in eastern Canada (Fig. 1) centered around 48°32′30″N and 56°07′30″W. Topography varies from relatively rugged with flat valley bottoms in the western part of the island to gently rolling relief with large areas of low relief in the central part, and a rolling plateau in the eastern part. The area is characterized by the presence of many lakes, bogs, and rivers (Rowe, 1972). Located within Canada's boreal forest, the two dominant species are black spruce and balsam fir. Black spruce accounts for approximately one-third of the forests found on the island. This slow-growing tree is usually found on very humid or very dry soils and especially in areas affected by forest fires (Government of Newfoundland and Labrador, 2011; Mullins and McKnight, 1981; USDA Forest Service, 1990). Balsam fir stands dominate mainly moist and well-drained sites.

2.2. Plot-level data

The Newfoundland Department of Natural Resources collects inventory data through a network of permanent sampling plots (PSPs). All plots are rectangular in shape, with size varying for immature and semi-mature stand types and fixed at 1/25 ha for mature and over-mature types. Plot size is dependent on stand density and as a rule should contain a minimum of 75 trees. The PSP program consists of about 1,000 different locations across Newfoundland in natural and managed stands, and each PSP is revisited every 4–6 years. All the trees inside a plot are numbered. Tree characteristics are recorded in a database and updated every time there is a new inventory (Newfoundland Forest Service, 2011). For this study, a subsample of 194 PSPs (77 black spruce-dominated plots and 117 balsam fir-dominated plots) was selected across the island. The subsample targeted three replicates within each combination of species, height, crown density, and site index classes in order to capture a wide range of forest growing conditions within the merchantable forest area.

At each PSP, wood cores were extracted from a sample of ten live merchantable trees to measure fiber attributes. These ten trees were selected starting at 10 m outside the plot (at a 130° angle) from the plot's corner where the site conditions were the most representative of the PSP. The cores were sent to the FPInnovations laboratory in Vancouver for analysis of the suite of fiber attributes using a combination of optical microscopy, image analysis, X-ray densitometry, and X-ray diffractometry (Downes et al., 2002; FPInnovations, 2009; Schimleck et al., 2002; Schimleck and Evans, 2004; Sherson et al., 2007). Density (kg/m^3) was measured at 8% moisture content by irradiating a sample with X-rays and detecting the amount of radiation transmitted through the sample. X-ray absorbance was related to density according to Beer's Law. The measured density was scaled to match the average density of the core measured from its volume (micrometry) and its mass to ensure that average density of the sample matched the average density predicted by *SilviScan* technology (FPInnovations, 2009). Coarseness (μg/m) was calculated combining wood density and tracheid diameter profiles obtained from the *SilviScan* analysis. Fiber length (mm) was measured using a HiRes Fiber Quality Analyzer (HiRes FQA (Hawkesbury, ON)) (a commercial instrument developed jointly by Paprican, the University of British Columbia, and OpTest Equipment Inc.) using a fiber solution made from macerated wood cores. Modulus of elasticity (MOE in GPa), which is a measure of wood stiffness, was estimated from wood density and diffraction patterns of the wood obtained from a wide-angle X-ray detector (Evans and Ilic, 2001; FPInnovations, 2009; Sherson et al., 2007).

For all plots with a minimum of three trees of the species of interest (balsam fir or black spruce), an average plot value (weighted by basal area of all the sampled trees based on the basal area of a given species) was calculated for each fiber attribute (Table 1):

$$\text{Averaged Mean} = \sum\nolimits_{PSP}\left(\frac{\text{Fiber Attribute}_{\text{tree}} \times \text{Basal Area}_{\text{tree}}}{\sum \text{Basal Area}_{\text{tree}}}\right) \tag{1}$$

For each PSP, individual tree measurements were recorded *in situ* and aggregated to derive plot-level estimates. Specifically, DBH and species were recorded for each tree. Height was measured for a sample of trees at each plot, and species-specific relationships between DBH and height were developed for each ecoregion and

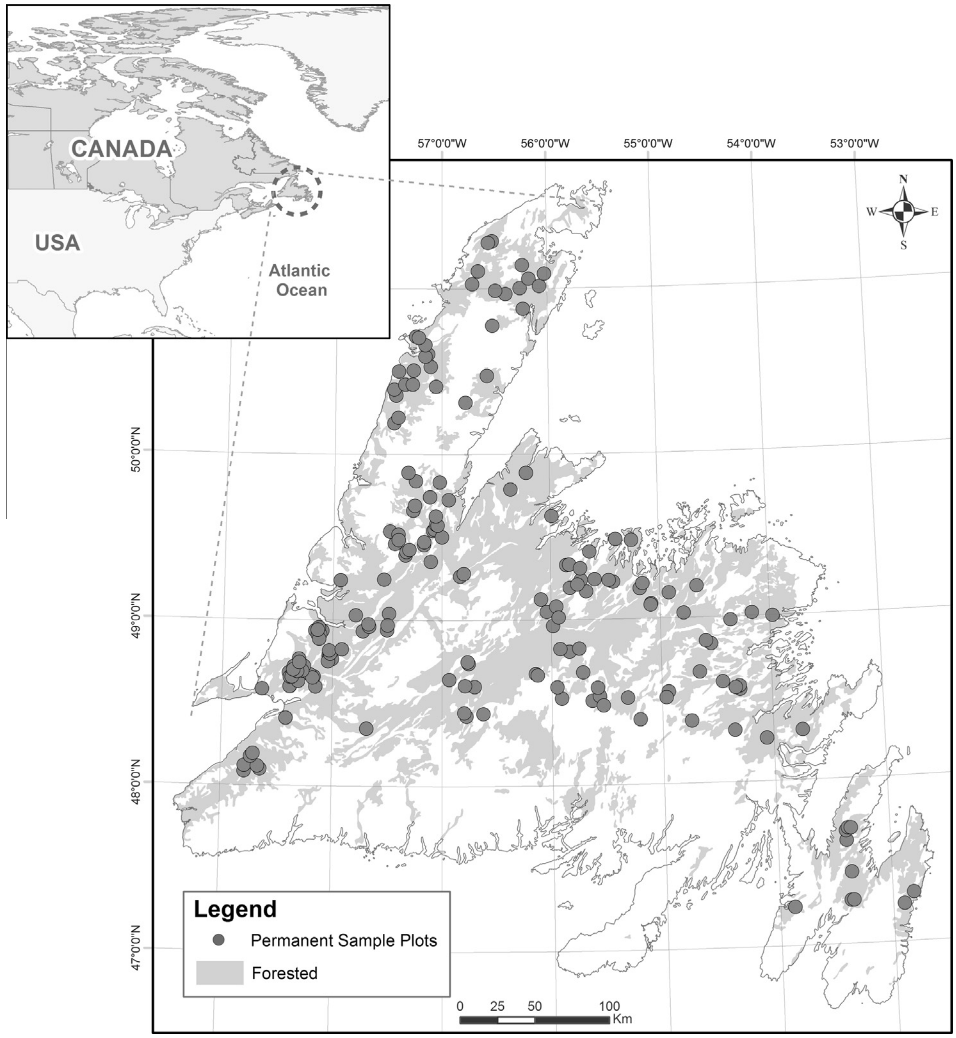

Fig. 1. Core-sampled plots and forested area across Newfoundland, Canada.

Table 1
Descriptive statistics of wood fiber attributes for black spruce and balsam fir field plots.

Fiber attributes	Black spruce ($n = 77$)			Balsam fir ($n = 117$)		
	Range	Mean	S.D.	Range	Mean	S.D.
Wood density (kg/m^3)	443.2–635.7	546.5	39.13	373.4–496.8	425.0	29.73
Coarseness (μg/m)	306.8–444.7	382.0	29.37	295.4–410.4	346.6	21.65
Fiber length (mm)	1.72–2.60	2.26	0.18	1.85–2.61	2.23	0.16
Modulus of elasticity (GPa)	7.10–17.63	13.92	2.29	7.61–15.02	11.19	1.48

used to predict height for all trees. The individual tree diameters for all trees >9 cm DBH were averaged (arithmetic mean) at the plot level to obtain an estimate of the mean DBH for each plot. Dominant height (Hdom) was calculated as the average height (in meters) of the tallest 100 living trees per hectare. Species composition was calculated as the ratio between the sum of all individual tree basal areas of a given species within a plot and the sum of all individual tree basal areas within a plot (as a percentage). Composition values for black spruce ranged from 16.4% to 100%, and values for balsam fir ranged from 19.2% to 100%. Stand age (in years) of the PSP was estimated according to the midpoint value of an age class range. Elevation (in meters) and latitude (in degrees–minutes–seconds) were recorded using a Trimble ProXL global positioning system (GPS). Precommercial thinning (PCT) was recorded for the managed stands.

Climatic variables were interpolated for each PSP using the *ANUSPLIN* interpolation method and weather measurements taken at Environment Canada's meteorological stations across Newfoundland (McKenney et al., 2007). We considered mean temperature during the growing season and annual precipitation relevant to forest productivity (Hamel et al., 2004). Annual precipitation (mm) was the sum of all monthly precipitation. The mean temperature of the growing season was estimated using temperature-based rules. The growing season began when the mean daily temperature was ⩾5 °C for 5 consecutive days after 1 March and ended when the average minimum temperature was ⩽2 °C beginning 1 August (McKenney et al., 2007).

2.3. Landscape-level data

Landscape-level forest stand data were acquired from the Government of Newfoundland and Labrador (Newfoundland Forest Service, 1991). The stand-level maps were polygon based, resulting from the interpretation of aerial photographs (scale of 1:12,500) acquired between 1995 and 2008. Several attributes were extracted from the mapped data, including species composition, age class, height class, and site class. Species composition at the landscape level reflected the percentage of balsam fir or black spruce basal area of a stand derived from the upper limit of the species composition (Delaney and Osmond, 1977). Crown density and height were estimated according to the midpoint value of interpreted class ranges. The same climatic variables described above were interpolated as raster layers with a 30 m × 30 m grid resolution from an original resolution of 150 arcseconds (McKenney, 2006; McKenney et al., 2007). Elevation was extracted from a province-wide elevation grid of 0.75 arcseconds (Canadian Digital Elevation Data, 2000).

3. Statistical analyses

3.1. Plot-level modeling

For this study, we adopted the information-theoretic approach based on Akaike's information criterion (AIC), which is widely used in ecology (Dochtermann and Jenkins, 2011; Mazerolle, 2006; Richards et al., 2011) and phylogenetics (Posada and Buckley, 2004). This approach was well adapted for the present study as the relationships modeled were complex and involved multiple predictors (Burnham and Anderson, 2002, 2004; Johnson and Omland, 2004; Mazerolle, 2006). The approach consists in specifying *a priori* a number of candidate models featuring the attributes of interest, each model representing a scientific hypothesis. Instead of relying on *P* values and the inherent problems of using significance testing to select variables, we compared models based on AIC (Burnham and Anderson, 2002; Mazerolle, 2006). The strength of evidence in favor of each model was based on the differences between each model relative to the most parsimonious model (ΔAIC) as well as the normalized weights (Akaike weights, ω_i). The latter weights were interpreted as probabilities that a given model was the most parsimonious based on the data set and the models considered (Burnham and Anderson, 2002). In cases where more than one model ranked highly, inference was based on the entire set of models by computing model-averaged estimates and predictions.

Candidate multiple regression models were developed with the wood fiber attributes as response variables (*Y*) and the forest stand and environmental data as explanatory variables (*X*) following the form: $Y = a + b_1X_1 + b_2X_2 + b_pX_p + \varepsilon_i$ (Liu et al., 2007; Watt et al., 2008b), where ε_i denotes normally distributed errors. Given the available sample sizes (black spruce $n = 77$, balsam fir $n = 117$), the models were limited to fewer than eight parameters (including the intercept and residual variance) in order to avoid overparameterization and to produce reliable estimates (Burnham and Anderson, 2002). The candidate model set was developed based on a thorough review of the literature to identify variables of influence from studies covering various softwood species and including general knowledge of tree allometry theory (van Leeuwen et al., 2011; Zobel and van Buijtenen, 1989). The explanatory variables were separated into four groups representing the main factors expected to influence the suite of fiber attributes: geography, climate,

Table 2
List of candidate plot- and landscape-level models applicable to both black spruce and balsam fir dominated stands.

Models	Plot	Landscape
Solo variables		
Mod1	Elevation	Elevation
Mod2	Latitude	Latitude
Mod3	Annual precipitation	Annual precipitation
Mod4	Mean temperature of growing season	Mean temperature of growing season
Mod5	Species composition[a]	Species composition[a]
Mod6	Dominant height	Height
Mod7	Mean DBH	Crown density
Mod8	Age	Age
Disturbance (D)		
Mod9	PCT	PCT
Geography (G)		
Mod10	Elevation + latitude	Elevation + latitude
Climate (C)		
Mod11	Mean temperature of growing season + annual precipitation	Mean temperature of growing season + annual precipitation
Vegetation (V)		
Mod12	Mean DBH + age	Crown density + age
Mod13	Species composition + dominant height + mean DBH + age	Species composition + height + crown density + age
Combined models		
Mod14 (G + C + V)	Elevation + mean temperature of growing season + annual precipitation + species composition + dominant height + mean DBH	Elevation + mean temperature of growing season + annual precipitation + species composition + height + crown density
Mod15 (G + C + D)	Elevation + mean temperature of growing season + annual precipitation + PCT	Elevation + mean temperature of growing season + annual precipitation + PCT
Mod16 (C + V + D)	Mean temperature of growing season + annual precipitation + species composition + mean DBH + age + PCT	Mean temperature of growing season + annual precipitation + species composition + crown density + age + PCT
Mod17 (G + V + D)	Elevation + latitude + species composition + age + dominant height + PCT	Elevation + latitude + species composition + age + height + PCT
Global model		
Mod18	Elevation + mean temperature of growing season + annual precipitation + age + mean DBH + PCT	Elevation + mean temperature of growing season + annual precipitation + age + crown density + PCT

[a] Species composition values are different for plot and landscape level.

Table 3
Pearson's correlation among fiber attributes estimated at the plot level for black spruce and balsam fir.

		Black Spruce			
		Density	Coarseness	Fiber Length	Mod. of elasticity
Balsam Fir	Density (kg/m^3)		0.816*	0.578*	0.750*
	Coarseness (μg/m)	0.696*		0.756*	0.782*
	Fiber Length (mm)	0.312*	0.645*		0.719*
	Modulus of Elasticity (GPa)	0.586*	0.650*	0.549*	

Correlation is significant at the 0.01 level (2-tailed).

vegetation, and disturbance. Models were then developed using each group of variables independently and in various combinations to represent the influence of each factor (Table 2). Explanatory variables with (Pearson $|r| > 0.70$) were not included in the same model in order to reduce potential collinearity. Considering that there were moderate to strong correlations among four fiber attributes (Table 3; Pearson $|r| > 0.54$ with one exception), the same candidate models were used to model all four fiber attributes. Assumptions of homogeneity of variance and normality of residuals were evaluated with residual plots and with Non-Constant Error Variance (NCV) and Shapiro–Wilk tests, respectively.

The candidate models were ranked according to the AIC corrected for small sample size (AIC$_c$), defined as:

$$AIC_c = -2(log - \text{likelihood}) + 2K + \frac{2K(K+1)}{(n-K-1)}, \quad (2)$$

where K is the number of estimated parameters in the model including the intercept and the error term. Models were compared with the top-ranking model with delta AIC_c (Δ_i):

$$\Delta_i = AIC_{ci} - \min AIC_{ci}, \quad (3)$$

where AIC_{ci} is the AIC_c value for a given model i and min AIC_{ci} is the AIC_c value for the "best" model (smallest AIC_c value). Usually, a $\Delta_i < 2$ suggests a good model, whereas $2 < \Delta_i < 4$ suggests a potentially useful model. Models with a Δ_i between 4 and 7 have a weaker value, whereas those with $\Delta_i > 10$ indicate models that have low support (Burnham and Anderson, 2002).

Normalizing the Δ_i yields Akaike weights (ω_i), which can be interpreted as the probability that a given model r is the best among the set of R models:

$$\omega_i = \frac{\exp\left(\frac{-\Delta_i}{2}\right)}{\sum_{r=1}^{R} \exp\left(\frac{-\Delta_r}{2}\right)}. \quad (4)$$

When the top-ranked model has a ω_i below 0.90, it indicates that other models also have some strength. In such cases, multimodel inference (or model averaging) was used to make model-averaged predictions of fiber attributes based on the entire model set (Burnham and Anderson, 2002). In essence, each prediction made by each model was weighted by its corresponding Akaike weight, such that a model with high support contributes more to the prediction than a model with a lower AIC$_c$ weight. This approach yielded weighted average predictions as well as unconditional standard errors and was used to construct 95% confidence intervals around predictions (Burnham and Anderson, 2002; Hegyi and Garamszegi, 2011; Johnson and Omland, 2004; Mazerolle, 2006). Following a similar strategy, the effects of the explanatory variables with the most support (i.e., those included in models with $\Delta_i < 4$) were determined by computing model-averaged estimates, unconditional standard errors, and 95% confidence intervals (Buckland et al., 1997; Burnham and Anderson, 2002; Mazerolle, 2012). Explanatory variables for which the 95% confidence interval excluded 0 indicated that the variable influenced the response variable.

The remaining explanatory variables were ranked according to the relative size of their standard error (SE) compared with their model-averaged estimate: the smaller SE compared with the model-averaged estimate, the more predictive power was assumed. A SE of more than half the model-averaged estimate was not considered to have a good predictive power. Ranking the explanatory variables of importance was thus possible from the ratio of SE over the model-averaged estimate.

3.2. Model validation

Model fit was assessed by the root mean square error (RMSE) and the relative RMSE (RMSE$_r$):

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{Y}_i - Y_i)^2}{n}} \quad \text{RMSE}_r = \sqrt{\frac{\sum_{i=1}^{n}[(\widehat{Y}_i - Y_i)]^2}{\sum_{i=1}^{n}[Y_i]^2}}, \quad (5)$$

where n is the number of PSPs, Y are the observed values of wood fiber attributes, and $\widehat{Y}$ are the predicted values of fiber attributes for each model.

Leave-one-out cross-validation (LOOCV) was used to estimate the prediction error. The sample (n) was divided into a training set (size $n - 1$) and a validation set (size 1). The models were fit using the training set with one observation left out. The process was repeated until all possible combinations (splits) were tried (Stone, 1974). From those splits, a cross-validation estimate of the prediction error was computed for each model. The cross-validation estimates were then weighted by the Akaike weights (ω_i) and summed to obtain a model-averaged estimate of prediction error. All analyses were executed in *R* 2.15.0 (R Development Core Team, 2012). Model selection and multimodel inference were conducted with the *AICcmodavg* package (Mazerolle, 2012), and the LOOCV procedure was executed with the *boot* package (Canty and Ripley, 2012).

3.3. Landscape-level modeling and mapping

The plot-level models allowed for the prediction of fiber attributes for plot locations, but they did not allow for producing a continuous map because not all explanatory variables were currently available as spatial layers. Therefore, landscape-level models were developed using variables that were conceptually similar to those used in the plot-level models but were available as spatial layers. For example, mean DBH was not available from the current stand-level inventory; therefore, crown closure was used to represent the vegetation structure. Similarly, height was derived from the height class interpretation rather than the measured heights of individual trees. Also, the species composition was derived from the more general stand-level species label rather than being estimated from the individual tree measurements. Otherwise, all other predictor variables were the same as those used in the plot-level modeling. Thus, the landscape-level modeling relied on the same methods (model selection and validation) as the plot-level modeling; however, the models were redeveloped using the explanatory variables that were available as spatial layers.

The species-specific models were implemented at the polygon level within ArcGIS™ software (ESRI®, Redlands, California, United States of America). A geometric intersection (Union) was first performed between the commercial forest stand and PCT layers of the provincial forest inventory in order to create spatially explicit polygons of PCT and non-PCT commercial forest stands. A minimal mapping unit of 0.5 ha was applied. We removed from the analysis all polygons that were outside the predictable range defined by the sampling design (i.e., commercial forest stand with height below 9.5 m; crown density lower than 25%). The predictor variables of interest from the forest inventory consisted of species composition, age class, height class, crown density class, and PCT. These variables were maintained in the attribute table of the resulting polygon layer.

We converted the ordinal variables age class, height class, and crown density class to numerical values data by using the class midpoints. PCT remained binary (i.e., 1 if PCT, 0 otherwise), whereas species percentages were derived from the species composition attribute using the upper class limit. For example, a stand with a species label of *bSbF* was assigned 75% black spruce and 25% balsam fir, as per Delaney and Osmond (1977). Mean zonal statistics of raster predictor variables (elevation, latitude, mean temperature of the growing season, annual precipitation) were computed for each polygon using the Geospatial Modelling Environment (GME) extension (http://www.spatialecology.com/gme/index.htm) and appended to the existing attribute table. For each species, the model-averaged equations were applied to each polygon where the respective species was present in the species composition attribute.

4. Results

4.1. Plot-level model selection and inference

Plots of residuals versus predicted values did not reveal significant outliers or issues with model assumptions. This was supported with graphical and statistical tests of homoscedasticity and normality (not shown). We identified the most parsimonious models based on model selection (Table 4). For black spruce, the same two or three models were always within the 95% confidence set (i.e., the sum of the ω_i values representing the "top models" was $\geqslant$0.95). For most fiber attributes, the top-ranking model had at least double the support of the other ones (based on evidence ratios or Akaike weights): i.e., Mod16 for wood density and coarseness, and Mod17 for modulus of elasticity. However, Mod13 and Mod17 were highly competitive models for fiber length, with Akaike weights of 0.51 and 0.48, respectively. The top models across all fiber attributes frequently included vegetation predictors (age, species composition, mean DBH) and the disturbance predictor (PCT). Among all the predictors, mean DBH and age were common to all high-ranking models (Mod16, Mod18, and Mod13). For balsam fir, the top models of fiber attributes varied among six candidate models: Mod12, Mod13, Mod14, Mod16, Mod17, and Mod18. Three models were included in the confidence set for wood density (Mod18, Mod16, and Mod12) and coarseness (Mod18, Mod17, and Mod13), whereas only one model was included for fiber length (Mod17) and modulus of elasticity (Mod14). The top

Table 4
Confidence set (95%)[a] for the plot-level models with the highest AIC_c weights.

	K	AIC_c	ΔAIC_c	ω_i	R^2	Adj. R^2	RMSE	$RMSE_r$
Black spruce								
Wood density								
Mod16	8	736.26	0.00	0.77	0.56	0.53	25.64	4.68%
Mod18	8	737.82	1.56	0.14	0.56	0.52	25.91	4.73%
Mod13	6	740.40	4.14	0.06	0.51	0.48	27.20	4.96%
Averaged predictions using all models					***0.57***			
Leave-one-out cross-validation							*28.88*	*5.28%*
Coarseness								
Mod16	8	689.19	0.00	0.70	0.58	0.54	18.89	4.93%
Mod17	8	691.18	1.98	0.26	0.57	0.53	19.14	5.00%
Averaged predictions using all models					***0.58***			
Leave-one-out cross-validation							*21.33*	*5.58%*
Fiber length								
Mod13	6	−84.44	0.00	0.51	0.49	0.46	0.13	5.67%
Mod17	8	−84.33	0.11	0.48	0.52	0.48	0.12	5.50%
Averaged predictions using all models					***0.52***			
Leave-one-out cross-validation							*0.14*	*6.19%*
Modulus of elasticity								
Mod17	8	291.28	0.00	0.82	0.61	0.57	1.43	10.11%
Mod16	8	295.08	3.80	0.12	0.59	0.55	1.46	10.36%
Mod13	6	296.51	5.23	0.06	0.55	0.53	1.52	10.80%
Averaged predictions using all models					***0.61***			
Leave-one-out cross-validation							*1.65*	*11.85%*
Balsam fir								
Wood density								
Mod18	8	1071.26	0.00	0.58	0.45	0.42	21.87	5.13%
Mod16	8	1073.14	1.88	0.23	0.45	0.42	22.04	5.17%
Mod12	4	1073.65	2.40	0.17	0.40	0.39	22.96	5.39%
Averaged predictions using all models					***0.45***			
Leave-one-out cross-validation							*23.39*	*5.50%*
Coarseness								
Mod18	8	1018.97	0.00	0.78	0.34	0.31	17.49	5.03%
Mod17	8	1022.65	3.69	0.12	0.32	0.28	17.77	5.11%
Mod13	6	1023.73	4.76	0.07	0.29	0.26	18.20	5.24%
Averaged predictions using all models					***0.35***			
Leave-one-out cross-validation							*18.66*	*5.38%*
Fiber length								
Mod17	8	−149.47	0.00	1.00	0.46	0.43	0.12	5.31%
Averaged predictions using all models					***0.46***			
Leave-one-out cross-validation							*0.13*	*5.83%*
Modulus of elasticity								
Mod14	8	365.01	0.00	0.97	0.47	0.44	1.07	9.47%
Averaged predictions using all models					***0.48***			
Leave-one-out cross-validation							*1.15*	*10.28%*

K; number of parameters including the intercept and the error term; AIC_c. Akaike's Information Criterion corrected for small sample size; Δ_i. AIC_c relative to the most parsimonious model; w_i. AIC_c model weight.

[a] The 95% confidence set was determined by summing the Akaike weights from largest to smallest until the sum $\geqslant$0.95.

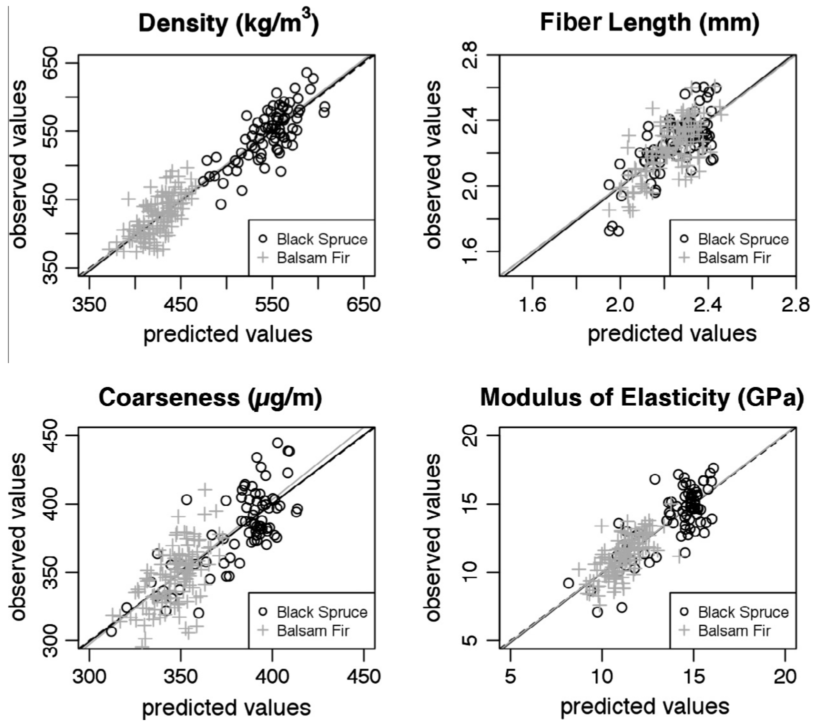

Fig. 2. Observed vs. predicted values for all fiber attributes (from plot-level model averaging).

three models for wood density had two predictors in common: mean DBH and age. For coarseness, age was the only common variable between the three models. For fiber length, the top model was a combination of geography, vegetation, and disturbance factors; whereas for modulus of elasticity, the top model included geography, climate, and vegetation factors.

Given that there was substantial model selection uncertainty for most of the fiber attributes for both species, we computed model-averaged predictions based on all the models in the candidate model set (Burnham et al., 2011). Inference based on all models in the candidate set resulted in model-averaged estimates of R^2 above 0.5 for all black spruce attributes and between 0.35 and 0.48 for all balsam fir attributes. The range of values for black spruce and balsam fir was relatively distinct for wood density, coarseness, and modulus of elasticity. Only fiber length showed similar range and spread for both species. Generally, the plots revealed a small overestimation of the lower values and a small underestimation of the higher values (Fig. 2). This tendency was similar for both species.

Wood density of black spruce and balsam fir varied mainly with mean DBH and age, but other variables also had an effect. Specifically, black spruce wood density increased with age and species composition (Table 5). In contrast, wood density decreased with mean DBH and annual precipitation (Table 5). Wood density in plots having undergone PCT was lower than in plots that were not thinned (Table 5). Similarly, balsam fir wood density increased with age and decreased with mean DBH and annual precipitation (Table 5).

For coarseness, fiber length, and modulus of elasticity, some explanatory variables remained important for all attributes (Table 5). For instance, age was generally a good predictor for most attributes and for both species, with only one exception (modulus of elasticity of balsam fir). In all cases, fiber attribute values increased with age. Similarly, PCT was often a good predictor, with lower fiber attribute values in the plots having undergone PCT. Furthermore, all fiber attributes of black spruce increased with species composition. In contrast, balsam fir fiber attributes did not vary with species composition, but varied with geography, climate, and disturbance variables. For example, coarseness, fiber length, and modulus of elasticity of balsam fir decreased with elevation, but for black spruce, only fiber length followed the same pattern. Additionally, fiber length and coarseness decreased with latitude, whereas coarseness and modulus of elasticity increased with the mean temperature of the growing season. Although there were some common variables among the different balsam fir models, the explanatory variables varied from one attribute to another.

Prediction errors calculated using LOOCV (Table 4) gave RMSE values for black spruce of 28.9 kg/m^3 (5.29%) for wood density, 21.3 μg/m (5.58%) for coarseness, 0.14 mm (6.19%) for fiber length, and 1.65 GPa (11.85%) for modulus of elasticity. RMSE for balsam fir were slightly lower at 23.4 kg/m^3 (5.51%) for wood density, 18.7 μg/m (5.39%) for coarseness, 0.13 mm (5.83%) for fiber length, and 1.15 GPa (10.21%) for modulus of elasticity. These values represent less than 7% of the mean values for each attribute, except for modulus of elasticity for which the percentage is a little over 10%.

4.2. Landscape-level model selection and inference

Results obtained at the landscape level were generally similar to those from the plot-level analysis (Tables 4 and 6). For black spruce, the same models were often selected but sometimes with slightly different weights. For balsam fir coarseness and fiber length, the same models were identified as the top models using both the landscape and plot-level explanatory variables. For wood density and modulus of elasticity, different sets of models ranked higher but with only subtle changes in the list of explanatory variables. The landscape-level models resulted in only slightly higher RMSE values from the plot-level models for black spruce (30.6 vs. 28.9 kg/m^3 for wood density; 21.9 vs 21.3 μg/m for coarseness; 1.69 vs 1.65 GPa for modulus of elasticity) and the same values for fiber length (0.14 mm). For balsam fir, RMSE values were also slightly higher for all attributes except modulus of elasticity (26.7 vs. 23.4 kg/m^3 for wood density, 18.8 vs. 18.7 μg/m for coarseness, and 1.15 vs 1.14 GPa for modulus of elasticity) and

Table 5
Explanatory variables influencing plot-level fiber attributes in Newfoundland (i.e., 95% CI excludes 0). The explanatory variables are in decreasing order of predictive capability. Values in parentheses under the unconditional SE are the ratio between SE and the model-average estimates.

	Model-averaged estimate	Unconditional SE	95% Unconditional confidence interval
Black spruce			
Wood density			
Age	0.95	0.15 (0.16)	0.65; 1.25
Mean DBH	−5.86	1.89 (0.32)	−9.57; −2.15
Annual precipitation	−0.07	0.03 (0.42)	−0.13; −0.02
PCT	−28.13	12.18 (0.43)	−52; −4.27
Species composition	0.33	0.16 (0.48)	0.02; 0.64
Coarseness			
Age	0.49	0.11 (0.22)	0.27; 0.71
Species composition	0.44	0.12 (0.27)	0.22; 0.67
PCT	−30.26	8.87 (2.93)	−47.64; −12.88
Fiber length			
Elevation	−0.0004	0.0002 (−0.5125)	−0.0009; 2e−06
Age	0.0034	0.0007 (0.2037)	0.0020; 0.0048
Species composition	0.0020	0.0007 (0.3735)	0.0005; 0.0034
Dominant height	0.0286	0.0116 (0.4065)	0.0058; 0.0515
Modulus of elasticity			
Latitude	−0.623	0.317 (−0.509)	−1.245; −0.002
PCT	−1.943	0.670 (−0.345)	−3.256; −0.630
Species composition	0.040	0.009 (0.214)	0.023; 0.057
Age	0.032	0.009 (0.269)	0.015; 0.049
Balsam fir			
Wood density			
Mean DBH	−5.79	1.01 (0.17)	−7.77; −3.81
Age	0.56	0.11 (0.20)	0.34; 0.77
Annual precipitation	−0.04	0.02 (0.50)	−0.08; −0.01
Coarseness			
Elevation	−0.05	0.02 (0.03)	−0.08; −0.01
Age	0.37	0.09 (0.24)	0.20; 0.55
Mean temperature of growing season	10.64	3.92 (0.37)	2.96; 18.33
Latitude	−5.65	1.79 (3.86)	−9.16; −2.13
PCT	−15.04	5.29 (9.75)	−25.41; −4.66
Fiber length			
PCT	−0.0880	0.0349 (−0.3964)	−0.1564; −0.0196
Latitude	−0.0450	0.0120 (−0.2661)	−0.0685; −0.0215
Elevation	−0.0005	0.0001 (−0.2152)	−0.0007; −0.0003
Age	0.0025	0.0005 (0.2069)	0.0015; 0.0035
Dominant height	0.0204	0.0056 (0.2753)	0.0094; 0.0314
Modulus of elasticity			
Elevation	−0.004	0.001 (−0.262)	−0.006; −0.002
Mean DBH	−0.232	0.052 (−0.226)	−0.334; −0.129
Dominant height	0.323	0.063 (0.194)	0.201; 0.446
Mean temperature of growing season	0.846	0.247 (0.292)	0.362; 1.330

similar values for fiber length (0.13 mm). Overall, these prediction errors represent <7% of the mean values for each attribute, except for modulus of elasticity for which the percentage is a little over 10%.

The maps generated using the landscape-level models show the spatial distribution of each attribute at the island scale (Fig. 3). The main forested area of black spruce is concentrated in the central portion of the island. The general distribution of patterns related to the four fiber attributes is similar, which follows the trend given in Table 3 for the correlation between fiber attributes. The main forested area of balsam fir is in the western portion of the island and the eastern-most peninsula. The four fiber attributes have different distribution patterns although there are some similarities. The ability to map the results with the landscape-level models generally came with a small loss of prediction ability when compared with the plot-level models, as shown by the results in Table 6. The only exception was the MOE for balsam fir, where prediction levels were similar.

5. Discussion

We used model selection and multimodel inference to identify environmental and forest inventory explanatory variables and to predict wood fiber attributes at the plot and landscape levels. The coefficients of determination (R^2) for black spruce (0.52–0.61) and for balsam fir (0.35–0.48) suggested a persistent trend: predictive models always had higher R^2 for black spruce than for balsam fir. However, the predictive models for both species showed relatively similar RMSE, indicating similar predictive ability for both species. The higher R^2 for black spruce are likely the result of a greater range of values for the response variables. Regardless, our model-averaging approach showed similar capabilities to predict fiber attributes for both species.

The predictive models of the two species were primarily influenced by two explanatory variables: stand age and PCT. Stand age was also raised as a potential variable by van Leeuwen et al. (2011) under the assumption that, when trees grow older, juvenile wood reduces or disappears, which favors increasing wood density. Not surprisingly, PCT also stands out as an important predictor of fiber attributes. Stand thinning reduces competition among the remaining trees by providing a wider space to grow, resulting in increased diameter growth (MacDonald and Hubert, 2002). The effect of other, less dominant, explanatory variables varied between fiber attributes and for both species. For instance, species composition influenced all black spruce attributes, but this was not the case for balsam fir. Besides stand age and PCT, black spruce wood density was also influenced by species composition, mean DBH, and annual precipitation, whereas balsam fir wood density

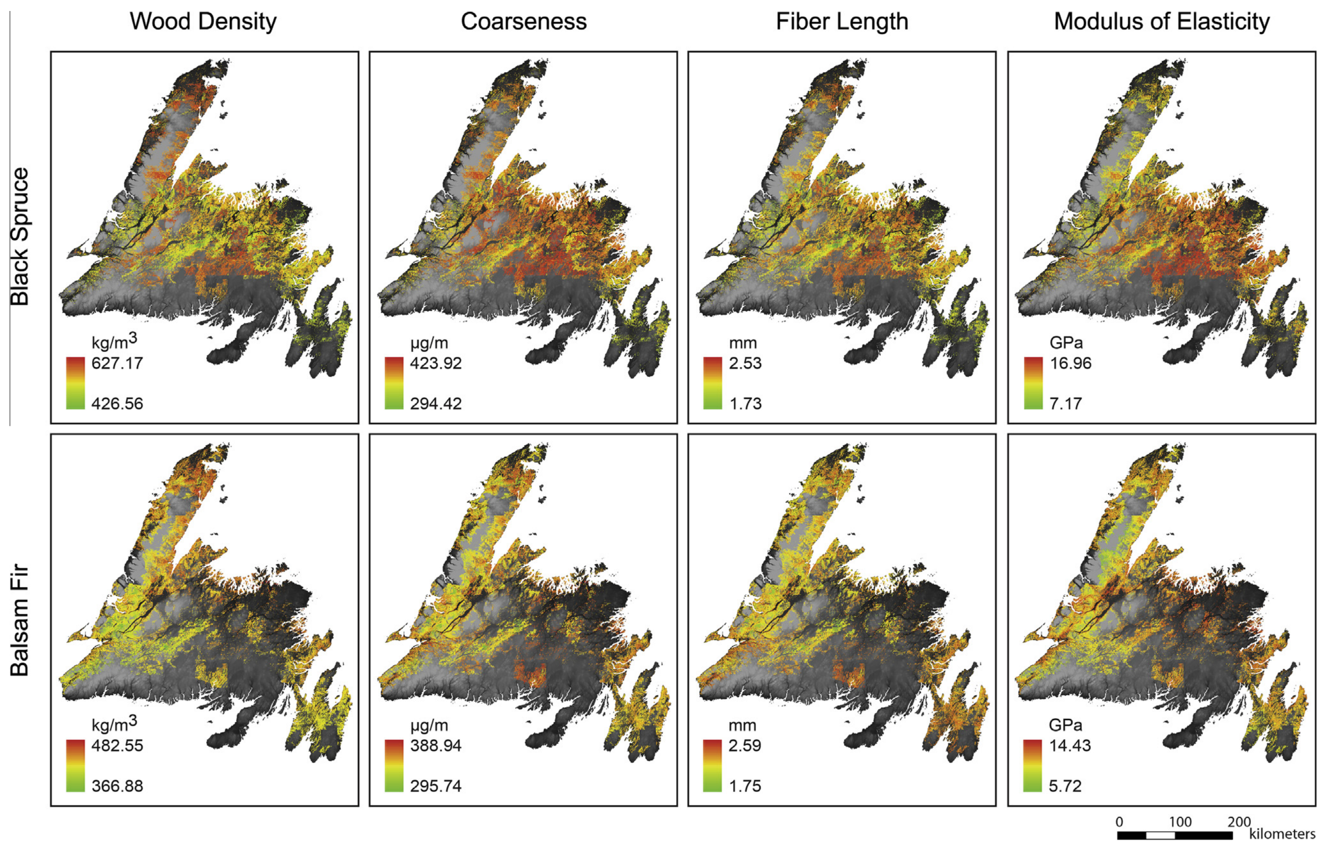

Fig. 3. Predicted spatial distribution of fiber attributes across Newfoundland for stands containing black spruce and balsam fir.

was influenced by only three explanatory variables: stand age, mean DBH, and annual precipitation. Relationships similar to those found in this study have been reported for other tree species (Kilpeläinen et al., 2005; MacDonald and Hubert, 2002; van Leeuwen et al., 2011). The influence of mean DBH on wood fiber properties was suggested by Liu et al. (2007) when investigating yield and lumber quality. In our study, mean DBH was a significant explanatory variable but only for wood density and generally not for the other fiber attributes (with the exception of the modulus of elasticity of the balsam fir). Overall, fiber characteristics were influenced most by vegetation and disturbance variables combined with additional influences from climate and geographic variables.

The information-theoretic approach permitted a comparison of models with different types of variables and provided a measure of support for each. We used this approach over the more commonly used stepwise regression approach, as the latter can be strongly dependent on the method (backward elimination, forward selection, stepwise) and the choice of α level, does not account for multiple testing, and assumes that the analyst knows nothing about the system under study (Burnham et al., 2011; Mazerolle, 2006). In contrast, the approach used in this study relied on the specification of relevant models that reflect biologically interesting hypotheses and provided measures of support in favor of each model/hypothesis. More importantly, model selection was based on information criteria and derived measures that quantified the uncertainty regarding the best model, acknowledging that some models may be equivalent. The results suggested that for wood density and coarseness, inferences be based on the entire model set, whereas for fiber length and modulus of elasticity, a single model was adequate.

The landscape models offer several advantages as an operational tool to support forest management planning. Implementation of the models in a GIS to generate maps reveals the spatial patterns of fiber attributes across the island. If a stand contains both spruce and fir according to the stand type, the models offer separate predictions of fiber attributes for each species. Moreover, now that the models are developed, it is not necessary to go back and take core samples and measure fiber attributes in order to update the maps. Rather, once the inventory stand maps are updated, the models can be used to predict the fiber attributes.

Although this study provides models that predict how fiber attributes vary from stand to stand and across landscapes, understanding "why" fiber attributes vary is equally important. Wood fiber attributes are determined by forest and environmental factors that interact with one another in complicated ways. Understanding the nature and complexity of these interactions is important to support forest management activities geared toward the production of wood with specific characteristics. Further research is thus necessary to test specific hypotheses related to tree growth, wood formation, and the development of fiber attributes.

Several additional limitations were identified in the study suggesting further research to improve the models and their application. Despite efforts to use relevant variables, other important explanatory variables may have been missed. For example, variables describing average wind speed, distance to the coast, soil moisture, and surficial geology may help to account for unexplained variance and improve predictions. As these variables were not available for landscape-level application, they were not pursued in this study. The analysis clearly showed the importance of variables describing the vegetation. Yet, the available explanatory variables (e.g., age, height, and crown density) provide a relatively coarse representation of structure. Some variables identified in the literature as important drivers for fiber attributes were not identified as important in the present study (i.e., stand density). The fact

Table 6
Confidence set (95%) for the best fiber attributes models for black spruce and balsam fir (landscape level).

Confidence set for the best model (95% confidence set)	K	AIC_c	ΔAIC_c	ω_i	R^2	Adj. R^2	RMSE	RMSE$_r$
Black spruce								
Wood density								
Mod17	8	744.64	0.00	0.66	0.51	0.47	27.08	4.94%
Mod13	6	746.57	1.94	0.25	0.47	0.44	28.31	5.17%
Mod16	8	749.65	5.01	0.05	0.48	0.44	27.97	5.11%
Averaged predictions using all models					***0.51***			
Leave-one-out cross-validation							*30.59*	*5.60%*
Coarseness								
Mod16	8	692.94	0.00	0.70	0.56	0.52	19.36	5.05%
Mod17	8	694.71	1.77	0.29	0.55	0.51	19.58	5.11%
Averaged predictions using all models					***0.56***			
Leave-one-out cross-validation							*21.87*	*5.73%*
Fiber length								
Mod17	8	-84.99	0.00	0.65	0.52	0.48	0.12	5.47%
Mod13	6	-83.62	1.37	0.33	0.48	0.45	0.13	5.70%
Averaged predictions using all models					***0.53***			
Leave-one-out cross-validation							*0.14*	*6.19%*
Modulus of elasticity								
Mod17	8	294.96	0.00	0.84	0.59	0.55	1.46	10.36%
Mod16	8	298.29	3.33	0.16	0.57	0.53	1.49	10.58%
Averaged predictions using all models					***0.59***			
Leave-one-out cross-validation							*1.69*	*12.14%*
Balsam fir								
Wood density								
Mod17	8	1102.44	0.00	0.53	0.29	0.25	24.98	5.86%
Mod18	8	1103.83	1.40	0.26	0.28	0.24	25.13	5.90%
Mod15	6	1105.02	2.58	0.14	0.24	0.22	25.76	6.05%
Mod13	6	1106.85	4.42	0.06	0.23	0.20	25.96	6.09%
Averaged predictions using all models					***0.33***			
Leave-one-out cross-validation							*26.74*	*6.29%*
Coarseness								
Mod18	8	1021.92	0.00	0.68	0.32	0.29	17.71	5.10%
Mod17	8	1023.45	1.53	0.32	0.32	0.28	17.83	5.13%
Averaged predictions using all models					***0.33***			
Leave-one-out cross-validation							*18.85*	*5.44%*
Fiber length								
Mod17	8	-145.61	0.00	1.00	0.44	0.41	0.12	5.39%
Averaged predictions using all models					***0.44***			
Leave-one-out cross-validation							*0.13*	*5.83%*
Modulus of elasticity								
Mod18	8	363.2	0.00	0.98	0.48	0.45	1.06	9.40%
Averaged predictions using all models					***0.48***			
Leave-one-out cross-validation							*1.14*	*10.19%*

that the fiber trees were selected outside the plot is also a possible source of error considering that differences may exist between the trees selected and those inside the plot. Recent research has shown that a more comprehensive representation of stand structure is possible from metrics derived from light detection and ranging (LiDAR) technologies (van Leeuwen et al., 2011). Even finer-scale structural metrics may be generated from terrestrial LiDAR scans combined with architectural models (Côté et al., 2012). Airborne laser scanning systems provide increasing capabilities to map detailed structural variables including mean DBH and dominant height of conifer forests (Luther et al., in press). With respect to the maps generated with the landscape-level models, we assumed that the explanatory variables available from the inventory stand maps were up to date and 100% correct. However, the inventory cycle is typically 10–15 years, meaning that the mapped information could be 10–15 years out of date. Moreover, the scale of mapping at the stand level was adequate for strategic planning, but increased precision would help to better inform operational harvest planning. Finally, although the RMSE provide a level of validation of the models, validation was not possible at the map level because validation of the input layers was not available. Advances in the availability and capabilities of airborne laser scanning systems offer increased opportunities to address current limitations in producing detailed forest structural information to support prediction and mapping of fiber attributes.

6. Conclusion

The results of this study show that wood fiber attributes can be modeled using explanatory variables contained in existing forest inventory systems combined with other environmental variables describing climate and geography. Our analyses showed that variables describing the vegetation (age and mean DBH) and disturbance (PCT) were important explanatory variables in all models developed at both the plot and landscape levels. Additionally, environmental variables describing elevation, latitude, annual precipitation, and mean temperature of the growing season, were linked to many fiber attributes but to a smaller extent than the vegetation and disturbance variables. Modeled average prediction errors were less than 5% for most fiber attributes and 10% for modulus of elasticity at both the plot and landscape levels. Accordingly, the landscape-level models could be used to make spatial predictions of fiber attributes spanning wide gradients of geography and climate across the productive forest area of the island of Newfoundland with a total land area >100,000 km^2.

Few studies have provided guidelines on the capacity to predict wood fiber attributes at the landscape level or over large areas. The apparent dominance of the vegetation variables to predict wood fiber is useful, so further research should focus on improved measurement capability in forest inventory for these variables. Spatially explicit estimation of relevant structural variables may be a challenge to map for large areas. However, the availability of high spatial resolution satellite images and airborne LiDAR data is likely to improve our ability to apply predictive models such as those presented in this study.

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