

Predicting black spruce fuel characteristics with Airborne Laser Scanning (ALS)

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Abstract. Wildfire decision support systems combine fuel maps with other fire environment variables to predict fire behaviour and guide management actions. Until recently, financial and technological constraints have limited provincial fuel maps to relatively coarse spatial resolutions. Airborne Laser Scanning (ALS), a remote sensing technology that uses LiDAR (Light Detection and Ranging), is becoming an increasingly affordable and pragmatic tool for mapping fuels across localised and broad areas. Few studies have used ALS in boreal forest regions to describe structural attributes such as fuel load at a fine resolution (i.e. $<100\text{ m}^2$ cell resolution). We used ALS to predict five forest attributes relevant to fire behaviour in black spruce (*Picea mariana*) stands in Alberta, Canada: canopy bulk density, canopy fuel load, stem density, canopy height and canopy base height. Least absolute shrinkage and selection operator (lasso) regression models indicated statistically significant relationships between ALS data and the forest metrics of interest ($R^2 \geq 0.81$ for all metrics except canopy base height which had a R^2 value of 0.63). Performance of the regression models was acceptable and consistent with prior studies when applied to test datasets; however, regression models presented in this study mapped stand attributes at a much finer resolution (40 m^2).

Keywords: remote sensing, fire behaviour, boreal ecosystems, fuel, planning, fuel maps, LiDAR, airborne laser scanning.

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Introduction

Wildfires consume live and dead biomass (i.e. fuels) that form the ground, surface and crown structures of a forested stand. Assemblages of fuel and non-fuel elements across space and their physical properties alone and in relation to each other define the fuel complex. Fuel properties such as chemistry, shape, size, and load or amount will vary naturally within forest ecosystems. Attributes that define the spatial relationship of individual fuel elements to each other such as vertical arrangement, horizontal distribution and compaction will also vary (Countryman 1972; Keane 2015). Fine-scale measurements of these varied fuel properties and attributes are largely limited to research conducted in localised areas such as experimental burning studies (e.g. Alexander *et al.* 2004) or laboratory experiments of fuel flammability typically designed to address one or more specific components of flammability proposed by Anderson (1970): ignitability, sustainability and combustibility (Varner *et al.* 2015). Fuel measurement using field sampling methods are resource- and time-intensive, which is impractical for collecting comprehensive inventories of fuel characteristics across vast and remote northern landscapes.

At landscape scales, fuels are typically mapped as categorical fuel types that represent fuel assemblages and related physical properties and spatial arrangement of fuels within major forested or open vegetated landcovers. In Canada, the Canadian Forest Fire Behaviour Prediction (FBP) System (Forestry Fire Danger Group Canada 1992) defines 16 standard fuel types that

can be mapped using satellite images and forest inventory data commonly available at coarse resolutions across broad forest management areas. At finer spatial scales, statistical models have been developed to estimate canopy fuel characteristics from field-measured data (e.g. Cruz *et al.* 2003). Photo-load visual guides (e.g. Scott and Reinhardt 2005) have also been used to derive site-specific estimates of fuel loads without the need for time- and resource-intensive fuel sampling; however, it is difficult to apply these methods across broad spatial scales without interpolating fuel characteristics.

Fuel attributes, in combination with weather and topography, dictate the manner in which fires ignite, spread and extinguish and are therefore critical inputs to all fire behaviour models. The contribution of canopy fuels to combustion is of particular importance for fire behaviour prediction. Involvement of canopy fuels in combustion generates higher intensities than surface or ground fires and can be expected to result in fire behaviour conditions that exceed the capabilities of suppression crews working directly on the fire front (Alexander 1982; Hirsch *et al.* 1998). Canopy fuel attributes used to model the onset of crowning and potential for sustained crown fire spread include canopy height, canopy base height (CBH), canopy fuel load (CFL) and canopy bulk density (CBD) (Keane *et al.* 2001; Cruz *et al.* 2003). Canopy height affects wind trajectory and speed (Finney 1998), which will influence fire intensity and affect the distance embers travel aloft (Chuvieco *et al.* 2003). Canopy base height is the vertical distance between the ground and live

foliage and is important for determining whether a surface fire will progress into a canopy fire (Van Wagner 1977). Canopy fuel load is the amount of fuel in the canopy per unit area that is available for combustion (Stocks *et al.* 2004) and is a determinant of fire intensity. Canopy bulk density describes the available canopy fuel per unit volume that affects the rate of fire spread (Van Wagner 1977; Chuvieco *et al.* 2003).

Advancements in remote sensing technologies provide an emerging means of quantifying fuel characteristics across broad areas at a level of detail and precision that far exceeds current fuel type categories and maps commonly derived from forest inventories and satellite imagery (e.g. Andersen *et al.* 2005). Airborne Laser Scanning (ALS), a form of remote sensing that utilises LiDAR (Light Detection and Ranging), and aerial imagery are both popular tools to characterise canopy fuels (e.g. Erdody and Moskal 2010; Bright *et al.* 2017); however, ALS is considered more accurate for describing forest characteristics (Erdody and Moskal 2010) because it penetrates through small openings in the canopy and can describe the three-dimensional structure of a forest (Vastaranta *et al.* 2012; White *et al.* 2016; Wu *et al.* 2016). Field measurements are almost always required as baseline data when developing vegetation models using remote sensing technologies and are also used to validate statistical models. Although field measurements will always be important, once confidence is achieved in a remote sensing model, vegetation data can be mapped at much higher resolution than possible with field sampling alone.

Pioneering work by Andersen *et al.* (2005) modelled the statistical relationship between ALS point clouds and field-measured fuel data. Numerous subsequent studies have developed ALS-based models for mapping forest fuel metrics across an area of interest (e.g. Erdody and Moskal 2010; Hermosilla *et al.* 2014; Botequim *et al.* 2019). Models that use ALS data to describe fine scale variability in fuel structure are species-specific and have yet to be developed for black spruce (*Picea mariana*) stands, a prominent stand type in boreal ecosystems that covers 2.7 million km² of land within Canada (National Forest Inventory 2013). Predicting fire behaviour in black spruce forests is of particular importance because these stands support high intensity crown fires. In this paper, we investigate the relationship between ALS data and canopy fuel attributes measured in boreal black spruce stands in Alberta, Canada. We use least absolute shrinkage and selection operator (lasso) regression to model the relationship between ALS data and five canopy fuel attributes: canopy bulk density, canopy fuel load, stem density, canopy height and canopy base height. Implications for fuel mapping and fire behaviour modelling are discussed.

Methods

The objectives of this study were to develop statistical regression models for estimating canopy fuel characteristics from ALS data in black spruce forests. Field plots were established in black spruce stands and measured to calculate canopy height, stem density, CBH, CFL and CBD. Airborne Laser Scanning data were collected over the study sites and processed to produce metrics that were related to the field data using lasso regression. A schematic overview of the methods used in this study is shown in Fig. 1.

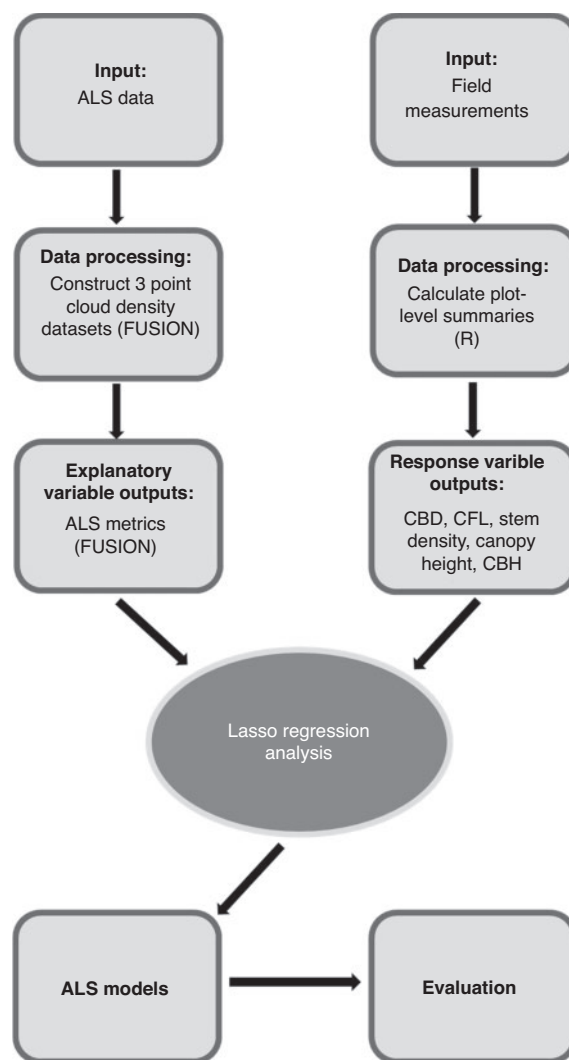


Fig. 1. Schematic diagram of the data processing and modelling methods used to compare Airborne Laser Scanning (ALS) data to field measurements.

Study area

Pure black spruce stands were selected for analysis to represent a range of natural and managed stand structures characteristic of the boreal region. In this study, managed stands refer to forests that were subjected to thinning and pruning treatments to reduce potential fire behaviour, typically in the vicinity of values such as communities. In total, 79 circular fixed inventory plots were analysed at two study sites in north-western Alberta (Fig. 2) that afforded both ease of access and a broad range of managed and natural stand densities: Pelican Mountain (59 stands), a fuel and fire behaviour research site operated by Alberta Agriculture and Forestry (Fig. 3a); and Conklin (20 stands), a small hamlet surrounded by both natural and managed black spruce stands (Fig. 3b).

The structure of black spruce stands varies naturally from stringers in open bogs to open black spruce woodlands (<2000 stems ha⁻¹) to very dense black spruce forests

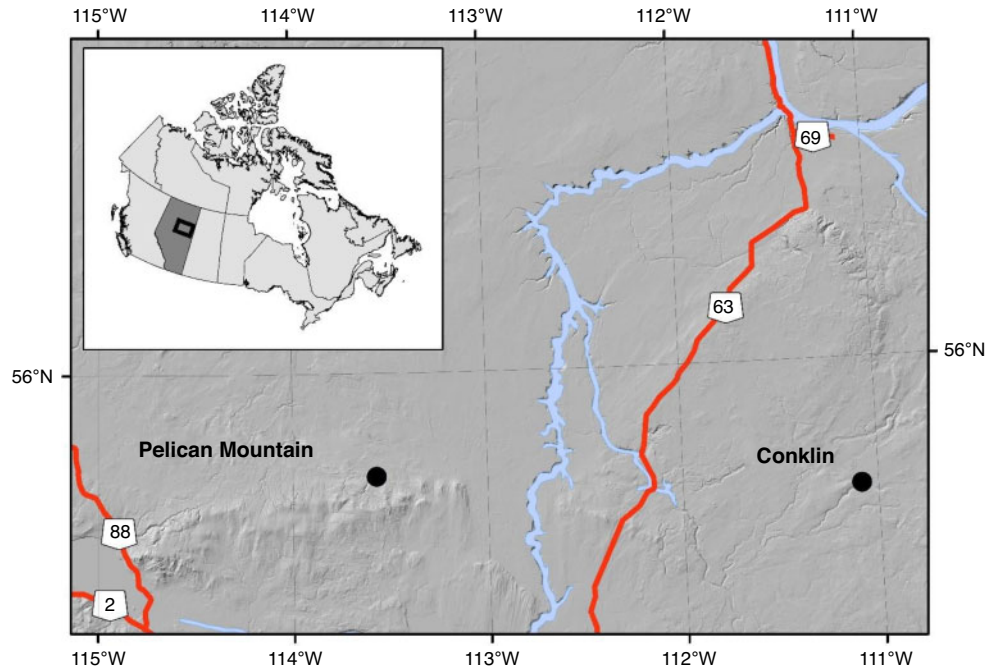


Fig. 2. Location of the study area within Alberta, Canada and location of the Pelican Mountain Research Site and community of Conklin within the study area. Major highway numbers are labelled.

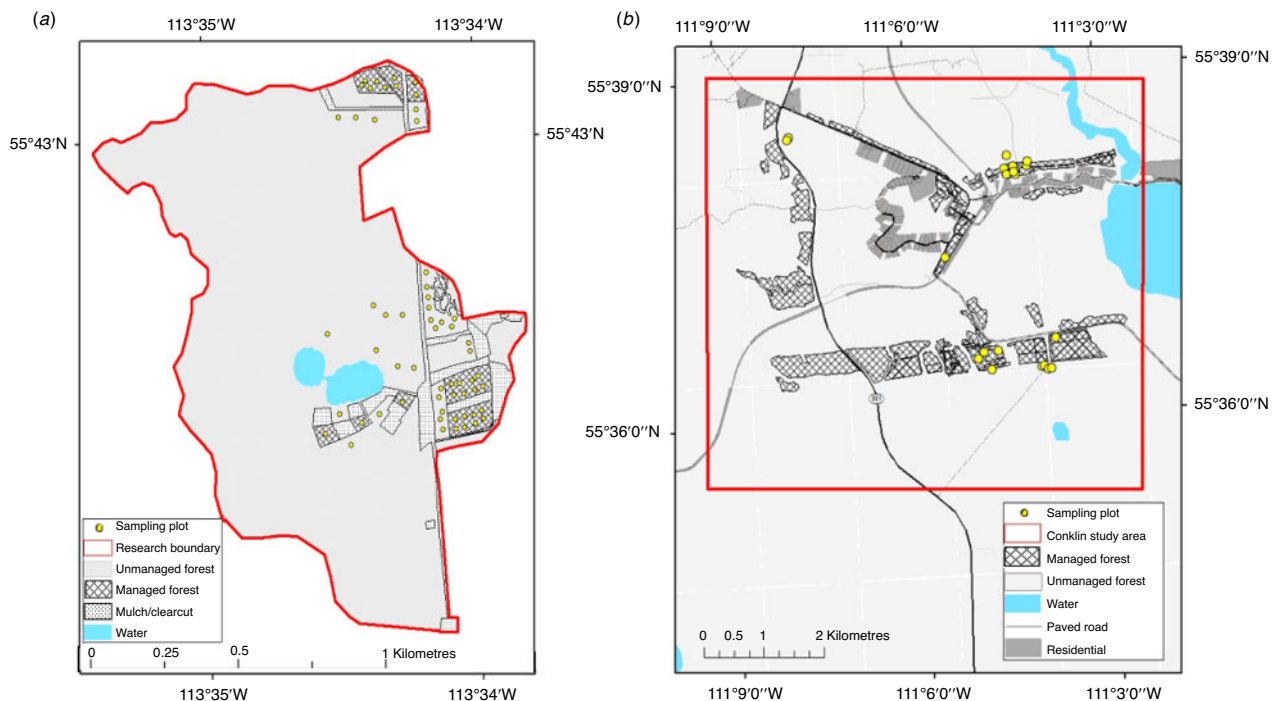


Fig. 3. (a) The Pelican Mountain Research Site and (b) Conklin community study area are both composed of unmanaged and managed forest. Managed forest stands have undergone stem thinning and have had the lower branches removed on remaining trees. Sampling plots ($n = 79$) were established to capture the full structure variability of black spruce stands across the research site.

(>35 000 stems ha^{-1}) (Jean *et al.* 2020). Managed stands approximate stand structures found in low density black spruce forests and were included in this study to provide a range of

stand densities within the localised study area. Including managed stands in this study also allows for results to be applied to both natural and managed stand structures.

Table 1. Study site descriptions for Pelican Mountain and Conklin

	Pelican Mountain	Conklin
Study area location (degrees north, degrees west)	55.7008, 113.5689	55.6323, 111.0838
Study area size (km ²)	1.2	10
Elevation (m)	590–657	530–624
Stand ages ^A (years)	40–100	40–110
Total plots established (control/managed stands)	59 (31/28)	20 (8/12)
Years since treatment for managed stands	0–2	7–17
Years that summer sampling took place	2017–2019	2018–2019

^ABased on tree core samples taken 0.25 m in height.

Characteristics of the Pelican Mountain and Conklin study sites are detailed in Table 1. Plot locations were selected using satellite imagery and site visits. Sample plots were located in varied stand structural conditions associated with natural, recently managed (1–2 years post-treatment) and older managed (7–17 years post-treatment) stands of pure black spruce. Dead branches draped with bearded lichens were common, and tree crowns in unmanaged stands extended to or near the ground. Forest floor conditions within the plots was often a nearly continuous cover of feather mosses, dominated by big red stem moss (*Pleurozium schreberi*) with occasional small hummocks of sphagnum moss, primarily common brown sphagnum (*Sphagnum fuscum*). Surface vegetation was dominated by Labrador tea (*Ledum groenlandicum*), lowbush cranberry (*Vaccinium vitis-idaea*), blueberry (*Vaccinium myrtilloides*) and bog cranberry (*Vaccinium oxycoccos*). Downed woody debris was largely absent in the natural stands, with a moderate presence in treated stands. Most sites had a thick organic layer, often >40 cm in depth.

Field measurements

At each plot, all trees with a height >1.3 m were measured to record species, status (live or dead), tree height, diameter at 1.3 m (DBH, diameter breast height), and the vertical distance between the ground and the base of live crown foliage. All height measurements were collected using a Hagl f Sweden  Vertex instrument, and DBH was measured using tree callipers. All vegetation with a height <1.3 m was deemed part of the surface or ladder fuel complex and omitted from canopy fuel measurements. The 1.3 m height threshold used to demarcate the lower limit of the canopy fuel strata is lower than the 2 m threshold used in other studies (e.g. Alexander and Cruz 2014), owing to the relatively short stature of the black spruce stands under investigation. The default sampling radius for ground plots was 3.57 m (76 plots). A larger 5.64 m radius was used when <20 trees occurred within the default sampling area (3 plots). Plot positions were determined to an average horizontal accuracy of 0.39 m using a Trimble  Geo7X global navigation satellite system device with a Trimble  Tempest Antenna (Sunnyvale, CA).

Field measurements were used to calculate plot-level canopy fuel attributes with the statistical software package R (R Core Team 2018). Canopy height (m) was defined as the tallest tree

within the sampling area. Maximum tree height was used to represent stand height in this forest type due to the small plot size and presence of abundant small and stunted trees. Canopy base height (m) was calculated following Van Wagner (1977) as the average live crown base height for all live trees within the sampling area. Stem density (stems ha^{−1}) was calculated as the sum of all trees >1.3 m in height divided by the plot area.

Canopy fuel load (CFL, kg m^{−2}) was defined as the canopy biomass per unit area available for combustion during the flaming stage of a passing canopy fire. Foliage and fine branchwood less than 1.0 cm in diameter were included in the CFL calculations following Stocks *et al.* (2004). Published allometric equations based on DBH and species type were used to calculate the mass of available canopy fuel for each tree over 1.3 m in height (Table 2). Canopy fuel load (kg m^{−2}) for the plot was then calculated as follows (Eqn 1):

$$CFL = \frac{\sum CF_i}{a} \quad (1)$$

where CF_i is the mass (kg) of canopy fuel contributed by an individual tree and a is the sampling area of the plot (m²). For dead trees, dead branchwood less than 1.0 cm was included in the calculation, but it was assumed that no foliage was present. Occasionally, conifer species other than black spruce were within the sample plots. Conifer species included in canopy fuel load calculations and associated allometric equations are listed in Table 2. Broadleaved trees do not contribute to canopy fuel load and were omitted from analysis.

Allometric equations for estimating crown fuel load are representative of natural, unmanaged crown morphology. In managed stands, where pruning is used to remove crown fuels on the lower portion of the tree bole, estimated crown fuel load was reduced proportionate to the reduction in crown length following fuel treatments. Post-treatment crown length was calculated from field measurements as the difference between tree height and crown base height. Pre-treatment crown length was estimated from the statistical relationship between tree height and live crown base height (Fig. 4), which was derived with linear regression from data collected in natural, unmanaged black spruce stands at Pelican Mountain and Conklin (Eqn 2):

$$CBH_{ni} = 0.53 \times h_i + 0.15 \quad (2)$$

where CBH_{ni} (m) is the estimated pre-treatment, natural crown base height of an individual tree and h_i is tree height (m). The equation used to estimate crown fuel load of pruned trees in managed stands is as follows (Eqn 3):

$$CF_{pi} = CF_{ni} \times \left[\frac{h_i - CBH_{pi}}{h_i - CBH_{ni}} \right] \quad (3)$$

where CF_{pi} is the mass (kg) of canopy fuel following pruning for the i th tree, CF_{ni} is the mass (kg) of canopy fuel given an unpruned, natural tree crown and the allometric equations from Table 2, and CBH_{pi} is the field-measured post-treatment crown base height (m) following pruning.

Canopy bulk density (CBD, kg m^{−3}) is the amount of fuel available for combustion during the passage of the fire front per

Table 2. Species-specific allometric equations used to calculate tree-level canopy fuel mass (CF_i , kg m^{-2})
Tree diameter at breast height (DBH) measurements are made in cm

Species	Source for calculating canopy fuel load	Equation
Black spruce (<i>Picea mariana</i>)	Alexander <i>et al.</i> (2004)	$CF_i = 0.23317(\text{DBH})^{1.25384} + 0.13267(\text{DBH})^{1.11546} + 0.05553(\text{DBH})^{1.12281} + 0.04995(\text{DBH})^{1.29626} + 0.000167(\text{DBH})^{3.81224}$
Jack pine (<i>Pinus banksiana</i>)	Alexander <i>et al.</i> (2004)	$CF_i = 0.00672(\text{DBH})^{2.25699} + 0.00478(\text{DBH})^{2.08881} + 0.00824(\text{DBH})^{1.88877} + 0.00105(\text{DBH})^{2.43234} + 0.00161(\text{DBH})^{2.30592}$
Lodgepole pine (<i>Pinus contorta</i>)	Johnson <i>et al.</i> (1990)	$CF_i = 0.0525(\text{DBH})^{1.6057} + 0.0533(\text{DBH})^{1.8052} + 0.1369(\text{DBH})^{1.3553}$
White spruce (<i>Picea glauca</i>)	Johnson <i>et al.</i> (1990)	$CF_i = 0.6373(\text{DBH})^{1.1457} + 0.0869(\text{DBH})^{1.8938} + 0.0304(\text{DBH})^{1.7481}$

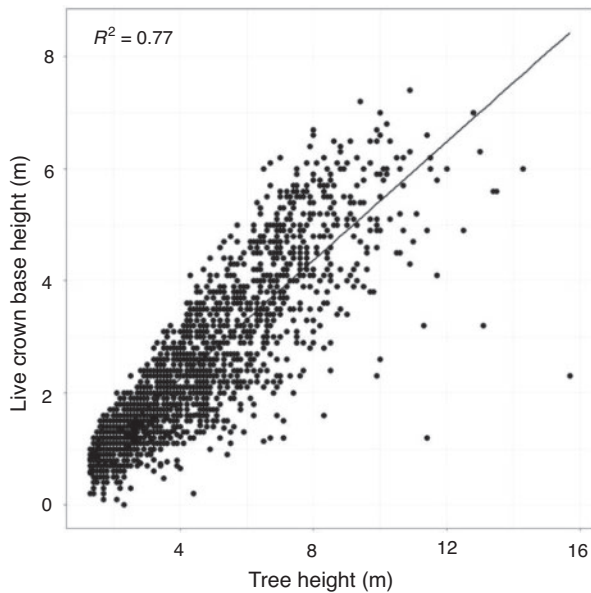


Fig. 4. Relationship between tree height and live crown base height for all black spruce trees from unmanaged stands used in this study.

unit volume and was calculated following the same methodology as the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS) (Reinhardt and Crookston 2003; Rebain *et al.* 2010). For each individual tree, a uniform distribution of fuels was assumed between the crown base height and height of the tree. Using the crown position above the ground, the fuel density for all trees within the plot was summed in 0.3 m horizontal increments from the ground to the top of the canopy. Canopy bulk density was defined as the maximum 4.6 m running mean of crown fuel density for the plot, as per FFE-FVS. It should be noted that the FFE-FVS only counts conifer trees over 1.8 m tall towards canopy fuels (Rebain *et al.* 2010). In this study, a slightly shorter threshold of 1.3 m was used because black spruce stands are typically stunted due to poor growing conditions, yet smaller trees still contribute significantly to the canopy (Johnston *et al.* 2015).

Airborne Laser Scanning data

Discrete return multi-spectral ALS data were acquired for both study sites in August 2018 using a Teledyne Optech Titan

multispectral sensor mounted on a Piper Navajo aircraft. This system emits 3 independent laser pulses in the 1550 nm (short wave infrared), 1064 nm (near infrared) and 532 nm (green) wavelengths. Metadata for the LiDAR system settings, flight parameters and data are shown in Table 3. The University of Lethbridge ARTEMis laboratory collected and preprocessed the data using the LiDAR Mapping Suite (LMS, proprietary software from Teledyne Optech) to generate a point cloud for each channel. The point clouds for each dataset were merged into a single dataset using the MergeData tool in FUSION (Version 3.80, McGaughey 2018a), an open source software specialised for LiDAR data processing. The GridSurfaceCreate tool within FUSION was used to generate a 1-m resolution digital elevation model (DEM) with returns that were classified as ground points. The elevation of ALS returns were calculated to height above the ground by subtracting the elevation from the DEM. The mean point density of the ALS datasets were 10.5 pulses per m^2 and 11.3 pulses per m^2 for Pelican Mountain and Conklin, respectively.

Processing and analysis of ALS data was generally consistent with procedures and recommendations outlined in White *et al.* (2013, 2017). The FUSION PolyClipData tool was used to cut ALS point clouds to each sample plot boundary. Airborne Laser Scanning point coordinates were transformed to height above ground with the DEM to enable comparisons across sample plots. Plot metrics were calculated using the CloudMetrics tool in FUSION. Procedures for calculating plot metrics are detailed in the FUSION software manual (McGaughey 2018b). Returns of LiDAR pulses < 1.3 m above ground were excluded to restrict data points to the canopy fuel stratum under analysis. Fifteen candidate ALS variables known to have relationships with forestry metrics from previous studies (e.g. Andersen *et al.* 2005; Erdody and Moskal 2010; Bright *et al.* 2017) were calculated with FUSION and output in the plot-level ALS metrics dataset (Table 4). ALS-based predictor variables consisted of a variety of height and strata metrics.

Model development and evaluation

We applied lasso regression in R with the 'glmnet' package (Friedman *et al.* 2010) to model the relationship between ALS point cloud metrics and canopy characteristics estimated from field measurements. Lasso (i.e. *least absolute shrinkage and selection operator*) was chosen for this analysis because it uses shrinkage (which reduces the coefficients of the variables) to generate simple prediction models that account for collinearity

Table 3. Airborne Laser Scanning (ALS) flight parameters and system settings

Abbreviations: altitude above ground level (AGL), channel 1 (C1), channel 2 (C2), channel 3 (C3), pulse repetition frequency (PRF)

Parameter	Study area	
	Pelican Mountain	Conklin
Area (ha)	150	1000
Survey date	19 August 2018	18 August 2018
LiDAR sensor channels (C1, C2, C3)	Teledyne Optech Titan (1550 nm, 1064 nm, 532 nm)	Teledyne Optech Titan (1550 nm, 1064 nm, 532 nm)
Camera sensor	CM-6500 (35 mm)	CM-6500 (35 mm)
Survey altitude (AGL)	1000 m	1000 m
PRF (total/per channel)	300 000/100 000	300 000/100 000
Scan frequency	32	32
Scan angle, full (degrees)	50	50
Side overlap (planned)	50%	50%
Camera overlap (along, across)	30%, 50%	30%, 50%
Aircraft speed (m s^{-1})	68	70
Point density, planned single returns (total points m^{-2} / per channel points m^{-2})	9/3	9/3
Point density, multiple returns (all, C1, C2, C3)	10.5, 4.8, 4.4, 1.3	11.3, 5.1, 4.7, 1.5
Datum	NAD83 CSRS Epoch 2002, UTM zone 12, ellipsoidal heights	NAD83 CSRS Epoch 2002, UTM zone 12, ellipsoidal heights

Table 4. FUSION plot metrics (McGaughey 2018b) included in lasso regression modelling

All height measurements are in metres

Source	Predictor name	Metric description
First returns above 1.3 m height threshold	h_{max}	Maximum height
	h_{mean}	Mean height
	h_{CV}	Coefficient of variation for heights
	h_{25}	Height of 25th percentile
	h_{50}	Height of 50th percentile
	h_{75}	Height of 75th percentile
	h_{90}	Height of 90th percentile
	h_{99}	Height of 99th percentile
	$Pc_{1.3}$	Percentage first returns above 1.3 m
	Pc_{mean}	Percentage first returns above mean height
All returns, including ground and nonground	$Prop_{<0.15}$	Percentage of first returns <0.15 m
	$Prop_{0.15\text{ to }1.30}$	Percentage of first returns >0.15 m and ≤ 1.30 m
	$Prop_{1.30\text{ to }5.00}$	Percentage of first returns >1.30 m and ≤ 5.00 m
	$Prop_{5.00\text{ to }10.00}$	Percentage of first returns >5.00 m and ≤ 10.00 m
	$Prop_{10.00\text{ to }20.00}$	Percentage of first returns >10.00 m and ≤ 20.00 m

between predictor variables (Tibshirani 1996; Babyak 2004). To satisfy the assumptions of linearity between the dependent and independent variables, a square root transformation was applied to CFL, CBD, stem density and CBH. Sample plots were

randomly pooled into training (52 plots) and validation (27 plots) datasets. A linear regression model was fitted to each response variable (stand height, sqrtCFL, sqrtCBD, sqrtDensity and sqrtCBH) in the training dataset using the cv.glmnet function. To enable reproducible results, the set.seed value was set to '123'. The set.seed function divides the data into training and testing datasets randomly, but by setting a value (i.e. 123) it ensures the training and testing datasets are always composed of the same data subset each time the script is executed. When performing lasso regression, λ is used to determine the amount of shrinkage of the coefficients. When λ is zero, the resulting regression model is equivalent to least square estimates. As the value of λ increases, shrinkage occurs so variables that are not good predictors can be removed from the regression model. To obtain the optimal value for lambda, 10-fold cross validation with mean squared error was used. Performance of each regression model was evaluated on the training and testing data using the coefficient of determination (R^2 , R^2_{test}) and root mean squared error (RMSE, $\text{RMSE}_{\text{test}}$). Similar values between the training and testing data indicate that the regression model has good predictive capabilities.

Results

Field measurements of canopy and stand characteristics are summarised in Table 5. Both sites captured a wide range of stand characteristics, and there was sufficient overlap between natural and managed stand attributes. Selected regression models for estimating each canopy fuel attribute are shown in Table 6. Regression models for all stand attributes except CBH performed well, with R^2 values ranging 0.81–0.89 for the training dataset and 0.78–0.85 for the test dataset. The RMSE and $\text{RMSE}_{\text{test}}$ values are also close enough to conclude that all regression models except for CBH are suitable for generalised use whereby predictions are generated with new data that was not used in the modelling process.

Table 5. Stand and canopy characteristics of field-measured black spruce stands by status (a) natural/unmanaged, (b) managed and (c) combined and study area (Pelican Mountain, Conklin)

Descriptive statistics of range, mean and standard deviation (s.d.) are shown by stand status to document variation in data sources. All data were combined irrespective of stand status for analysis and model building

	Range	Mean	s.d.	Range	Mean	s.d.
(a) Unmanaged stands						
	Pelican (31 plots)			Conklin (8 plots)		
Tallest tree height (m)	5.5–13.1	8.7	2.2	9.9–15.7	11.5	2.3
Stem density (tree ha ⁻¹)	3996–35 989	14 711	6577	5320–33 967	14 536	9413
Canopy fuel load (kg m ⁻²)	1.10–6.57	3.31	1.22	1.54–6.63	3.72	1.48
Canopy bulk density (kg m ⁻³)	0.17–1.06	0.57	0.19	0.24–1.07	0.55	0.24
Canopy base height (m)	1.17–3.83	2.19	0.75	1.25–3.95	2.64	0.79
(b) Managed stands						
	Pelican (28 plots)			Conklin (12 plots)		
Tallest tree height (m)	4.5–11.3	8.7	1.8	2.6–17.2	10.6	4.3
Stem density (tree ha ⁻¹)	250–3497	1629	877	749–4995	2529	1339
Canopy fuel load (kg m ⁻²)	0.08–2.12	1.02	0.51	0.07–4.59	1.69	1.43
Canopy bulk density (kg m ⁻³)	0.02–0.34	0.19	0.09	0.03–0.62	0.24	0.19
Canopy base height (m)	1.56–5.48	3.45	0.91	0.32–5.13	2.44	1.53
(c) All data						
	Combined (79 plots)					
Tallest tree height (m)	2.6–17.2	9.3	2.6			
Stem density (tree ha ⁻¹)	250–35 989	8206	8156			
Canopy fuel load (kg m ⁻²)	0.072–6.63	2.30	1.55			
Canopy bulk density (kg m ⁻³)	0.02–1.07	0.38	2.72			
Canopy base height (m)	0.32–5.48	2.72	1.10			

Table 6. Lasso linear regression models and performance metrics predicting the square root of canopy bulk density (CBD), square root of canopy fuel load (CFL), square root of stem density, stand height and square root of canopy base height (CBH) using ALS data

Models were generated using 52 observation points and performance metrics were evaluated on 27 data points.

Equation	R^2	R^2_{test}	RMSE	RMSE _{test}
$\sqrt{\text{CBD}(\text{kg m}^{-3})} = 0.63 + (0.0032)Pc_{1.30} + (0.0000075)Pc_{\text{mean}} + (-0.40)Prop_{<0.15} + (0.013)Prop_{1.30\text{to}5.00}$	0.84	0.78	0.087	0.098
$\sqrt{\text{CFL}(\text{kg m}^{-2})} = 1.11 + (0.012)Pc_{1.30} + (-0.49)Prop_{<0.15}$	0.84	0.85	0.23	0.22
$\sqrt{\text{stem density}(\text{stems ha}^{-1})} = 57.96 + (-3.27)h_{\text{mean}} + (-3.28)h_{CV} + (0.61)Pc_{1.37} + (-23.22)Prop_{<0.15} + (123.99)Prop_{1.30\text{to}5.00}$	0.89	0.81	15.24	23.24
Height (m) = $2.71 + (0.79)h_{\text{Max}}$	0.81	0.84	1.29	0.96
$\sqrt{\text{CBH}(\text{m})} = 1.02 + (0.19)h_{25}$	0.63	0.51	0.24	0.20

Scatter plots of observed versus predicted values (Fig. 5) further confirmed goodness of fit. Data points for natural and managed stands exhibited a consistent trend and were therefore grouped for analysis. Data points for all regression models apart from stem density and CBH exhibited symmetrical scatter around the 1:1 line of perfect agreement, indicating good model fit. The stem density regression model showed bias towards underpredicting high field-measured values. This bias was also slightly apparent with the CBD and CFL regression models. The canopy height regression model showed some bias at overpredicting low field-measured values (<7.5 m). The scatter plot for the CBH regression model shows significant scatter around the 1:1 line indicating poor predictive ability.

The regression models derived in this study can produce significantly more detailed forest structure maps compared to the FBP fuel type maps (Fig. 6a). Photographs of canopy structure taken from the field sampling plots indicate that the models are able to correctly capture the natural variability of canopy bulk density in black spruce stands (Fig. 6b, c).

Discussion

Black spruce stands can be found in abundance in all Canadian provinces and territories (National Forest Inventory 2013). The black spruce stands analysed in this study represent typical black spruce stands observed throughout the boreal forest (Forestry Fire Danger Group Canada 1992; Johnston *et al.* 2015). Results indicate that ALS data are able to describe black spruce forest structure characteristics important to wildfire behaviour at a fine scale. Five canopy metrics of interest were evaluated in this study (CFL, CBD, canopy height, stem density and CBH), and all models comparing field-measured data to ALS metrics had R^2 values ≥ 0.81 except for CBH which had an R^2 value of 0.63. The ability to use these statistical models and ALS data to map fuels at a fine resolution could have profound impacts for fire management practices and the underlying fire research and decision support tools that guide them. Availability of detailed fuel attributes will enable development of new empirical models that relate ALS-derived forest structural attributes to observed fire

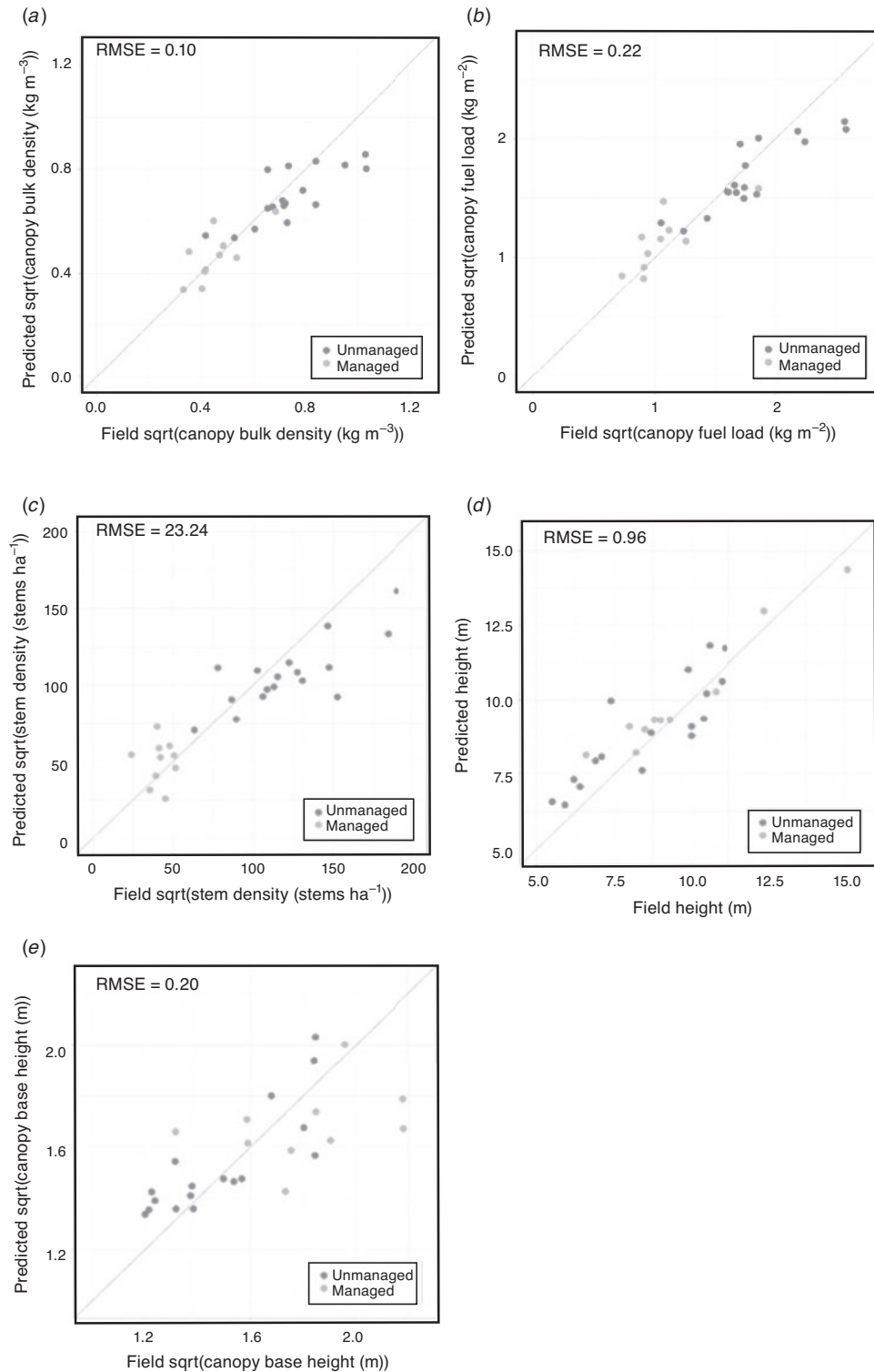


Fig. 5. Plot level (a) square root transformed canopy bulk density, (b) square root transformed canopy fuel load, (c) square root transformed stem density, (d) canopy height and (e) square root transformed canopy base height estimated from ALS data ($n = 27$) for the testing dataset (predicted) versus field-measured values (observed). Solid line shows 1:1 relationship denoting perfect model fit.

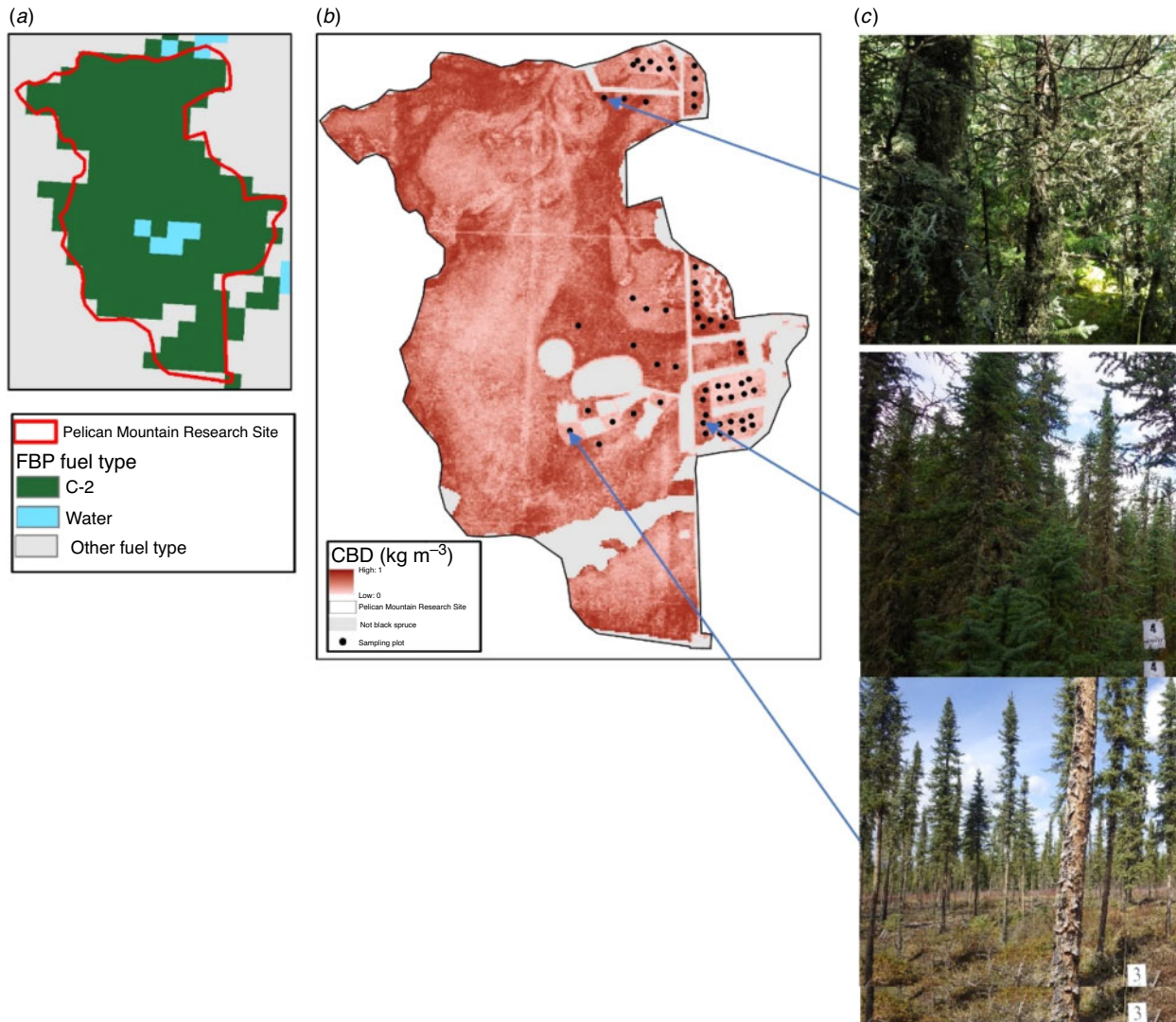


Fig. 6. (a) The Fire Behaviour Prediction (FBP) fuel type map shows that Pelican Mountain is almost entirely covered by the C-2 boreal spruce fuel type. The ALS-derived fuel attributes show that canopy bulk density can vary substantially within black spruce stands; (b) model results also correspond well with field photos that show the model is accurately detecting areas of high (c, top), intermediate (c, middle) and low (c, bottom) canopy bulk density values (Photographer: Hilary Cameron (author)).

occurrence and fire behaviour. Ongoing enhancements to the Canadian Forest Fire Behaviour Prediction (FBP) System (Canadian Forest Service Fire Danger Group 2021) have been designed to accommodate new and emerging sources of information about forest structure and composition that could be supplied by ALS-generated fuel maps. High resolution fuel maps could also be used to inform strategic fire risk assessments and prioritise proactive mitigation measures such as fuel treatments, as well as monitor forest structural changes over time and in response to management actions. Similar studies completed for other forest types have reported varying degrees of success when comparing ALS data with field-based measurements of forest characteristics important to wildfire (Table 7); however, results of this study were designed to map forest attributes at a much finer scale (40 m^2 resolution) compared with the published studies listed in Table 7. Regression models performed similarly or better

than those estimated for other stand types in prior studies with the exception of the CBH regression model, which performed poorly in comparison. The canopy height regression model performed similarly to other studies but not as well as expected. Given the relatively high density of the ALS data we had expected R^2 values similar to those derived in Andersen *et al.* (2005) and Erdody and Moskal (2010) studies (i.e. >0.90). This may reflect the shorter canopy heights of the black spruce stands included in the present study, which had an average stand height of 9.3 m compared with average stand heights $>11.9 \text{ m}$ associated with the forest types investigated in the studies listed in Table 7.

CBD, CFL and stem density regression models under-predicted at the high-end range of values (Fig. 5). This may be an artefact of the lasso method, which shrinks the coefficients to create a ‘flatter’ model. This introduces a small amount of bias with the objective of decreasing the variance of the model and

Table 7. Basic site descriptions and coefficient of determination values (R^2) for previous studies that utilised Airborne Laser Scanning (ALS) data to predict forest characteristics important to wildfire behaviour

Modelled attributes include canopy bulk density (CBD), canopy fuel load (CFL), stem density, canopy height and canopy base height (CBH) values. For comparison, R^2 values using the testing data for regression models derived in this study are also shown

Author	Study site description	Grid resolution (m ²)	R^2 by modelled canopy characteristic/range of field-measured values				
			CBD	CFL	Stem density	Canopy height	CBH
Andersen <i>et al.</i> (2005)	Capital State Forest in western Washington State	900	0.84 ^A	0.86 ^B	n/a	0.98	0.77
Erdody and Moskal (2010)	Ponderosa pine stands in eastern Washington State	400	0.83 ^A	0.88 ^A	n/a	0.94	0.78 ^B
Skowronski <i>et al.</i> (2011)	Pinelands National Reserve of southern New Jersey	400	0.83	0.71	n/a	n/a	n/a
González-Olabarria <i>et al.</i> (2012)	Forested areas in the Mediterranean	500	n/a	n/a	0.64	0.91	0.56
Hermosilla <i>et al.</i> (2014)	Mixedwood forest in north-west Oregon	804 ^C	0.67	0.79	n/a	0.79	0.78
Bright <i>et al.</i> (2017)	Mountain pine beetle affected stands in a coniferous montane forest in Colorado	200	0.46	0.56	n/a	0.66	0.28
Engelstad <i>et al.</i> (2019)	Boundary Waters Canoe Area in northern Minnesota	100	0.48	n/a	n/a	n/a	0.7
Results from present study	Black spruce stands in north-western Alberta	40	0.78 ^B	0.85 ^B	0.81 ^B	0.84	0.51 ^B

^ANatural log-transformation was used in derived model.

^BSquare root transformation was used in derived model.

^CGrid resolution inferred from plot size as no maps were produced in study.

increasing predictive power. It could also be due to other factors, given that prior studies that related ALS data to CBD and CFL also under-predicted at the high-end range of values, even when lasso regression was not employed. For example, Hermosilla *et al.* (2014) reported similar findings in predictions of CBD from ALS data in mixedwood forests and suggested the under-prediction was caused by outliers. Predicted versus observed CBD values reported by Erdody and Moskal (2010) and Andersen *et al.* (2005) also exhibited underprediction at the high end of the range. These discrepancies could also be due to the nature of forest structure and ALS data. In very dense stands, which would be associated with high values of CFL and CBD, the ALS laser pulse will be obscured by the continuous upper canopy vegetation, inhibiting reflectance and leading to occlusion of data at lower elevations (e.g. Vauhkonen *et al.* 2012; Kandare *et al.* 2016). Further studies of how stand density impacts occlusion in black spruce stands are required to confirm the underlying factors responsible for underprediction of CBD and CFL from ALS and potentially correct any inherent bias through data transformation (e.g. Lefsky *et al.* 2002).

Underprediction at the high-end values could also be due to the use of fixed interval height metrics. For example, if dense stands happen to be stunted, then ALS metrics such as the percent of first returns above 1.3 m ($P_{C1.3}$) may be smaller than that for taller stands. This would occur when the ALS laser pulse has a shorter travel distance through the canopy to reach the height threshold. Given the volume of ALS models that have been developed using height strata values (e.g. Andersen *et al.* 2005; Erdody and Moskal 2010; Bright *et al.* 2017; Engelstad *et al.* 2019), more research is needed to investigate the effects of fixed height variables on model results.

Results of this study confirm the widely acknowledged limitation of ALS data for predicting stem density (e.g. Kandare *et al.* 2016). In addition to underprediction of high-density field-measured values, the relatively large differences between the

RMSE and RMSE_{test} values for the stem density regression model indicate overfitting of the training dataset. Despite these issues, the R^2_{test} values were similar or better than those reported by Treitz *et al.* (2012) and Luther *et al.* (2014), who both related ALS data to black spruce forest characteristics in eastern Canada.

Despite prior studies successfully predicting CBH using ALS data, our results indicated the success of a CBH regression model likely depends on vegetation type. When the understorey vegetation is close to the base of the canopy, it can be difficult to define CBH using ALS (Popescu and Zhao 2008). Black spruce trees tend to have crowns that extend to the forest floor with a build-up of dead branches and lichen. The relatively poor CBH regression model generated support that ALS data is not well suited for measuring the distance between the ground and the base of the canopy in stands where tree morphology includes crown vegetation that extends continuously from the top of the tree to the forest floor. Given that vertical fuel connectivity in black spruce dominated stands is a determinant of wildfire behaviour, future studies could focus on relating ALS to the vertical continuity of canopy fuels, rather than CBH. It would also be beneficial for future studies to explore the use of ALS to predict surface fuel loads (e.g. Stefanidou *et al.* 2020).

It is also noteworthy that the CFL, canopy height and CBH regression models had smaller RMSE_{test} values compared with RMSE values. Although differences were small, this was unusual given that the regression model was designed to fit the training data best. The lower testing errors may indicate that the regression models were generalising well and were able to properly adapt to new data. It could also reflect the relatively small size of the testing data and random chance. If the testing error was much larger than the training error, it could indicate that the training and testing groups were not randomly selected. Given that the errors were similar in value, this was likely not the case for the regression models developed in this study and it can be assumed that the low testing errors were due to random chance.

Although results of this study are promising, sources of error for this research include the following: human error during field measurements; the influence of plot edge effects and the assumption of stand homogeneity (White *et al.* 2013); use of allometric equations to calculate canopy fuel load values; and the time elapsed between field measurements and ALS data collection. The small plot size used in this study, which allowed for the high resolution of the produced models (White *et al.* 2017), increased the influence of edge effects due to the higher perimeter to area ratio. The strong observed relationships between field measurements and ALS metrics suggests the small plot size was acceptable for our black spruce stands that have a narrow columnar crown morphology, which may not be the case for other stand types.

Given the prevalence of black spruce across Canada (National Forest Inventory 2013), we expect the models developed in this study to be suitable for applied use by researchers and fire managers for estimating stand structure in similar black spruce ecosystems with structural characteristics that fall within the range of variability observed in our source data. Stand structural characteristics present at Pelican Mountain and Conklin research sites are unlikely to represent the full range of variability in black spruce stands in the Canadian boreal forest. To improve the robustness of the regression models, additional plots could be collected for black spruce stands with a wider range of structural variability. A larger sample size of field measurements would also be expected to reduce bias observed in some of the predictive regression models.

In conclusion, the results of this study indicate that ALS data are a viable resource for predicting forest structural characteristics important to wildfire behaviour in black spruce stands. Timely and cost-effective mapping of canopy fuel characteristics across large landscape areas could have a profound impact on fire management practices and the underlying fire research and decision support tools that guide them. This study confirmed the potential to utilise ALS data to map canopy fuels in black spruce forests at higher resolution than ever before. These data could eventually be used to develop empirical models predicting fire behaviour and fire occurrence, and for strategic planning. Management applications include documenting fuel structure changes over time, prioritising stands for fuel treatments based on stand structure, and documenting pre- and post-treatment stand structure to determine whether hazard reduction targets have been met. Mapping forest structure to the level of detail analysed in this study could also have profound impact in areas of research beyond wildfire management. For example, canopy fuel information derived from the models presented in this study could be used to assess habitat suitability or ecological impacts of disturbances (i.e. insect attack, wind damage, disease epidemics) or to analyse post-harvest forest structure.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

Jen Beverly is an Associate Editor of *International Journal of Wildland Fire* but was blinded from the peer-review process for this paper.

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