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Research note / Note de recherche

Aboveground large tree mass estimation in a coastal forest in British Columbia using plot-level metrics and individual tree detection from lidar

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Abstract. Plot-level large tree and snag aboveground mass (TSAM) in a second-growth coastal Douglas-fir forest stand in British Columbia was estimated using light detection and ranging (lidar) combining metrics from individually identified trees and snags and plot-level lidar canopy return density. Individual trees were identified using the tree variable window (TreeVaW) algorithm, which identifies tree crowns using a circular moving filter and the relationship between tree height and crown diameter. A multiple linear regression model was then developed to predict plot-level TSAM as determined from ground plots. The predicted heights of individually identified trees were very accurate (r^2 = 0.92, SE_E = 0.69 m). Plot TSAM was predicted with an r^2 = 0.75 and SE_E = 29.68 Mg/ha using lidar density and height metrics alone, and a slightly lower r^2 = 0.71 and SE_E = 31.95 Mg/ha using lidar density metrics with individually identified tree heights. Using individual tree metrics did not improve plot-level TSAM estimation, since a large component of TSAM is contained in complex canopy levels where individual trees are difficult to identify.

Résumé. On a estimé la biomasse aérienne des gros arbres et des chicots (« large tree and snag aboveground mass » (TSAM)) au niveau de la parcelle dans une forêt côtière de pins Douglas de seconde venue en Colombie-Britannique à l'aide de données lidar (détection et télémétrie par ondes lumineuses) en combinaison avec des mesures d'arbres et de chicots identifiés individuellement et de mesures de densité de retours lidar du couvert au niveau de la parcelle. Les arbres individuels ont été identifiés à l'aide de l'algorithme TreeVaW (« tree variable window ») qui permet d'identifier les couronnes d'arbres en utilisant un filtre circulaire mobile et de la relation entre la hauteur des arbres et le diamètre de la couronne. Un modèle de régression linéaire multiple a ensuite été développé pour prédire la valeur de TSAM au niveau de la parcelle telle que déterminée à partir des parcelles échantillons au sol. Les hauteurs estimées des arbres identifiés individuellement étaient très précises (r^2 = 0,92, SE_E = 0,69 m). Les valeurs de TSAM au niveau de la parcelle ont été estimées avec une valeur de r^2 = 0,75, SE_E = 29,68 Mg/ha en utilisant les mesures de densité et de hauteur lidar seules, et une valeur légèrement plus faible de r^2 = 0,71, SE_E = 31,95 Mg/ha en utilisant les mesures de densité lidar avec les hauteurs d'arbres identifiés individuellement. L'utilisation des mesures d'arbres individuels n'a pas amélioré l'estimation de TSAM au niveau de la parcelle étant donné qu'une partie importante de TSAM est contenue dans les niveaux complexes du couvert où les arbres individuels sont difficiles à identifier.
[Traduit par la Rédaction]

Introduction

Aboveground forest carbon (C) stocks are closely linked to canopy height and stem size. Carbon composes approximately half of the dry mass of the live vegetation in forests (biomass), including trees (trunks, branches, foliage, and roots), shrubs, herbs, mosses, and decaying forest detritus (snags (i.e., standing dead trees), woody debris, forest floor litter, and humus) (Chapin et al., 2006; Landsberg and Waring, 1997). National reporting requirements for the United Nations Framework Convention on Climate (UNFCC), as well as national- and regional-level policy decisions (Gillis et al., 2005), make the timely, accurate, and cost-effective measurement of forest biomass a common goal. Light detection

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and ranging (lidar) is a relatively new remote sensing technology that is well suited to describing the vertical structure of forest canopies (Coops et al., 2007; Wulder et al., 2008) and has significant potential to measure aboveground forest biomass.

Lidar data are commonly acquired from an airborne platform equipped with a lidar instrument that emits pulses of infrared light in a scanning pattern, measuring the time for an emitted pulse to reflect from ground surfaces and return to the sensor. Using accurate positional information obtained from a global positioning system (GPS) and detailed data on aircraft orientation from an inertial measurement unit (IMU), the height and position of features on the ground can be determined very accurately. Small-footprint lidar devices often use beam footprints approximately 20 cm in diameter with very close spacing (~1.5 m between returns). Discrete-return lidar devices may record up to five returns from an emitted pulse, with first returns typically incident from branches, foliage, and stems at the top of the canopy, subsequent returns originating from objects within the canopy, and the final return originating from the underlying terrain (Wulder et al., 2008). As part of national operational forest inventories, lidar data have been applied to measure plot-level, aboveground mass of trees including trunks, branches, and foliage of living and dead standing trees (Næsset, 2004). To predict plot-level aboveground biomass, inferential relationships are often applied using descriptive statistics from the point cloud of returns as predictor variables, including percentiles of return heights, and density of returns at height intervals within the canopy (Næsset, 2004; Lefsky et al., 1999; Næsset and Gobakken, 2008).

In contrast to approaches that use lidar return height and density metrics to estimate plot-level biomass, high-density small-footprint lidar data have also been used to identify individual tree crowns, measure individual tree height, and subsequently estimate individual tree biomass (Hyyppa et al., 2001; Popescu and Wynne, 2004; Popescu, 2007; Persson et al., 2002). For trees that are individually identified, height measurements from lidar data have accuracy approaching that of ground-based measurements commonly made using vertex hypsometers, but covering much broader spatial extents (Andersen et al., 2006; Persson et al., 2002). As a result, biomass and volume have been accurately estimated using allometric relationships using height and crown size derived from lidar data (Hyyppa et al., 2001; Persson et al., 2002; Popescu, 2007).

Thus, lidar data have successfully been used to measure forest biomass using two broad methods: (*i*) the estimation of plot-level biomass using return heights and densities summarized within a forest stand or plot, and (*ii*) the estimation of individual tree biomass by identifying individual trees and using lidar height and crown dimensions. Despite these successes, however, few studies have combined these approaches by first identifying individual trees and then combining these tree-level lidar results with plot-level lidar metrics of height and density to calculate plot-level aboveground biomass. In this short communication, we develop and apply this approach to estimate large tree and snag aboveground mass (total live and dead standing) (TSAM) in a forest in coastal British Columbia and compare the predictions with measurements derived from Canadian National Forest Inventory (NFI) style ground plots (NFI, 2004).

Methodology

Study site and ground plots

The study site is located in the Oyster River watershed on the east coast of Vancouver Island, near Campbell River, British Columbia, Canada, within the Coastal Western Hemlock very dry maritime biogeoclimatic subzone (CWHxm) (Pojar et al., 1991). The site is one of three flux tower sites in coastal British Columbia being studied as part of the Canadian Carbon Program (CCP) Fluxnet Canada Research Network (FCRN) (available from www.fluxnet-canada.ca/home.php?page=home&setLang=en). This second-growth stand was established by planting in 1949 following clearcut harvesting and broadcast burning of the original old-growth stand. The overstory is dominated by Douglas-fir (*Pseudotsuga menziessi* var. *menziessi*) with smaller amounts of western hemlock (*Tsuga heterophylla*), western red cedar (*Thuja plicata*), and red alder (*Alnus rubra*). Though the site is mapped as a single forest cover type and site index by forest companies operating in the area, the sloping topography (260–470 m elevation) and disturbance history have resulted in finer scale variation in forest cover across the 33 ha study site.

In the autumn of 2002, field measurements were made at 12 ground plots following NFI guidelines (NFI, 2004) to determine the range of stand characteristics at the study site. Plots were clustered in groups of three, systematically located at representative sites according to the range of mapped forest cover and ecosite series within the forest area estimated in 2002 to be contributing to flux tower measurements (Humphreys et al., 2006). Live and dead trees (snags) greater than 9.0 cm diameter at breast height (DBH, measured 130 cm above ground) were measured for species, height, diameter, height to live crown, canopy class (dominant, codominant, intermediate, and suppressed), and stem location in 11.28 m radius circular large tree plots (0.04 ha). Tree height measurements were made using a vertex hypsometer, and stem mapping was completed using a compass and vertex hypsometer. In some cases, in dense homogeneous parts of the stand, half plots (0.02 ha) were measured when representative of stand conditions. All measured trees within the full extent of each plot were used for assessment of TreeVaW measurements of stem location and height. For consistency in this study, all full plots were then divided into half plots, and only half of the plot, selected at random, was used to estimate plot-level tree and snag mass. The same plot boundaries that were used for calculation of plot-level tree and snag mass from biometric data were also used for calculation of plot-level TreeVaW metrics and lidar return metrics. Small trees (0.5–9.0 cm DBH) were measured on the large plot or in a nested 3.99 m radius small tree plot but

Table 1. Matches between TreeVaW-identified trees (TVT) and ground plot measured trees (GP).

	GP (no. of stems)	One GP : one TVT (% of GP stems)	Many GP : one TVT (% of GP stems)	Unmatched GP (% of GP stems)	Zero GP : one TVT (no. of unmatched TVT stems)
All trees	302	12	38	50	17
Trees ≥ 28 m	105	41	27	32	7

Note: Matches occur when the crown radius of a tree located by TreeVaW encompasses a stem mapped tree in a ground plot.

were not used in this analysis, which focused on large trees only. Field data were submitted to the NFI database compilation program for calculation of large tree and snag aboveground mass (stem, bark, branches, and foliage of live trees; stem, bark, and branches of standing dead trees) using published national species-specific allometric equations (NFI, 2004). Estimates for each tree were then summed within each plot to determine plot-level large tree and snag aboveground mass (TSAM).

Individual tree detection from lidar data

Lidar data were collected on 8 June 2004 with a beam footprint of 0.19 m and ground point sampling density vendor reported scene-wide average of 0.7 returns/m^2 (Coops et al., 2007). Within the sample plots, actual return density ranged between 1.8 and 7.3 returns/m^2 (mean = 5.3 returns/m^2, standard deviation = 1.9 returns/m^2). A 50 cm digital elevation model (DEM) and a canopy height model (CHM) were built using Fusion v2.6 software (Remote Sensing Applications Centre, USDA Forest Service, Salt Lake City, Utah). Individual trees were detected from the canopy height model using TreeVaW v1.2 software (Popescu et al., 2003), which identifies high points in the CHM that are likely to be tree tops using local maximum filtering, with a circular window sized proportionally with the relationship between tree height and crown diameter (Popescu and Wynne, 2004; Popescu et al., 2002). To parameterize TreeVaW for Douglas-fir, a regression model was developed from live tree height and crown diameter data available in Coops et al. (2007).

Lidar aboveground mass estimation

Two sets of predictor variables were used to estimate TSAM: (*i*) metrics calculated from lidar returns within each plot, including height of percentiles of nonground returns (10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th, and 95th percentiles, or P10–P95, respectively), and metrics from measurements of individually identified trees; and (*ii*) the canopy return density over a range of relative heights, i.e., proportion of laser returns in 10 even height intervals (D0, D1, D2, D3, D4, D5, D6, D7, D8, D9) between 0.5 m (D0) and the 95th (D9) percentile of maximum height (Næsset, 2004; Næsset and Gobakken, 2008). Summary descriptive statistics for the TreeVaW-identified trees (TVT) included maximum height (MaxHt), minimum height (MinHt), and variance in heights (HtCV) and stem density (Den) for trees ≥ 28 m height in each ground plot (the mean height of trees with codominant canopy status). All predictor and target variables were transformed using the natural logarithm to improve linearity. A linear multiple regression model was developed based on maximum coefficient of determination r^2 selection. Variables were not transformed any further (e.g., principal component analysis), making explanation of lidar measurements in terms of stand structure more straightforward. A correlation matrix was used to test for models with combinations of variables with high collinearity. To reduce the bias often present in logarithm-transformed allometric equations, a correction factor was applied to all variables when back-transforming to original units (following Sprugel, 1983). All statistical analysis was performed using the Statistical Analysis System (SAS) version 9 (SAS Institute Inc., Richmond, Va.).

Results

The relationship between stem locations identified by TreeVaW and live stem locations measured in the field is shown in **Table 1**. Initially, a comparison of all trees, regardless of height, was undertaken. Second, a minimum height cutoff of 28 m was applied to both TreeVaW-identified trees and live inventory measured trees, and the relationship was reassessed. As expected, the results indicate that many of the smaller trees lower in the canopy were not consistently detected using TreeVaW because of the dense overstory canopy structure. Also, TreeVaW parameterization uses only live trees, and only three of 117 dead standing trees were correctly identified. Restricting our analysis to live dominant and codominant trees (>28 m) resulted in a greater proportion of correctly identified trees.

A strong linear relationship (r^2 = 0.92, and standard error of the estimate SE_E = 0.69 m) was observed for correctly identified trees greater than 28 m in height between tree height identified by TreeVaW and height measured in ground plots (**Figure 1**), though the TreeVaW-predicted heights deviated from a 1:1 line with a constant bias such that TVT heights were about 1 m less than ground plot measured tree heights.

Correlations between TSAM and predictor variables from lidar (**Figure 2a**) and TreeVaW (**Figure 2b**) showed that the lidar return density at 60% maximum height (D_6) had the highest correlation with TSAM and that correlations with all TreeVaW variables were low.

The two most applicable multiple linear regression models (highest r^2 and lowest SE_E) used either the best plot-level lidar variables alone (model 1) or the best TreeVaW plot summary individual tree variables in combination with plot-level lidar

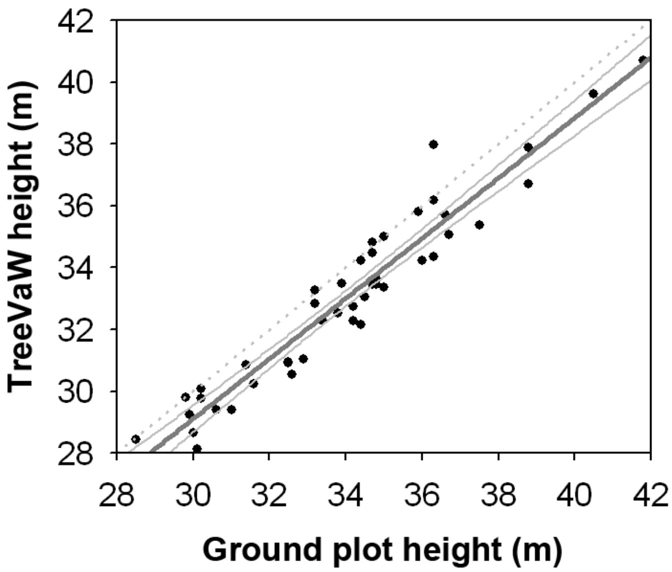

Figure 1. For trees greater than 28 m in height, tree heights measured using TreeVaW matched tree heights measured in ground plots, with r^2 = 0.92 and SE_E = 0.69 m. The 95% confidence interval of the prediction is given by the light grey lines, and the 1:1 line by the grey dots.

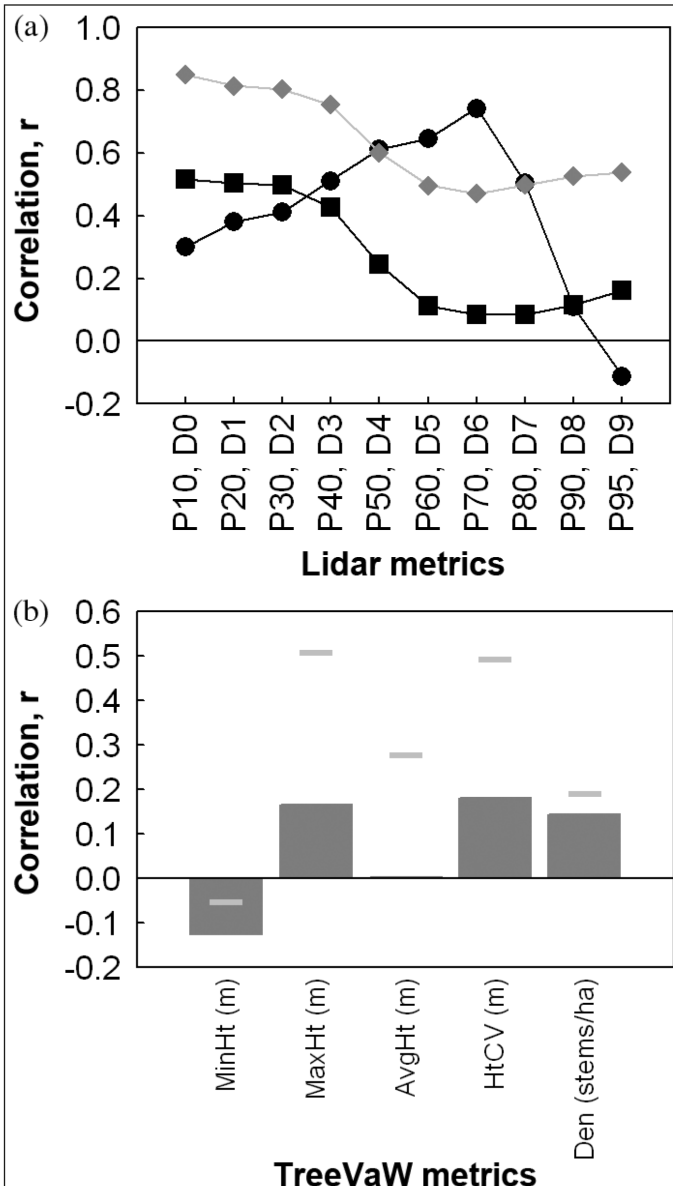

Figure 2. (a) Pearson's correlation coefficients between TSAM and lidar plot metrics (height percentiles P10–P95 as black line with solid circles; height densities D0–D9 as black line with solid squares), and height percentiles (P0–P10) and D6 (the most highly correlated plot-level metric; grey line with diamonds). (b) Pearson's correlation coefficient between TSAM and TreeVaW metrics (grey bars) and between TreeVaW metrics and D6 (most highly correlated plot-level metric; grey lines).

variables (model 2) (**Table 2**). For both models, a variable representing lidar canopy return density at 60% maximum plot height (D_6) was chosen. For the lidar plot-level model, a variable representing crown height was also chosen (P80, the 80th percentile of the height of nonground returns). The Pearson's correlation coefficient between the two variables in the model was 0.49, indicating that collinearity was not a problem for this model. A plot of the model 1 TSAM estimates demonstrated it deviated from the 1:1 line with variable bias such that it overestimated TSAM at low levels (**Figure 3a**). For model 2, in addition to D6, the second variable selected was maximum height of TreeVaW-identified trees in each ground plot (TVT_{MaxHt}). The Pearson's correlation coefficient between the two variables in the model was 0.51, indicating that collinearity was not a problem for this model. A plot of the model 2 predicted TSAM demonstrated it deviated from the 1:1 line with variable bias such that it overestimated TSAM at low levels (**Figure 3a**). The variable bias in both models is likely the result of the use of logarithm-transformed data for the regression.

Discussion

TreeVaW software was used to identify the locations and heights of live trees from lidar data collected over a Douglas-fir dominated stand on eastern Vancouver Island, British Columbia, Canada. The detection algorithm was initially developed for tree identification in plantation-like stands of loblolly pine (*Pinus taeda*) in the southeastern United States, often using high return density lidar data. In these complex, multilayered stands of the Pacific Northwest, multiple trees often compose canopy units that are challenging to separate, resulting in multiple stems falling within a single lidar-delimited crown. As well, in this stand, standing dead trees contribute more than 10% of the overall large tree mass; however, TreeVaW is not parameterized to measure these, and few were accurately detected. When our analysis was restricted to taller live trees in the canopy, the TreeVaW algorithm was much more successful in identifying individual trees, and height was determined with considerable accuracy.

Measures of canopy return density were more successful than measures of height for predicting TSAM. On its own, the proportion of lidar returns at 60% of maximum tree height and

Table 2. Multiple linear regression models for large tree and snag aboveground mass (TSAM).

	β_0	β_1	x_1	β_2	x_2	r^2	SE'_E
Model 1	8.91****	1.14***	D_6	–0.86**	P_{80}	0.75	29.68
Model 2	8.3***	1.09***	D_6	–0.64*	TVT_{MaxHt}	0.72	31.95

Note: Models take the form $\ln Y = \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + e$, where Y is the aboveground mass; r^2, coefficient of determination; SE'_E, standard error of the estimate (in Mg/ha TSAM). Significance levels are as follows: *, <0.2; **, <0.1; ***, <0.05; ****, <0.001.

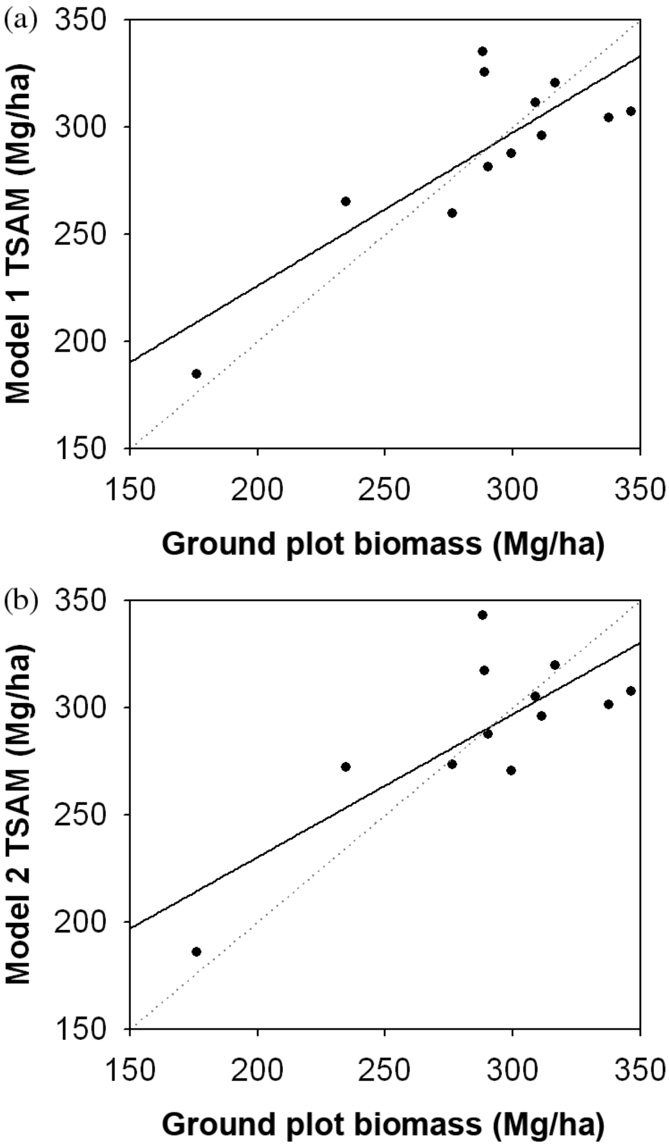

Figure 3. Lidar multiple regression model estimates of large tree and snag aboveground mass (TSAM) versus ground plot measurements using (a) model 1 and (b) model 2. See **Table 2** for model variables. The 1:1 line is given by the grey dots.

higher (D_6) explained 65% of the variation in TSAM. Height percentile measures were less successful individually, with lower percentiles explaining more of the variation in TSAM, and were highly correlated with measures of canopy density. As a result, multiple linear regression models with two variables were examined in an attempt to explain more of the variation in TSAM.

Two multiple linear regression models were developed for plot-level TSAM. The first model selected predictor variables for lidar return height (P_{80}) and return density (D_6). The second model selected predictor variables for TreeVaW maximum height (TVT_{MaxHt}) and lidar return density (D_6) and explained 72% of the variance. The 80th percentile return height performed slightly better than TVT_{MaxHt}, explaining 75% of the variance. For both models, canopy return density was the most significant variable for determining TSAM, with a less significant relationship between TVT_{MaxHt} in the plot and TSAM. For this study, individual tree measurements did not improve TSAM estimates. This is most likely due to a number of the TSAM components not being well captured using individual tree based approaches. A study by Falkowski et al. (2008) shows that in conifer forests with high canopy cover, individual tree detection algorithms commonly make errors of omission, such as missing subdominant stems or clumping multiple stems together into single canopy objects. As a result of these trees not being measured properly, the accuracy of TSAM estimations in conifer forest with high canopy cover may be limited. For example, in this study, TSAM is distributed throughout the canopy in dead standing trees (not measured by TreeVaW), closely spaced shoulder-height trees (as indicated by the success of the P_{80} lidar metric), and very tall live standing dominant and codominant trees. Individual tree based approaches may be more successful for plot-level estimates of TSAM in stands where canopy units are more distinct, such as in conifer forests with less dense canopy cover. Given our successes in estimating TSAM despite difficulties detecting individual suppressed or dead standing trees, for other studies seeking to estimate TSAM in stands with complex canopies, it may be more economical to collect lower density lidar data and utilize plot-level lidar return metrics.

This study demonstrates that it is practical to apply published techniques for individual tree detection and canopy return density using small-footprint discrete return lidar data and use the results to estimate large tree and snag aboveground mass.

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