Carbon estimation using sampling to correct LiDAR-assisted enhanced forest inventory estimates

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ABSTRACT

Light Detection and Ranging (LiDAR) scanning has been increasingly applied in forest ecosystem surveys. Data from LiDAR describe forest structure and provide attribute information for forest inventory. These attributes can potentially aid in the estimation of biomass and carbon by providing sampling covariates. Therefore, this study explored the accuracy of estimating carbon storage by calibrating LiDAR attributes using list sampling with a ratio estimator. Standing tree carbon and down woody debris carbon were estimated across 10 broad forest types. LiDAR-derived gross total volume was used as a listing factor and big BAF samples to collect field data. Gross total volumes were “corrected” using a ratio estimator. The results show that standing tree carbon was $58.5 \text{ Mg C} \times \text{ha}^{-1}$ ($\pm 2.9\%$ SE), and dead woody debris carbon $1.8 \text{ Mg C} \times \text{ha}^{-1}$ ($\pm 7.2\%$ SE). With the exception of one forest type, these estimates were comparable to those derived from the carbon budget model of the Canadian forest sector (CBM-CFS3).

Key words: forest inventory, aboveground carbon stocks, enhanced forest inventory calibration

RÉSUMÉ

Les lasers à balayage aéroporté permettant la détection et la télémétrie par ondes lumineuses (LiDAR) sont de plus en plus utilisés à des fins d'inventaire des écosystèmes forestiers. Les données obtenues par LiDAR décrivent la structure forestière et apportent des informations sur les caractéristiques recherchées en inventaire forestier. Ces caractéristiques peuvent potentiellement permettre des estimations de la biomasse et du carbone en échantillonnant les covariables. À cet effet, cette étude étudie la précision des estimations de carbone stocké suite à un étalonnage des caractéristiques relevées par LiDAR à partir d'un estimateur de ratio. Le carbone des arbres sur pied ainsi que celui des débris au sol a été estimé dans 10 grandes unités forestières. Le volume total brut obtenu par les données LiDAR a été utilisé comme coefficient d'inscription et pour déterminer la valeur générale de l'échantillonnage en forêt. Les volumes bruts totaux ont été corrigés au moyen d'un estimateur de ratio. Les résultats indiquent que le carbone des arbres sur pied était de $58,5 \text{ Mg C} \times \text{ha}^{-1}$ (é.t. $\pm 2,9\%$) et que le carbone des débris de bois mort était de $1,8 \text{ Mg C} \times \text{ha}^{-1}$ (é.t. $\pm 7,2\%$). À l'exception d'un type d'unité forestière, ces estimés étaient comparables à ceux dérivés du modèle du bilan du carbone du secteur forestier canadien (MBC-SCF3).

Mots clés : inventaire forestier, stocks de carbone en surface, étalonnage de l'inventaire forestier amélioré

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Introduction

Globally, forests have significant effects on atmospheric carbon (C) sequestration (Kurz *et al.* 2016). Increased atmospheric carbon dioxide (CO₂) is one of many greenhouse gases (GHG) responsible for global warming and climate change (Neilson *et al.* 2007), and much effort has focused on reducing GHG emissions and increasing atmospheric C removal (Smyth *et al.* 2017). Forest offset projects are an increasingly frequent management objective for many landowners (Canadian Council of Forest Ministers 2009). While GHGs and associated climate change impacts are a global issue, forest offset projects must be assessed at a local scale.

Across all carbon pools, aboveground tree biomass and dead wood are two important carbon pools in forest ecosystems. Consistent and precise sample estimates of C storage in these pools is an important component of forest offset projects. Directly estimating C from field measurements is the most conventional method and is considered to provide precise and repeatable estimates (Brown 1999); however, this method can be time consuming and costly, especially for large forest areas (Vashum 2012). For example, in a review by Brown (2002), permanent, fixed-area plots were the recommended protocol for estimating C in forest offset projects. While these plots may provide convenient verification, the costs of such inventories are often prohibitively high and may exclude smaller landowners from entry into carbon markets (Russell-Roy *et al.* 2014; Chen *et al.* 2019). Variable probability sampling techniques such as horizontal point sampling (Bitterlich 1984; Iles 2003; Kershaw *et al.* 2016) and big BAF (basal area factor) sampling (Iles 2003; Marshall *et al.* 2004; Yang *et al.* 2017) have been shown to be very efficient for estimating volume. Recently, Chen *et al.* (2019) reported that big BAF sampling can be easily, accurately, and affordably adapted to estimate aboveground forest C.

Airborne Light Detection and Ranging (LiDAR) scanning is increasingly applied in forest ecosystem surveys to provide landscape information for large forest areas (Corona and Fattorini 2008). LiDAR is an active remote sensing technique that provides direct measurement of vegetation canopy height and sub-canopy topography (Wulder *et al.* 2008; Kershaw *et al.* 2016) as well as a spatially rich point cloud of the vegetation structure (Lefsky *et al.* 2002; Dassot *et al.* 2011; Clementel *et al.* 2012). In many jurisdictions, strategic-level “enhanced” forest inventories (EFIs), which provide various LiDAR-derived forest attributes, are becoming readily available. For example, in New Brunswick, Canada, the province is in the process of developing freely available EFIs for the entire province (Dick 2019). While these EFIs are often produced at very high spatial resolutions (20-m cells in New Brunswick), these estimates should only be considered accurate at larger spatial resolutions and local biases may exist (Hsu 2019).

While LiDAR-derived EFIs may have local errors, they represent a significant new source of information forest managers can use when designing operational inventories. Hsu (2019) demonstrated how EFI estimates could be used as covariates in a “sampling to correct” approach (Iles 2003) to locally calibrate EFI estimates of total volume for operational forest inventories. “Sampling to correct” is a form of double sampling where the small sample estimates the total popula-

tion and the large sample spreads that total over the individuals within the population (Iles 2003). The research of Hsu (2019) showed that list sampling (Freese 1962; Kershaw *et al.* 2016) with ratio estimation was a cost-effective approach for small-scale operational inventories. Yang *et al.* (2019) similarly showed that variable probability selection based directly on LiDAR attributes and ratio estimation performed superior to model-assisted estimation at larger scales.

While the EFIs being developed in New Brunswick provide estimates of biomass, these are not of sufficient accuracy nor consistency to meet most carbon offset standards (Climate Action Reserve 2019; Verified Carbon Standard 2019); however, it may be possible to use EFI estimates as covariates to aid in the estimation of biomass and carbon in an approach similar to what Hsu (2019) did for volume. Double sampling, (or sampling with covariates or “sampling to correct” as it is variously known), is an effective sample design (Iles 2003; Kershaw *et al.* 2016; Hsu 2019) long known in the forest inventory literature (Freese 1962). The potential to leverage EFI estimates to make statistically-efficient and cost-effective biomass and carbon estimates has the potential to make the verification standards required by carbon offset programs more affordable and accessible to smaller land owners.

This study implemented a “sampling to correct” approach based on EFI estimates. Stratified list sampling was used as the selection method with big BAF sample points used in the field to operationally estimate aboveground C stocks. The specific objectives were: 1) to characterize standing tree C stocks and dead woody debris (DWD) carbon stocks using a “sampling to correct” approach; 2) to compare the precision obtained to those required by carbon offset protocols; and, 3) to compare the derived C estimates with those obtained using the carbon budget model of the Canadian forest sector (CBM-CFS3; Kurz *et al.* 2009).

Methods

Study site

This study was conducted in the forest management area on the 5th Canadian Division Support Base Gagetown (5CDSB; N 45° 50' 16", W 66° 26' 12"), a large Canadian Forces Base covering an area over 110 000 ha and located in southwestern New Brunswick, Canada (Fig. 1). The landbase was divided into four zones, including two zones for military training, the forest management zone, and one ecological reserve zone. This study focuses on the forest management zone which was approximately 44 000 ha. Tree species in the study area included: tolerant hardwoods such as sugar maple (*Acer saccharum* Marsh.), yellow birch (*Betula alleghaniensis* Britton), American beech (*Fagus grandifolia* Ehrh.), red oak (*Quercus rubra* L.) and white ash (*Fraxinus americana* L.); intolerant hardwood species such as white birch (*Betula papyrifera* Marsh.), red maple (*Acer rubrum* L.), trembling aspen (*Populus tremuloides* Michx.) and bigtooth aspen (*Populus grandidentata* Michx.); and softwood species such as balsam fir (*Abies balsamea* (L.) Mill), spruce (*Picea*), eastern white pine (*Pinus strobus* L.) and eastern hemlock (*Tsuga canadensis* (L.) Carrière). The EFI for this area was based on 2017 airborne LiDAR scans. Field data collection was completed in summer 2018.

Fig. 1 Map of 5CDSB Gagetown location (marked as a star on the left map) and the forest management area (grey area) location within 5CDSB Gagetown

Forest-level sample design

A LiDAR-enhanced forest inventory (EFI) was commercially developed based on airborne LiDAR scans acquired in summer/fall 2017. The forest management area was divided into 10 broad forest types (FUNAs) based on aerial interpretation of species composition from images acquired in 2004. The EFI utilized 20 m × 20 m cells intersected with the forest type map and assigned to one of the 10 forest types based on the centre point of each cell. Gross total volume (GTV) predictions from the EFI were used as the covariate. Using proportional allocation across the 10 FUNAs, 200 sample cells were selected using list sampling protocols (Freese 1962; Cochran 1977; Kershaw *et al.* 2016). List sampling selects units proportionally to their contribution to the total estimate. The probability of any cell selected was calculated as:

$$(1) \quad P(\text{selection}) = \text{GTV}_{ij} / \sum_{i=1}^{N_j} \text{GTV}_{ij}$$

where, GTV_{ij} = the gross total volume in the i th cell of the j th FUNA and N_j = the number of cells in the j th FUNA. Selection probabilities were summed across the cells and standardized between 0, 1 as a cumulative probability. Random numbers, U (0, 1), were generated to select cells from the cumulative probabilities. Table 1 shows a summary of total EFI cells, sample sizes, and GTV values by FUNAs.

Field plot measures

Data for standing trees were collected using big BAF sampling (Iles 2003; Marshall *et al.* 2004) for all trees with diameter at breast height (dbh) ≥ 6.0 cm. With big BAF sampling, there are two types of sample trees: “count” trees which are identified as “in” using a small BAF angle gauge, and “measure” trees which are identified using a large BAF angle gauge (Iles 2003; Marshall *et al.* 2004). A 2-m BAF angle gauge was used for selecting “count” trees and a 27 M BAF angle gauge used for selecting “measure” trees for detailed measurement.

Table 1. Summary of total number of EFI cells, sampled cells and mean GTV value (standard error in brackets) by FUNAs

FUNA ¹	Total Number of EFI cells	Total Number of sample cells	Mean GTV (m ³ /ha)
IHHW	153106	24	151.4 (0.18)
IHSW	255154	40	149.7 (0.15)
THHW	62216	11	161.4 (0.26)
THSW	44973	9	119.8 (0.39)
BFHW	186424	40	179.3 (0.19)
BFSW	80065	18	185.4 (0.24)
SPHW	119919	18	197.9 (0.25)
SPSW	222582	31	183.0 (0.16)
WPMX	64793	5	250.2 (0.39)
SWMX	26530	4	211.2 (0.58)

¹IHHW = intolerant hardwood; IHSW = intolerant hardwood, softwood mix; THHW = tolerant hardwood; THSW = tolerant hardwood, softwood mix; BFHW = balsam fir, hardwood mix; BFSW = balsam fir, softwood mix; SPHW = spruce, hardwood mix; SPSW = spruce, softwood mix; WPMX = white pine, mixed species; SWMX = softwood mixed species

For all “count” trees, species and stem type (Pelletier *et al.* 2016) were recorded. For “measure” trees, dbh (nearest 0.1 cm) and total height (nearest 0.1 m) were measured. Heights were measured using a TruPulse (Laser Tech, Denver, CO) laser hypsometer and dbh measured using a diameter tape.

Data for dead woody debris (DWD) were collected using the line intersect method (Shiver and Borders 1996; Kershaw *et al.* 2016). Two 50-m transects were centred at the plot centre and ran north/south and east/west. Each transect was measured independently from the other, such that a piece of DWD crossing both transects was recorded twice. A tape was laid out on the ground marking off each transect. A piece of DWD was measured if it intersected the transect. All DWDs with intersection diameters ≥ 6.0 cm were measured. Diameter at the intersection point was measured with calipers (nearest 0.1 cm) and the total length of the piece measured (nearest 0.1 m) using a logger’s tape. Each piece of DWD was also classified into one of five decay classes (Table 2).

Sample estimation

Big BAF estimation

Volume, biomass and carbon were calculated for each “measure” tree using Honer *et al.* (1983) equations, Lambert *et al.* (2005) Canadian biomass equations (dbh and height equations, Table 4 in Lambert *et al.* 2005), and Lamtom and Savidge (2003) species-specific C conversion factors, respectively. This is a standard inventory compilation process (Kershaw *et al.* 2016), and while the individual calculations have associated errors, the resulting calculations are consistent across different inventory efforts. In this study, the emphasis is on sampling error. XBAR (X denotes volume, biomass, or carbon) was calculated by dividing the estimated factor (volume, biomass, or carbon) by tree basal area. For example, the VBAR (volume: basal area ratio) was calculated as:

$$(2) \quad \text{VBAR}_r = \frac{V_r}{\text{BA}_r}$$

where, VBAR_r = the volume: basal area ratio for the r th tree; V_r = estimated volume (m³) for the r th tree; BA_r = basal area (m²) for the r th tree. BBAR (biomass: basal area ratio) and CBAR (carbon: basal area ratio) were calculated by substituting biomass (BM_r) and carbon content (C_r) for V_r in eq. 2. Mean XBAR (X denotes volume, biomass, or carbon) was calculated for each FUNA and estimated factor using a mean ratio approach (Iles 2003; Marshall *et al.* 2004):

$$(3) \quad \overline{\text{XBAR}}_j = \frac{\sum_{r=1}^{n_j} \text{XBAR}_r}{n_j}$$

where, $\overline{\text{XBAR}}_j$ = mean volume, biomass or carbon to basal area ratio for the j th FUNA; XBAR_r = volume, biomass or carbon to basal area ratio for the r th tree; n_j = number of sample trees for the j th FUNA. Totals per hectare for each plot were then calculated using:

$$(4) \quad \hat{X}_k = \text{BAF} \times M_k \times \overline{\text{XBAR}}_j$$

Table 2. Dead woody debris (DWD) classification (adapted from Russell *et al.* 2013)

Decay Class	Structural Integrity	Texture of Rotten Portions	Color of wood	Invading Roots	Branches and Twigs
1	Sound, freshly fallen, intact logs	Intact, no rot; conks of stem decay absent	Original color	Absent	If branches are present, five twigs are still attached and have tight bark
2	Sound	Mostly intact; sapwood partly soft (starting to decay) but can't be pulled apart by hand	Original color	Absent	If branches are present, many fine twigs are gone and remaining fine twigs have peeling bark
3	Heartwood sound; piece supports its own weight	Hard, large pieces; sapwood can be pulled apart by hand or sapwood absent	Reddish-brown or original color	Sapwood only	Branch stubs will not pull out
4	Heartwood rotten; piece does not support its own weight, but maintains its shape	Soft, small blocky pieces; a metal pin can be pushed into heartwood	Reddish or light brown	Throughout	Branch stubs pull out
5	None, piece on longer maintain its shape, it spreads out on ground	Soft; powdery when dry	Red-brown to dark brown	Throughout	Branch stubs and pitch pockets have usually rotted down

Table 3. Mean, standard error (in brackets) and range (in braces) of estimated basal area ratios by FUNAs (FUNA types are defined in Table 1)

FUNA	Basal Area Ratios		
	Volume (m ³ ×m ⁻²)	Biomass (kg×m ⁻²)	Carbon (kg×m ⁻²)
IHHW	7.7 (0.45) {4.1, 10.6}	5370 (395.0) {3453, 9452}	2626 (199.1) {1626, 4691}
IHSW	6.8 (0.44) {3.0, 9.1}	4454 (237.2) {3076, 6210}	2171 (112.1) {1494, 3004}
THHW	6.7 (0.72) {4.5, 8.8}	4455 (347.9) {3409, 5360}	2142 (163.5) {1655, 2515}
THSW	6.9 (0.79) {5.4, 9.0}	4199 (614.1) {3096, 5741}	2054 (302.7) {1503, 2792}
BFHW	6.0 (0.26) {3.5, 9.0}	3962 (189.6) {3074, 6198}	1933 (90.9) {1512, 2998}
BFSW	4.9 (0.96) {1.4, 7.1}	4038 (616.5) {2591, 7324}	1958 (297.1) {1260, 3543}
SPHW	6.6 (0.65) {3.8, 11.5}	4942 (433.3) {2863, 7217}	2417 (215.4) {1390, 3582}
SPSW	6.6 (0.36) {1.3, 11.6}	4315 (179.8) {2825, 7839}	2129 (89.0) {1330, 3950}
WPMX	6.8 (1.15) {3.3, 8.9}	4513 (256.0) {3754, 5347}	2231 (125.5) {1826, 2518}
SWMX	4.3 (1.81) {1.3, 7.5}	10031 (5299.1) {3368, 20500}	4948 (2714.6) {1635, 10330}

Where, $\hat{X}_k$ = estimated total volume, biomass or carbon per hectare for the k th plot; BAF = 2 (count BAF = 2M BAF in this study); M_k = number of “count” trees for the k th plot.

Dead woody debris estimation

Volume for DWD was calculated by decay class. Volume per hectare for each piece of DWD was calculated by multiplying piece volume by piece factor (Kershaw *et al.* 2016):

$$(5) \quad VF_q = V_q \times PF_q$$

Where,

$$(6) \quad PF_q = \frac{10000\pi}{2 \times S \times L_q},$$

$$(7) \quad V_q = 0.00007854 \times D_q^2 \times L_q$$

VF_q = volume per hectare of the q th piece; V_q = volume of the q th piece; PF_q = piece factor for the q th piece; S = the length of transect line (100 m in this study); D_q = the diameter of the q th piece at the intersection point; and L_q = the piece length for the q th piece. DWD volume per hectare was calculated for each decay class by summing all VF_q s in each decay class. To convert dead wood volume to biomass, we used the dead wood densities (0.4747 g×cm⁻³ for decay class 1; 0.3646 g×cm⁻³ for decay class 2; 0.2699 g×cm⁻³ for decay class 3; 0.1931 g×cm⁻³ for decay class 4 and 0.1215 g×cm⁻³ for decay class 5) for birch (*Betula pendula* and *B. pubescens*) from the Swedish NFI-system (Sandström *et al.* 2007). We considered that this was a reasonable choice, given the abundance of white birch in the overstory, the stage of develop-

Table 4. Correction ratios for the EFI cells' GTV values for volume, biomass, standing tree C and DWD C by FUNAs (see Table 1 for FUNA type definitions)

FUNA	Volume: GTV (m ³ ×m ⁻³)	Biomass: GTV (kg×m ⁻³)	Standing Carbon: GTV (kg×m ⁻³)	Carbon: DWD GTV (kg×m ⁻³)
IHHW	1.5 (0.15)	1071.8 (101.95)	524.1 (49.85)	12.8 (2.16)
IHSW	1.0 (0.07)	669.8 (42.61)	326.5 (20.77)	9.5 (1.43)
THHW	1.1 (0.13)	759.0 (87.06)	364.9 (41.85)	8.6 (2.15)
THSW	0.9 (0.20)	562.4 (119.30)	275.1 (58.35)	11.6 (3.67)
BFHW	0.9 (0.06)	611.5 (38.62)	298.4 (18.84)	9.1 (1.53)
BFSW	0.8 (0.07)	694.2 (60.63)	336.6 (29.40)	15.1 (7.05)
SPHW	1.0 (0.06)	728.0 (46.93)	356.0 (22.95)	11.7 (2.22)
SPSW	0.9 (0.05)	588.4 (32.47)	290.3 (16.02)	7.7 (0.99)
WPMX	0.6 (0.06)	393.4 (41.81)	194.5 (20.67)	11.3 (1.23)
SWMX	0.5 (0.12)	1245.3 (287.98)	614.3 (142.06)	9.9 (3.52)

ment of most stands in the forest management area, and the lack of similar conversion tables for Canadian species. A conversion factor of 0.5 was used to convert DWD biomass to DWD carbon (Sandström *et al.* 2007). Total DWD C for each plot was the sum of C across the five decay classes.

EFI adjustment

The plot totals ($\hat{X}$) estimated above were used to develop correction ratios for the GTVs from the EFI cells. For each cell sampled, a ratio between $\hat{X}$ and GTV was calculated ($R(X)_k = \hat{X}_k / \text{GTV}_k$) and the mean ratios by FUNA were estimated using a mean ratio approach:

$$(8) \quad \overline{R(X)}_j = \frac{\sum_{k=1}^{P_j} R(X)_k}{P_j}$$

where $\overline{R(X)}_j$ = mean $\hat{X}$ to GTV ratio for the j th FUNA; $R(X)_k$ = $\hat{X}$ to GTV ratio for the k th plot; P_j = the number of cells (plots) selected in the j th FUNA. In addition to the standing volume, biomass, and carbon, ratios were also calculated for DWD biomass and carbon.

Adjusted values for all EFI cells in the entire forest management area were estimated using:

$$(9) \quad X_i = \text{GTV}_i \times \overline{R(X)}_j$$

where X_i = total volume, total biomass or total carbon for the i th cell; GTV_i = GTV for the i th cell; $\overline{R(X)}_j$ = the mean ratio for the j th FUNA.

Percent sampling error (se% – the combined small sample error and large sample error as a percentage of the corrected mean) for volume, biomass and carbon for each FUNA was estimated using Bruce's formula (Goodman 1960; Yang *et al.*

2017):

$$(10) \quad se\%(\bar{X}) = \sqrt{se\%(\overline{R(X)})^2 + se\%(\overline{\text{GTV}})^2}$$

where,

$$(11) \quad se\%(\bar{Y}) = 100 \left(\frac{S_{\bar{Y}}}{\bar{Y}} \right) = 100 \left(\frac{s}{\sqrt{n}} \right) \left(\frac{1}{\bar{Y}} \right) = \frac{CV(\bar{Y})}{\sqrt{n}}$$

and $\bar{Y}$ = either $\overline{R(X)}$ or $\overline{\text{GTV}}$, $S_{\bar{Y}}$ = the associated standard error, s = standard deviation; $CV(\bar{Y})$ = coefficient of variation; n = sample size.

Comparison with CBM-CFS3 estimates

Finally, the estimates derived here were compared with estimates derived using CBM-CFS3 (Kurz *et al.* 2009). Merchantable volumes were derived from the total volumes using Honer's merchantable volume ratios (Kershaw *et al.* 2007). Merchantable volume to GTV ratios were estimated for each FUNA and were used to adjust the EFI GTV values for each cell. The adjusted merchantable volumes were then converted to C values using CBM-CFS3 which uses the associated leading species for each FUNA for conversion. These estimates were then compared to our field data-derived estimates.

Results

Field plot measurements

Mean VBAR did not vary much across the different FUNAs, except for BFSW and SWMX (Table 3). VBAR for BFSW was 4.9 m³×m⁻² and for SWMX was 4.3 m³×m⁻², while all other FUNAs had a range of 6.0 to 7.7 m³×m⁻². Mean BBAR (kg×m⁻²) ranged from 3962 to 10031 kg×m⁻² (Table 3). For BBAR, SWMX was the only outlying FUNA with BBAR

Table 5. Mean and standard error (in brackets) of estimated standing tree C, DWD C by FUNAs (see Table 1 for FUNA type definitions)

FUNA	Mean standing tree C (Mg C×ha ⁻¹)	Mean DWD C (Mg C×ha ⁻¹)
IHHW	79.3 (7.55)	1.9 (0.33)
IHSW	48.9 (3.11)	1.4 (0.21)
THHW	58.9 (6.75)	1.4 (0.35)
THSW	33.0 (6.99)	1.4 (0.44)
BFHW	53.5 (3.38)	1.6 (0.27)
BFSW	62.4 (5.45)	2.8 (1.31)
SPHW	70.4 (4.54)	2.3 (0.44)
SPSW	53.1 (2.93)	1.4 (0.18)
WPMX	48.7 (5.17)	2.8 (0.31)
SWMX	129.7 (30.00)	2.1 (0.74)
Weighted Mean	58.5 (1.68)	1.8 (0.13)

equal to 10031 kg×m⁻², for all other FUNAs, the range was 3962 to 5370 kg×m⁻² (Table 3). Similar to BBAR, mean CBAR ranged from 1933 to 4948 kg×m⁻², with SWMX having a mean of 4948 kg×m⁻² and the next largest value being 2626 kg×m⁻² for IHMW (Table 3). Overall, the XBARs did not vary much across the different FUNA types, except for SWMX. SWMX had the lowest VBAR but the largest BBAR, the largest CBAR, and the highest standard errors of 5299.1 and 2714.6 for BBAR and CBAR, respectively (Table 3).

EFI adjustment

Standing tree C to GTV ratios (kg×m⁻³) ranged from 275.1 to 614.3 across FUNAs and DWD C to GTV ratios (kg×m⁻³) ranged from 7.7 to 15.1 across different FUNA types (Table 4). From our results, the average standing tree C was estimated to be 58.5 Mg C×ha⁻¹ with a 2.9% sampling error, and the average total DWD C was estimated to be 1.8 Mg C×ha⁻¹ with a 7.2% sampling error (Table 5). For standing tree C, most cells fell into the 50 Mg C×ha⁻¹ level of carbon storage (Fig. 2). SWMX has the highest estimated standing tree C of 129.7 Mg C×ha⁻¹, while THSW has the lowest estimated standing tree C of 33.0 Mg C×ha⁻¹ (Table 5). For DWD C, most stands fell into the 1 to 2 Mg C×ha⁻¹ level (Fig. 3). WPMX had the highest DWD C estimated at 2.8 Mg C×ha⁻¹, while IHHW, THHW, THSW and SPSW had the lowest estimated DWD C of 1.4 Mg C×ha⁻¹ (Table 5).

Comparison with CBM-CFS3 estimation

Mean aboveground C (standing tree + DWD) was estimated to be 60.3 Mg C×ha⁻¹ with 2.8% sampling error for our field data derived estimates, compared to 65.0 Mg C×ha⁻¹ with 2.5% sampling error for the CBM-CFS3 derived estimates (Fig. 4). CBM-CFS3 carbon estimates in most of the FUNA types were higher than our field derived estimates; however, many of the values between the two methods were very close. Seven of the ten FUNAs had CBM-CFS3 estimates that were greater than our field estimates, though only the IHSW estimate was significantly greater ($p < .05$). The biggest difference appeared in SWMX where field derived estimates were three

times higher than CBM-CFS3 derived estimates (Fig. 4). The field estimates were based on very small sample sizes (Table 1) and were greatly influenced by an odd large diameter but very short tree present in the “measure” trees.

Discussion

Accurately, precisely and repeatably estimating carbon storage is important for forest offset projects (Brown 2002) and for making management plans. Our study implemented a LiDAR-assisted forest inventory with a “sampling to correct” approach for aboveground C estimation on the forest management area in 5CDSB Gagetown. Two components of aboveground C (standing trees and DWD) were estimated separately. From our results, the estimated standing tree C in our study area was 58.5 Mg C×ha⁻¹ and DWD C was 1.8 Mg C×ha⁻¹. The overall aboveground C was estimated to be 60.3 Mg C×ha⁻¹ with 2.8% sampling error. Our mean estimates are about half of those reported by Smith *et al.* (2006) for mature northeastern US forests. 5CDSB was established in the 1960s by expropriating farmland in central New Brunswick. The forests today are the product of old field revegetation, fires (prescribed or wild), extensive partial harvesting, and various undocumented military activities. The low C estimates reflect a forest that has been used extensively and are similar to those reported by Nunery and Keeton (2010) for partially harvested forests in New England.

Our study demonstrated an efficient approach for estimating carbon storage in a specific area based on a LiDAR-derived enhanced forest inventory. This approach could help local landowners or woodlot owners to characterize their carbon storage for the purposes of entering carbon markets. The target sampling error for most forest protocol requirements for carbon estimation is $\pm 5\%$ with 90% confidence interval (Climate Action Reserve 2019). Our results produced estimates of standing tree C using a “sampling to correct” approach that could generally meet this target with small sample sizes and small numbers of trees measured. Leveraging the LiDAR-derived estimates aides in the estimation of aboveground carbon and can provide accurate estimates for local conditions.

As Iles (2003) points out, the covariates do not need to be correct, only consistent. The corrected estimates can be accurate even if the covariates are biased (Hsu 2019). In our case, the EFI estimates were derived using random forest imputation (Breiman 2001) and plot matching algorithms (Lamb *et al.* 2017, 2018). No actual field data from 5CDSB Gagetown was used. The purpose of a probabilistic sample is to obtain an estimate of the total (Freese 1962; Cochran 1977; Iles 2003; Kershaw *et al.* 2016); everything else spreads that total over the landscape (Iles 2003). In this case, the EFI estimates are the spread and our field data are the sample. Thus, “sampling to correct” can overcome biases within covariates and produce accurate, unbiased total estimates, as shown here.

The CBM-CFS3 model has been widely used to estimate greenhouse gas emissions and removals at stand, regional and national scales, and to evaluate effects of disturbances and management practices on forest C stocks and dynamics in Canada (Hararuk *et al.* 2017). We compared the estimated C storage from our field derived method to the CBM-CFS3

Fig. 2 Standing live carbon distribution across the forest management area

derived estimates. Our results showed that the field derived estimates were close to the CBM-CFS3 derived estimates for most FUNAs except for the SWMX. In this case, the differences were caused by very small sample size (Table 1) and a single tree whose stem was broken-off very low but still alive. The volume equations (Honer *et al.* 1983) capture this condition well, but the biomass equations (Lambert *et al.* 2005) missed this condition due to the larger effects of diameter rather than height in the biomass equations. Because volume and biomass were estimated separately, and because SWMX had a very small sample in our field measurements, the effect of this big tree was large. On the other hand, CBM-CFS3 used mean merchantable volume for each FUNA type to predict biomass rather than directly estimating biomass from individual trees. Understanding sources of prediction errors within subsampling schemes is important when compiling inventory results. If this tree is removed from our data, the results are similar to the other FUNAs.

“Sampling to correct” approach for carbon estimation is a potential option for estimating carbon storage for local regions and can yield consistent and precise estimates. The

comparable estimations derived from a “sampling to correct” approach could provide information for landowners who are interested in quantifying C storage on their landscape and making appropriate forest offset management plans. The efficiency of the method coupled with big BAF sampling also makes this an affordable approach for many landowners.

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Fig. 3 Dead woody debris carbon distribution across the forest management area

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Fig. 4 Field derived total aboveground C estimation versus CBM-CFS3 estimation (see Table 1 for FUNA type definitions)

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