Effect of scan angle on ALS metrics and area-based predictions of forest attributes for balsam fir dominated stands

Olivier R. van Lier1,*, Joan E. Luther2, Joanne C. White3, Richard A. Fournier4 and Jean-François Côté5

1Canadian Forest Service, Canadian Wood Fibre Centre, Natural Resources Canada, 26 University Drive, Newfoundland and Labrador, A2H 5G4, Canada
2Canadian Forest Service, Atlantic Forestry Centre, Natural Resources Canada, 26 University Drive, Newfoundland and Labrador, A2H 5G4, Canada
3Canadian Forest Service, Pacific Forestry Centre, Natural Resources Canada, 506 West Burnside Road, British Columbia, V8Z 1M5, Canada
4Department of Applied Geomatics, Centre d’Applications et de Recherche en Télédétection, Université de Sherbrooke, 2500 Boulevard de l'Université, Quebec, J1K 2R1, Canada
5Canadian Forest Service, Canadian Wood Fibre Centre, Natural Resources Canada, 1055 Rue du Peps, Quebec, G1V 4C7, Canada

*Corresponding author: Tel: 1 (709) 637-4944. E-mail: Olivier.vanLier@Canada.ca

Received 26 February 2021

In this study, we assessed the effect of airborne laser scanning (ALS) scan angle on point cloud metrics and the estimation of forest attributes in balsam fir (Abies balsamea (L.) Mill.) dominated forests of western Newfoundland, Canada. We collected calibration data from ground plot locations representing varying scan angles from two flight lines: within 4° of nadir in one flight line, and either 11–20° from nadir (low scan angle plots: L), or 21–30° from nadir (high scan angle plots: H) in an adjacent flight line. We computed three sets of ALS point cloud metrics for each ground plot using ALS data from: individual flight lines (near-nadir and off-nadir) and data from all available flight lines (up to 4) combined (aggregated, as commonly used in an operational inventory context). We generated three sets of models for each of the L and H plots using the ALS metric sets, and applied the models to independent validation data. We analysed the effect of scan angle on both the ALS metrics and performance statistics for area-based models generated using the L and H datasets. Our results demonstrate that off-nadir scan angles significantly affected (P < 0.05) specific metrics from both L (i.e. coefficient of variation (COVAR)) and H (i.e. maximum height, 95th percentile of height, mean height) plots, although the effects were trivial (mean absolute differences were ≤ 0.01 for COVAR and < 0.3 m for the height metrics). Forest attribute predictions using these and other metrics were also significantly affected (P < 0.05), namely gross merchantable volume (GMV), total volume (TVOL) and aboveground tree biomass (AGB) from L; and Lorey’s mean height (HGT), mean diameter at breast height (DBH), and GMV from H. We further demonstrated that combining ALS data from all available flight lines significantly increased errors for the predictions of HGT, GMV, and TVOL using L, and significantly reduced errors of HGT using H when compared to errors resulting from models developed with near-nadir data. While the differences in prediction errors were significant, they were small, with differences in mean absolute prediction errors all <1.3 per cent. Based on our results, we concluded that the effects of large scan angles, up to 30° off-nadir, on area-based forest attribute predictions were minimal in this study, which used ALS metrics calculated from ALS returns with a height above ground >2 m for balsam fir-dominated forests. This result may provide for operational efficiencies in implementing enhanced forest inventories in this particular forest environment.

Introduction

Over the last two decades, airborne laser scanning (ALS) has become an important technology for acquiring data in support of forest management in many jurisdictions (Hyppä et al. 2008; Naesset 2014; Reutebuch et al. 2005; White et al. 2016). These data are being used operationally over large continuous areas due in part to the decreasing costs associated with data acquisition. These data provide precise and accurate measurements of tree heights and detailed characterizations of the forest’s vertical structure with three-dimensional (3D) point clouds (Lim et al. 2003). Statistics generated from the ALS point cloud (ALS
metrics) are used to describe the configuration of returned laser energy through the canopy’s vertical profile. These metrics are subsequently used as predictor variables typically in conjunction with ground plot measurements to model forest inventory attributes with an area-based approach (ABA) (Naesset et al. 2014; White et al. 2013, 2017).

ALS acquisition parameters can determine the quality and usability of the ALS data for various applications, and ultimately can influence the derived forest attribute information (Hopkinson 2007; Montaghi 2013). Acquisition parameters directly influence the costs of ALS surveys and are therefore pragmatic considerations for forest managers (Reutebuch et al. 2005). As survey costs for ALS data are primarily a function of aircraft flight time, parameters that can be adjusted to increase spatial coverage and reduce flight time are of particular interest (Hopkinson et al. 2013). For example, comparable area coverage can be achieved either by increasing acquisition altitude using a narrower scan angle, or via a lower acquisition altitude and a wider scan angle (Keränen et al. 2016). However, there are complex interactions between acquisition parameters, as well as between the laser pulses and the nature and configuration of the forest target, that complicate investigations into these parameters (Disney et al. 2010; Roussel et al. 2017). For example, the influence of scan angle is linked to the penetration of the laser pulse into the canopy (Montaghi 2013). Holmgren et al. (2003a) observed an increase in canopy crown area visible to a laser pulse with increasing scan angles. The path length travelled by a laser pulse through the forest canopy therefore increases with larger scan angles, increasing the probability of canopy interception (Goodwin et al. 2007) and potentially introducing biases in derived ALS metrics (Roussel et al. 2018).

The ALS acquisition parameter scan angle has been the subject of extensive research in a forestry context (Table 1). The scan angle is defined as the angle at which the laser beam is directed away from the focal plane of the instrument (nadir) (Gatziolis and Andersen 2008). Acquisition guidelines for forest applications have been informed by this science (Gatziolis and Andersen 2008; Laes et al. 2008; White et al. 2013), although yet, no consensus can be drawn from studies attempting to quantify the effect of this parameter on ALS derived metrics and models (Roussel et al. 2018). Further, as technology continues to evolve rapidly, revisiting the state of knowledge associated with these parameters is warranted.

General statements about the influence of bias from scan angle on the accuracy of forest attribute predictions is highly dependent on which ALS metrics are used (Roussel et al. 2018). Montaghi (2013) demonstrated that the vegetation ratio and understory ratio from scanning angles >10° off-nadir were significantly different from those derived from nadir, and hence would not be stable predictors in an ABA. Vegetation ratio, otherwise also referred to as canopy cover, is determined as the number of ALS returns above a certain height threshold (commonly 2 m above ground) divided by all returns, and is a measure of vertical vegetation density. Conversely, the understory ratio is calculated as the total number of returns below a specified height threshold (e.g. 2 m) that are not classified as ground, divided by all returns (including ground returns). Given that the calculation of these metrics includes ground returns, and as wider scan angles (i.e. > 15° off-nadir) decrease the probability of obtaining returns from the ground (Ahokas et al. 2005) while also increasing the probability of vegetation returns (Hopkinson et al. 2005; Montaghi 2013), it is understandable that the vegetation and understory ratio metrics have been found to be unstable with increasing scan angles. Notably, it is common to exclude returns below a specified height threshold in calculating ALS metrics used in an ABA. For example, most metrics from an ABA excluding returns below a threshold value of 2 m have been demonstrated to be relatively unaffected by high scanning angles of up to 20° off-nadir for boreal and hemi-boreal forests of Sweden (Maltamo et al. 2011). However, it is not the case for density metrics and specific structural descriptor metrics when derived using all returns, including ground returns (Montaghi 2013). Moreover, Naesset (1997) found no significant effect from off-nadir scan angles ranging up to 20° in using ALS metrics to determine mean tree height in Norway spruce (Picea abies Karst.) and Scots pine (Pinus sylvestris L.) dominated forests of southeast Norway.

The aforementioned studies provide substantial insight into the influence of various acquisition parameters on ALS data point distributions, derived metrics, and forest attribute predictions across a range of forest environments (Table 1). However, the majority of studies assessed the effects of a limited scan angle range and often used simulated forest environments and/or simulated ALS data (e.g. Holmgren et al. 2003a; Lovell et al. 2005; Disney et al. 2010; Yang et al. 2011; Qin et al. 2017). Commonly, the range of scan angles considered was limited to a maximum of 20° off-nadir (e.g. Naesset 1997; Lovell et al. 2005; Leiterer et al. 2015; Keränen et al. 2016; Roussel et al. 2017) and focused on the impacts of scan angle on ALS point cloud metrics and not on forest attribute predictions derived using these metrics (e.g. Holmgren et al. 2003a; Ahokas et al. 2005; Bater et al. 2011; Montaghi 2013; Roussel et al. 2017, 2018; Dayal et al. 2020). The overall goal of this study was to investigate the effect of ALS acquisition scan angles up to 30° off-nadir on ALS metrics and forest attribute predictions obtained from an ABA applied in a natural forest environment. Based on past research, we first hypothesized that larger scan angles would significantly affect some ALS metrics commonly used in an ABA. We tested this hypothesis by assessing differences in ALS metric values developed using ALS data acquired with near-nadir (nn) and off-nadir (on) scan angles, and also assessed ALS metric values when data from all available flight lines were combined (i.e. aggregated; agg) as commonly used in operational ALS-derived forest inventories. Our second hypothesis was that prediction errors for ABA models of forest attributes developed with on scan angles would differ from those developed with nn scan angles. We tested this hypothesis by comparing performance statistics of ABA models developed using ALS metrics derived with the different scan angle configurations. We developed the ABA models from single flight line metrics (nn or on), as well as from aggregated flight line metrics (agg), in order to assess if systematic bias or uncertainty would be offset when all flight lines were aggregated. We assumed that differences observed for derived ALS metrics or ABA model outcomes under these extreme-case controlled scenarios (nn or on) would inherently impact these metrics and models, relative to a scenario when there are a mix of scan angles, which is commonly the case when ALS acquisitions are used operationally in support of forest inventory applications. Quantifying the influence of scan angle on
Table 1 Earlier studies considering scan angle effects on ALS metrics and/or ABA predictions

| Study | Instrument (configuration; scanning pattern) | Absolute scan angle(s) tested | Overlap with adjacent flightline (%) | What was evaluated? | Forest type (Dominant species) | Results |
|-------|-----------------------------------------------|-----------------------------|------------------------------------|---------------------|-------------------------------|---------|
| Næsset 1997 | Optech ALTM 1020 (DR; seesaw) | 20° | 15% | ABA predictions: mean height | Boreal (Norway spruce, Scots pine) | Off-nadir scan angle coefficient in the regression model were found to be not significant for estimating mean height. |
| Magnussen and Baudrewyn 1998 | Optech ALTM 1020 (DR; seesaw) | 12° | Two parallel double flights (i.e. back and forth) | ABA predictions: stand height | Coastal temperate (Douglas fir) | Cosine correction for scan angle was not successful in improving estimates of stand height. Integrated over angles from -10° to 10°, the average bias introduced by scan angle amounted to 0.5%. Compared with other sources of noise, the authors considered scan angle to be of minor importance. |
| Holmgren et al. 2003a | Simulated data (DR; seesaw) | 30°, in 5° increments | 100% between simulations | ALS metrics: height percentiles and proportion of canopy returns | Simulated pine and spruce | Height percentiles and proportion of canopy returns varied more with increasing scan angle (> 10°) for species with longer crowns (i.e. spruce), and for sparse forests (i.e. < 200 stems/ha). Change of height percentiles due to scanning angle was greater for the lower height percentiles. The proportion of canopy returns was more affected by scanning angle than were the laser height percentiles. |
| Holmgren et al. 2003b | TopEye (DR; helicopter) — Nadir (0–10°) and off-nadir (10–30°) | Overlap between flight lines not specified | ABA predictions: Lorey’s height, crown coverage area | Boreal (Norway spruce, Scots pine, birch) | No significant effect on the estimation of tree heights from both nadir and off-nadir datasets. Underestimation of crown coverage area from off-nadir scanning angles compared to nadir estimates. |
| Ahokas et al. 2005 | Simulated data (DR; helicopter and Optech ALTM 2033 (DR; seesaw) | 15° | Overlap between flight lines not specified | ALS metrics: number of returns classified as ‘ground’ | Boreal (pine, spruce, birch) | A relatively small effect of scan angle on the precision of the ALS-derived DTM was observed and appeared to be highly dependent on the density of the forest. Authors suggested scan angles up to 15° off-nadir for high altitude ALS scanning in boreal forest zones. |
| Lowell et al. 2005 | Simulated data (DR; helicopter) | 5°, 7°, 10°, 15°, 20° | 100% between simulations | ABA predictions: stand height | Simulated plantations (conical and ellipsoidal crowns) | Increasing trend in normalized predominant height difference (NPHD, difference between true and simulated height estimate) with increasing scan angle (e.g. NPHD ∼ 0.12 m at 20°). |
| Su and Bork 2006 | Optech ALTM 2025 (DR; seesaw) | 15°, in 3° increments | Overlap between flight lines not specified | ALS metric: elevation | Temperate (trembling aspen) | Scan angle had relatively little impact on measured errors in elevation. |
| Monsdorf et al. 2008 | TopEye Falcon II (DR; parallel) | 10° | ~50% | ABA predictions: individual tree height, LAI, fractional cover | Coniferous (hemlock pine, mountain pine, Norway spruce, larch) | No significant differences for LAI or tree height estimates for data acquired at different scan angles. Significant differences for fractional cover estimates, but no significant trend with increasing scan angle - but note limited range in angles tested. |
| Disney et al. 2010 | Simulated data (DR, N/A) | 30°, in 5° increments | 100% between simulations | ALS metrics: mean and maximum first-return height | Simulated (downy birch, Scots pine) | Mean first return height generally increased with increasing scan angle by 8% for birch and 19% for pine at a scan angle of 30°. Maximum first-return height generally increased with increasing scan angle, but only for the pine canopy where the maximum height increased significantly by 17% from nadir to 30°. Proposed guide limiting data collection to scan angles < 15° off-nadir. |
| Bote et al. 2011 | TRLS Mark II (DR; seesaw) | 15° | 100% (single repeat flight lines) | ALS metrics: ratio of first returns to last returns | Coastal temperate (Douglas-fir, western red cedar, red alder) | No obvious effect on the ratio of first returns to last returns; however, scan angles were not significantly different between flight lines, indicating the flight profile was consistent during the survey, with scan angle varying by <4°. |
| Karhunen et al. 2011 | Optech ALTM 100 (DR; seesaw) and Leica ALS50 II (DR; sinusoidal) | 11°, 14°, 15°, 32.5° | 55-60% | ABA predictions: vertical canopy cover and angular canopy closure | Boreal (Norway spruce, birch, European aspen, Scots pine) | The low scan angles and low power settings that are typically applied to topographic LiDARs are not suitable for angular canopy closure estimation as they measure in wrong geometry and cannot easily detect small within-crown gaps. Authors suggest if there is a need for a better areal coverage with the same number of scan lines, it is better to increase the acquisition altitude rather than the scan angle. |

(Continued)
Earlier studies considering scan angle effects on ALS metrics and/or ABA predictions

| Study          | Instrument (configuration; scanning pattern) | Absolute scan angle ranges (◦) tested | Overlap with adjacent flight line (%) | What was evaluated?                                      | Forest type (Dominant species) | Results                                                                 |
|----------------|---------------------------------------------|--------------------------------------|--------------------------------------|----------------------------------------------------------|-------------------------------|-------------------------------------------------------------------------|
| Yang et al. 2011 | Simulated data (FW; N/A)                    | 16°                                  | N/A                                  | ALS metrics: heights percentiles P25, P50, P75, P100     | Simulated deciduous (ellipsoidal crowns) | Upper height percentiles (P100) are most affected by off-nadir painting angle, whereas P50 is more stable. Interactive effects of off-nadir painting angle and topography result in larger errors and overestimation of height by as much as 50%. |
| Montaghi 2013  | Leica ALS60 and ALS50-II (DR; sinusoidal)   | 20°                                  | 20%                                  | ALS metrics: point density, distribution, height, layer density, structural descriptor | Boreal (coniferous: Scots pine, Norway spruce) | The majority of metrics commonly used in ABA were relatively unaffected by scanning angles, up to 20° off-nadir. All point density metrics and structural descriptor metrics (vegetation ratio and understory ratio metrics) from scanning angles >10° were significantly different from those derived from nadir (scan angle = 0°). |
| Chen et al. 2014 | RIEGL LMS-Q560 (FW; parallel)               | 15°                                  | 90%                                  | ABA predictions: gap fraction                          | Coniferous (Zingha sp.)       | Gap fraction model was shown to be stable across different off-nadir scan angles. Scan angle effects on the RFDs tend to be negligible, particularly if grid-cell sizes > 5 × 5 m are used. |
| Listerer et al. 2015 | RIEGL LMS-Q680i (FW; parallel)             | 0°–5°, 5–10° and 10–15°             | 50%                                  | ALS metrics: relative-frequency distribution (RFD)     | Young deciduous stands and old evergreen stands | Results indicated that the narrower scan angle range (15°) resulted in slightly more accurate estimates of plot volume (RMSE%: 21–24 vs. 22.5–25) and mean height (RMSE%: 8.5–11 vs. 9–12). |
| Keränen et al. 2016 | Leica ALS70-MA (DR; sinusoidal)              | 15° and 20°                          | 20%                                  | ABA predictions: plot volume and mean height           | Boreal (Norway spruce, Scots pine, birch) | Developed approach to correct for bias in ALS estimates of canopy height by correcting for pulse density and footprint size. Considerable residual bias was observed in the mean height of the canopy surface model as a function of scan angle. No significant effect of scan angle on maximum height. |
| Roussel et al. 2017 | Optech ALTM 3100 (DR; seesaaw)              | 10° and 16°                          | 30% and 50%                          | ALS metrics: mean height of canopy height model, maximum height | Northern hardwood (sugar maple) | Scan angle was an important factor in the foliage profile retrieval, and the optimal scan angle was 20°. RMSE decreased when the scanning angle increased from 0° to 20°, and increased when the scanning angle increased from 20° to 30°. Scan angle combinations of 15° and 25°, and 15° and 30° can improve the foliage profile estimation accuracy. |
| Qin et al. 2017    | Simulated data (FW; N/A)                    | 30°, in 5° increments                | Overlap between flight lines not specified | ALS foliage profile                                   | Simulated deciduous (sola)     | Scan angle was an important factor in the foliage profile retrieval, and the optimal scan angle was 20°. RMSE decreased when the scanning angle increased from 0° to 20°, and increased when the scanning angle increased from 20° to 30°. Scan angle combinations of 15° and 25°, and 15° and 30° can improve the foliage profile estimation accuracy. |
| Liu et al. 2018    | RIEGL LMS-Q680i (DFW; parallel)             | Nadir (0°–7°), small off-nadir (7°–23°), and large off-nadir (23°–38°) | 30–50%                               | ABA predictions: gap fraction, vertical gap fraction profile | Mixedwood (Norway spruce, European beech) | Underestimation of gap fraction amplifies at large off-nadir scan angles. The impact was more severe for plots with discontinuous or sparse canopies where the estimated gap fraction and vertical gap fraction profiles are maximum when observed from nadir, and decrease with increasing scan angle. |
| Roussel et al. 2018 | Optech ALTM 3300 (DR; seesaaw)             | Sampled up to 16°, modelled up to 30° | 30%                                  | ALS metrics: mean, sd, covar, P30, P50, P70, kurtosis, skewness, entropy | Northern hardwood (sugar maple) | More returns in the upper canopy at 30° than 0°. Biases in height metrics can be non-monotonic with respect to scan angle as a function of stand structure. The average overestimation of mean height was 40 cm at 15°. The impact of scan angle depends on forest structure and can therefore be site specific. Authors recommended determining whether or not the effect of scan angle can be ignored on a case-by-case basis, by analyzing each flight line separately and comparing the metrics obtained from different angles. |
| Crespo-Peremarch and Ruiz 2020 | LiteMapper 6800 (FW, parallel)             | Nadir (0°–5°) and off-nadir (15°–20°) | 55–77%                               | ALS metrics: return waveform energy (RWE) ABA predictions: canopy fuel load, canopy height, canopy base height | Mediterranean (Aleppo, maritime pines and cork oak) | RWE had larger associated error when derived from nadir versus off-nadir (RMSE% difference of 15.4%). Predictions of forest fuel variables have slightly higher R² and lower RMSE when derived from off-nadir compared to nadir, for radiometrically uncorrected full-waveform data. |
| Dayal et al. 2020  | Riegl VQ580 (DFW; parallel)                 | 0–10°, 10–20°, 20–30° and 30–40°    | 35–40%                               | ALS metrics: Max, mean, sd, cv, P10, P30, P50, P70, rumple, gap fraction | Riparian ecosystem (up to 33 different species) | Max height and higher height percentiles were relatively more stable than the lower percentiles. Gap fraction and rumple index were affected more by increasing scan angle than sd. |

Note: ABA: Area-based approach; ALS: Airborne laser scanning; DR: discrete return; FW: full waveform; DFW: discretized full waveform; sd: standard deviation of height.
area-based inventory model outcomes in this forest environment can inform operational ALS-based forest inventory programs.

Material and methods

Figure 1 provides an overview of the methodological approach of the study. We collected ground plot data to develop area-based models of six forest inventory attributes: Lorey’s mean height (HGT), diameter at breast height (DBH), basal area (BA), total volume (TVOL), gross merchantable volume (GMV), and aboveground tree biomass (AGB). We selected calibration plot locations to represent varying scan angles from two flight lines: within 4° of nadir in one flight line, and either 11–20° or 21–30° from nadir (low scan angle plots: L), or 21–30° from nadir (high scan angle plots: H) in the second flight line. We computed three sets of ALS point cloud metrics for each ground plot using points from: each flight line (nn and on) and all flight lines combined (agg). We generated three sets of models for each of the L and H plots using the ALS metrics sets, and applied the models to independent validation data. We analysed the effect of scan angle on both the ALS metrics (Experiment 1) and model performance statistics (Experiment 2) from both the L and H datasets.

Study area

Centred at 48.77° N and 58.19° W, the study area is approximately 950 km² and is located in western Newfoundland, Canada.
Located in the eastern extent of the Boreal Shield Ecozone (Marshall et al. 1999), the landscape has a gently undulating to hilly surface, segmented by numerous ponds, lakes and streams. Elevation ranges from 28 m to 638 m above sea level. Forested land is naturally fragmented with bog, barren and ponds. The area is characterized by balsam fir (Abies balsamea (L.) Mill.), black spruce (Picea mariana (Mill.) BSP), eastern larch (Larix laricina (Du Roi) K. Koch), white birch (Betula papyrifera Marsh.), white spruce (Picea glauca (Moench) Voss) and yellow birch (Betula alleghaniensis Britton). The dominant species by volume is balsam fir, which represents more than 90 per cent of the growing stock. Growth conditions are favourable due to the orthic and gleyed podzols; however, the growth season is relatively short from mid-June to the end of September. The forest understory varies with stand density and age, soil conditions, status of regeneration, and silvicultural treatments such as pre-commercial thinning. Understory vegetation can be composed of tree saplings and seedlings, ferns (e.g. Dryopteris carthusiana (Vill.) HP Fuchs) and to a lesser extent ericaceous shrubs (e.g. Kalmia angustifolia L., Rhododendron groenlandicum (Oeder) Kron and Judd, Vaccinium spp.).

**ALS data**

Full waveform ALS data were acquired for the extent of the study area in 2016 (August 15 through September 24) using a RIEGL LMS-Q680i sensor. This sensor has a beam divergence of 0.5 mrad, yielding a footprint of approximately 0.5 m. Flight altitude averaged 1000 m above ground level with an approximate aircraft speed of 100 knots. Data were collected with a field of view of 60° and a minimum 50 per cent overlap between flight trajectories. The ALS acquisition was extended beyond all study area borders to ensure necessary over-edge coverage. A total of 153 flight lines were acquired in a series of parallel flight lines, oriented in a southwest to northeast direction (Figure 2) and distributed to accommodate changes in ground elevation. Less than 2 per cent of the study area was sampled only once (i.e. covered by one flight line) due to variability in terrain, while the remainder of the study area was covered by at least two flight lines. The waveforms were discretized by the data provider (Leading Edge Geomatics, Canada) using the Gaussian pulse estimation computation method (Jutzi and Stilla 2006). Depending on the individual pulse’s target and associated returned energy, the processing yielded a maximum of four discretized returns from each pulse.
Not excluding waterbodies, we calculated the resulting average point density to be 7.3 points m⁻² with a standard deviation of 2.4 points m⁻². ALS returns were classified according to standard LAS specification classes (ASPRS 2013) by the data provider and delivered in LAS 1.2 format.

**Ground plot sample designs**

We collected two independent datasets of ground plots for calibrating and validating models of forest attributes within the study area (Figure 1), each with their respective sample design. The calibration data were collected in 2018 to represent low scan angle plots (up to 20°, the extent examined by most past studies; dataset L) and high scan angle plots (up to 30°, a novelty of our study; dataset H). We selected potential plot locations using a stratified random sampling design guided by ALS predictions of total volume (further described in Section 2.6 of Luther et al. 2019). Of the five forest attributes mapped, total volume (predicted with regression; \( R^2 = 0.91 \); RMSD% = 17.57 per cent; Bias% = -6.27 per cent) best characterized the complete 3D structure of the forest as the computation of total volume was based on all trees and not limited to merchantable trees having a diameter at breast height (DBH) ≥ 9 cm. In order to capture the full range of variability in total volume (3.6–439.9 m³ha⁻¹), we divided the range of volume values into 20 equal strata. We randomly selected two plot locations per strata, one from each scan angle group, L and H. We only established plots at locations where ALS data from two different flight lines were available such that the first was scanned from near nadir (average absolute scan angle of 0° to 4°), and the second was scanned with an absolute off-nadir average scan angle ranging from 11° to 19° for dataset L, and 21° to 30° for dataset H (Figure 3). Furthermore, to ensure plots were sampled with a similar density of pulses, we only included plots that had a point density difference that was less than 1 point m⁻² between the nadir and off-nadir ALS data from first returns classified as vegetation and having heights between 2 and 30 m (min. diff. = 0; max. diff. = 30.9; mean diff. = 10.3; sd diff. = 7.5 per cent relative to the greater total number of points from either \( nn \) or \( on \)). Additionally, we used photo-interpreted species composition (delineated from 25 per cent classes of basal area) to restrict sample selection to balsam fir dominated stands. The field sampling resulted in 40 balsam fir dominated plots, 20 for each of the L and H calibration datasets used in both experiments. Through this sample design, we targeted extreme-case scenarios with respect to scan angle in order to test our hypotheses for both L and H (first and second flight line, Figure 4).

We collected the ground plot data used for validation in 2016 and 2017, following a structurally-guided sampling approach without consideration of scanning angles. This design yielded a more heterogeneous mix of angles in the agg validation ALS data than for agg from both L and H (aggregated flight lines, Figure 4) and is typical of an operational ABA scenario. To guide our design, we used principal components of ALS metrics as a basis for stratification. We constructed a covariance matrix using a suite of 29 ALS metrics consisting of height, density and structural statistics and submitted it to a principal component analysis (PCA) (Frazer et al. 2011; White et al. 2017). As for the calibration data, we restricted the analysis to areas dominated by balsam fir according to photo-interpreted forest inventory stand polygons. We used the first two principal components extracted as a basis for stratification as they accounted for 82.8 per cent of the total variance found within the ALS data. The first component explained 67.9 per cent of the total variance and was positively correlated (\( r = 0.98 \)) with median ALS canopy height as expected per established guidelines (White et al. 2017). Similarly, the second component accounted for 14.8 per cent of the total variance, and was positively correlated (\( r = 0.80 \)) with the coefficient of variation of ALS canopy height. We selected plot locations by dividing the range of values for each PCA component into 10 equal strata and randomly selecting a sample plot location from each combination of PCA strata. In total, we sampled 41 balsam fir dominated plots and used these as independent validation data for our second experiment.

**Ground plot positioning**

We positioned all ground plots used in our study using a Trimble GeoExplorer 6000 series GeoXTM decimeter system with Floodlight satellite shadow reduction technology in order to maximize under canopy GPS accuracy (Trimble Navigation Limited 2011). In order to secure proper initialization, the unit was receiving positions from a minimum of four satellites for a minimum of 5 minutes prior to data capture. We surveyed plot centre locations by averaging 1000 GPS positions collected during a time interval of 25–40 minutes, and post-processed these for differential correction. Base station observation data for post-processing were obtained from the closest reference station which was within 60 kilometres from all plot locations. We observed a mean vertical precision of 1.1 m and 1.0 m, a mean horizontal precision of 0.9 m and 0.9 m, and a mean standard deviation of 1.5 m and 1.2 m from the post-processing of the respective plot locations from the calibration and validation datasets, respectively. We deemed the positional errors to be less than 5 m, which has been shown to not substantially affect ALS-based predictions of forest attributes using plots ranging in size from 300 to 400 m² (Gobakken and Næsset 2008).

**Tree measurements and forest attribute calculations**

We followed plot measurement guidelines established for Canada's National Forest Inventory (NRCan 2008). We established fixed-area circular plots with 11.28 m radius (area of 400 m²) using the ultrasound’s horizontal distance feature of the Postex® instrument (Haglöf Sweden AB, Längsele, Sweden). We recorded species, living status, DBH and height for all merchantable trees on all calibration plots. In addition, we recorded these same attributes on all plots for all trees with a minimum height of 1.3 m for a centred subplot of radius 3.99 m (area of 50 m²). We measured diameters at 1.3 m using a diameter tape and heights using the height vertex feature of the Postex®. We sampled validation plots with the same prescription as the calibration plots with the exception of 18 plots, where we measured heights only for a sample of trees and predicted the remainder. We predicted heights by developing species-specific relationships between DBH and height using...
Forestry

Figure 3 Simplified schematic representing sample design for plot selection of the calibration data with: a) swath breakdown by scan angle for flight line (fl) 3, and location of b) a low scan angle plot, and c) a high scan angle plot. ALS point cloud metrics were computed for each ground plot using points from: each flight line independently (near-nadir (nn) and off-nadir (on)) and all available flight lines combined (aggregated (agg)). Note: schematic is not to scale; flight altitude was consistent for all flight lines averaging 1000 m above ground level with a minimum of 50 per cent overlap between swaths.

Figure 4 Violin plots illustrating the distribution of mean absolute scan angles obtained from first (nn, Valnn) and second (on) single, and aggregated (agg, Valagg) flight line ALS data observed for the calibration (L and H) and validation datasets. Mean (point) and standard deviation (line) are illustrated in red, while the median, interquartile range, percentiles (25th and 75th), minimum, maximum, and outliers are depicted in black by the overlaid boxplots.

The Gompertz function for plot-specific mixed-effects models per Mehtätalo et al. (2015). Height-diameter curves were developed with the lme4 package (Mehtätalo 2018) in the R programming environment (R Core Team 2019).

From these standard measurements, we derived a suite of structural attributes for all plots from all the live tree measurements. As the subplot was 1/8 of the area of the plot, we replicated these measurements seven times (8 repetitions in total) in order to be representative of the plot area. We computed Lorey’s mean height (HGT, in m) as the weighted average of tree heights, weighted by their respective basal areas; DBH (cm), simply as the mean diameter at breast height. We calculated basal area (BA) by summing all individual merchantable tree basal areas within a plot. Similarly, we estimated gross merchantable volume (GMV, in m$^3$ ha$^{-1}$), total volume (TVOL, in m$^3$ ha$^{-1}$) and aboveground tree biomass (AGB, in t ha$^{-1}$) by summing individual tree values estimated with species-specific allometric equations. Regional volume and biomass equations were available from Warren and Meades (1986). For species and cases where coefficients were not available, we used equations from Ker (1974). For AGB, we used national equations from Lambert et al. (2005). We scaled plot estimates for BA, GMV, TVOL and AGB to per hectare estimates.
Effect of scan angle on ALS metrics and ABA predictions

Figure 5 Violin plots illustrating the distribution of forest attributes observed for the calibration (L and H) and validation datasets. Mean (point) and standard deviation (line) are illustrated in red, while the median, interquartile range, percentiles (25th and 75th), minimum, maximum, and outliers are depicted in black by the overlaid boxplots. Note: Lorey’s mean height (HGT); mean diameter at breast height (DBH); basal area (BA); total volume (TVOL); gross merchantable volume (GMV), and biomass (AGB).

ALS plot metrics

We first processed the ALS data to generate a digital terrain model (DTM) with spatial resolutions of 1 m x 1 m using the LTK™ extension (Lim Geomatics 2016) for ArcGIS (ESRI 2016). To do so, we generated a triangular irregular network (TIN) using returns classified as ground obtained from all available flight lines and interpolated a raster surface from the TIN using natural neighbor interpolation. To avoid introducing potential noise throughout our experiments and isolate for an effect of scan angle, we normalized all ALS data (nn, on, agg) to the common DTM. We calculated individual flight line and aggregated ALS metrics for each plot, with a precision of 11 and a scale of 9, with the lidR package (Roussel and Auty 2017) in the R programming environment (R Core Team 2019). For each calibration plot of dataset L and H, we computed three sets of ALS metrics (i.e. predictor variables): i) using ALS points from a single flight line acquired at near-nadir (nn); ii) using ALS points from a second single flight line acquired off-nadir (on), and iii) using aggregated (agg) points from all available flight lines, resulting in three sets of metrics for each of the L (L_{nn}, L_{on}, L_{agg}) and H (H_{nn}, H_{on}, H_{agg}) datasets (b, c) in Figure 3. Absolute off-nadir scan angle averages ranged from 11° to 19° for dataset L, and 21° to 30° for dataset H (Figure 4). Similarly, for each validation plot used in our second experiment, we computed ALS metrics: i) from single flight line ALS data (dataset Val_{fl}) and ii) from aggregated ALS data obtained from all overlapping flight lines (Val_{agg}) (Figure 4). The standard deviation of scan angles was higher for the validation data set compared to the calibration data set. The higher standard deviation is due to the fact that we did not target specific scan angles in the sample design for the validation data. However, since all models were applied to the same set of validation data, comparisons of the associated prediction errors are possible, regardless of the higher standard deviation of scan angles found in the validation data. As suggested by White et al. (2013), we first applied a threshold of 2 m to separate canopy returns from ground and low vegetation returns, which has been demonstrated to be appropriate for the mature boreal forest conditions of our study site (Luther et al. 2019). Further, we applied an upper threshold of 30 m in order to

Based on plot size. The ranges of these structural forest attributes are summarized in Figure 5.
limit erroneous returns that exceeded the maximum tree height in the region (Government of Newfoundland and Labrador 2020). We calculated the average point densities of the first returns (i.e. pulse densities) within these thresholds from the single flight line data to be 2.9 (sd = 1.0) and 3.1 (sd = 1.1) points m⁻² from the calibration and validation plot locations, respectively. The corresponding average point densities from the agg points were 6.1 (sd = 1.9) and 6.4 (sd = 1.8) points m⁻². The total number of individual flight lines contributing to agg averaged 3.1 (sd = 0.2), 2.9 (sd = 0.6), and 3.0 (sd = 0.6) flight lines for $L_{agg}$, $H_{agg}$, and $Val_{agg}$, respectively.

We divided the metrics into four groups commonly used in area-based forest inventory approaches (White et al. 2013): canopy height, vertical structure, density, and cover metrics. The height metrics included minimum, maximum, mean, median, standard deviation and percentiles of return heights (i.e. the height below which a proportion of ALS returns are found, e.g. 95th percentile implies that 95 per cent of ALS returns are lower than this height). The vertical structure metrics comprised statistical measures of skewness, kurtosis, coefficient of variation, vertical distribution ratio (Goetz et al. 2006) and a vertical complexity index (van Ewijk et al. 2011). We calculated the density metrics, by dividing the range of heights from ALS for each plot into 10 equal intervals and calculated the cumulative proportion of returns found in the first nine intervals per Woods et al. (2008). We computed cover metrics by first deriving a canopy height model (CHM) of 1 m x 1 m resolution where each cell was assigned to the maximum height value. Then, at 2 m height intervals, and for heights (z) up to 18 m, we returned the number cells found in the CHM with a height value > z m and divided it by the number of nonvoid cells (Penner et al. 2013). We manually selected a reduced set of metrics from each metric group by first avoiding very highly correlated metrics within each group (Pearson correlation coefficient, r > 0.95) and assessed variable importance during the initial model development. Finally, we retained 13 metrics with a mean decrease accuracy (%IncMSE) > 3 per cent for the final models (Table 2). Figure 6 illustrates the mean and standard deviation of each ALS plot metric grouped by ALS configuration (nn, on, agg) from both L and H datasets.

Forest attribute models

We modelled the relationship between the aforementioned six forest attributes and the ALS metrics obtained from the different ALS configurations (nn, on, agg) within each scan angle group ($L$, $H$) using random forest regression. The non-parametric approach is well known (White et al. 2017) and its application in ALS-based inventories is well established (e.g. Luther et al. 2019). We built random forest models (Breiman 2001) in R (R Core Team 2019) with ModelMap (Freeman and Frescino 2009). ModelMap automates the process of model building by calling upon the randomForest package (Liaw and Wiener 2002). Each random forest model consisted of 500 trees with infinite tree depth. Each tree was developed with a bootstrapped random subset of the calibration data and a random selection of predictors at each node of the tree to determine the split. We then used tuneRF to determine the optimal number of predictor variables to retain at each node (mtry) for each model. The tuneRF algorithm’s default value for mtry is the number of predictors divided by three. The algorithm then searches for the optimal mtry value according to out-of-bag error estimates which varied by attribute. We evaluated the random forest models according to out-of-bag errors during model development.

To evaluate the predictive performance of the forest attribute models, we calculated the coefficient of determination ($R^2$; Equation (1)), root mean square error (RMSE, absolute and relative; Equations (2) and (3), respectively) as a measure of error spread and the average bias (absolute and relative; Equations (4) and (5), respectively):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$

$$\text{RMSE\%} = \frac{\text{RMSE}}{\bar{y}} \times 100$$

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)$$

$$\text{Bias\%} = \frac{\text{Bias}}{\bar{y}} \times 100$$

where n is the number of validation plots, $y_i$ is the observed value for plot i, $\hat{y}_i$ is the predicted value for plot i, and $\bar{y}$ is the mean of the observed variable, i.e. HGT, DBH, BA, GMV, TVOL, or AGB. We repeated the forest attribute modelling with five seeds, generated pseudorandomly, whereby the seeds influenced the selection of samples and predictors for the random forest models.

Experimental design to assess the effects of scan angle

We partitioned our analyses of scan angle effects into two experiments (Figure 1). We first assessed whether effects of scan angle could be observed directly on the stability of the ALS metrics obtained from the different ALS configurations (nn, on, agg) within each group of calibration plots ($L$, $H$) (Experiment 1). We performed an Anderson-Darling test of normality on the metric distributions using the rtest package (Gross and Ligges 2015) in the R programming environment (R Core Team 2019). Since this test indicated that the majority of data did not fit the normal distribution, we used a nonparametric two sample (i.e. paired ALS configurations for each plot within $L$ and $H$) Wilcoxon signed-rank test (WSRT) (Hollander and Wolfe 1999) to assess our null hypothesis ($H_0$) that ALS metrics derived from the three ALS configurations originate from the same population. We further conducted a post-hoc power analysis for the Wilcoxon signed-rank test in G’Power (Faul et al. 2013) to determine the sensitivity of our analysis. We based this analysis on accepting a 5 per cent probability of incorrectly rejecting $H_0$ (i.e. probability of Type I error/true positive) and similarly, accepting a 5 per cent probability of incorrectly failing to reject $H_0$ (i.e. probability of Type II error/false negative). We proceeded to analyse the observed difference in values using statistics of mean difference
Effect of scan angle on ALS metrics and ABA predictions

Table 2 Description of selected ALS metrics

| ALS metrics   | Unit | Description                                                                 |
|---------------|------|-----------------------------------------------------------------------------|
| Height metrics|      |                                                                              |
| MAX           | m    | Maximum height (first returns)                                              |
| P95           | m    | Height of the 95th percentile (first returns)                               |
| MEAN          | m    | Mean height (first returns)                                                 |
| Structural metrics |   |                                                                              |
| SK EW         |      | Skewness (first returns)                                                    |
| COVAR         |      | Coefficient of variation—Standard deviation/mean (first returns)            |
| VDR           |      | Vertical distribution ratio (all returns) (Goetz et al. 2006)                |
| VCI           |      | Vertical complexity index (all returns) (van Ewijk et al. 2011)              |
| Density metrics|     |                                                                              |
| Di            | %    | Percentage of all returns found in bins 1 through i of 10 where bin i       |
|               |      | represents the ith decile height for i = 2, 5, 8 (i.e. D2, D5, D8) (all    |
|               |      | returns) (Woods et al. 2008)                                                |
| Cover metrics |      |                                                                              |
| CCI           | %    | Number of 1 m x 1 m canopy height surface cells that have a height value > 1 |
|               |      | m divided by the number of nonvoid cells for i = 2, 6, 14 (i.e. CC2, CC6,  |
|               |      | CC14) (first returns) (Penner et al. 2013)                                  |

Note: All metrics derived from points with height ≥ 2 m.

(MD; Equation (6)), a measure of bias, and mean absolute difference (MAD; Equation (8)). We further calculated values relative to the observed mean value for each group (MD% and MAD%; Equations (7) and (9), respectively).

\[
MD = \frac{1}{n} \sum_{j=1}^{n} \left( y_{(\text{nn|agg})_j} - y_{(\text{nn|agg})_j} \right)
\]

\[
MD\% = \frac{MD \times 100}{\bar{y}}
\]

\[
MAD = \frac{1}{n} \sum_{j=1}^{n} \left| y_{(\text{nn|agg})_j} - y_{(\text{nn|agg})_j} \right|
\]

\[
MAD\% = \frac{MAD \times 100}{\bar{y}}
\]

where \(y_{(\text{nn|agg})_j}\) is the ALS metric (\(y\)) derived from either \(\text{nn}\), \(\text{on}\) or \(\text{agg}\) for plot \(j\), and \(y_{(\text{nn|agg})_j}\) is the ALS metric (\(y\)) derived from \(\text{nn}\) or \(\text{agg}\) for plot \(j\), where \(n\) is the number of plots and \(\bar{y}\) is the mean for each ALS metric (i.e. MAX, P95, MEAN, SK EW, COVAR, VDR, VCI, D2, D5, D8, CC2, CC6, or CC14), as derived from \(\text{nn}\), and from \(\text{on}\), when considering the \(\text{nn}\) vs. \(\text{on}\) and \(\text{nn}\) vs. agg comparisons and the \(\text{on}\) vs. agg comparison, respectively.

In order to assess the effect of scan angle on forest attribute predictions (Experiment 2), we first made comparisons of \(\text{on}\) and \(\text{agg}\) derived random forest model performance measures with those obtained from a \(\text{nn}\) ALS configuration within each scan angle group. We assessed models developed from single flight line data (models within MS_{L_\text{in}}, MS_{L_\text{on}}, MS_{H_\text{nn}}, and MS_{H_\text{on}}) using the single flight line validation dataset (Val_{\text{fl}}). Similarly, we assessed models developed from aggregated flight line data (models within MS_{L_\text{agg}} and MS_{H_\text{agg}}) using the aggregated flight line validation dataset (Val_{\text{agg}}). We assessed the final model performances by comparing measures (\(R^2\), RMSE%, Bias%) commonly used to evaluate area-based model performance (Piñeiro et al. 2008; White et al. 2017). Furthermore, we calculated prediction errors (PE = observed—predicted) for each forest attribute at each plot location by comparing predicted values from the models constructed for the different ALS configurations to respective observed values. We then subjected prediction errors to repeated measures analyses of variance (RMANOVA) treating the different scan angle groups (\(L\), \(H\)) as fixed effects, and making comparisons of the different ALS configurations (\(nn\), \(on\), \(agg\)) with multivariate tests (Wilks lambda). We calculated effect sizes as generalized eta squared (\(\eta^2\); Olejnik and Algina 2003) and performed post-hoc tests on the effected groups. We used post-hoc analyses using univariate tests (pairwise paired t-test) with a Bonferroni adjustment (Bonferroni 1936) to reveal pairwise differences, between ALS configurations, that were statistically significantly different (\(P < 0.05\)). We tested whether the mean prediction error for each attribute among the ALS configurations was significantly different. In order to determine whether each set of prediction errors met the normality assumptions of RMANOVA, we used the Shapiro–Wilk Test for normality of residuals (Royston 1982) and normal QQ plots. These analyses indicated that all prediction errors fit the normal. The assumption of sphericity was automatically checked and corrected for eventual deviation during the computation of the RMANOVA test. Sphericity is the condition where the variances of the differences between all combinations of the within-subject groups (\(nn\), \(on\), \(agg\)) are equal, where a violation would cause the RMANOVA test to become too liberal (i.e. increase in Type I error) (Howell, 2009). The Greenhouse–Geisser sphericity correction (Greenhouse and Geisser 1959) was automatically applied only to within-subject factors violating the sphericity assumption (i.e. where Mauchly’s test (Mauchly 1940) p-value is significant, \(P < 0.05\)). We performed all analyses of variance using the R-package rstatix (Kassambara 2019). We computed mean prediction errors (MPE; Equation (10)) and mean absolute prediction errors (MAPE; Equation (12)), and further calculated values relative to the observed values...
Figure 6 Boxplots illustrating the distribution of ALS metrics observed from the calibration (for both $L$ and $H$) plots grouped by ALS configuration ($nn$, $on$, $agg$). Mean (point) is illustrated in red, while the median, interquartile range, percentiles ($25^{th}$ and $75^{th}$), minimum, maximum, and outliers are depicted in black by the boxplots.
Table 3 Mean and relative mean difference (MD, MD%) and mean and relative mean absolute difference (MAD, MAD%) and results of the Wilcoxon signed rank test (WSRT) in comparing ALS metrics derived from near-nadir and off-nadir single flight line, and aggregated, ALS data. Values are presented in the units of their respective metric. Significance levels: *** $P < 0.001$; ** $P < 0.01$; * $P < 0.05$; blank = not significant.

| ALS metric | Height metrics | Structural metrics | Density metrics | Cover metrics |
|------------|----------------|-------------------|----------------|--------------|
|            | MAX (m) | P95 (m) | MEAN (m) | SKEW | COVAR | VDR | VCI | D2 (%) | D5 (%) | D8 (%) | CC2 (%) | CC6 (%) | CC14 (%) |
| Low scan angle plots | Differences between near-nadir and off-nadir configuration [on–nn] | | | | | | | | | | | | | |
| MD | 0.14 | -0.02 | -0.08 | -0.02 | 0.01 | 0.01 | 0.01 | 0.03 | 2.85 | 0.82 | 0.01 | 0.17 | -0.03 |
| MD% | 1.04 | -0.14 | -0.98 | 118.86 | 3.40 | 2.33 | 1.43 | 2.66 | 8.12 | 0.89 | 0.01 | 0.23 | -0.28 |
| MAD | 0.33 | 0.12 | 0.16 | 0.09 | 0.01 | 0.02 | 0.01 | 0.54 | 4.71 | 1.86 | 0.01 | 1.60 | 0.51 |
| MAD% | 2.42 | 1.06 | 2.05 | -516.28 | 5.30 | 4.16 | 2.14 | 54.01 | 13.43 | 2.01 | 0.01 | 2.20 | 4.17 |
| WSRT | * | * | * | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| Differences between near-nadir and aggregate configuration [agg–nn] | | | | | | | | | | | | | |
| MD | 0.24 | -0.06 | -0.17 | -0.03 | 0.03 | 0.03 | 0.01 | 2.81 | 4.22 | 1.43 | -1.44 | 1.81 | 1.84 |
| MD% | 1.73 | -0.51 | -2.10 | 140.40 | 13.73 | 5.91 | 1.08 | 280.90 | 12.01 | 1.55 | -1.44 | 2.49 | 15.03 |
| MAD | 0.24 | 0.08 | 0.18 | 0.07 | 0.04 | 0.03 | 0.01 | 2.85 | 4.48 | 1.48 | 1.46 | 0.90 | 0.00 |
| MAD% | 1.73 | 0.77 | 2.29 | -385.70 | 14.07 | 6.20 | 1.43 | 284.72 | 12.75 | 1.60 | 1.46 | 2.60 | 15.05 |
| WSRT | ** | * | ** | *** | *** | *** | *** |*** | *** | *** |*** | *** | *** |
| Differences between off-nadir and aggregate configuration [agg–on] | | | | | | | | | | | | | |
| MD | 0.09 | -0.04 | -0.09 | 0.00 | 0.03 | 0.02 | 0.00 | 2.78 | 1.37 | 0.61 | -1.45 | 1.64 | 1.87 |
| MD% | 0.68 | -0.36 | -1.13 | 9.84 | 10.00 | 3.50 | -0.34 | 271.02 | 3.60 | 0.65 | -1.45 | 2.25 | 15.35 |
| MAD | 0.09 | 0.10 | 0.18 | 0.07 | 0.03 | 0.02 | 0.01 | 2.92 | 2.54 | 0.89 | 1.45 | 2.31 | 1.88 |
| MAD% | 0.68 | 0.95 | 2.32 | -173.81 | 13.00 | 4.35 | 0.89 | 284.39 | 6.70 | 0.95 | 1.45 | 3.16 | 15.42 |
| WSRT | * | * | * | * | ** | ** | ** | ** | ** | ** | ** | ** | ** |
| High scan angle plots | Differences between near-nadir and off-nadir configuration [on–nn] | | | | | | | | | | | | | |
| MD | 0.17 | 0.18 | 0.13 | -0.02 | 0.00 | 0.00 | 0.00 | 0.13 | 0.56 | -0.44 | -0.11 | 0.37 | 0.19 |
| MD% | 1.21 | 1.67 | 1.63 | 500.47 | 0.45 | 0.50 | 0.48 | 7.61 | 1.42 | -0.47 | -0.11 | 0.51 | 1.50 |
| MAD | 0.27 | 0.19 | 0.15 | 0.10 | 0.01 | 0.02 | 0.01 | 0.46 | 4.30 | 1.02 | 0.11 | 1.06 | 0.46 |
| MAD% | 1.96 | 1.72 | 1.88 | -2790.06 | 3.96 | 3.72 | 1.62 | 27.15 | 10.95 | 1.08 | 0.11 | 1.46 | 3.54 |
| WSRT | * | ** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| Differences between near-nadir and aggregate configuration [agg–nn] | | | | | | | | | | | | | |
| MD | 0.22 | 0.07 | 0.05 | 0.00 | 0.00 | 0.01 | 0.00 | 0.14 | 2.05 | 0.28 | -0.02 | 0.97 | 1.20 |
| MD% | 1.59 | 0.66 | 0.60 | 54.81 | 0.54 | 1.89 | 0.36 | 8.17 | 5.22 | 0.30 | -0.02 | 1.34 | 9.28 |
| MAD | 0.22 | 0.09 | 0.07 | 0.05 | 0.01 | 0.01 | 0.00 | 0.26 | 3.08 | 0.53 | 0.02 | 1.32 | 1.20 |
| MAD% | 1.59 | 0.80 | 0.90 | -1473.95 | 2.01 | 2.61 | 0.74 | 15.01 | 7.85 | 0.56 | 0.02 | 1.82 | 9.32 |
| WSRT | *** | *** | ** | ** | ** | ** | ** | ** | ** | ** | ** | ** | ** |
| Differences between off-nadir and aggregate aggregate configuration [agg–on] | | | | | | | | | | | | | |
| MD | 0.03 | -0.11 | -0.08 | 0.02 | 0.00 | 0.01 | 0.00 | 0.01 | 1.49 | 0.72 | 0.10 | 0.60 | 1.00 |
| MD% | 0.18 | -0.39 | -1.02 | -74.22 | 0.09 | 1.38 | -0.12 | 0.52 | 3.75 | 0.76 | 0.10 | 0.83 | 7.67 |
| MAD | 0.03 | 0.12 | 0.08 | 0.05 | 0.01 | 0.01 | 0.01 | 0.24 | 1.84 | 0.76 | 0.10 | 1.24 | 1.04 |
| MAD% | 0.18 | 1.08 | 1.07 | -237.05 | 2.14 | 1.56 | 0.95 | 13.18 | 4.62 | 0.81 | 0.10 | 1.70 | 7.92 |
| WSRT | *** | *** | ** | ** | ** | ** | ** | ** | ** | ** | ** | ** | ** |

for each group (MPE% and MAPE%); Equations (11) and (13), respectively).

\[
MPE = \frac{1}{n} \sum_{j=1}^{n} (y_j - \hat{y}_{\text{nn}(j)})
\]

\[
MPE = \frac{MPE}{\bar{y}} \times 100
\]

\[
\text{MAPE} = \frac{1}{n} \sum_{j=1}^{n} \left| y_j - \hat{y}_{\text{nn}(j)} \right|
\]

\[
\text{MAPE}\% = \frac{\text{MAPE}}{\bar{y}} \times 100
\]

where \( y_j \) is the observed value (y) derived from our tree measurements and forest attribute calculations for plot \( j \), \( \hat{y}_{\text{nn}(j)} \).
is the predicted value (\(\hat{y}\)) derived from either \(nn\), on or \(agg\), from either \(MS_L\) or \(MS_H\), for plot \(j\). \(\hat{y}\) is the mean of the observed value (\(y\)) (i.e. \(HGT, DBH, BA, GMV, TVOL, AGB\)) and \(n\) is the number of plots. In order to understand the magnitude of the differences in MPE tested by the RMANOVA and associated post-hoc analysis, we assessed the differences in MPE and MAPE when derived from either on or and \(agg\) with \(nn\) ALS configurations (e.g. \(MPE_{\text{diff}} = \text{MPE}_{\text{on}} - \text{MPE}_{\text{agg}}\) — \(\text{MPE}_{\text{nn}}\); \(\text{MAPE}_{\text{diff}} = \text{MAPE}_{\text{on}} - \text{MAPE}_{\text{agg}}\) — \(\text{MAPE}_{\text{nn}}\)) and when derived from \(agg\) with an ALS configuration (e.g. \(\text{MPE}_{\text{diff}} = \text{MPE}_{\text{agg}} - \text{MPE}_{\text{nn}}\); \(\text{MAPE}_{\text{diff}} = \text{MAPE}_{\text{agg}} - \text{MAPE}_{\text{nn}}\)) for both \(L\) and \(H\). Similarly, in order to assess the magnitude of differences between predicted forest attributes relative to one another, we assessed the differences in MPE% and MAPE%.

Finally, we highlighted which of these interactions were statistically significant with the results from RMANOVA post-hoc tests.

**Results**

**Scan angle effects on ALS metrics**

The results of the Wilcoxon signed-rank test (Table 3) indicated that the majority of ALS metrics from \(L\) plots were not significantly different (\(P < 0.05\)) when derived from either \(nn\) or \(agg\) ALS data (\(|0–4|\) vs. \(|11–19|\)), with the exception of COVAR. For \(H\) plots, all three height metrics were significantly different (\(P < 0.05\) for \(MAX\); \(P < 0.001\) for \(P95\), MEAN) when derived from \(nn\) or \(agg\) ALS data (\(|0–4|\) vs. \(|21–30|\)). When assessing whether a difference was present between metrics derived from either \(nn\) or \(agg\) ALS data, we observed all metrics to be significantly different (\(P < 0.05\)) from \(L\) plots, with the exception of SKEW, CC2 and CC14. Surprisingly, for this same comparison from the \(H\) plots, we only observed all height metrics and upper cover metrics to be significant differences.
significantly different ($P < 0.001$ for MAX; $P < 0.01$ for P95, MEAN, CC14). Contrastingly, we found the opposite with the agg versus on scenario. Herein, the majority of metrics were not significantly different for L plots, while several metrics were significantly different for H plots. Although we observed extremely large MD% and MAD% for SKEW and D2, the differences were found to be not significant. Of note, the height metrics P95 and MEAN were consistently significantly different from all ALS configurations for
Figure 8 Boxplots illustrating the distribution of prediction errors derived from the application of the developed forest attribute models (from both MS\_L and MS\_H) to the validation plots, grouped by ALS configuration (nn, on, agg). Values are presented in the units of their respective forest attribute and are the average results of each model implemented with five random seeds. Mean (point) is illustrated in red, while the median, interquartile range, percentiles (25th and 75th), minimum, maximum, and outliers are depicted in black by the boxplots.

Assessment of area-based forest attribute models

The model performance measures according to out-of-bag errors for the six model sets are shown in Table 4. Overall, the results indicated high correspondence between predicted and observed values for L plots ($R^2 > 0.80$), with lower correspondence for H plots ($R^2 > 0.69$, with the exception of DBH, which had $R^2 > 0.43$). Errors in prediction were lower for L plots ($\text{RMSE}\% < 24; \text{Bias}\% < 1.5$) and higher for H plots ($\text{RMSE}\% < 35; \text{Bias}\% < 3$). Of particular relevance for this study, we observed minimal variation in model performance for each attribute among the ALS configurations (differences in $R^2 < 0.05$, $\text{RMSD}\% < 2.3$ and $\text{Bias}\% < 1.6$) (Table 3). From these results, we deemed the ALS-based models were sufficiently accurate to be applied to the independent validation data to allow for a meaningful comparison of error statistics between ALS configurations within each calibration dataset (Experiment 2).

Scan angle effects on area-based model performance

We applied the L and H models fitted with ALS metrics derived independently from the ALS configurations to all 41 validation plots. Figure 7 illustrates the model performance measures of MS\_L and MS\_H for all ALS configurations assessed with the independent validation plots. Model performance measures showed minimal variation by ALS configuration within each attribute and model set (differences in $R^2 < 0.03$, $\text{RMSE}\% < 2$ per cent, $\text{Bias}\% < 3.5$ per cent from MS\_L; differences in $R^2 < 0.07$, $\text{RMSE}\% < 1.7$ per cent, $\text{Bias}\% < 2.9$ per cent from MS\_H). Although, coefficients of determination were particularly stable for each attribute regardless of the ALS configuration or model set, we observed consistently lower $R^2$ from models developed...
with an ALS metrics in comparison with those developed from nn ALS metrics, with the exception of BA from MS_Lagg. We observed slightly higher RMSE% (increases ≤2 per cent) for most attributes derived from on in comparison to those derived from nn with the exception of HGT from MS_L and HGT, GMV and TVOL from MS_H, for which we observed slight decreases (decreases <0.5 per cent). Associated Bias% were variable for MS_Lon and was consistently lower from all attributes predicted from MS_Hon. Similarly, when comparing the model performance measures derived from agg with those derived from nn, $R^2$ remained very stable (differences in $R^2$ ≤ 0.03). We observed marginally higher RMSE% (decreases <1.5 per cent) for most attributes predicted from both MS_Lagg and MS_Hagg and Bias% (decreases <3.5 per cent). Associated Bias% were all higher from MS_Lagg, and variable by attribute predicted from MS_Hagg.

In summary, $R^2$’s remained very stable regardless of the ALS configuration or model set, while values for bias and RMSE were generally lower for nn than for on or agg for L plots. Similarly, for H plots, values for RMSE were marginally lowest when derived from nn; however, in contrast, biases were lowest when derived from on.

Figure 8 illustrates the distribution of prediction errors resulting from the different ALS configurations within each forest attribute of each model set. Except for DBH and BA from MS_L and BA from MS_H, the RMANOVA indicated that the mean prediction errors were significantly different for all other attributes (Table 5; $P < 0.05$) and hence an effect of ALS configuration was observed, albeit for very small effect sizes ($\eta^2 G > 0.01$).

Table 6 denotes the differences in relative and absolute MPE and MAPE when derived from either on and agg compared to nn, and from agg compared to on ALS configurations, as well as the results of the pairwise comparison post-hoc analysis. Although no trend was apparent in significance of the pairwise comparisons from either modelset (MS_L or MS_H), the relationship between on and nn prediction errors were significantly different ($P < 0.05$) for GMV, TVOL and AGB from MS_L and HGT, DBH and GMV from MS_H. From the agg and nn comparison, we observed prediction errors from half of the six predicted attributes from MS_L (HGT, GMV, TVOL) to be significantly different ($P < 0.05$), while surprisingly, only HGT from MS_H. As for the agg and on comparison, we found prediction errors from HGT from MS_L, and from GMV, TVOL and AGB from MS_H to significantly differ ($P < 0.05$ and $P < 0.01$, respectively). Of note, differences in mean absolute prediction errors relative to the ground measurements (MAPE%diff) from models developed from Lagg plots, in comparison with those derived from Lon plots, were slightly higher than from H plots (≤1 per cent) (based on $|$MAPE%diff$|$).

Discussion

Scan angle effects on ALS metrics

In the context of previous research, we hypothesized that some ALS metrics derived from data acquired with off-nadir scan angles would be significantly different from metrics derived using ALS data acquired with near-nadir scan angles (within 4° of nadir). The literature demonstrates contrasting findings with respect to the effect of scan angle and specific ALS metrics. Consistent with the work of Montaghi (2013), we found no significant difference in ALS metrics generated using ALS data with nn or on L scan angles ([11–19]), with the exception of COVAR from the vertical structure metrics group. Contrary to our results, Yang et al. (2011) demonstrated that the error for the vegetation height metric RH100 (i.e. MAX) ranged from 2 m to >12 m for a 20° off-nadir scan angle for simulated waveform data in simulated deciduous forests. Consistent with our results, and contrary to Yang et al. (2011), Roussel et al. (2017), using discrete return ALS in real deciduous forests, found no significant effects of scan angle on MAX for scan angles up to 16°. Disney et al. (2010) found that MAX and MEAN generally increased with increasing scan angle from nadir to 30°, by 0 per cent and 8 per cent, respectively, for simulated birch canopies; and by 17 per cent and 19 per cent, respectively, for simulated pine canopies. In our study, we found MAX, P95, and MEAN increased significantly from values for nn observations when generated using ALS data with on H scan angles (21–30°), albeit for a minimal amount (MAD <0.3 m).

These results highlight the dependency of scan angle effects on site specific forest structure. It is known that crown shape affects the interception of laser pulses within forest canopies (e.g. Lovell et al. 2005). Nelson (1997) demonstrated that as canopy shape progressed from a conic form to a more spheric structure, average canopy height, canopy profile area, and canopy volume increased, canopy height variation decreased, and coefficients of variability remained stable or decreased. Similarly, in assessing the effect of scan angle on height percentiles, Holmgren et al. (2003a) simulated pine and spruce stands with digitally reconstructed solid trees (i.e. impermeable to pulse beam penetration) and found more variation associated with species that have longer crowns (i.e. spruce) and sparse forests. Plots in our study were sampled in natural, predominantly single-layered, balsam fir stands. Balsam fir trees have symmetrical spike-like crowns, which taper gradually to a narrow conical spire-like top, allowing for more penetration of the laser pulse through the canopy. Further, the natural forest environment (i.e. non-simulated; permeable to pulse beam penetration) increased the probability of penetration of laser beams through openings in the forest canopy, hence facilitating sampling by the ALS.

Broader scan angles (i.e. >15°) increase the probability of upper canopy vegetation returns and decrease the likelihood of obtaining ground returns (Hopkinson et al. 2005; Montaghi 2013). Research has demonstrated patterns relating bias to scan angle to be most prominent for point density and structural descriptor metrics that are calculated with ground returns (e.g. understory ratio, vegetation ratio (Montaghi 2013); gap fraction, vertical gap fraction profile (Liu et al. 2018)). In our study, all structural and density metrics from both L and H, with the exception of COVAR from L, were not significantly different when generated from nn or on ALS data; the computation of the ALS metrics used in our analysis excluded returns below 2 m, and hence, excluded ground returns.

Any potential effects associated with larger scan angles are frequently offset by maintaining sufficient overlap between flight lines and using aggregated flight line data (Evans et al. 2009). When we compared ALS metrics from H, we found that height metrics P95 and MEAN were significantly different not only for the
Table 6 Differences in relative and absolute mean prediction errors (MPE) and mean absolute prediction errors (MAPE) when derived from either on and agg compared to nn, and from agg compared to on ALS configurations, as well as the results of the pairwise comparison (pwc) RMANOVA post-hoc analysis. Forest attributes for which differences in mean prediction error among the ALS configurations, within L or H, were deemed significant from pwc are indicated with asterisks (***P < 0.001; **P < 0.01; *P < 0.05; blank = not significant; n/a = not applicable).

| Forest attribute | HGT (m) | DBH (cm) | BA (m² ha⁻¹) | GMV (m³ ha⁻¹) | TVOL (m³ ha⁻¹) | AGB (t ha⁻¹) |
|------------------|--------|---------|--------------|---------------|----------------|--------------|
| Models developed from low scan angle plots |        |         |              |               |                |              |
| Differences between near-nadir and off-nadir configuration [on—nn] |        |         |              |               |                |              |
| MPEdiff          | 0.05   | 0.10    | −0.27        | −5.04         | −4.17          | −0.05        |
| MPE%diff         | 0.39   | 0.89    | −0.71        | −2.35         | −1.65          | −0.04        |
| MAPEdiff         | 0.00   | 0.03    | 0.11         | 2.23          | 2.02           | 0.04         |
| MAPE%diff        | −0.01  | 0.30    | 0.29         | 1.04          | 0.80           | 0.03         |
| pwc              | n/a    | n/a     |              | ***           | *              |              |
| Differences between near-nadir and aggregate configuration [agg—nn] |        |         |              |               |                |              |
| MPEdiff          | −0.10  | −0.11   | −0.08        | −7.34         | −6.78          | −2.18        |
| MPE%diff         | −0.81  | −0.98   | −0.22        | −3.43         | −2.68          | −1.41        |
| MAPEdiff         | 0.07   | 0.07    | −0.21        | 2.00          | 3.16           | 0.22         |
| MAPE%diff        | 0.54   | 0.64    | −0.55        | 0.93          | 1.25           | 0.14         |
| pwc              | *      | n/a     | n/a          | ***           | *              |              |
| Differences between aggregate and off-nadir configuration [agg—on] |        |         |              |               |                |              |
| MPEdiff          | −0.15  | −0.22   | 0.19         | −2.31         | −2.61          | −2.12        |
| MPE%diff         | −1.20  | −1.86   | 0.50         | −1.08         | −1.03          | −1.38        |
| MAPEdiff         | 0.07   | 0.04    | −0.33        | −0.23         | 1.14           | 0.17         |
| MAPE%diff        | 0.55   | 0.35    | −0.84        | −0.11         | 0.45           | 0.11         |
| pwc              | *      | n/a     | n/a          | ***           | *              |              |
| Models developed from high scan angle plots |        |         |              |               |                |              |
| Differences between near-nadir and off-nadir configuration [on—nn] |        |         |              |               |                |              |
| MPEdiff          | 0.27   | 0.33    | 0.38         | 6.56          | 3.57           | 2.78         |
| MPE%diff         | 2.26   | 2.84    | 0.98         | 3.06          | 1.41           | 1.80         |
| MAPEdiff         | −0.04  | 0.14    | 0.30         | −0.67         | 0.28           | 0.68         |
| MAPE%diff        | −0.30  | 1.20    | 0.78         | −0.31         | 0.11           | 0.44         |
| pwc              | ***    | **      | n/a          | ***           | ***            |              |
| Differences between near-nadir and aggregate configuration [agg—nn] |        |         |              |               |                |              |
| MPEdiff          | 0.20   | 0.13    | −0.01        | 0.50          | −0.37          | −0.45        |
| MPE%diff         | 1.63   | 1.09    | −0.02        | 0.23          | −0.15          | −0.29        |
| MAPEdiff         | 0.04   | 0.05    | 0.10         | 1.24          | 0.63           | 0.11         |
| MAPE%diff        | 0.34   | 0.41    | 0.26         | 0.58          | 0.25           | 0.07         |
| pwc              | **     | n/a     |              | ***           | ***            |              |
| Differences between aggregate and off-nadir configuration [agg—on] |        |         |              |               |                |              |
| MPEdiff          | −0.08  | −0.20   | −0.39        | −6.06         | −3.94          | −3.23        |
| MPE%diff         | −0.63  | −1.75   | −1.00        | −2.83         | −1.56          | −2.10        |
| MAPEdiff         | 0.08   | −0.09   | −0.20        | 1.91          | 0.34           | −0.57        |
| MAPE%diff        | 0.64   | −0.79   | −0.51        | 0.89          | 0.14           | −0.37        |
| pwc              | n/a    | **      |              | **            | **             |              |

Note: Positive values indicate larger MPE or MAPE from models generated using metrics derived from either on and agg for the [on—nn] or [agg—nn] differences and from agg for the [agg—on] differences.

nn and on comparison, but consistently for all ALS configuration comparisons (nn vs. on, nn vs. agg, agg vs. on). Surprisingly, we observed all metrics with the exception of SKEW, CC2, and CC14 were significantly different when derived using nn versus agg ALS configurations from L, whereas this same trend was not apparent from H. Possibly this is because the distribution of angles within Lagg were more mixed (i.e. less clustered at the extremes of the range assessed ([0–20°])) when compared to those in Hagg (i.e. clustered around 0° and 25°) (Figure 4). The probability of canopy interception is known to increase with larger scan angles (Goodwin et al. 2007), and it was not surprising that we observed consistently, for both L and H, more accurate sampling
of maximum height by combining all available flight lines (agg) in comparison with ALS data acquired from nn (MD = 0.22–0.24 m).

Post-hoc power analysis determined an associated large effect size of 0.87, indicating that if the means of the metrics being compared do not differ by 0.87 standard deviations or more, the difference in metric values is considered inconsequential, even if it is statistically significant. In our analysis, all metrics from the various ALS configurations differed by <0.87 standard deviations and hence, all significant differences found between metrics can be considered inconsequential. Nonetheless, differences that were deemed as significant from the WSRT provide evidence that the distribution of median values for that given ALS metric is shifted to the left or right from the other. It is therefore important to consider not only whether there was a shift in the population’s distribution, but also the magnitude of differences being observed (absolute and relative MD, MAD) in the interpretation of the results. Given this, we confirmed our stated hypothesis that larger scan angles would significantly affect some ALS metrics commonly used in an ABA. We found that specific ALS metrics derived from on scan angles (as well as some metrics derived with agg), differed significantly, albeit minimally, from those derived with nn scan angles.

Scan angle effects on area-based model performance

Our second hypothesis was that prediction errors for ABA models of forest attributes developed with on scan angles, including agg, would differ from those developed solely with nn scan angles. We expected that the use of ALS metrics developed with large on scan angles would significantly affect predictions of forest attributes derived from an ABA. This expectation was based on previous studies and guidelines that cautioned the use of ALS data acquired with large on scan angles (> 15°) for forest characterization (Ahokas et al. 2005; Disney et al. 2010; Laes et al. 2008). In our study, we found significant variations, albeit trivial, in ALS metrics derived from the three ALS configurations. The variations in ALS metrics did have an effect on prediction errors associated to certain attributes; however, significant differences in mean absolute prediction errors were all <1.3 per cent.

Interestingly, although the observed biases in the ALS metrics were all deemed trivial, we found them to be inherent in the area-based prediction errors. The RMANOVA indicated that the mean prediction errors were significantly different for all attributes (P < 0.05) for a very small effect size (g^2G ≤ 0.006) with few exceptions, and hence an effect of ALS configuration was observed for most predicted attributes. Naesset (1997) reported no significant effect of scan angle using regression to estimate stand height (i.e. mean height) for boreal forests using ALS data acquired with scan angles up to 20° off-nadir. Surprisingly, we found smaller prediction errors when we predicted HGT (MS_L) from on relative to when predicted from nn, with an associated bias of 0.05 m (MPE_diff). The latter reported bias is however consistent with findings of Lovell et al. (2005), who similarly observed a slightly larger bias of 0.12 m in predicting stand height using simulated ALS data acquired at 20° off-nadir. Moreover, Keränen et al. (2016) demonstrated that the narrower scan angle range, 15° compared to 20°, resulted in slightly more accurate predictions of mean height (RMSE%: 8.5–11 vs. 9–12 per cent) and plot volume (RMSE%: 21–24 vs. 22.5–25 per cent). This trend was consistent with our results in predicting TVOL from MS_L (|0–4|° compared to |11–19|°, with RMSE% of 21.36 vs. 22.59 per cent respectively, and contradictory in predicting HGT with RMSE% of 11.36 vs. 11.27 per cent, respectively. The innovative aspects of our study, namely the larger range of scan angles we assessed and the diversity of forest attributes included in our analyses, make direct comparisons with past research challenging. Nonetheless, consistent with our findings in predicting HGT from MS_H, Holmgren et al. (2003b) found no significant effect on the prediction of height from both nadir (|0–10|°) and off-nadir (|10–30|°) simulated ALS datasets.

Finally, and of practical interest, we found no significant evidence that using aggregated flight line metrics would offset any potential systematic bias or uncertainty introduced by using wider scan angles in the forest attributes we assessed. In fact, we found significantly larger prediction errors in the predictions of HGT, GMV, and TVOL from MS_Lagg than MS_Lnn, although these differences were minimal (MAPE%diff ≤ 1.25 per cent). We observed the same for HGT from MS_H, albeit for a difference in MAPE of only 0.04 m (MAPE%diff 0.34 per cent). We also found significant differences in prediction errors associated to HGT predicted from MS_L, and GMV, TVOL and AGB from MS_H in comparing observations from agg with those obtained from on, albeit for a maximum MAPE%diff of <1 per cent. We therefore confirmed our hypothesis that prediction errors for ABA models of specific forest attributes developed with on scan angles, including models developed with agg, differed, although minimally, from those developed with nn scan angles.

Experimental considerations

Throughout our experiments, we assumed that if we observed no or minimal impact on derived ALS metrics or ABA model outcomes under our extreme scan angle scenarios (nn, on), we would not expect there to be an impact when we have a mix of scan angles, which manifest in typical ALS acquisitions in support of forest inventory applications. In real-world ABA applications, ALS metrics are commonly derived from ALS data obtained with 2 overlapping flight lines. For our plot dataset, ALS metric were generated using data from up to 4 overlapping flight lines. Since these data were acquired at varying scan angles, it is difficult, if not impossible, to isolate the effects of scan angle when using aggregated flight line data. We therefore attempted to isolate the impact of scan angle by deriving metrics using only a single flight line of data (nn, on) and keeping all other experimental considerations constant, including height normalization of the point clouds. We normalized all data to a common DTM, derived from aggregated flight line data, which would be the case for an operational EFI using an ABA. We therefore assessed the effect of scan angle with respect to how ALS sampled the canopy only from the varying angle groups, and further assessed whether these effects, if any, would be inherent in the ABA predictions of forest attributes.

In order to assess the effect of scan angle on the stability of ALS metrics, the target must be sampled in the same manner from all the various ALS configurations. Commonly used oscillating mirror mechanisms yield a seesaw scanning pattern and tend
to accumulate points at the swath boundaries, the end of a laser system's arc, as it reverses direction (Balsa-Barreiro and Lerma 2014). Ultimately, it is the spatial point distribution on the target area that provides information about the real quality of the data: a uniform point pattern will yield reliable sampling of the target, while an irregular point pattern produces inconsistent sampling and hence less stable information and derived ALS metrics. Lovell et al. (2005) confirmed this by simulating ALS data with a seesaw scanning pattern and demonstrated that maximum tree height retrieval is less accurate at the scanned swaths edges due to uneven spacing in sampling. ALS systems which uses a rotating mirror, as is the case with the RIEGL LMS-Q680i sensor used in this study, yield uniform parallel sampling patterns throughout the sampled swath (RIEGL Laser Measurement Systems 2012) and hence minimize uneven spacing in sampling at the swath's edge. Nonetheless, when considering establishing a plot representing an on scan angle of 30°, we had to ensure that the full extent of tree heights were sampled for all trees within the plot. Theoretically, the pulses would potentially not sample the height extent of trees at this extreme angle. In our dataset, one plot represented an average on scan angle of −30°. At this location, we observed 42 per cent of points acquired from −29°, and the remainder from −30°, hence not sampling the extreme swath boundary but rather sampling the extremity of data acquired at −29°. Using trigonometry, we calculated the swath width to be 1154.7 m, of which 23 m is associated to data acquired at −30°. Given the proportion of the plot sampled from −30° (58 per cent) and the plot radius, the minimum distance from the swath's edge to the plot's perimeter was calculated to be 10 m. We determined the theoretical maximum height at this location to be 17.3 m. As the ground measured maximum tree height for this plot was 15.5 m (i.e. < 17.3 m), we can assume that despite this plot's position near the edge of the swath, the ALS uniformly sampled the height extent of all trees in the plot representing an on scan angle of −30°. This demonstrates that the scanning mechanism of the ALS instrument and uniformity in horizontal sampling must also be considered when examining the effects of scan angle.

In establishing ground plot locations, it was also important to consider proximity to the nearest base station. Ten ground plots exceeded national guidelines (Donohue et al. 2013) which suggest establishing control points within 50 km of survey locations; nonetheless all plots were within 60 km from the nearest reference base station. We did not consider the potential positional errors to be a limiting factor in our study as the ALS metric pairs being compared, and associated forest attribute prediction errors, were derived from the same location, slightly miss-positioned or not.

Although Goodwin et al. (2007) demonstrated that the effects of topography on the probability of interception in the canopy and ground surface were most evident at scan angle ranges greater than 15°, Ørka et al. (2018) concluded that terrain effects, including slope and aspect, were negligible in operational ALS-derived forest inventories for slopes ranging up to 43°. As with our analysis, the latter study derived ALS metrics from returns with a height threshold > 2 m. For that reason, we did not consider topography in our sample designs and did not consider slope to be a limiting factor in our study because our ground plot data consisted of slopes ranging from 0°–26° (mean = 7.7, 3.9, 9.1; min. = 2.3, 0, 0.5; max. = 20.6, 24.1, 26.5; sd = 5.0, 5.1, 6.5 degrees for L, H, and validation datasets, respectively).

Finally, we also considered the possible effects of the time lag between the ALS data acquisition and ground plot sampling which were of 1–2 growing seasons. In our study area, the growing season is relatively short from mid-June to the end of September and growth rates are slow. As long as growth is similar across our study area, we would not expect the time lag to affect the results. However, since growth is dependent on site productivity, non-uniform increases in growth between plots may be present. Since we calibrated the 2016 acquired ALS data with measurements sampled in 2018 and applied the developed models to ground plots sampled in 2016–2017, we would expect a slight bias in predicted attributes from growth alone. Therefore, it is possible that a portion of the observed prediction errors could be attributed to the aforementioned temporal discrepancies between ALS acquisition and ground sampling. However, at the plot level, error associated with growth would be uniform across all predicted attributes, regardless of the model set or ALS configuration, thus permitting assessments of the effect of scan angle on ALS metrics and model predictions.

Implications of scan angle on area-based forest inventory

Understanding and quantifying scan angle effects can aid in guiding acquisition efforts and refining forest attribute predictions by identifying those metrics that are sensitive to scan angle. Large off-nadir scan angles can reduce acquisition costs because more area can be sampled in a single flight line, and flying time is reduced. However, acquisition parameters are related, and no single factor can be considered in isolation (Montaghi 2013). Previously, and based on technology available at the time, recommendations from the literature focused on scan angle for forest applications to <15° (Ahokas et al. 2005; Disney et al. 2010; Laes et al. 2008). ALS technology has evolved rapidly over the past two decades, as have other associated technologies that are integral to ALS data acquisition and processing (e.g. global positioning systems, inertial measurement unit, gyro-stabilized mount, etcetera). These advancements in technology have contributed to acquisition efficiencies and higher point densities (Jakubowski et al. 2013). Nonetheless, researchers have used ALS data acquired at scan angles exceeding these recommendations to successfully predict forest attributes from these data. Luther et al. (2019) predicted Lorey's mean height, basal area, volume and AGB explaining over 83 per cent of the variability of the response data (RMSD% < 26 per cent) using the ALS data analyzed in this study. Similarly, Cao et al. (2016) used ALS data acquired within 30° of nadir to predict Lorey's mean height (R2 0.84; RMSE% 8.28 per cent) and AGB (R2 0.74; RMSE% 15.21 per cent) in secondary subtropical dominated forests. Guerra-Hernández et al. (2016) modelled a set of forest stand variables for 4 different forest types (pure stone pine, mixed, maritime pine, and Pyrenean oak) using ALS data acquired at scan angles up to 50° from nadir and explained 61–85 per cent, 67–98 per cent and 74–98 per cent of the variability in ground-truth stand height, basal area and volume, respectively (associated range in RMSE% of 6.01–20.42 per cent, 7.95–32.62 per cent and 8.9–31.95 per cent, respectively). The success of
more recent studies using scan angles >15° could be partially due to the advancements in ALS and associated technologies. Although single flight line ALS metrics have previously been demonstrated to support model development of forest attributes (e.g. Luther et al. 2014), for the purpose of calibrating satellite imagery (e.g. McInerney et al. 2010), and/or upscaling to a large-area inventory (e.g. Wulder et al. 2012), it is more common practice to use ALS metrics derived from multiple adjacent flight lines for predicting forest attributes in support of operational forest inventories (White et al. 2013). Maintaining overlap between flight lines not only prevents data gaps and enables higher pulse densities from multiple look angles (providing a more complete 3D sampling of any given object), it also increases the likelihood of ground returns in dense forest canopy (Ahokas et al. 2005) or in steep topography (Lin et al. 2013). Adjoining flight lines also enable co-registration to remove swath biases. Our analysis demonstrated a benefit in aggregating ALS data from overlapping flight lines as we observed the maximum canopy height to be best captured from off-nadir scan angles, further supporting established guidelines (e.g. White et al. 2013) of maintaining >50 per cent overlap between flight lines. Negative values of MPE_diff from MS_Lagg indicate the prediction errors are less when the attributes are predicted with agg obtained from scan angles up to 20° off-nadir than from MS_Lan, (significant for HGT, GMV, TVOL) or MS_Lon (significant for GMV, TVOL, AGB) for the majority of attributes (Table 6). Similarly, we observed smaller prediction errors by including the large off-nadir scan angles up to 30° from MS_Hagg than from MS_Hon (significant for GMV, TVOL, AGB). When comparing prediction errors from MS_Hagg with those from MS_Hon, the trend is consistent for TVOL and AGB; however, these relationships were not deemed significant from the pairwise comparison tests. Although not always deemed significant, prediction errors were actually larger for HGT, DBH and GMV when derived from MS_Hagg than from MS_Hon, which is indicative of no improvement in model predictions for these attributes by including large off-nadir (> 20°) acquired ALS data.

Conclusion

In this study, we hypothesized that specific ALS metrics derived from data acquired with large off-nadir scan angles up to 30° would be significantly different from ALS metrics derived using data acquired with near-nadir scan angles and that these differences would inherently affect ABA predictions of forest attributes. A major finding of this study is that the ALS acquisition parameter scan angle significantly affected (P < 0.05) specific single flight line metrics from both [11–19° (L); namely COVAR] and [21–30° (H); namely MAX, P95, MEAN] off-nadir scan angles but that the effects, although statistically significant, were inconsequential. Forest attribute predictions using these and other metrics were also significantly affected (P < 0.05), namely GMV, TVOL and AGB from L, and HGT, DBH and GMV from H. We further demonstrated that combining ALS data from all available adjacent flight lines significantly (P < 0.05) increased accurate measurement of maximum canopy height from both L and H relative to measurements derived from single flight line data. Although prediction errors increased when derived from aggregate ALS data in comparison to those derived from single flight line near-nadir ALS data for

the predictions of HGT, GMV and TVOL from L, and significantly reduced errors for HGT from H, the significant differences in mean absolute prediction errors were all <1.3 per cent. Based on these findings, we conclude that the influence of large scan angles, up to 30° off-nadir, on area-based forest attribute predictions were minimal in this study which used ALS metrics based exclusively on ALS returns >2 m for balsam fir dominated forests. These results suggest that larger ALS acquisition scan angles could be used in these forest types with minimal impacts on area-based model outcomes, enabling operational efficiencies for implementing enhanced forest inventories in these forest environments.

Data availability statement

The data underlying this article will be shared on reasonable request to the corresponding author.

Acknowledgements

The authors are grateful to forest technicians Jody Nicholas, Kieran Smith, and Whitney Swyers for their assistance in collecting the ground plot data. We thank the journal’s Associate Editor and two anonymous reviewers for their constructive feedback and suggestions for improving the manuscript.

Conflict of interest statement

The authors declare no conflict of interest.

Funding

This work was supported by the Canadian Forest Service—Canadian Wood Fibre Centre; and the Assessment of Wood Attributes using Remote Sensing Project (National Sciences and Engineering Research Council of Canada Collaborative Research and Development Grant PJ-462973-14, grantee Nicholas C. Coops, UBC); in collaboration with Corner Brook Pulp and Paper Limited; the Université de Sherbrooke; and the Newfoundland and Labrador Department of Fisheries and Land Resources.

References

Ahokas, E., Yu, X., Oksanen, J., Kaartinen, H. and Model, D.T. 2005 Optimization of the scanning angle for countrywide laser scanning. In Proceedings of the ISPRS Workshop on Laser Scanning 2005. International Society of Photogrammetry and Remote Sensing (ISPRS), Enschede, the Netherlands, pp. 115–119.

ASPRS 2013 Las specification 1.4 R13. The American Society for Photogrammetry & Remote Sensing. Methesda, Maryland, p. 28.

Balsa-Barreiro, J. and Lerma, J.L. 2014 A new methodology to estimate the discrete-return point density on airborne LiDAR surveys. Int. J. Remote Sens. 35, 1496–1510.

Bater, C.W., Wulder, M.A., Coops, N.C., Nelson, R.F., Hilker, T. and Næsset, E. 2011 Stability of sample-based scanning-LiDAR-derived vegetation metrics for forest monitoring. IEEE Trans. Geosci. Remote Sens. 49, 2385–2392.

Bonferroni, C.E. 1936 Teoria statistica delle classi e calcolo delle probabilità. Pubblicazioni del R Istituto Superiore di Scienze Economiche e Commerciali di Firenze, 8, 3–62.
Breiman, L. 2001 Random forests. Mach. Learn. 45, 5–32.
Cao, L., Coops, N.C., Innes, J.J., Sheppard, S.R.J., Fu, L., Ruan, H. et al. 2016 Estimation of forest biomass dynamics in subtropical forests using multi-temporal airborne LiDAR data. Remote Sens. Environ. 178, 158–171.
Chen, X.T., Disney, M.I., Lewis, P., Armstrong, J., Han, J.T. and Li, J.C. 2014 Sensitivity of direct canopy gap fraction retrieval from airborne waveform LiDAR to topography and survey characteristics. Remote Sens. Environ. 143, 15–25.
Cohen, J. 1988 Statistical power analysis for the behavioral sciences. 2nd edn. Lawrence Erlbaum Associates, Hillsdale, NJ, USA, p. 567.
Crespo-Peremarch, P. and Ruiz, L.A. 2020 A full-waveform airborne laser scanning metric extraction tool for forest structure modelling. Do scan angle and radiometric correction matter? Remote Sens. (Basel) 12, 292.
Dayal, K.R., Durrieu, S., Alleaume, S., Revers, F., Larmanou, E., Renaud, J.-P. et al. 2020 Scan angle impact on LiDAR-derived metrics used in ABA models for prediction of forest stand characteristics: a grid-based analysis. In Proceedings of the Int. arch. photogramm. remote sens. spat. inf. sci. Copernicus Publ. (XLIII-B3–2020). International Society for Photogrammetry and Remote Sensing, Germany, Göttingen, pp. 975–982.
Disney, M.I., Kalogirou, V., Lewis, P., Prieto-Blanco, A., Hancock, S. and Pfeiffer, M. 2010 Simulating the impact of discrete-return LiDAR system and survey characteristics over young conifer and broadleaf forests. Remote Sens. Environ. 114, 1546–1560.
Donahue, B., Wentzel, J. and Berg, R. 2013 Guidelines for RTK/RTN GNSS Surveying in Canada. Ver. 1.1. Natural Resources Canada, Ottawa, ON, Canada, p. 29.
Evans, J., Hudak, A., Faux, R. and Smith, A.M. 2009 Discrete return LiDAR in natural resources: Recommendations for project planning, data processing, and deliverables. Remote Sens. (Basel) 1, 776–794.
ESRI 2016 ArcGIS Desktop (Release 10.4) [Computer software]. Environmental Systems Research Institute, Redlands, CA, USA.
Faul, F., Enderfelder, E., Buchner, A. and Long, A.-G. 2013 G-POWER (Version 3.1.7) [Computer software]. Universität Kiel, Germany.
Frazer, G.W., Magnusson, S., Walder, M.A. and Niemann, K.O. 2011 Simulated impact of sample plot size and co-registration error on the accuracy and uncertainty of LiDAR-derived estimates of forest stand biomass. Remote Sens. Environ. 115, 636–649.
Freeman, E.A. and Frescino, T.S. 2009 Modeling and map production using random forest and stochastic gradient boosting. USDA Forest Service, Rocky Mountain Research Station, Ogden, UT, USA, p. 65.
Gatziolis, D. and Andersen, H.E. 2008 A guide to LiDAR data acquisition and processing for the forests of the pacific northwest. In General Technical Report, PNW-GTR. Vol. 768. United states Department of Agriculture, Forest Service, Portland, OR, USA, pp. 1–32.
Gobakken, T. and Nässset, E. 2008 Assessing effects of laser point density, ground sampling intensity, and field sample plot size on biophysical stand properties derived from airborne laser scanner data. Can. J. For. Res. 38, 1095–1109.
Goetz, S.J., Steinberg, D., Dubayah, R. and Blair, B.J. 2006 Laser remote sensing of canopy habitat heterogeneity as a predictor of bird species richness in an eastern temperate forest, USA. Remote Sens. Environ. 108, 254–263.
Goodwin, N., Coops, N. and Culvenor, D. 2007 Development of a simulation model to predict LiDAR interception in forested environments. Remote Sens. Environ. 11, 481–492.
Government of Newfoundland and Labrador. 2020. Forest Types | Forestry and Agrifoods Agency. Government of Newfoundland and Labrador, Corner Brook, NL, Canada. Available online: https://www.fao.gov.nl.ca/forestry/our_forest/forest_types.html (accessed on 11 March 2020).
Greenhouse, S.W. and Geisser, S. 1959 On methods in the analysis of profile data. Psychometrika 24, 95–112.
Gross, J., and Liggens, U. 2015 No test: Tests for normality. https://CRAN.R-project.org/package=nortest.
Guerra-Hernández, J., Tomé, M. and González-Ferreiro, E. 2016 Cartography of variables dosimétricas en bosques Mediterráneos mediante análisis de los umbrales de Altura e inventario a nivel de masa con datos LiDAR de Baja resolución. Rev. de Teledetección 46, 103–117.
Hollander, M. and Wolfe, D. 1999 Nonparametric Statistical Methods. 2nd edn. John Wiley & Sons, New York, USA, p. 162.
Holmgren, J., Nilsson, M. and Olsson, H. 2003a Simulating the effects of LiDAR scanning angle for estimation of mean tree height and canopy closure. Can. J. Remote Sens. 29, 623–632.
Holmgren, J., Nilsson, M. and Olsson, H. 2003b Estimation of tree height and stem volume on plots using airborne laser scanning. For. Sci. 49, 419–428.
Hopkinson, C., Chasmer, L., Colville, D., Fournier, R.A., Hall, R.J., Luther, J.E. et al. 2013 Moving towards consistent ALS monitoring of forest attributes across Canada; the ‘C-CLEAR’ approach. Photogramm. Eng. Remote Sensing. 79, 159–173.
Hopkinson, C. 2007 The influence of flying altitude, beam divergence, and pulse repetition frequency on laser pulse return intensity and canopy frequency distribution. Can. J. Remote Sens. 33, 312–324.
Hopkinson, C., Chasmer, L.E., Sass, G., Creed, I.F., Sitar, M., Kalbfleisch, W. et al. 2005 Vegetation class dependent errors in LiDAR ground elevation and canopy height estimates in a boreal wetland environment. Can. J. Remote Sens. 31, 191–206.
Howell, D. 2009 Statistical methods for psychology. 7th edn. Wadsworth Publishing, Belmont, CA, USA, p. 792.
Hyppä, J., Hyppä, H., Leckie, D., Gougeon, F., Xu, Y. and Malatamo, M. 2008 Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. Int. J. Remote Sens. 29, 1339–1366.
Jakubowski, M.K., Guo, Q. and Kelly, M. 2013 Tradeoffs between LiDAR pulse density and forest measurement accuracy. Remote Sens. Environ. 130, 245–253.
Jutzi, B. and Stillo, U. 2006 Range determination with waveform recording laser systems using a Wiener filter. ISPRS J. Photogramm. Remote Sens. 61, 95–107.
Kassambara, A. 2019 rstatix: Pipe-Friendly Framework for basic Statistical Tests. https://github.com/kassambara/rstatix.
Ker, M.F. 1974 Metric Yield Tables for the Major Forest Cover Types of Newfoundland. In Information Report M-X-141. Natural Resources Canada, Canadian Forest Service, Atlantic Forestry Centre, St. John’s, NL, Canada, p. 79.
Keränen, J., Malatto, M. and Packalen, P. 2016 Effect of flying altitude, scanning angle and scanning mode on the accuracy of ALS based forest inventory. Int. J. Appl. Earth Obs. Geoinf. 52, 349–360.
Karhonen, L., Korpela, I., Heiskanen, J. and Malatto, M. 2011 Airborne discrete-return LiDAR data in the estimation of vertical canopy cover, angular canopy closure and leaf area index. Remote Sens. Environ. 115, 1065–1080.
Laes, D., Reutenbuch, S., McGaughey, R.J., Maus, P., Mellin, T., Wilcox, C. et al. 2008 Practical LiDAR acquisition considerations for forestry applications. In Gen. Tech. Rep. PNW-GTR-768. Department of Agriculture, Forest Service, Pacific Northwest Research Station, Portland, OR, USA, p. 32.
Lambert, M.-C., Ung, C.-H. and Raulier, F. 2005 Canadian national tree aboveground biomass equations. Can. J. For. Res. 35, 1996–2018.
Effect of scan angle on ALS metrics and ABA predictions

Leitner, R., Furrer, R., Schaepman, M.E. and Morsdorf, F. 2015 Forest canopy-structure characterization: A data-driven approach. For. Ecol. Manage. 358, 48–61.

Liaw, A. and Wiener, M. 2002 Classification and regression by random Forest. R News 2, 18–22.

Lim, K., Treitz, P., Wulder, M., St-Ongé, B. and Flood, M. 2003 LiDAR remote sensing of forest structure. Prog. Phys. Geogr. 27, 88–106.

Lim Geomatics 2016 LTKiLAS Toolkit (Version 1.2) [Computer software]. Lim Geomatics Inc., Canada, Ottawa, ON.

Lin, Z., Kana, H., Mukoyama, S., Asada, N. and Chiba, T. 2013 Detection of subtle tectonic-geomorphic features in densely forested mountains by very high-resolution airborne LiDAR survey. Geomorphology 182, 104–115.

Liu, J., Skidmore, A.K., Jones, S., Wang, T., Heurich, M., Zhu, X. et al. 2018 Large off-nadir scan angle of airborne LiDAR can severely affect the estimates of forest structure metrics. ISPRS J. of Photogramm. Remote Sens. 136, 13–25.

Lovell, J.L., Jupp, D.L.B., Newnham, G.J., Coops, N.C. and Culvenor, D.S. 2005 Simulation study for finding optimal LiDAR acquisition parameters for forest height retrieval. For. Ecol. Manage. 214, 398–412.

Luther, J.E., Skinner, R., Fournier, R.A., van Lieshout, O.R., Bowers, W.W., Côté, J.-F. et al. 2014 Predicting wood quantity and quality attributes of balsam fir and black spruce using airborne laser scanner data. Forestry 87, 313–326.

Luther, J.E., Fournier, R.A., van Lieshout, O.R. and Bujold, M. 2019 Extending ALS-based mapping of forest attributes with medium resolution satellite and environmental data. Remote Sens. (Basel) 11, 1092.

Magnussen, S. and Boudewyn, P. 1998 Derivations of stand heights from airborne laser scanner data with canopy-based quantile estimators. Can. J. For. Res. 28, 1016–1031.

Maltamo, M., Bollandsas, O.M., Naesset, E., Gobakken, T. and Packalen, P. 2011 Different plot selection strategies for field training data in ALS-assisted forest inventory. Forestry 84, 23–31.

Marshall, I.B., Schut, P.H. and Ball, M. 1999 A National Ecological Framework for Canada: Attribute Data. Agriculture and Agri-Food Canada, Research Branch, Centre for Land and Biological Resources Research and Environment Canada, State of the Environment Directorate, Ecozone Analysis Branch, Ottawa/Hull, Canada.

Mauchly, J.W. 1940 Significance test for Sphericity of a normal n-variate distribution. Ann. Math. Stat. 11, 204–209.

McInerney, D.O., Suarez-Miguez, J., Valbuena, R. and Nieuwenhuis, M. 2010 Forest canopy height retrieval using LiDAR data, medium-resolution satellite imagery and KNN estimation in Aberfoyle, Scotland. Forestry 83, 195–206.

Mehtätalo, L. 2018 Irmfor: Functions for Biometrics. https://rdrr.io/cran/irmfor/

Mehtätalo, L., de-Miguel, S. and Gregoire, T.G. 2015 Modeling height-diameter curves for prediction. Can. J. For. Res. 45, 826–837.

Montaghi, A. 2013 Effect of scanning angle on vegetation metrics derived from a nationwide airborne laser scanning acquisition. Can. J. Remote Sens. 39, 5152–5173.

Morsdorf, F., Frey, O., Meier, E., Itten, K.I. and Allgöwer, B. 2008 Assessment of the influence of flying altitude and scan angle on biophysical vegetation products derived from airborne laser scanning. Int. J. Remote Sens. 29, 1387–1406.

Naesset, E. 1997 Determination of mean tree height of forest stands using airborne laser scanner data. ISPRS J. of Photogramm. Remote Sens. 52, 49–56.

Naesset, E. 2014 Area-Based Inventory in Norway—From Innovation to an Operational Reality. In 2014 Forestry applications of airborne Laser scanning – concepts and case studies. M., Maltamo, E., Naesset, J., Vauhkonen (eds.). Vol. 27. Springer, Dordrecht, Netherlands, pp. 215–240.

Nelson, R. 1997 Modeling forest canopy heights: The effects of canopy shape. Remote Sens. Environ. 60, 327–334.

NRCan. 2008 Natural Resources Canada, canadian forest Service. Canada’s National Forest Inventory ground sampling guidelines. Natural Resources Canada, Ottawa, ON, Canada. Available online: https://cfs.nrcan.gc.ca/publications?id=29402 (accessed on 11 February 2020).

Oléjnik, S. and Alqlina, J. 2003 Generalized eta and omega squared statistics: Measures of effect size for some common research designs. Psychol. Methods 8, 434–447.

Ørka, H.O., Bollandás, O.M., Hansen, E.H., Naesset, E. and Gobakken, T. 2018 Effects of terrain slope and aspect on the error of ALS-based predictions of forest attributes. Forest. 91, 225–237.

Penner, M., Pitt, D.G. and Woods, M.E. 2013 Parametric vs. nonparametric LiDAR models for operational forest inventory in boreal Ontario. Can. J. Remote Sens. 39, 426–443.

Pieheiro, G., Perelman, S., Guerschman, J.P. and Paruelo, J.M. 2008 How to evaluate models: Observed vs. predicted or predicted vs. observed? Ecol. Model. 216, 316–322.

Qin, H., Wang, C., Xi, X., Tian, J. and Zhou, G. 2017 Simulating the effects of the airborne LiDAR scanning angle, flying altitude, and pulse density for Forest foliage profile retrieval. Appl. Sci. 7, 712.

R Core Team. 2019 R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.r-project.org/

Reutebuch, S.E., Andersen, H.E. and McGaughey, R.J. 2005 Light detection and ranging (LiDAR): An emerging tool for multiple resource inventory. J. For. 103, 286–292.

RIEGL Laser Measurement Systems 2012 LMS-Q680i Data Sheet. Horn, Austria, p. 8.

Roussel, J.-R., and Auty, D. 2017 lidR: Airborne LiDAR data manipulation and visualization for forestry applications. https://github.com/Jean-Romain/lidR

Roussel, J.R., Béland, M., Cospersen, J. and Achim, A. 2018 A mathematical framework to describe the effect of beam incidence angle on metrics derived from airborne LiDAR: The case of forest canopies approaching turbid medium behaviour. Remote Sens. Environ. 209, 824–834.

Roussel, J.R., Cospersen, J., Béland, M., Thomas, S. and Achim, A. 2017 Removing bias from LiDAR-based estimates of canopy height: Accounting for the effects of pulse density and footprint size. Remote Sens. Environ. 198, 1–16.

Royston, J.P. 1982 Algorithm AS181: The W test for normality. Appl. Stat. 31, 176.

Su, J. and Bork, E. 2006 Influence of vegetation, slope, and LiDAR sampling angle on DEM accuracy. Photogramm. Eng. Remote Sensing. 72, 1265–1274.

Trimble Navigation Limited 2011 Trimble Floodlight Technology. Trimble Navigation Limited, Westminster, CO, USA, p. 2.

van Ewijk, K.Y., Treitz, P.M. and Scott, N.A. 2011 Characterizing Forest succession in Central Ontario using LiDAR-derived indices. Photogramm. Eng. Remote Sensing 77, 261–269.

Warren, G.R. and Meades, J.P. 1986 Wood defect and density studies II: Total and net volume equations for Newfoundland forest management units. In Information Report N-X-242. Canadian Forestry Service, Newfoundland Forestry Centre, St. John’s, NL, Canada, p. 14.
White, J.C., Coops, N.C., Wulder, M.A., Vastaranta, M., Hilker, T. and Tompalski, P. 2016 Remote sensing Technologies for Enhancing Forest Inventories: A review. *Can. J. Remote Sens.* 42, 619–641.

White, J.C., Wulder, M.A., Varhola, A., Vastaranta, M., Coops, N.C., Cook, B.D. et al. 2013 A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. In *Information Report FI-X-010*. Natural Resources Canada, Canadian Forest Service, Canadian Wood Fibre Centre, Victoria, BC, Canada, p. 41.

White, J.C., Wulder, M.A., Varhola, A., Vastaranta, M., Coops, N.C., Cook, B.D. et al. 2017 A model development and application guide for generating an enhanced forest inventory using airborne laser scanning data and an area-based approach. In *Information Report FI-X-018*. Natural Resources Canada, Canadian Forest Service, Canadian Wood Fibre Centre, Victoria, BC, Canada, p. 50.

Woods, M., Lim, K. and Treitz, P. 2008 Predicting forest stand variables from LiDAR data in the Great Lakes–St. Lawrence forest of Ontario. *For. Chron.* 84, 827–839.

Wulder, M.A., White, J.C., Nelson, R.F., Næsset, E., Ørka, H.O. and Coops, N.C. 2012 Lidar sampling for large-area forest characterization: A review. *Remote Sens. Environ.* 121, 196–209.

Yang, W., Ni-Meister, W. and Lee, S. 2011 Assessment of the impacts of surface topography, off-nadir pointing and vegetation structure on vegetation LiDAR waveforms using an extended geometric optical and radiative transfer model. *Remote Sens. Environ.* 115, 2810–2822.