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ARTICLE

Evaluating the impact of leaf-on and leaf-off airborne laser scanning data on the estimation of forest inventory attributes with the area-based approach

Joanne C. White, John T.T.R. Arnett, Michael A. Wulder, Piotr Tompalski, and Nicholas C. Coops

Abstract: In this study, we explored the consequences of using leaf-on and leaf-off airborne laser scanning (ALS) data on area-based model outcomes in a lodgepole pine (*Pinus contorta* var. *latifolia* Engelm.) dominated forest in the foothills of the Rocky Mountains in Alberta, Canada. We considered eight forest attributes: top height, mean height, Lorey's mean height, basal area, quadratic mean diameter, merchantable volume, total volume, and total aboveground biomass. We used 787 ground plots for model development, stratified by ALS acquisition conditions (leaf-on or leaf-off) and dominant forest type (coniferous or deciduous). We also generated pooled models that combined leaf-on and leaf-off ALS data and generic models that combined plot data for all forest types. We evaluated differences in ALS metrics and leaf-on and leaf-off model outcomes, as well as the impacts of pooling leaf-on and leaf-off ALS data, creating generic models, and of applying leaf-on models to leaf-off data (and vice versa). In general, leaf-off and leaf-on ALS metrics were not significantly different ($p < 0.05$), except for the 5th percentile of height (coniferous) and canopy density metrics (deciduous). Overall, coniferous leaf-on and leaf-off models were comparable, with differences in relative root mean square error (RMSE) and bias of <2% for all attributes except volume, which differed by <4%. RMSE and bias for deciduous leaf-on and leaf-off models for height attributes and quadratic mean diameter differed by <2%, whereas models for volume and biomass differed by <7%. These results affirm that leaf-off data can be used in an area-based approach to estimate forest attributes for both coniferous and deciduous forest types. Relative RMSE and bias for pooled models (combining leaf-on and leaf-off ALS data) differed by <2% relative to leaf-on and leaf-off models, suggesting that in the forests studied herein, combining leaf-on and leaf-off data in an area-based approach does not adversely impact model outcomes. Generic models that did not account for forest type had large errors for volume and biomass (e.g., the relative RMSE for merchantable volume was twice as large as forest type specific models). Likewise, the mixing of leaf-on models with leaf-off data and vice versa resulted in large RMSE and bias for both forest types, and therefore mixing of models and data types should be avoided.

Key words: airborne laser scanning, lidar, forest inventory, leaf-off, area-based approach.

Résumé : Dans cette étude, nous explorons les conséquences de l'utilisation des données de balayage laser aéroporté (BLA), acquises avec ou sans feuilles, sur les résultats d'un modèle par surface dans une forêt dominée par le pin tordu latifolié (*Pinus contorta* var. *latifolia* Engelm.) dans les contreforts des montagnes Rocheuses en Alberta, au Canada. Nous avons examiné huit caractéristiques de la forêt : la hauteur dominante, la hauteur moyenne, la hauteur moyenne de Lorey, la surface terrière, le diamètre moyen quadratique, le volume marchand, le volume total et la biomasse aérienne totale. Nous avons utilisé 787 placettes au sol pour l'élaboration du modèle, stratifiées par les conditions d'acquisition du BLA (avec ou sans feuilles) et le type forestier dominant (conifères ou feuillus). Nous avons également généré des modèles regroupés qui combinaient les données de BLA avec feuilles aux données sans feuilles, et des modèles génériques qui combinent les données des placettes de tous les types forestiers. Nous avons évalué les différences dans les mesures de BLA et les résultats des modèles avec ou sans feuilles, ainsi que les impacts du regroupement des données de BLA avec et sans feuilles, de la création de modèles génériques et de l'application des modèles étalonnés avec feuilles aux données sans feuilles (et vice versa). En général, les mesures de BLA avec et sans feuilles n'étaient pas significativement différentes ($p < 0,05$), sauf pour le 5^{e} percentile de hauteur (conifères) et pour les mesures de densité du couvert (feuillus). Dans l'ensemble, les modèles de conifères avec et sans feuilles étaient comparables : les écarts de l'erreur quadratique moyenne (EQM) et du biais relatifs étaient <2 % pour tous les attributs, sauf pour les volumes pour lesquels ils étaient <4 %. Dans le cas des modèles de feuillus, avec et sans feuilles, les écarts de l'EQM et du biais relatifs pour les attributs de hauteur et le diamètre moyen quadratique étaient <2 %, tandis qu'ils étaient <7 % pour le volume et la biomasse. Ces résultats confirment que les données sans feuilles peuvent être utilisées dans une approche par surface pour estimer les caractéristiques de la forêt pour les deux types forestiers, soit les conifères et les feuillus. Les écarts de l'EQM et du biais relatifs pour les modèles regroupés (combinant des données avec et sans feuilles) étaient <2 % par rapport aux modèles avec et sans feuilles, ce qui indique que dans les forêts étudiées, le fait de combiner les données avec et sans feuilles dans une approche par surface ne nuit pas aux résultats du modèle. Les modèles génériques, qui ne tenaient pas compte du type forestier, avaient de grandes erreurs de volume et de biomasse (p. ex., l'EQM relative du volume marchand était deux fois plus grande que pour les

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modèles spécifiques au type forestier). De même, le mélange des modèles avec feuilles et des données sans feuilles, et vice versa, a produit une EQM et un biais élevés pour les deux types forestiers. Par conséquent, le mélange des modèles et des types de données devrait être évité. [Traduit par la Rédaction]

Mots-clés : balayage laser aéroporté, lidar, inventaire forestier, sans feuilles, approche par surface.

1. Introduction

Airborne laser scanning (ALS) is a remote sensing technology that can be used to derive precise and accurate information characterizing forest structure (Næsset 2002; Lim et al. 2003). Unlike passive remote sensing technologies (e.g., optical sensors), ALS data uses LiDAR (light detection and ranging), which is an active remote sensing technology that measures reflected laser pulses to map the geometry of remote objects (Wehr and Lohr 1999). For some nations, including Finland, ALS data are fundamental to forest inventory programs (Holopainen et al. 2014). Although Canadian forest inventory procedures have traditionally relied on data collected from a variety of sources, including permanent growth plot data, aerial photography, and satellite imagery (Leckie and Gillis 1995), ALS data are being increasingly used in Canada to enhance existing forest inventory information (Woods et al. 2011; White et al. 2013, 2014; Penner et al. 2013).

ALS data can be used to describe a number of forest structural attributes with varying levels of accuracy (Dubayah and Drake 2000; Næsset 2007). Relationships between forest inventory attributes can be statistically modelled using regression or nonparametric modelling approaches (Penner et al. 2013). Measures such as stand height and density can be attained with minimal processing and a relatively high level of confidence (e.g., Andersen et al. 2006), whereas other inventory attributes such as volume or biomass are more complex to estimate accurately because they rely on response data that is not directly measured in the field, but rather derived from field measurements using allometric equations. As a result, these derived attributes typically have greater error associated with them (Pesonen et al. 2008; Gobakken et al. 2013). The area-based approach and the individual tree detection approach are the two methods commonly used to relate ALS data to ground-measured response variables (Yu et al. 2010). The area-based approach is the most common method for modelling forest attributes from ALS data (White et al. 2013) and relies on the establishment of ground plots to construct a relationship between ground measures and the ALS point cloud (Nilsson 1996; Næsset and Økland 2002; van Leeuwen and Nieuwenhuis 2010).

Seasonal changes in canopy condition such as leaf-on and leaf-off influence the physical structure of vegetation and thereby impact the penetration and configuration of ALS pulses in the canopy (Wasser et al. 2013). For example, ALS data flown during leaf-on conditions above a dense canopy may result in a concentration of returns near the top of the canopy, with a lower proportion of returns interacting with understorey vegetation and the forest floor (Raber et al. 2002; Hill and Broughton, 2009). Given the comparatively high cost of acquiring ALS data (Jakubowski et al. 2013), forest management agencies will often take advantage of ALS data acquired for other applications such as detailed terrain mapping (e.g., Nord-Larsen and Schumacher 2012; Alexander et al. 2014). These data are preferentially acquired under leaf-off conditions, as the greater penetration of laser pulses through the canopy can improve the accuracy of the derived digital terrain models (Raber et al. 2002). Although operational guidelines typically recommend the acquisition of leaf-on ALS data to support the area-based approach, other recommendations have included avoiding the mixing of leaf-on and leaf-off data and models and ensuring that area-based models are developed separately for leaf-on and leaf-off data (White et al. 2013).

Much of the research into the use of leaf-off data has focussed on individual-tree detection. Numerous studies have demonstrated that leaf-off ALS data can be used successfully to detect (Brandtberg et al. 2003), delineate (Lu et al. 2014), measure (Ørka et al. 2010), and identify to species (Brandtberg et al. 2007; Kim et al. 2009) individual trees. Some applications such as tree species identification may actually benefit from the greater spread of the point cloud in three-dimensional space under leaf-off conditions, as ALS pulses are better able to interact with the woody elements of the tree and lower portions of the canopy (Næsset 2005; Brandtberg et al. 2007; Ørka et al. 2010).

The impact of leaf-off data on the estimation of forest inventory attributes using an area-based approach has been studied in a range of forest environments (Table 1). Næsset (2005) was the first to explore the implications of using leaf-off or leaf-on ALS data in an area-based approach to estimate mean height, basal area, and volume in mixed forest conditions. The study area was located in Norway, in a managed boreal forest site dominated by Norway spruce (*Picea abies* (L.) Karst) and Scots pine (*Pinus sylvestris* L.), with younger stands dominated by downy birch (*Betula pubescens* Ehrh.). Ground plots that had less than 90% of their total volume from coniferous species were classified as mixed forest. Næsset (2005) found that the leaf-off coefficient of variation of ALS heights was significantly higher than leaf-on, whereas canopy density metrics from the lower and intermediate parts of the canopy were significantly lower. Conversely, maximum canopy height was not influenced by acquisition conditions. Næsset (2005) also found that metrics derived from leaf-off data were more strongly correlated with biophysical properties than metrics derived from leaf-on data and, moreover, that models for estimating Lorey's mean height, basal area, and volume developed from leaf-off data had higher R^2 values (0.92, 0.66, and 0.81, respectively) and lower RMSE values (0.07, 0.28, and 0.29, respectively) compared with models generated using leaf-on data (R^2 = 0.88, 0.62, and 0.73, respectively; RMSE = 0.09, 0.30, and 0.34, respectively). Overall, Næsset (2005) reported that the accuracy of model estimates was unaffected or slightly improved under leaf-off conditions for mixed forest types and that canopy conditions at the time of acquisition had an effect on ALS-derived height and canopy metrics that was 10–50 times the effect of flying altitude.

The second major study that has explicitly explored the impacts of leaf-on and leaf-off data on the area-based approach is that of Villikka et al. (2012). In this study, not only were leaf-on and leaf-off models of dominant height and volume generated and their performance compared, but also leaf-on models were applied to leaf-off data (and vice versa) to examine the impacts of mixing models and data types. The study was conducted in a managed boreal forest area in Finland that was dominated by Scots pine and Norway spruce, with unspecified deciduous species. The authors found that accuracies for dominant height and volume were similar, with leaf-off data providing a minor improvement in accuracy over leaf-on data, except in the estimation of deciduous plot volume, which was estimated with markedly greater accuracy using leaf-off data. Villikka et al. (2012) found that when leaf-off models were applied to leaf-on data, inventory attributes were systematically overestimated; when leaf-on models were applied to leaf-off data, attributes were underestimated. Although these results are not surprising given the different penetration of ALS pulses in deciduous stands in leaf-off conditions, similar trends in bias were also reported for coniferous stands, albeit at a much lower magnitude. Overall, the results of Villikka et al. (2012) are similar to those of Næsset (2005): model outcomes in an area-based approach are similar or may be slightly improved using

Table 1. Summary of existing studies that have explored the use of leaf-on and leaf-off data using the area-based approach.

Study	Study area	Ecosystem	Definition of forest types	Target attributes	ALS points·m^{-2}	No. (n) of plots (plot size, m^2)	Results
Næsset (2005)	Managed boreal forest in Norway (3000 ha)	Norway spruce (*Picea abies* (L.) Karst), Scots pine (*Pinus sylvestris* L.), and birch (*Betula pubescens* Ehrh.)	Mixed forest: <90% of total volume from coniferous species	Lorey's height; basal area; volume	0.8–1.0	n = 51 (232.9) Large test plots, n = 27 (3435)	Leaf-on: R^2 = 0.62–0.73, RMSE = 0.09–0.34; leaf-off: R^2 = 0.66–0.81, RMSE = 0.07–0.29
Hawbaker et al. (2010)	Baraboo Hills, southwestern Wisconsin, USA (4580 ha)	Oak (*Quercus* spp.), ash (*Fraxinus* spp.), hickories (*Carya* spp.), maples (*Acer* spp.)	Mixed hardwood forest (no stratification for modelling)	Tree density, dbh, basal area, mean height, Lorey's height, sawtimber and pulpwood volume	Not specified but described as "low density"	n = 114 (730.62)	Leaf-off: R^2 = 0.13–0.65, SEM ranged by 1%–4%; leaf-off, low density lidar is valuable for broad-scale hardwood forest inventories
Villikka et al. (2012)	Managed boreal forest in Finland (5000 ha)	Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst), unspecified deciduous species	Coniferous forest ≥ 50% of total volume = coniferous; otherwise deciduous	Dominant height; total volume	0.6	n = 192 (254.5)	Dominant height: leaf-on (RMSE, 9.87%; bias, –0.05%); leaf-off (RMSE, 9.78%; bias, –0.07%) Coniferous volume: leaf-on (RMSE, 21.41%; bias, –0.17%); leaf-off (RMSE, 19.96%; bias, –0.02%) Deciduous volume: leaf-on (RMSE, 27.63%; –bias, 0.31%); leaf-off (RMSE, 21.51%; bias, –0.06%)
Anderson and Bolstad (2013)	Park Falls District, Chequamegon–Nicolet National Forest (area not reported), northern Wisconsin, USA	Northern mixed upland hardwoods, lowland hardwoods, aspen–fir, upland conifers, northern white cedar dominated swamp conifers, black spruce–tamarack dominated conifer wetlands, alder, and mixed forests	Membership in deciduous, coniferous, and mixed determined using an existing land cover map	Woody biomass and annual biomass increment	1.6–2.1	n = 169 (167.41)	Comparable results from both leaf-on and leaf-off data for estimating biomass and biomass increment across a range of forest types.
Wasser et al. (2013)	Spring Creek Watershed, central Pennsylvania, USA (area not reported)	Lowland: black walnut (*Juglans nigra*), maple (*Acer* spp.); ridge tops: oak (*Quercus* spp.) and maple; lower ridges: eastern hemlock (*Tsuga canadensis*), black birch (*Betula nigra*), and maple	Membership based on leaf structure types: deciduous simple, deciduous compound, mixed deciduous–needle, conifer needle	Average canopy height (H) and fractional canopy cover (FC)	1.4	n = 80 (400)	Leaf-off data underestimates H in deciduous compound canopies; leaf-on estimates of FC are within 10% of observed values for all plots and in mixed canopies during leaf-off. FC greatly underestimated for deciduous canopies in leaf-off
Bouvier et al. (2015)	Fragmented and highly managed forest (6000 ha) in Lorraine region of northeastern France	European beech (*Fagus sylvatic* L.), European hornbeam (*Carpinus betulus* L.), and Sycamore maple (*Acer pseudoplatanus* L.).	Deciduous-dominated area	Wood volume, stem volume, aboveground biomass, basal area	17.9–20.7	n = 28 (706.85)	Leaf-off models provided slightly better results with similar R^2 values but relative standard deviation (RSD) values that were 0.2% to 2.0% lower

leaf-off data. Unique to the study of Villikka et al. (2012) is the conclusion that mixing leaf-off and leaf-on data and models can result in serious bias and decreased accuracy.

Several studies have explored the use of leaf-off data in North American mixed forests. Hawbaker et al. (2010) evaluated the utility of low-density, leaf-off ALS data collected for terrain mapping in the estimation of forest inventory attributes in a mixed hardwood forest in southwestern Wisconsin and concluded that these data were indeed valuable for broad-scale inventories in mixed hardwoods. Wasser et al. (2013) explored the effects of leaf-off data on estimates of plot height and fractional cover (density) for deciduous simple (more branches, fewer leaves), deciduous compound (more leaves, fewer branches), coniferous, and mixed forest types in central Pennsylvania, USA. The authors found that the use of leaf-off ALS data resulted in underestimates of height in deciduous compound canopies and underestimates of fractional cover for both deciduous simple and deciduous compound forest types. Anderson and Bolstad (2013) explored the impacts of leaf-on and leaf-off data on the estimation of biomass for a range of forest types in a complex, managed forest in northern Wisconsin, USA. The authors found that the superiority of leaf-on or leaf-off models varied by forest type, that leaf-on models were superior for seven of the 12 forest types that they examined (including deciduous forest types), and that the differences in model performance were relatively minor, suggesting that either leaf-on or leaf-off data could provide acceptable results for estimating biomass. Most recently, Bouvier et al. (2015) examined the impact of leaf-on and leaf-off data on the predictive capacity of models for deciduous stands in a highly managed and fragmented forest in Lorraine, France, and found that leaf-on and leaf-off models had similar R^2 values but that errors for leaf-off models were 0.2%–2.0% lower than for leaf-on models. The authors noted that no definitive conclusions could be drawn from their results and called for further research to determine the impacts of using leaf-off data in an area-based approach.

To summarize, research to date has indicated that leaf-off data can be used in an area-based approach for coniferous forest types with minimal impact on the estimation of forest inventory attributes. The results for mixed forest types appear to be consistent with those of coniferous forest types; however, these results are likely somewhat dependent on species composition in the response data (e.g., in Næsset (2005), mixed forest types had 58%–69% coniferous species). Results for deciduous forests are less definitive, as some studies have indicated that the use of leaf-off data provides comparable or improved results for deciduous stands (Hawbaker et al. 2010; Villikka et al. 2012; Bouvier et al. 2015), whereas other studies have found that leaf-on models may perform slightly better for some deciduous types (Anderson and Bolstad 2013) or that leaf-off models can result in underestimation of canopy height and fractional cover in certain deciduous forest types (Wasser et al. 2013).

Our overall goal in this study was to investigate the differences between forest attribute models derived from ALS data acquired during leaf-on and leaf-off canopy conditions in a lodgepole pine (*Pinus contorta* var. *latifolia* Engelm.) dominated forest in the foothills of the Rocky Mountains in Alberta, Canada. Our forest attributes of interest were top height (H_{TOP}), mean height (H_{MEAN}), Lorey's mean height (H_L), basal area (BA), quadratic mean diameter (QMD), merchantable volume (V_{MERCH}), total volume (V_{TOT}), and total aboveground biomass (TAGB). We identified four specific objectives: (1) to assess how ALS metrics are impacted by canopy conditions at the time of ALS acquisition (leaf-on versus leaf-off); (2) to evaluate the relative performance of leaf-on and leaf-off area-based models for the aforementioned inventory attributes for different forest types; (3) to explore the implications of mixing models and data types (i.e., applying leaf-off models to leaf-on data and vice versa), and (4) to compare the performance of acquisition condition specific models to pooled models generated from combining leaf-on and leaf-off ALS data, as well as to generic models generated from pooling all data, irrespective of forest type.

2. Materials and methods

2.1. Study area

The study was conducted in the Hinton Forest Management Area (FMA), located in western Alberta, Canada (Fig. 1). At approximately one million hectares in size, the FMA is the oldest in Alberta and is managed by Hinton Forest Products, a division of West Fraser Mills Ltd. The Hinton FMA is located at the foothills of the Rocky Mountains, in the Foothills Natural Region (Natural Regions Committee 2006). Elevations in the study area range from 830 to 2400 m. The Foothills Natural Region is a transition zone between the Rocky Mountain Region to the southwest and the Boreal Forest Natural Region to the northeast and is characterized by a variable climate, with warmer temperatures and greater precipitation than the Boreal Forest region. The FMA contains a range of forest age classes, management histories, and disturbance types and is dominated by coniferous forests, which comprise 80% of the FMA area (White et al. 2014). Lodgepole pine is the main coniferous species (by volume), with other common species including black spruce (*Picea mariana* (Mill.) Britton, Sterns & Poggenb.) and white spruce (*Picea glauca* (Moench) Voss). Trembling aspen (*Populus tremuloides* Michx.) is the dominant deciduous species. Leaf-on conditions in the Hinton FMA typically occur around 15–30 May, and leaf-off conditions typically occur around 15–30 September (T. Trahan, Area Silviculturalist, personal communication, 2013).

2.2. Ground-plot data

Data from 787 permanent growth sample (PGS) plots were used as response data for model development. Plots were selected based on their date of remeasurement (within 2 years of their corresponding ALS acquisition) and planimetric error in GPS plot positioning (<1 m). All plots were square in shape and were either 400 m² (20 × 20 m; n = 462) or 800 m² (28 × 28 m; n = 325). Within each plot, individual-tree measures included diameter at breast height (dbh; cm), stem height (m), species, and other mensurational data. Plot-level estimates of basal area ($m^2 \cdot ha^{-1}$) and quadratic mean diameter (cm) were estimated from dbh measurements. Merchantable and total stem volumes ($m^3 \cdot ha^{-1}$) were estimated for all live trees with stem heights greater than 2 m, and biomass components (stem, branch, bark, and foliage) and total aboveground biomass ($Mg \cdot ha^{-1}$) were estimated from measurements of stem height and dbh using the national allometric equations of Lambert et al. (2005) and Ung et al. (2008). Three different estimates of plot height were generated using measures from trees with a dbh greater than 7.1 cm: top height (m) (i.e., average height (m) of the tallest 100 trees per hectare: prorated to 4 and 8 stems per 0.04 ha and 0.08 ha plot, respectively); average height (m); and Lorey's mean height (m). Finally, plot-level summaries of basal area, quadratic mean diameter, volume attributes, and TAGB were generated from the individual-tree measures. These plot-level summary variables were used as response variables for generating predictive models. Using a Shapiro–Wilk test, we determined that none of the eight ground-plot forest attributes considered for modelling (Table 2) were normally distributed ($p < 0.001$).

Forest cover type (i.e., coniferous, deciduous, mixed) was determined according to standards used by Canada's National Forest Inventory (Canadian Forest Service 2004): a plot is identified as coniferous (or deciduous) when coniferous (or deciduous) trees represent 75% or more of the total tree basal area in the plot, and a mixed forest type is assigned to the plot when neither coniferous nor deciduous trees account for 75% or more of the basal area in the plot. PGS plots were spatially distributed across the FMA

Fig. 1. Map showing the Hinton Forest Management Area (FMA) located in the foothills of the Rocky Mountains in Alberta, Canada.

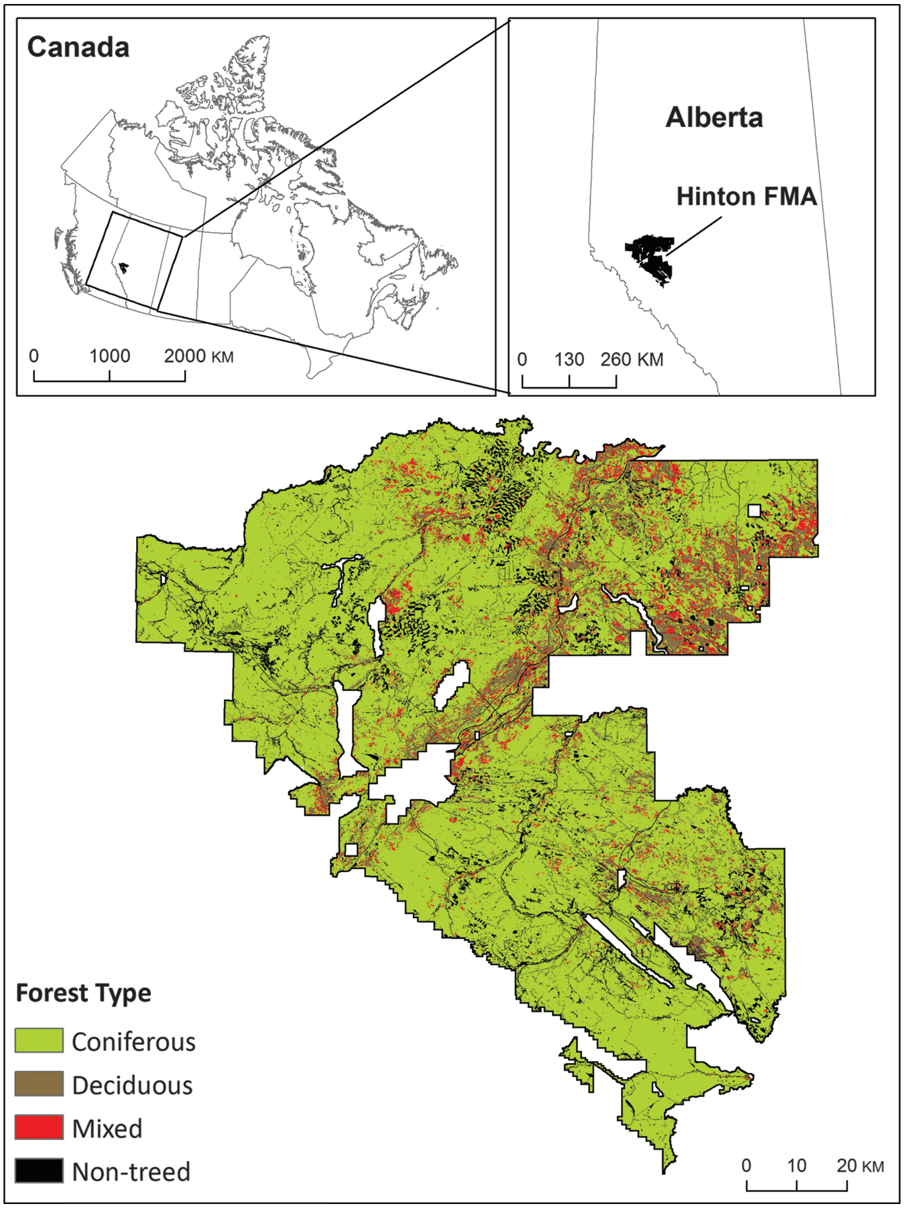


Table 2. Summary of the Hinton Forest Management Area permanent growth sample (PGS) plots.

Plot attribute	Units	Minimum	Median	Maximum	Mean	SD
Top height (H_{TOP})	m	2.10	13.12	34.89	14.24	7.31
Mean height (H_{MEAN})	m	2.10	9.30	26.73	10.39	5.56
Lorey's mean height (H_L)	m	2.10	10.69	30.70	13.91	6.25
Basal area (BA)	$m^2 \cdot ha^{-1}$	0.01	17.14	64.07	19.40	14.82
Quadratic mean diameter (QMD)	cm	1.20	11.92	38.83	13.91	7.21
Merchantable volume (V_{MERCH})	$m^3 \cdot ha^{-1}$	0.47	53.96	639.20	115.60	131.09
Total volume (V_{TOTAL})	$m^3 \cdot ha^{-1}$	0.01	81.18	659.20	128.30	132.38
Total aboveground biomass (TAGB)	$Mg \cdot ha^{-1}$	0.01	60.70	385.00	84.61	77.95

Note: The majority of plots were found in the conifer forest type (n = 571), followed by mixed (n = 129) and deciduous (n = 87) forest types.

(Fig. 2). Ground plots were allocated by forest type and canopy conditions at the time of ALS data acquisition (leaf-on or leaf-off), resulting in six subsets of response data (Table 3).

As we used independent samples to assess the influence of leaf-on and leaf-off canopy conditions and not dependent samples (i.e., not repeated measures of the same samples from subsequent surveys), we evaluated the similarity of our ground sample subsets using histograms and the Mann–Whitney U test prior to conducting further analysis (Table 4). Ground sample subsets were evaluated according to the forest attributes of interest: H_{TOP}, H_{MEAN}, H_L, BA, QMD, V_{MERCH}, V_{TOT}, and TAGB. In addition, ground sample subsets were evaluated on the basis of elevation, leading species

Fig. 2. Map showing permanent growth sample (PGS) plot locations and canopy conditions (leaf-on or leaf-off) at the time of ALS data acquisition.

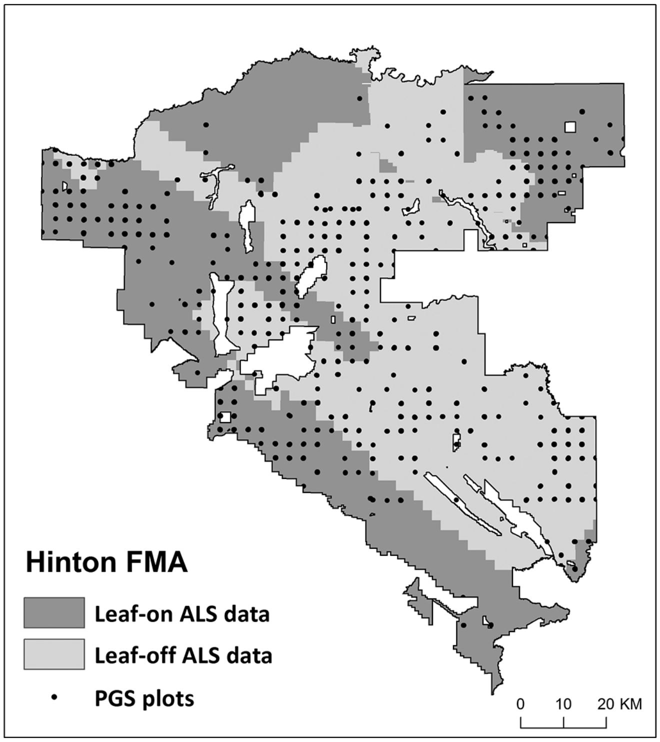


Table 3. Data subsets used for model development.

Forest cover type	Canopy conditions at the time of ALS acquisition	No. of PGS sample plots
Coniferous	Leaf-on	260
	Leaf-off	311
	Total	571
Deciduous	Leaf-on	28
	Leaf-off	59
	Total	87
Mixed	Leaf-on	44
	Leaf-off	85
	Total	129

Note: Permanent growth sample (PGS) sample plots were grouped according to forest type (coniferous, deciduous, mixed) and canopy conditions at the time of ALS data acquisition (leaf-on or leaf-off). Models were also generated for a pooled data subset (leaf-off and leaf-on data combined).

proportion, age, and crown closure. No significant differences were found between the leaf-on and leaf-off ground data subsets for the deciduous forest types, and the only significant difference for the coniferous forest subsets was for elevation. For mixed forest types, significant differences were found for all of the inventory attributes, with the exception of quadratic mean diameter. An examination of histograms for ground-plot attributes further confirmed the similarity between data subsets for the coniferous and deciduous forest types. Histograms for H_L, BA, and V_{MERCH} are shown in Fig. 3; histograms for other attributes (not shown) were similar. Therefore, all subsequent analyses of leaf-on and leaf-off data were conducted using only the coniferous and deciduous data subsets identified in Table 3. Of note, we did use the mixed-forest data to produce a generic model for each forest attribute in which data from all forest types were combined.

Table 4. Evaluation of ground-plot leaf-on and leaf-off data subsets using Mann–Whitney *U* test (*p* values shown).

Attribute	Coniferous	Deciduous	Mixed
H_{TOP}	0.291	0.239	0.003*
H_{MEAN}	0.091	0.085	0.010*
H_L	0.283	0.099	0.005*
BA	0.986	0.892	0.010*
QMD	0.512	0.066	0.053
V_{MERCH}	0.583	0.278	0.009*
V_{TOTAL}	0.659	0.493	0.006*
TAGB	0.460	0.552	0.007*
Elevation	0.000*	0.768	0.282
Leading species %	0.584	0.062	0.235
Age	0.617	0.361	0.080
Crown closure	0.657	0.889	0.841

Note: Asterisk (*) indicates significance at $\alpha = 0.05$. See Table 2 or the text for explanation of attribute abbreviations.

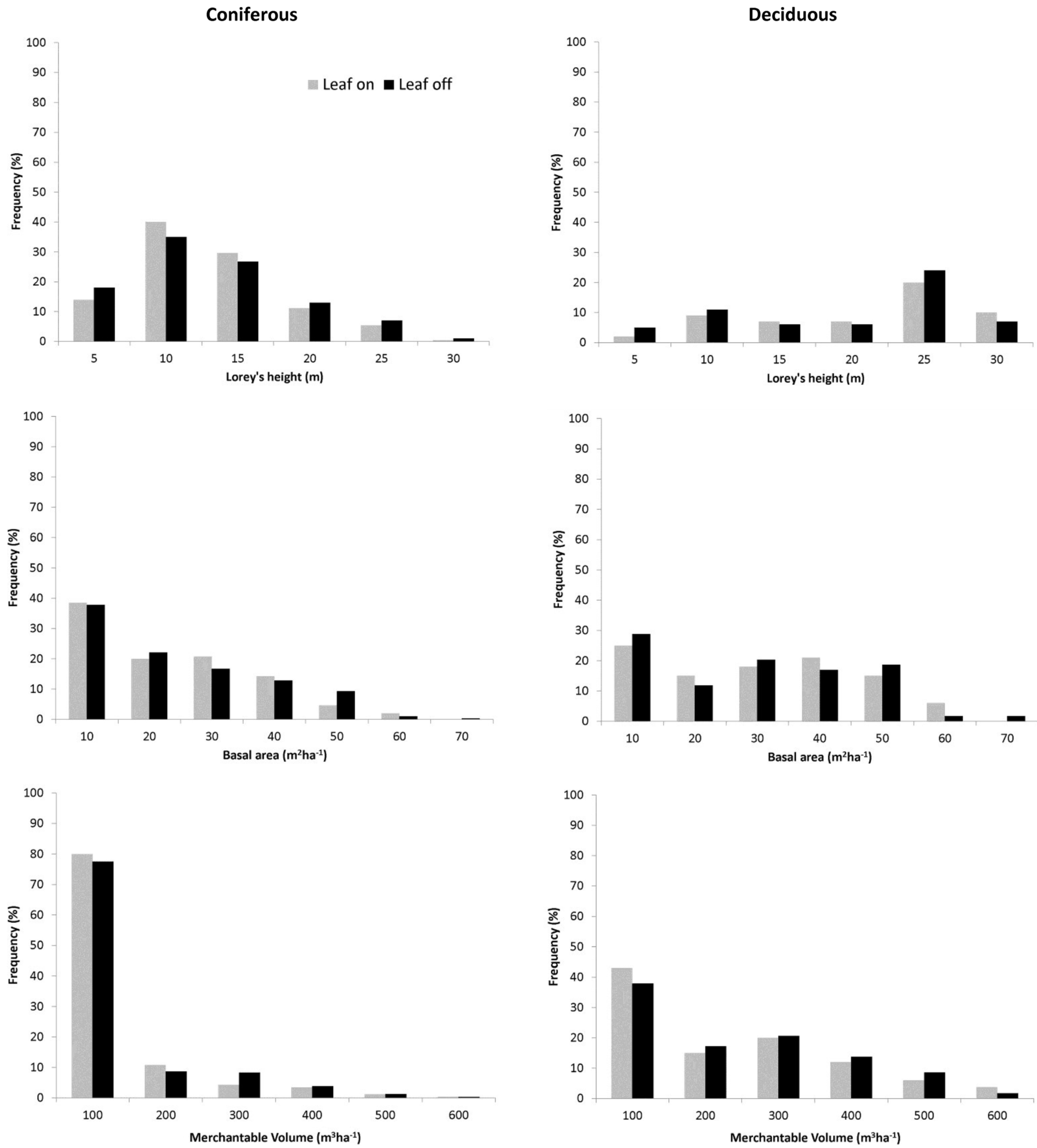
2.3. Airborne laser scanning data

The ALS data used in this study were acquired as part of a larger, coordinated ALS data acquisition program by the Alberta Government to support forest companies operating in areas impacted by the mountain pine beetle (White et al. 2013), as well as to enable a province-wide wet areas mapping initiative (White et al. 2012). More than 29 million ha of ALS data have been acquired in Alberta since 2003. In the Hinton FMA, ALS data were acquired via fixed-wing aircraft between 2004 and 2007 using an Optech 3100 sensor operated at an average flying altitude of 1400 m above ground level. The sensor's pulse rate was 70 kHz, with a capability to record 4 returns per laser pulse. The estimated positional accuracy of the sensor was 0.45 m in the horizontal direction and 0.30 m in the vertical direction. Data were acquired with an average point spacing of 0.75 m, with a 50% overlap between flight lines. All ALS *x*, *y*, and *z* points were georeferenced using a UTM Zone 11 North projection and NAD83 (horizontal) and CGVD28 (vertical) datums. Final point clouds were delivered in .LAS file format (American Society for Photogrammetry and Remote Sensing 2011), and each georeferenced point was classified as ground or non-ground with TerraScan v0.6 software (Terrasolid, Helsinki, Finland) using an algorithm based on Axelsson (2000). ALS ground points were subsequently used to construct a 1 m bare-earth digital elevation model (DEM). ALS data were identified as being leaf-on or leaf-off according to the date of ALS data acquisition (Fig. 2), and approximately 50% of the ALS data in the FMA were acquired under leaf-off conditions. Based on local knowledge, we theoretically defined leaf-on as 15 May to 15 September; however, all leaf-on acquisitions were made in June, July, and August. Dates for leaf-off acquisitions were therefore theoretically considered to be those made between 16 September and 14 May. The earliest leaf-off acquisition was 30 September, and the latest leaf-off acquisition was 30 April.

2.4. Area-based approach to model inventory attributes

To establish relationships between the ALS data and ground sample measures, we clipped the ALS point cloud data to the spatial extent of the PGS plots. We then processed the clipped ALS point clouds using FUSION software (McGaughey 2014) and generated a suite of ALS metrics describing the three-dimensional distribution of the ALS point cloud. Following the approach similar to that of Li et al. (2008), we used principal component analysis (PCA) to identify a parsimonious subset of ALS metrics that were suitable for model development (Table 5). The first three principal components accounted for 92% of the total variation found in the Hinton ALS data, and metrics that were strongly positively correlated (i.e., $r > 0.6$) with these first three principal components were used for subsequent model development. This approach helps to reduce the occurrence of highly correlated metrics being used as predictors. Using a Shapiro–Wilk test, we determined that

Fig. 3. Comparison of ground-plot data estimates of Lorey's height, basal area, and merchantable volume for leaf-on and leaf-off subsets for coniferous and deciduous forest types.



none of the ALS metrics listed in Table 5 were normally distributed ($p < 0.001$).

A nonparametric modelling approach was implemented using Random Forests (RF) (Breiman 2001). RF uses an ensemble of decision trees built from bootstrapped training data and has been demonstrated as an effective means for implementing the area-based approach (Hudak et al. 2008; Penner et al. 2013). Using the randomForest package in R (version 4.6–10; Liaw and Wiener 2002), we created separate RF models for each of the eight forest attributes (Table 2) for the coniferous and deciduous leaf-off and leaf-on data subsets (Table 3). We also combined the leaf-on and leaf-off data to generate a pooled model for each of the coniferous and deciduous forest types, as well as a generic model that combined all data, regardless of forest type or acquisition condition. As per Vastaranta et al. (2013), we accounted for randomness by running the RF method 100 times (for each attribute model); the final result is the average of these 100 runs. Model performance was evaluated with out-of-bag samples, which were used to calculate bias and RMSE. RF ranks the importance of input variables based on their cumulative influence on model mean square error (MSE) when the variable is removed from the model. We recorded this variable importance measure for each of our 21 ALS metrics

Table 5. Summary of the 21 ALS metrics used in the area-based approach in this study.

Metric	Description
LHMEAN	Average of point heights > 2 m
LHAAD	Average absolute deviation of point heights > 2 m
LHLCOV	Second L-moment ratio (coefficient of variation) of point heights > 2 m
LHLSKEW	Third L-moment ratio (coefficient of skewness) of point heights > 2 m
LHLKURT	Fourth L-moment ratio (coefficient of kurtosis) of point heights > 2 m
LH05	5th percentile of point heights > 2 m
LH10	10th percentile of point heights > 2 m
LH20	20th percentile of point heights > 2 m
LH25	25th percentile of point heights > 2 m
LH30	30th percentile of point heights > 2 m
LH40	40th percentile of point heights > 2 m
LH50	50th percentile of point heights > 2 m
LH60	60th percentile of point heights > 2 m
LH70	70th percentile of point heights > 2 m
LH75	75th percentile of point heights > 2 m
LH80	80th percentile of point heights > 2 m
LH90	90th percentile of point heights > 2 m
LH95	95th percentile of point heights > 2 m
CC2M	% canopy density (cover) at 2 m
CCMEAN	% canopy density (cover) at mean canopy height
CCMODE	% canopy density (cover) at modal canopy height

for each model and subsequently used these for comparative purposes.

2.5. Metric comparison and evaluation

Our first objective was to assess how ALS metrics were impacted by canopy conditions at the time of ALS acquisition. We used a Mann–Whitney *U* test to compare values for leaf-on and leaf-off versions of the 21 ALS metrics (Table 5) selected for model development. To examine how the relationships between the ALS metrics and the forest inventory attributes varied according to canopy conditions at the time of ALS acquisition, we estimated correlations between the leaf-on and leaf-off metrics and the plot attributes, by forest type, using the Pearson's correlation coefficient.

2.6. Model comparison and evaluation

Our second objective was to evaluate and compare the performance of models developed using leaf-on and leaf-off ALS data. The RF models for the eight forest attributes of interest were compared and evaluated using relative RMSE and bias (eqs. 1 and 2). Relative bias (bias%) and RMSE (RMSE%) were calculated by normalizing bias and RMSE to the mean of the observed (ground plot) value for each attribute and expressed as a percentage to enable comparisons between attributes (eqs. 1 and 2).

$$\text{(1)} \qquad \text{Relative bias} = \frac{\left[\sum_{i=1}^{n}(y_i - \hat{y}_i)\right]/n}{\bar{y}} \times 100$$

$$\text{(2)} \qquad \text{Relative RMSE} = \frac{\sqrt{\left[\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right]/n}}{\bar{y}} \times 100$$

where y_i is the observed value at ground plot *i*, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the mean of the observed value, and *n* is the number of plots.

Our third objective was to evaluate the implications of estimating forest attributes from mixing models and input data types. To this end, we applied the RF leaf-on model to the leaf-off data and the RF leaf-off model to the leaf-on data for each forest type. As above, we evaluated and compared model performance using relative RMSE and bias. Our fourth and final objective was to assess the relative performance of our leaf-on and leaf-off models to a pooled model, generated by combining leaf-on and leaf-off data, as well as to a generic model that was generated using all data, irrespective of forest type. Again, we used relative RMSE and bias to enable model comparisons.

3. Results

3.1. Metric comparison and evaluation

We examined the impact of canopy condition at the time of ALS data acquisition on ALS plot metrics (Table 6). For both forest types, mean values for leaf-off height percentile metrics were consistently greater than mean values for leaf-on metrics. The average absolute difference between leaf-on and leaf-off metrics was 0.51 m for coniferous and 1.77 m for deciduous plots. Differences were larger for the upper height percentiles (LH60–LH95) relative to the lower height percentiles (LH05–LH50), particularly for deciduous plots, where the difference between leaf-off and leaf-on upper height percentiles was 2.54 m versus 0.7 m for coniferous plots. For lower height percentiles (LH05–LH50), differences between mean values for leaf-on and leaf-off metrics were 0.33 m for coniferous and 1.11 m for deciduous plots. Mean values for leaf-on canopy density metrics were consistently greater than leaf-off metrics. The average absolute difference between leaf-on and leaf-off canopy density metrics was 0.85% for coniferous plots compared with 11.65% for deciduous plots. Of note, leaf-off canopy density above 2 m (CC2M) was 16.82% less than the corresponding leaf-on value for deciduous plots. The only metrics that had a statistically significant difference between leaf-on and leaf-off ALS data were the 5th percentile of ALS heights for coniferous plots and the three canopy density metrics (CC2M, CCMEAN, CCMODE) for deciduous plots. The coefficient of variation of height (LHCOV) was consistently greater under leaf-off conditions for both forest types.

A subset of the estimated correlations between the eight inventory attributes and the 21 ALS metrics are reported in Table 7. Overall, we found that for coniferous plots, leaf-off metrics were more strongly correlated with the forest inventory attributes (with the exception of LHLCOV and LHLSKEW). Conversely, for deciduous forest types, leaf-on metrics were more strongly correlated with the inventory attributes (with the exception of the canopy density metrics, in which case leaf-off metrics were more strongly correlated with inventory attributes). Of note, the magnitude of the differences in correlation between leaf-on and leaf-off ALS metrics was greater for the lower height percentiles compared with the upper height percentiles, for both forest types.

3.2. Model comparison: leaf-on versus leaf-off versus pooled models

Tables 8 and 9 summarize the model results for coniferous and deciduous forest types, respectively. For the majority of attributes, leaf-off models resulted in lower RMSE for both coniferous and deciduous forest types. For coniferous plots, leaf-off models had lower RMSE% for all eight inventory attributes, and the average difference in RMSE% between leaf-off and leaf-on models was 1.39%. For deciduous plots, the results were mixed: for half of the attributes (BA, V_{MERCH}, V_{TOT}, and TAGB), leaf-off models had lower RMSE% (average difference = 4.26%), whereas for the other half of the attributes (H_{TOP}, H_{MEAN}, H_{L}, and QMD), leaf-on models had lower RMSE% (average difference = 0.72%) (Fig. 4). The magnitude of the differences in RMSE% between leaf-on and leaf-off models was greater for deciduous forest types for volume attributes and TAGB, particularly for V_{MERCH}, where RMSE% differed by 7%. For both forest types, V_{MERCH} had the largest RMSE%. With a few exceptions (i.e., H_{L}, TAGB for deciduous plots), bias was negative for all attributes for both forest types (Fig. 5). Leaf-on models generally had larger biases for the majority of attributes, particu-

Table 6. Comparison of metrics for leaf-off and leaf-on acquisition conditions for coniferous and deciduous forest types and for all plots combined.

	Coniferous					Deciduous					Combined				
	Leaf-on (n = 332)		Leaf-off (n = 455)			Leaf-on (n = 28)		Leaf-off (n = 59)			Leaf-on (n = 456)		Leaf-off (n = 332)		
ALS metric	Mean	SD	Mean	SD	p	Mean	SD	Mean	SD	p	Mean	SD	Mean	SD	p
LHMEAN	6.475	3.547	6.987	3.767	0.100	10.581	5.850	12.382	5.188	0.176	7.043	4.075	8.252	4.502	**0.000**
LHAAD	1.885	1.240	2.067	1.352	0.125	3.090	1.977	3.807	1.710	0.107	2.081	1.404	2.541	1.627	**0.000**
LHLCOV	0.190	0.056	0.193	0.055	0.514	0.190	0.053	0.210	0.054	0.081	0.192	0.053	0.201	0.054	**0.039**
LHLSKEW	0.079	0.143	0.075	0.140	0.163	–0.048	0.193	–0.059	0.210	0.546	0.066	0.154	0.047	0.153	**0.009**
LHLKURT	0.093	0.050	0.093	0.056	0.527	0.085	0.068	0.087	0.087	0.803	0.092	0.052	0.087	0.060	**0.043**
LH05	2.851	0.960	3.040	1.128	**0.020**	3.775	1.525	4.166	1.973	0.361	2.954	1.046	3.282	1.322	**0.000**
LH10	3.410	1.506	3.661	1.675	0.052	5.051	2.547	5.494	2.722	0.462	3.603	1.682	4.043	1.942	**0.000**
LH20	4.407	2.569	4.661	2.564	0.135	7.192	4.333	8.077	4.181	0.272	4.748	2.886	5.357	3.057	**0.001**
LH25	4.805	2.920	5.092	2.874	0.126	8.095	5.083	9.196	4.658	0.212	5.220	3.341	5.955	3.490	**0.000**
LH30	5.162	3.189	5.525	3.179	0.105	8.916	5.715	10.234	5.053	0.218	5.642	3.702	6.520	3.875	**0.000**
LH40	5.813	3.587	6.276	3.693	0.110	10.096	6.402	11.862	5.642	0.203	6.381	4.201	7.490	4.501	**0.000**
LH50	6.433	3.922	6.957	4.109	0.117	11.213	6.841	13.057	6.029	0.247	7.077	4.603	8.340	4.982	**0.000**
LH60	7.043	4.181	7.629	4.468	0.135	12.121	7.179	14.233	6.354	0.230	7.738	4.896	9.169	5.414	**0.000**
LH70	7.694	4.452	8.322	4.802	0.152	12.886	7.392	15.283	6.601	0.176	8.427	5.162	10.001	5.800	**0.000**
LH75	8.050	4.609	8.713	4.963	0.128	13.359	7.484	15.802	6.715	0.183	8.805	5.311	10.447	5.978	**0.000**
LH80	8.439	4.759	9.161	5.140	0.106	13.861	7.613	16.349	6.836	0.162	9.220	5.457	10.948	6.169	**0.000**
LH90	9.447	5.143	10.256	5.586	0.108	14.930	7.846	17.733	6.898	0.152	10.264	5.790	12.164	6.603	**0.000**
LH95	10.274	5.460	11.116	5.921	0.114	15.636	8.035	18.672	6.903	0.119	11.106	6.051	13.083	6.891	**0.000**
CC2M	39.471	17.696	38.775	19.662	0.932	49.366	20.353	32.543	16.967	**0.000**	41.783	18.324	39.720	18.673	0.181
CCMEAN	19.302	9.651	19.210	10.822	0.986	27.170	13.108	17.954	10.425	**0.001**	20.745	10.458	20.021	10.449	0.455
CCMODE	23.462	11.412	21.708	11.491	0.081	22.032	11.657	13.123	8.920	**0.001**	23.891	11.550	21.657	11.792	**0.007**

Note: Significant differences (p < 0.05), identified with the Mann–Whitney U test, are indicated in bold. See Table 5 for explanation of ALS metrics.

Table 7. Pearson correlation coefficients for forest inventory attributes and a subset of the 21 ALS metrics used for model development.

ALS metric	H_{TOP}	H_{MEAN}	H_L	BA	QMD	V_{MERCH}	V_{TOT}	TAGB
Coniferous leaf-on								
LHAVG	0.92	0.95	0.94	0.85	0.83	0.90	0.94	0.91
LHLCOV	0.56	0.41	0.55	0.29	0.57	0.24	0.23	0.31
LH10	0.74	0.80	0.75	0.78	0.62	0.74	0.84	0.80
LH50	0.88	0.93	0.91	0.84	0.80	0.90	0.94	0.90
LH90	0.95	0.94	0.98	0.82	0.88	0.87	0.90	0.89
CC2M	0.61	0.56	0.56	0.65	0.50	0.39	0.53	0.56
Coniferous leaf-off								
LHAVG	0.95	0.95	0.95	0.83	0.88	0.91	0.93	0.89
LHLCOV	0.46	0.41	0.45	0.20	0.47	0.23	0.20	0.23
LH10	0.78	0.80	0.79	0.79	0.70	0.79	0.86	0.82
LH50	0.93	0.95	0.94	0.83	0.86	0.92	0.94	0.88
LH90	0.95	0.94	0.96	0.78	0.89	0.88	0.89	0.85
CC2M	0.73	0.69	0.68	0.81	0.59	0.53	0.70	0.71
Deciduous leaf-on								
LHAVG	0.96	0.98	0.98	0.86	0.92	0.88	0.90	0.90
LHLCOV	0.39	0.18	0.33	0.25	0.35	0.22	0.19	0.21
LH10	0.75	0.81	0.76	0.69	0.66	0.64	0.69	0.69
LH50	0.95	0.98	0.97	0.84	0.92	0.89	0.90	0.90
LH90	0.99	0.95	0.99	0.86	0.93	0.87	0.88	0.89
CC2M	0.64	0.62	0.60	0.69	0.47	0.43	0.55	0.57
Deciduous leaf-off								
LHAVG	0.88	0.93	0.95	0.72	0.89	0.77	0.76	0.76
LHLCOV	0.11	–0.04	0.01	0.05	0.00	–0.01	0.01	0.03
LH10	0.56	0.65	0.67	0.54	0.60	0.59	0.57	0.57
LH50	0.85	0.91	0.92	0.68	0.87	0.74	0.72	0.72
LH90	0.93	0.93	0.97	0.77	0.91	0.79	0.79	0.80
CC2M	0.68	0.65	0.57	0.79	0.49	0.72	0.75	0.75

Note: See Table 2 or the text for forest attribute abbreviations. See Table 5 for explanation of ALS metrics.

larly for BA and V_{MERCH}. The average difference in bias between leaf-on and leaf-off models was –0.19% for coniferous plots and –0.27% for deciduous plots. The largest bias, for both forest types, was for V_{MERCH} for leaf-off models. Of note, biases for deciduous models of TAGB were positive.

The performance of the pooled models for coniferous forest types were middling, with pooled models generally having higher RMSE% than leaf-off models and lower RMSE% than leaf-on models. The average difference in RMSE% between pooled and leaf-on models was –0.62%, whereas the average difference in RMSE% between pooled and leaf-off models was 0.61%. Bias% was negative for all the coniferous pooled models and was less than 1% for all attributes. Of note, pooled model bias was lower than leaf-on and leaf-off model bias for BA (Table 8; Fig. 5) and was larger for TAGB. For deciduous forest types, pooled model RMSE% differed from leaf-on RMSE% by an average of –1.75%, whereas pooled model RMSE% and leaf-off RMSE% differed by an average of 0.016%. Pooled model bias% was small and positive (0.061%) for V_{MERCH} compared with leaf-on and leaf-off models, which had bias% values of –1.3% and –0.5%, respectively (Table 9; Fig. 5). Pooled model bias% was greater for H_{TOP} and QMD.

When compared with the aforementioned models, generic models, produced with all data pooled regardless of forest type (including mixed forest plots), had comparable RMSE% to that of forest type specific models for height attributes and BA, with larger RMSE% for QMD, V_{TOT}, and TAGB (Table 10) and markedly larger RMSE% for V_{MERCH}. Bias% was likewise larger and positive for QMD, V_{MERCH}, V_{TOT}, and TAGB. Trends across generic leaf-on, leaf-off, and pooled models were similar, and in particular, V_{MERCH} had RMSE% values greater than 50% and bias values greater than 10% for all three model types.

In RF, variable importance is a measure of the proportion of mean square error explained if the variable is withheld from the model. Figure 6 illustrates the relative importance of the 21 ALS metrics to the estimation of the eight attributes. Overall, the relative importance of the metrics to the leaf-on and leaf-off models was similar. Notable exceptions were the greater importance of canopy density metrics to leaf-off models for BA, TAGB, V_{MERCH}, and V_{TOT}, particularly for deciduous forest types, as well as the greater importance of the upper height percentiles for the leaf-on models of the plot height attributes.

Table 8. Model results for coniferous plots.

	Leaf-on model/Leaf-on data				Leaf-off model/Leaf-off data				Difference	
Attribute	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%
H_{TOP}	0.725	5.891	−0.017	−0.135	0.620	4.759	−0.015	−0.114	1.132	−0.021
H_{MEAN}	0.603	6.811	−0.018	−0.203	0.566	5.877	−0.016	−0.167	0.934	−0.036
H_L	0.486	5.042	0.007	0.064	0.546	4.745	−0.014	−0.127	0.297	0.191
BA	2.576	14.729	−0.038	−0.215	2.608	14.589	−0.017	−0.094	0.139	−0.122
QMD	1.132	9.206	−0.044	−0.354	1.120	8.880	−0.038	−0.303	0.326	−0.052
V_{MERCH}	14.888	24.782	−0.543	−0.904	14.591	21.716	−0.088	−0.131	3.066	−0.773
V_{TOT}	18.398	18.106	−0.654	−0.644	16.352	14.618	−0.087	−0.077	3.488	−0.566
TAGB	10.706	17.234	−0.214	−0.310	13.606	15.461	−0.079	−0.100	1.773	−0.210
	Leaf-on model/Leaf-off data				Leaf-off model/Leaf-on data				Difference	
	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%
H_{TOP}	1.838	14.936	−0.066	−0.534	1.904	14.624	0.001	0.010	0.312	−0.544
H_{MEAN}	1.363	15.402	0.142	1.607	1.481	15.383	−0.191	−1.987	0.019	3.594
H_L	1.587	15.500	−0.129	−1.256	1.164	10.757	0.042	0.384	4.744	−1.640
BA	7.129	40.765	−1.160	−6.633	6.698	37.466	0.979	5.478	3.299	−12.111
QMD	2.678	21.777	−0.384	−3.119	2.763	21.899	0.225	1.787	−0.122	−4.906
V_{MERCH}	33.387	55.576	−8.568	−14.263	34.433	51.247	1.784	2.655	4.329	−16.917
V_{TOT}	42.014	41.346	−6.195	−6.096	39.024	34.885	3.726	3.331	6.461	−9.427
TAGB	35.858	51.784	0.813	1.174	30.600	38.759	−1.130	−1.432	13.025	2.606
	Pooled model (combined leaf-on and leaf-off data)				Difference (Pooled RMSE% – Leaf-on RMSE%)		Difference (Pooled RMSE% – Leaf-off RMSE%)			
	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%	ΔRMSE%	ΔBias%		
H_{TOP}	0.662	5.211	−0.019	−0.152	−0.680	−0.017	0.452	−0.038		
H_{MEAN}	0.565	6.088	−0.016	−0.174	−0.723	0.029	0.211	−0.007		
H_L	0.516	4.893	−0.011	−0.105	−0.149	−0.169	0.148	0.022		
BA	2.628	14.848	−0.003	−0.017	0.119	0.198	0.259	0.077		
QMD	1.079	8.650	−0.034	−0.275	−0.556	0.079	−0.230	0.028		
V_{MERCH}	14.908	23.310	−0.290	−0.453	−1.472	0.451	1.594	−0.322		
V_{TOT}	16.941	15.803	−0.383	−0.357	−2.303	0.287	1.185	−0.280		
TAGB	12.459	16.715	−0.265	−0.355	−0.519	−0.045	1.254	−0.255		

Note: See Table 2 or the text for forest attribute abbreviations.

3.3. Model comparison: mixing models and input data types

The impacts of mixing models and input data types (i.e., applying leaf-on models to leaf-off data and vice versa) are summarized in Tables 8 and 9. Overall, RMSEs were consistently greater relative to the control. For coniferous plots, the application of leaf-off models to leaf-on data resulted in a larger average absolute increase in RMSE% (16.79%) relative to the control when compared with leaf-on models applied to leaf-off data (9.54%) (Fig. 7). Conversely, for deciduous plots, the application of leaf-on models to leaf-off data resulted in a markedly larger average absolute increase in RMSE% (25.75%) relative to the control when compared with leaf-off models applied to leaf-on data (13.42%). The application of deciduous leaf-on models to leaf-off data for V_{MERCH} resulted in the largest increase in RMSE% (40.18%).

Although the application of leaf-off models to leaf-on data resulted in larger increases in RMSE% relative to the control, for coniferous plots, bias% was greater when leaf-on models were applied to leaf-off data. The average absolute difference in bias% was 4.13% compared with 2.21% when leaf-off models were applied to leaf-on data. For deciduous plots, the average absolute difference in bias% was similar, being 5.01% for leaf-on model – leaf-off data and 5.89% for leaf-off model – leaf-on data; however, Figure 8 indicates that although differences in leaf-on model – leaf-off data bias% relative to the control were greater for some deciduous leaf-on models, V_{MERCH}, V_{TOT}, and TAGB had larger bias% as a result of leaf-off models applied to leaf-on data.

4. Discussion

The overall goal in this study was to investigate the differences between forest attribute models derived from ALS data acquired during leaf-on and leaf-off canopy conditions. The Hinton FMA is approximately one million hectares in size, and about half of the ALS data within the Hinton FMA was acquired in leaf-off conditions (Fig. 2). As noted earlier, these data are part of a larger province-wide ALS acquisition program that has resulted in the collection of more than 29 million ha of ALS data. These data were primarily acquired to support improved digital terrain mapping (White et al. 2012) but have also been released to forest companies to support forest management and enhance forest inventories (White et al. 2014). In this study, we evaluated the relationship between eight forest inventory attributes and 21 ALS-derived metrics acquired during leaf-on and leaf-off conditions. Differences between leaf-on and leaf-off metrics for coniferous and deciduous forest types were examined and quantified. Models developed separately using leaf-on and leaf-off data, by forest type, were compared to evaluate their relative performance, as were pooled models generated by combining leaf-on and leaf-off data. The effects of mixing models and data types were explored by applying leaf-on models to leaf-off data and vice versa. Lastly, model performance was compared with that of generic models generated from all data pooled together (regardless of forest type).

Differences between ALS metrics for leaf-on and leaf-off data primarily result from the reduced volume of biophysical material in the canopy available to intercept ALS pulses under leaf-off conditions. As per Næsset (2005), we found that the variation in

Table 9. Model results for deciduous plots.

	Leaf-on model/Leaf-on data				Leaf-off model/Leaf-off data				Difference	
Attribute	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%
H_{TOP}	0.793	4.499	−0.006	−0.035	1.146	5.761	−0.045	−0.228	−1.262	0.193
H_{MEAN}	0.721	5.568	−0.064	−0.491	0.953	6.051	−0.055	−0.346	−0.483	−0.145
H_L	0.563	3.738	0.015	0.098	0.824	4.612	0.001	0.005	−0.874	0.093
BA	3.967	16.727	−0.297	−1.253	3.646	15.153	−0.053	−0.220	1.574	−1.033
QMD	1.439	8.947	−0.127	−0.788	1.888	9.205	−0.159	−0.777	−0.258	−0.012
V_{MERCH}	38.869	26.197	−1.947	−1.313	35.969	19.195	−0.902	−0.481	7.002	−0.831
V_{TOT}	38.280	21.031	−0.719	−0.395	34.412	16.712	−0.559	−0.272	4.319	−0.123
TAGB	23.180	20.919	0.020	0.018	20.950	16.781	0.414	0.332	4.138	−0.314
	Leaf-on model/Leaf-off data				Leaf-off model/Leaf-on data				Difference	
	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%
H_{TOP}	3.138	17.796	−0.377	−2.139	1.395	7.014	0.298	1.496	10.782	−3.635
H_{MEAN}	2.814	21.737	0.896	6.924	1.710	10.853	−0.790	−5.017	10.884	11.942
H_L	2.014	13.367	0.553	3.669	1.054	5.895	−0.312	−1.748	7.472	5.416
BA	10.360	43.685	−1.636	−6.898	7.696	31.990	−0.528	−2.197	11.695	−4.701
QMD	4.418	27.467	1.424	8.856	3.305	16.113	−1.539	−7.504	11.354	16.360
V_{MERCH}	98.489	66.379	−5.510	−3.714	81.868	43.689	−22.905	−12.223	22.691	8.509
V_{TOT}	103.012	56.595	−8.241	−4.528	78.497	38.123	−19.049	−9.251	18.473	4.723
TAGB	60.002	54.149	−2.442	−2.203	43.716	35.017	−6.378	−5.109	19.133	2.905
	Pooled model (combined leaf-on and leaf-off data)				Difference (Pooled RMSE% – Leaf-on RMSE%)		Difference (Pooled RMSE% – Leaf-off RMSE%)			
	RMSE	RMSE%	Bias	Bias%	ΔRMSE%	ΔBias%	ΔRMSE%	ΔBias%		
H_{TOP}	0.989	5.157	−0.074	−0.388	0.658	−0.353	−0.604	−0.160		
H_{MEAN}	0.906	6.103	−0.053	−0.360	0.535	0.131	0.052	−0.014		
H_L	0.628	3.702	−0.007	−0.040	−0.036	−0.138	−0.910	−0.045		
BA	3.548	14.816	−0.012	−0.049	−1.911	1.204	−0.337	0.171		
QMD	1.625	8.513	−0.166	−0.867	−0.434	−0.079	−0.692	−0.090		
V_{MERCH}	34.815	19.913	0.107	0.061	−6.284	1.374	0.718	0.542		
V_{TOT}	35.599	17.960	−0.467	−0.235	−3.071	0.160	1.248	0.037		
TAGB	20.976	17.432	−0.246	−0.205	−3.487	−0.223	0.651	−0.537		

Note: See Table 2 or the text for forest attribute abbreviations.

Fig. 4. A summary of model root mean square error (RMSE) for the coniferous and deciduous Random Forest models for each of the eight forest attributes (H_{TOP}, top height; H_{MEAN}, mean height; H_L, Lorey's mean height; BA, basal area; QMD, quadratic mean diameter; V_{MERCH}, merchantable volume; V_{TOT}, total volume; TAGB, total aboveground biomass).

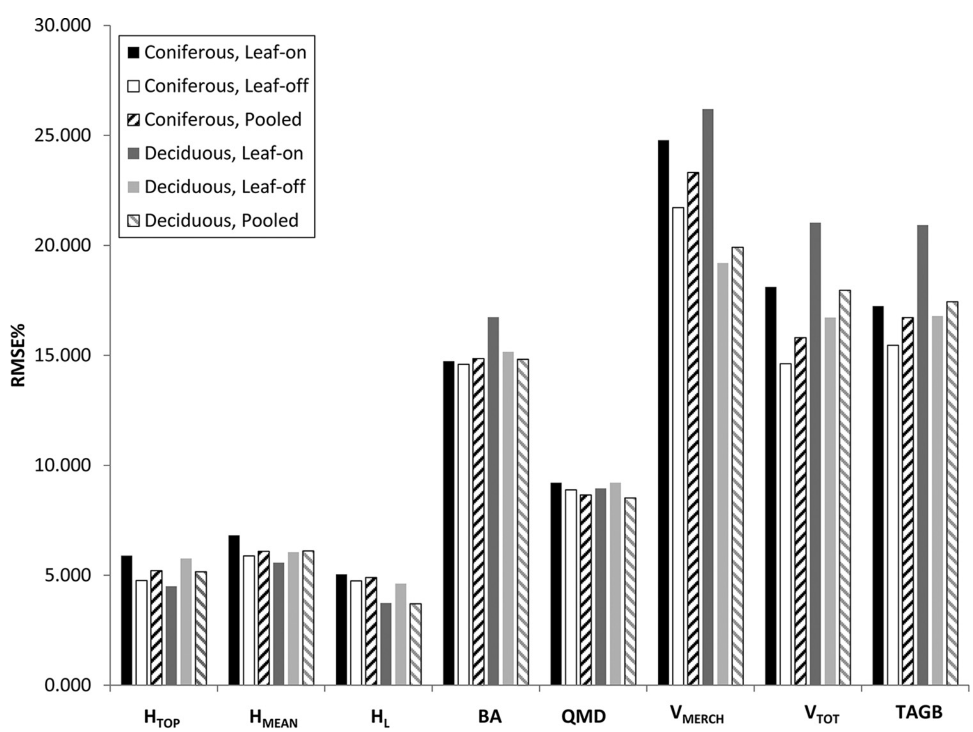


Fig. 5. A summary of model bias for the coniferous and deciduous Random Forest models for each of the eight forest attributes (H_{TOP}, top height; H_{MEAN}, mean height; H_L, Lorey's mean height; BA, basal area; QMD, quadratic mean diameter; V_{MERCH}, merchantable volume; V_{TOT}, total volume; TAGB, total aboveground biomass).

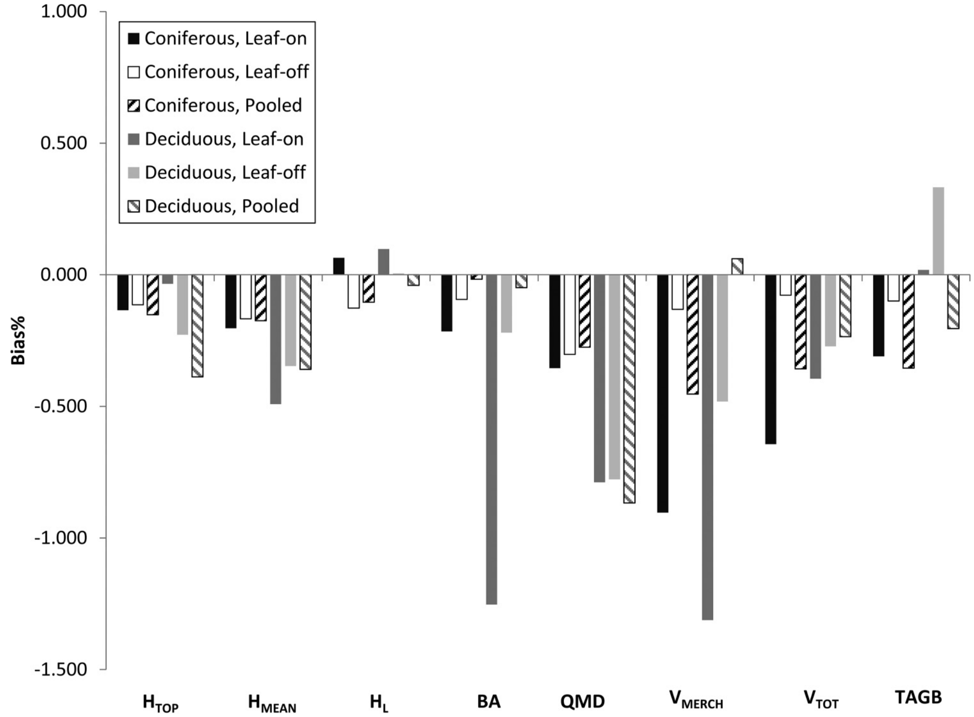


Table 10. Model results for generic models (combined coniferous, deciduous, and mixed plots).

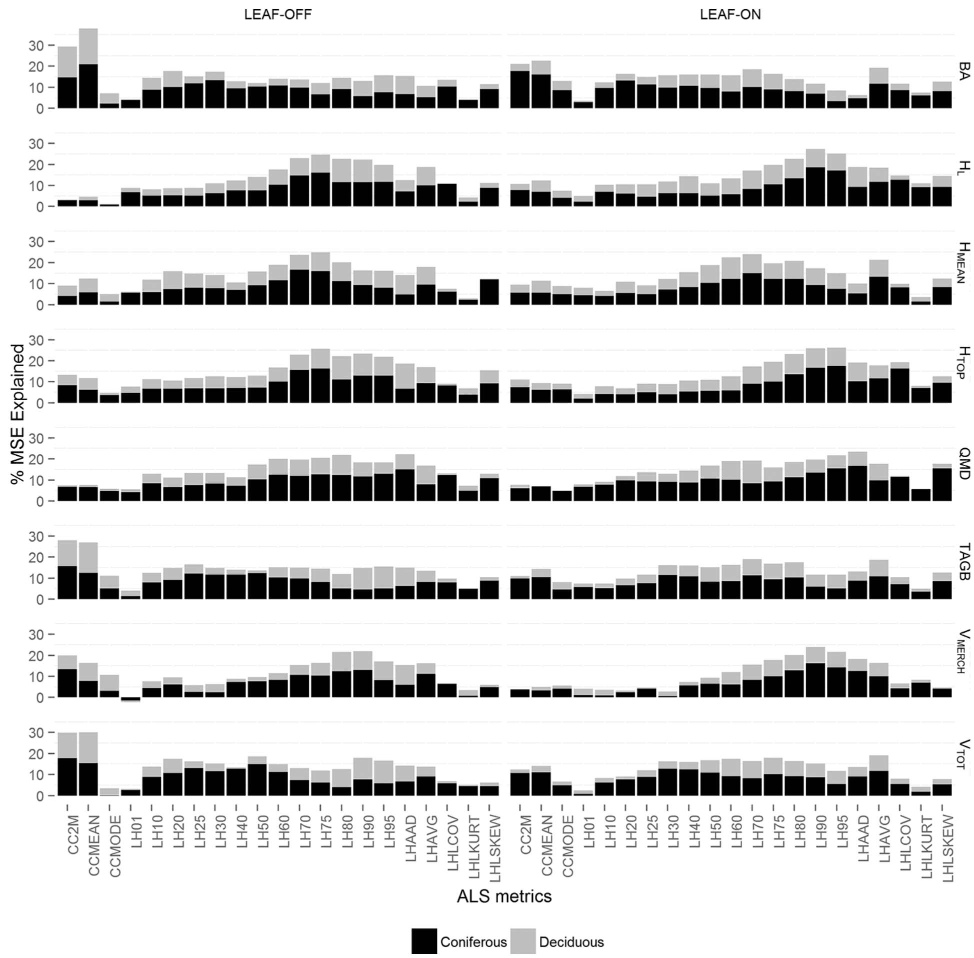
	Leaf-on				Leaf-off				Pooled			
Attribute	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%	RMSE	RMSE%	Bias	Bias%
H_{TOP}	0.731	5.557	−0.011	−0.083	0.726	4.831	−0.013	−0.087	0.728	5.114	−0.012	−0.086
H_{MEAN}	0.625	6.621	−0.015	−0.161	0.676	6.105	0.004	0.036	0.655	6.307	−0.004	−0.040
H_L	0.510	4.653	0.004	0.038	0.613	4.838	0.008	0.059	0.572	4.785	0.006	0.051
BA	2.813	15.324	−0.028	−0.153	2.806	13.978	−0.011	−0.054	2.805	14.498	−0.018	−0.093
QMD	1.163	8.969	−0.039	−0.304	1.926	13.183	0.192	1.315	1.648	11.843	0.095	0.680
V_{MERCH}	54.041	73.603	12.869	17.528	49.960	51.201	12.920	13.241	44.906	51.380	9.757	11.163
V_{TOT}	35.187	31.239	4.571	4.058	29.436	21.452	2.585	1.884	31.801	25.067	3.382	2.666
TAGB	18.161	24.249	1.197	1.598	18.144	19.831	0.903	0.987	18.140	21.467	1.026	1.214

Note: See Table 2 or the text for forest attribute abbreviations.

canopy heights (LHCV) was greater under leaf-off conditions for both coniferous and deciduous forest types. Næsset (2005) looked primarily at mixed forest types and found that canopy height measurements in the lower and intermediate parts of the canopy (10th and 50th percentiles) were more strongly influenced by canopy conditions at time of acquisition than the maximum height, which was found to be little influenced by leaf-on or leaf-off conditions. In this study, we found that ALS measurements in the upper canopy were more strongly influenced by acquisition conditions than those in the lower canopy and that this effect was much greater for deciduous forest types (Table 6), as would be expected given the greater proportion of deciduous species in our deciduous plots relative to the more mixed forest conditions of the Næsset (2005) study. The lack of an effect on maximum height in the Næsset (2005) study was posited to result from the dominance of coniferous species in the mixed forest plots (58%–69%). This hypothesis is somewhat corroborated by the results of this study in that the difference between leaf-off and leaf-on measures of the 95th percentile of height was only 0.84 m for coniferous plots compared with 3.03 m for deciduous plots. Of note, differences between leaf-on and leaf-off conditions were also found for the coniferous plots, and as documented by both Næsset (2005) and Villikka et al. (2012), deciduous components within coniferous-dominated plots can impact ALS metrics and area-based model outcomes for coniferous forest types.

Næsset (2005) found that leaf-off ALS metrics for mixed forest types were more strongly correlated with ground-plot measures (or estimates) of biophysical attributes, which therefore led to the improved performance of the leaf-off models relative to the leaf-on models. For deciduous plots, we found that leaf-on ALS metrics were generally more strongly correlated with ground-plot measurements for our inventory attributes of interest (Table 7), suggesting that if we follow the same logic as Næsset (2005), then leaf-on models for deciduous plots would have lower errors and bias relative to leaf-off models. Indeed, we found that leaf-on models performed better for height-related attributes and QMD but that the differences between leaf-on and leaf-off model RMSE% values for these attributes were relatively small. Our results are similar to those of Anderson and Bolstad (2013) and Bouvier et al. (2015). Conversely, leaf-off models performed markedly better for BA, volume attributes, and TAGB. For example, deciduous leaf-off models for V_{MERCH} had an RMSE% of 19.19% compared with an RMSE% of 26.19% for leaf-on models. For coniferous plots, leaf-off metrics were more strongly correlated with forest inventory attri-

Fig. 6. Variable importance, defined as the proportion of mean square error (MSE) explained, for RF models for prediction of forest inventory attributes (BA, basal area; H_L, Lorey's mean height; H_{MEAN}, mean height; H_{TOP}, top height; QMD, quadratic mean diameter; TAGB, total aboveground biomass; V_{MERCH}, merchantable volume; V_{TOT}, total volume).



butes, and leaf-off model performance was comparable to leaf-on models for all attributes.

Our results are also similar to those of Villikka et al. (2012). Although differences in leaf-on and leaf-off model performance for dominant height were not reported by forest type in Villikka et al. (2012), their pooled results for dominant height indicate that leaf-on and leaf-off model performance was similar. Likewise, in this study, we found that differences in leaf-on or leaf-off model performance were much smaller for height-related attributes compared with volume attributes and TAGB. Villikka et al. (2012) found that leaf-off models produced more accurate estimates of volume for both coniferous and deciduous forest types and that differences in model performance were much greater for deciduous forest types: deciduous leaf-off volume models had an RMSE% of 21.51% and a bias% of −0.06% compared with an RMSE% of 27.63% and a bias% of −0.31% for leaf-on models. In our study, deciduous leaf-off models for V_{TOT} had an RMSE% of 16.78% and a bias% of −0.39% compared with an RMSE% of 20.92% and a bias% of −0.272% for leaf-on models. Thus, although model performance may be similar for leaf-on and leaf-off data for some attributes, the improved performance of leaf-off models for volume and TAGB suggests that leaf-off data may not only be acceptable for use in an area-based approach that involves a deciduous component, but it may actually be preferable in some circumstances, as has been posited by others (Hawbaker et al. 2010).

Interestingly, we found that pooled models generated from combining leaf-on and leaf-off data for each forest type had comparable results to their leaf-on and leaf-off counterparts. For coniferous forest types, pooled models yielded differences in RMSE% and bias% that were less than 1% for most attributes, with the exception of V_{MERCH}, V_{TOT}, and TAGB, which exceeded the RMSE% of their leaf-off counterparts by less than 2% (Table 8). For deciduous forest types, pooled models performed similarly to leaf-off models, with differences in RMSE% and bias% of less than 1.3%. Pooled models had lower RMSE% for volume attributes and TAGB relative to deciduous leaf-on models, particularly for V_{MERCH}, which was more than 6% lower for the pooled model. Generic models, for which data were pooled irrespective of forest type, had comparable performance to other models for height attributes and BA but resulted in increases in RMSE% and bias% for QMD, V_{MERCH}, V_{TOT}, and TAGB. There are at least two practical implications associated with these findings. The first implication is confirmation of the need to generate models specific to forest types or species functional groups to reduce error and bias when estimating forest inventory attributes, particularly when these types or groups exist in relatively pure stands. The importance of this was demonstrated by the work of Næsset (2004), who found that coniferous models applied to birch-dominated stands resulted in an overestimation of stand density and volume by up to 90%. The second implication and the novel contribution of this study is the finding that data from leaf-on and leaf-off ALS acquisitions may be combined or pooled with little impact on model performance or increase in bias. Large forest management areas, in particular, may have a greater likelihood of ALS acquisitions

Fig. 7. Absolute difference in relative RSME (ΔRSME%) between control (leaf-on model applied to leaf-on data or leaf-off model applied to leaf-off data) and leaf-on models applied to leaf-off data (ON/OFF) or leaf-off models applied to leaf-on data (OFF/ON) (H_{TOP}, top height; H_{MEAN}, mean height; H_L, Lorey's mean height; BA, basal area; QMD, quadratic mean diameter; V_{MERCH}, merchantable volume; V_{TOT}, total volume; TAGB, total aboveground biomass).

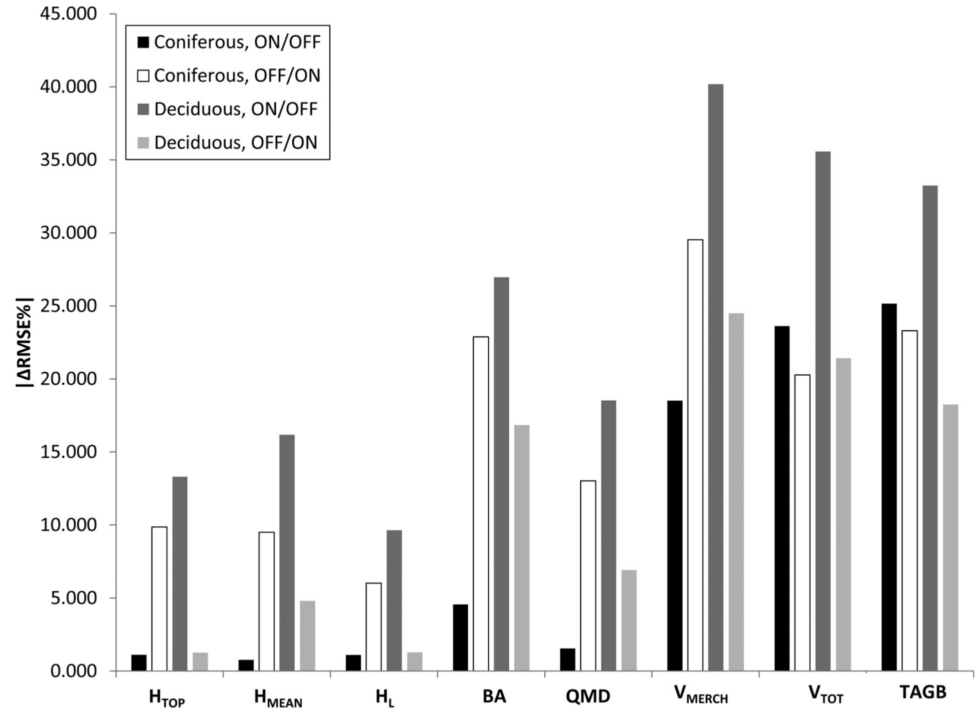
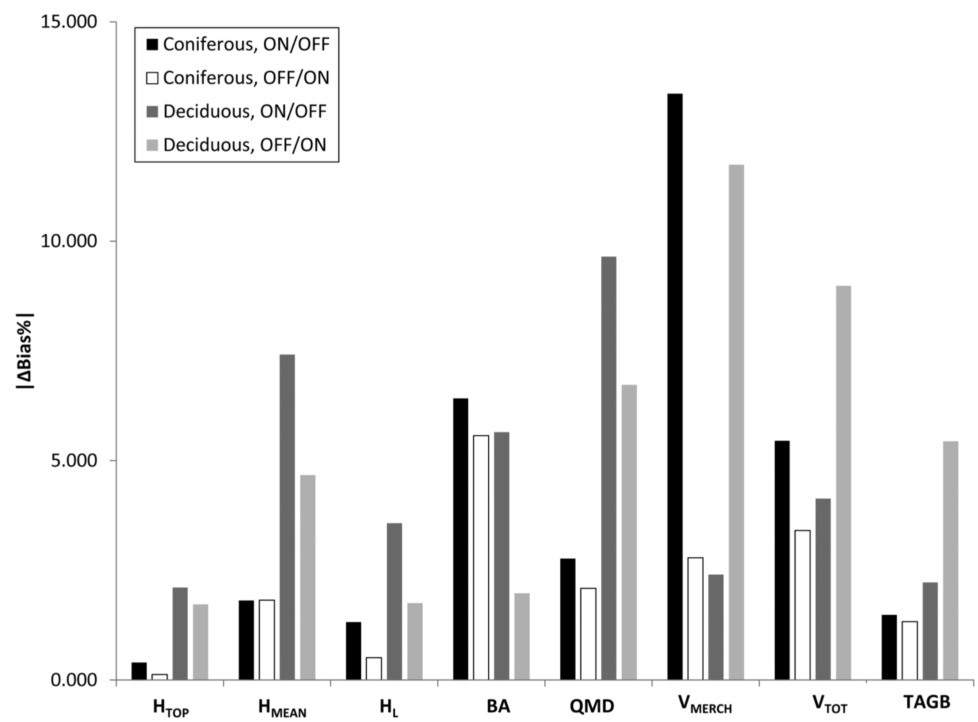


Fig. 8. Absolute difference in relative bias (ΔBias%) between control (leaf-on model applied to leaf-on data or leaf-off model applied to leaf-off data) and leaf-on models applied to leaf-off data (ON/OFF) or leaf-off models applied to leaf-on data (OFF/ON) (H_{TOP}, top height; H_{MEAN}, mean height; H_L, Lorey's mean height; BA, basal area; QMD, quadratic mean diameter; V_{MERCH}, merchantable volume; V_{TOT}, total volume; TAGB, total aboveground biomass).



that span leaf-on and leaf-off conditions. Our results would suggest that in the lodgepole pine dominated forest of our study area, there is minimal penalty in terms of model performance if leaf-on and leaf-off data are pooled in an area-based approach.

As per Villikka et al. (2012), we found that mixing models and data types resulted in large errors and bias in model outcomes and, moreover, that this increase in error and bias was greater for deciduous plots. However, in contrast to the findings of Villikka et al. (2012), we found that mixing leaf-on-models with leaf-off data had a greater impact on deciduous model outcomes than the application of leaf-off models to leaf-on data. Similarly, although Villikka et al. (2012) found that leaf-on models applied to leaf-off data resulted in poorer model estimates for coniferous plots, we found the opposite in our study area (Figs. 7 and 8). Causes for these differences may result from the different forest environments and species studied, as well as differences in how forest types were defined. These differences notwithstanding, a conclusion that can be drawn from both the work of Villikka et al. (2012) and that of this study is that the mixing of models and data types should be avoided, as it results in increased model error and bias, particularly for deciduous forest types.

There is increasing evidence in the literature, across a range of forest environments, suggesting that the use of leaf-off ALS data in an area-based approach can provide acceptable estimates of forest inventory attributes for both coniferous and deciduous forest types. These findings are consistent despite differences in ALS data, modelling methods, and forest environments (Table 1). The method by which plots are assigned to a particular forest type likely influences model outcomes. For example, we identified our plots as being either coniferous or deciduous based on which forest type accounted for 75% or more of the basal area in the plot. Villikka et al. (2012) assigned their plots according to volume using a threshold of 50% and indicated that the volume of deciduous trees in their plots ranged from 50% to 100%, with an average of 85%. A volume-based assignment of plots to a particular forest type may result in plots with more mixed conditions, and an examination of the ground-plot data summary in Villikka et al. (2012) would suggest that there is more coniferous volume found in plots identified as deciduous than there is deciduous volume found in plots identified as coniferous. As noted earlier, Næsset (2005) defined mixed forest plots as those that had less than 90% of the total plot volume from coniferous species, with coniferous species still accounting for 58%–69% of the trees in the mixed forest plots. The forest conditions and species in our study site are also different to those of other studies. Our study site was dominated by natural stands of lodgepole pine and trembling aspen, whereas the study sites in Næsset (2005) and Villikka et al. (2012) were intensively managed boreal forest stands dominated by Scots pine and Norway spruce, with unspecified deciduous species in the case of Villikka et al. (2012). Because deciduous forest types are less likely to occur in pure stands, the degree to which plots are mixed and the nature of the tree species in question must also be considered, as also indicated by Wasser et al. (2013) and Anderson and Bolstad (2013). The practical implication of these results, particularly when examined in the larger context offered by the scientific literature, is this: if one is planning a new ALS acquisition for the purpose of deriving forest inventory information over a large area and that area has a significant deciduous or mixed-forest component, then one should examine results from studies conducted in similar forest environments before determining optimal acquisition conditions. If, on the other hand, one is in a position of having to use ALS data acquired under leaf-off conditions in an area-based approach (i.e., data that was collected for a different application such as terrain mapping), it is possible to produce accurate estimates of inventory attributes, provided that sufficient ground samples have also been collected representing the full range of forest structural variability present in the management area. Alternatively, if one is in the position of having a combination of leaf-on and leaf-off ALS acquisitions across a forest management area, pooled models may provide reasonable model outcomes. Finally and unequivocally, the mixing of models and data types (i.e., leaf-on model with leaf-off data and vice versa) should be avoided.

5. Conclusions

In this study undertaken in a lodgepole pine dominated forest in the foothills of the Rocky Mountains, we found that models generated using leaf-off ALS data provided comparable results to leaf-on models for predicting forest inventory attributes using an area-based approach for coniferous forest types. Leaf-off models also provided comparable results to leaf-on models for estimating basal area, volume, and biomass in deciduous forest types, with leaf-on models having lower errors for estimation of height attributes and quadratic mean diameter. Overall, differences in model performance between leaf-on and leaf-off models were larger for deciduous forest types. We found that pooling leaf-on and leaf-off ALS data resulted in models with comparable performance to their leaf-on and leaf-off counterparts, with no large increase in RMSE or bias for any of the inventory attributes that we considered. Conversely, we found that the mixing of models and input data types resulted in increased RMSE and bias, particularly for deciduous forest types; this result is in keeping with that of Villikka et al. (2012) and indicates that operational guidelines advising against mixing of leaf-on and leaf-off data and models for inventory attribute modelling with an area-based approach are well founded (White et al. 2013). This study has demonstrated that in the forest environment studied herein, poor model outcomes result when leaf-off models are applied to leaf-on data (and vice versa), poor model outcomes result for volume and TAGB attributes when models do not account for forest type, leaf-off data can be used effectively in an area-based approach, and the combination of leaf-on and leaf-off ALS data in an area-based approach does not adversely impact model outcomes.

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