OPERATIONALIZING THE USE OF LIDAR IN FOREST RESOURCE INVENTORIES: WHAT IS THE OPTIMAL POINT DENSITY?

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ABSTRACT

Literature from the past two decades documents how airborne LIDAR can be used to predict forest inventory variables, such as basal area, volume, and biomass, at the plot and stand level. However, a key question that has yet to be fully addressed, and that the forest industry continues to ask as it considers operationalizing the use of LIDAR in forest resource inventories, is: What is the optimal point density for predicting forest inventory variables? For example, is a point density of 0.5 points/m^2 sufficient for making accurate predictions of forest inventory variables or is a point density of 3 points/m^2 the minimum required? To investigate this key question, a three-year project was launched in 2007 in Ontario, Canada. Field data for approximately 180 plots, sampling a broad range of forest types and conditions in Ontario, were collected over two study sites. Airborne LIDAR data, characterized by 3 points/m^2 were systematically decimated to produce datasets with point densities of approximately 1.5 and 0.5 points/m^2. Models, developed using stepwise regression, were developed for each of the three lidar datasets to estimate several forest inventory variables including: (1) basal area (R^2=0.25-0.94); (2) gross total volume (R^2=0.46-0.95); (3) gross merchantable volume (R^2=0.37-0.94); (4) stem density(R^2=0.23-0.89); (5) quadratic mean diameter (R^2=0.59-0.86); (6) total aboveground biomass (R^2=0.26-0.93); (7) average height (R^2=0.76-0.95); and (8) top height (R^2=0.75-0.98). Aside from two cases, no decimation effect was found for predictions of forest variables, which suggests that a point density of 0.5 points/m^2 is sufficient for plot and stand level modelling under these forest conditions.

INTRODUCTION

Forest inventory and management requirements are changing rapidly as forest industries try to satisfy an increasingly complex set of rules, standards, business practices, and public expectations (i.e., economic, environmental and social policy goals). To satisfy these expectations, there is a critical need to develop accurate inventory systems that spatially quantify forest structure and related attributes to enable product segregation and resource value maximization (Pitt and Pineau, 2009). Over the past decade, research has clearly demonstrated the capacity for light detection and ranging (LIDAR) and methodological approaches (i.e., derived LIDAR metrics and models) to enhance our capacity for acquiring forest biophysical variables for forest planning and operations (Lim and Treitz, 2004; Rooker Jensen et al. 2006; Gobakken and Næsset 2007; Bollandsås and Næsset 2007; Stephens et al. 2007; Thomas et al., 2008; Woods et al., 2008). These technologies and methods are now starting to be implemented operationally in forests around the world (Næsset 2004; Holmgren and Jonsson 2004). However, standards for the acquisition, processing, and application of LIDAR data for forestry and natural resources inventory and management do not currently exist. For example, data acquisition standards (e.g., sampling density) that determine the optimal acquisition of LIDAR data for forestry (in terms of forest variable estimation and cost efficiency) have yet to be developed. These standards are required if the forest industry is to gain the best possible return from the technology across a range of forest conditions and for specific operational requirements. The goal of this research is to identify standards for collecting, processing and analysing LIDAR data to derive forest inventory attributes that lead to the production of an enhanced forest resource inventory (eFRI) for Ontario forests. Here, we report on the impact of LIDAR point density on the prediction of forest inventory variables.

STUDY AREAS

Two study areas, Swan Lake Research Reserve (SLRR) and the Romeo Malette Forest (RMF) provided a range of forest species common to central and northern Ontario (Figure 1).

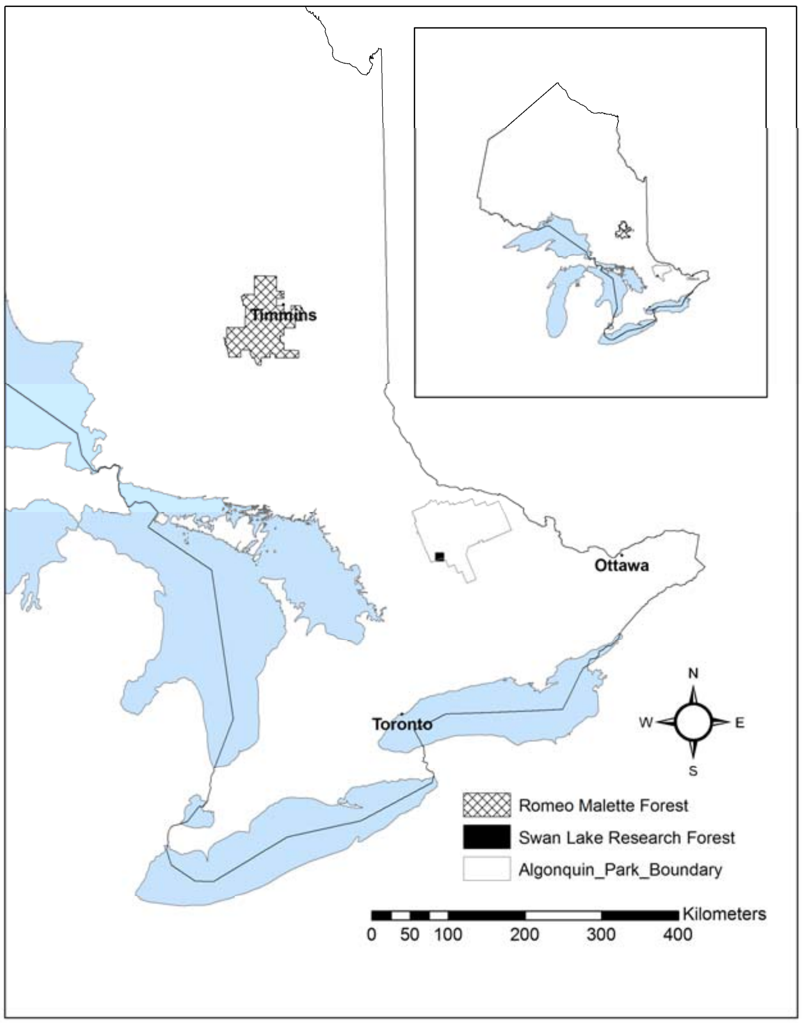

Figure 1. The geographic location of the Swan Lake Research Reserve and Romeo Malette Forest in Ontario, Canada.

Swan Lake Research Reserve

The SLRR is located 250 km north of Toronto and east of Huntsville, Ontario, within Algonquin Provincial Park. The 2,000 hectares (ha) site situated in Peck Township is located at 45° 28' N, 78° 45' W and ranges in elevation from 410 to 590 m above sea level (asl). This site lies on the Precambrian Shield and is characterized by rolling hills and high rocky ridges that are separated by valleys scoured by glaciation. Outwash flats, ablation moraines, and drumlinoid deposits provide soil deposits ranging from coarse to medium texture. The Algonquin Dome, due to its elevation, has a climate that is generally more cool and wet than its surrounding areas (Cole and Mallory 2005).

The site is within the Great Lakes–St. Lawrence Forest region and comprises mature stands of shade– and mid–tolerant hardwoods (sugar maple [*Acer saccharum* Marsh.], American beech [*Fagus grandifolia* Ehrh.], soft maple [*Acer rubrum* L.], yellow birch [*Betula alleghaniensis* Britt.], ironwood [*Ostrya virginiana* (Mill.) K. Koch]), conifers (eastern hemlock [*Tsuga canadensis* (L.) Carrière], white pine [*Pinus strobus* L.], white spruce [*Picea glauca* (Moench) Voss], red spruce [*Picea rubens* Sarg.], eastern larch [*Larix laricina* (Du ROI) K. Koch], eastern white cedar [Thuja occidentalis L.], balsam fir [*Abies balsamea* (L.) Mill.]), and minor proportions of mid–tolerant and intolerant hardwoods (i.e., white birch [*Betula papyrifera* Marsh.], black cherry [*Prunus serotina* Ehrh.], white ash [*Fraxinus americana* L.], black ash [Fraxinus nigra Marsh.], and trembling aspen [*Populus tremuloides* Michx.]).

Romeo Malette Forest

The RMF is located in the northeast portion of Ontario's Boreal Forest near Timmins, Ontario. The RMF is an active forest management unit with approximately 532,000 productive forest hectares. The forest is characterized by extensive coniferous stands on poorly drained lowlands and gently rising uplands. The northern portion (40% of the forest area) located on clay is best described as relatively flat to gently rolling, interspersed with depressions and eskers. The elevation ranges from 305 to 320 metres above sea level with extensive clay deposits, high water table and poor drainage. The remaining southern area of the forest consist mainly of glacial deposits of bouldery sand till overlying bedrock with elevation ranges from 305 to 380 metres asl with moderately rolling topography with generally good drainage. The dominant species are black spruce [*Picea mariana* (Mill) B.S.P.], white birch, trembling aspen, jack pine [*Pinus banksiana* Lamb.], eastern white cedar, white spruce, eastern larch, and balsam fir. Other minor species include black ash, yellow birch, soft maple and red [*Pinus resinosa* Ait.] and white pine.

The RMF has a relatively cool climate with a mean annual temperature of 1.4°C. Temperature ranges from an extreme low of –45 °C to an extreme high of 35 °C. The growing season (period when mean temperature is above 5.6°C) is approximately 160 days. The average annual precipitation is 77.5 cm with 50.8 cm falling as rain, the balance as snow. Average annual snowfall is 275.8 cm and summer rainfall (May to September) is approximately 37.6cm.

METHODS

Field Data

Ground reference data were collected for the two study areas during the period of November to December 2007 and May to October 2008. A circular fixed area plot of 400 m^2 was established for sampling all forest types except for the tolerant hardwood group where a 1000 m^2 plot size was used to better represent metrics of uneven-aged size class structures. Forest types sampled were: (i) tolerant hardwoods (sugar maple, beech, and yellow birch); (ii) black spruce; (iii) jack pine; (iv) intolerant hardwoods (white birch and trembling aspen); and (v) mixedwoods.

For each plot, all trees larger than or equal to 9.1 cm diameter at breast height (DBH) were measured with a diameter tape. Each tree was assessed for species, status (live or dead), crown class (dominant, co–dominant, etc.) and visual quality. A Vertex™ hypsometer was used to measure height to base of live crown and total tree height for every tree. Heights of deciduous species were measured in a leaf–off period to obtain the most accurate height possible. The centre of each circular plot was geo–referenced with a Trimble Pro XT™ kinematic GPS unit connected to a Hurricane™ antenna, which was mounted on a tripod. A minimum of 300 points were collected for each post position and later post–processed against a base station to achieve sub–meter accuracy. Plot data consisting of individual tree data were compiled to per ha values using the equations presented in Table 1.

Summary plot statistics, including top height (TOPHT), average height (AVGHT), basal area (SUMBA), density (DENSITY), quadratic mean DBH (QMDBH), gross total volume (SUMGTV), gross merchantable volume (SUMGMV), and aboveground biomass (BIOMASS), are presented in Table 2 by study site and forest or species grouping if applicable.

LIDAR Data and Data Processing

LIDAR data were collected in August 2007 using an Optech ALTM3100 airborne laser scanner mounted in a Cessna 208B Grand Caravan. The base mission was flown at 1000 m with a scan rate of 54 Hz and a maximum pulse repetition frequency of 100,000 Hz. This configuration resulted in a cross track spacing of 0.50 m, an along track spacing of 0.57 m, an average sampling density of 3.2 points/m^2, and a swath width of approximately 475 m. The LIDAR point cloud data were classified as ground or vegetation by the vendor using proprietary algorithms. A bald-earth DEM was derived from the classified ground returns. All LIDAR point data were normalized to the terrain (i.e., given a return and its x-y coordinate, subtract the z-value for that x-y coordinate on the DEM from its original z-value).

Table 1. Equation or method used to calculate forest variables

Ground Metric	Description
Top Height (m)	Calculated as the average of the largest 100 stems per hectare.
Average Height (m)	Calculated as the average height of all trees 9.1 cm and larger.
Density (stems ha^{-1})	Number of live trees 9.1 cm and larger expressed per hectare.
Quadratic Mean DBH (cm)	$\sqrt{\left[\left(\sum DBH^{2} / n\right)\right]}$ where *n* is stems per plot.
Basal Area (m^2 ha^{-1})	DBH^2 * .00007854 Per hectare value calculated by summing each tree per plot.
Gross Total Volume (m^3 ha^{-1}) (Honer et al. 1983)	= ß$_1$ * DBH^2*(1-0.04365* ß$_2$)^2/(ß$_3$+(0.3048 * ß$_4$/Ht)) Individual tree volume equation. Coefficients vary by species. Per hectare value calculated by summing each tree per plot.
Gross Merchantable Volume (m^3 ha^{-1}) (Honer et al. 1983)	= SUMGTV * (ß$_1$ + ß$_2$(X) + ß$_3$(X)) X = [(1+hs/ht)(Dtop2/DBH2)] HS = Stump Height HT = Total Height Dtop = Minimum Top Diameter MV = Merchantable Volume Individual tree volume equation. Coefficients varies by species. Per hectare value calculated by summing each tree per plot.
Aboveground Biomass (Kg ha^{-1}) (Ter-Mikaelian and Korzukhin, 1997)	= ß$_1$ * Dbh^{ß}2 Individual tree above ground biomass equation. Coefficients vary by species. Per hectare value calculated by summing each tree per plot.

Table 2. Summary plot statistics for the SLRR and PRF

Variable	SLRR				RMF			
	Tolerant Hardwood (N=32)				Intolerant Hardwoods (N=33)			
	Mean	Mean	Mean	Mean	Mean	Min.	Max.	Std. Dev.
TOPHT (m)	24.9	22.6	22.6	22.6	22.6	17.3	35.8	5.4
AVGHT (m)	18.9	16.7	16.7	16.7	16.7	11.7	32,9	5.3
SUMBA (m^2/ha)	25.9	31.4	31.4	31.4	31.4	13.5	58.8	13.8
DENSITY (stems/ha)	421.0	1198.5	1198.5	1198.5	1198.5	75.0	1826.2	393.8
QMDBH (cm)	28.5	18.2	18.2	18.2	18.2	13.89	55.3	10.4
SUMGTV (m^3/ha)	232.8	266.5	266.5	266.5	266.5	106.9	770.9	209.3
SUMGMV (m^3/ha)	201.9	216.2	216.2	216.2	216.2	75.5	742.9	206.7
BIOMASS (Kg/ha)	203514	128732	128732	128732	128732	60853	246965	56780
Variable	**RMF**							
	Jack Pine (N=35)				**Black Spruce (N=34)**			
	Mean	**Mean**	**Mean**	**Mean**	**Mean**	**Min.**	**Max.**	**Std. Dev.**
TOPHT (m)	20.2	16.7	16.7	16.7	16.7	11.7	24.8	3.1
AVGHT (m)	16.1	12.9	12.9	12.9	12.9	8.9	19.8	2.1
SUMBA (m^2/ha)	21.2	25.8	25.8	25.8	25.8	12.9	53.9	9.6
DENSITY (stems/ha)	1414.5	1643.0	1643.0	1643.0	1643.0	600.4	2376.6	470.5
QMDBH (cm)	17.0	14.2	14.2	14.2	14.2	12.2	22.7	2.8
SUMGTV (m^3/ha)	248.8	162.7	162.7	162.7	162.7	57.7	464.0	94.1
SUMGMV (m^3/ha)	105.4	109.0	109.0	109.0	109.0	28.3	401.1	88.7
BIOMASS (Kg/ha)	127458	100833	100833	100833	100833	43966	244507	45404

The LIDAR data were decimated according to the methodology described by Raber *et al.* (2007). Decimation level 0 (D0) represents the original dataset characterized by a point density of approximately 3 points/m^2. The decimation level 1 (D1) LIDAR dataset was derived by taking alternating points along each scan line with each scan line retained, thereby increasing the cross track spacing by a factor of two. For the decimation level 2 (D2) LIDAR dataset, every fourth point along each scan line was retained, thereby increasing the cross track spacing by a factor of 4, and every other scan line was retained, resulting in an increase in the along track spacing by a factor of 2. The systematic decimation resulted in the D1 and D2 LIDAR datasets possessing point densities of approximately 1.5 and 0.5 points/m^2, respectively.

LIDAR Canopy Height and Density Predictors

Three types of predictors (i.e., statistical, canopy height, and canopy density) were derived from the normalized LIDAR data. No height thresholds were used to filter any of the point data. The statistical group of predictors included mean height and standard deviation (stddev) of LIDAR height measurements. The canopy height predictors consisted of deciles of LIDAR canopy height (i.e., p10…p90) and the maximum (max) LIDAR height. For each plot the range of LIDAR height measurements was divided into 10 equal intervals and the cumulative proportion of LIDAR returns found in each interval, starting from the lowest interval (i.e., d1), was calculated. Since the last interval always sums to a cumulative probability of 1, it was excluded resulting in 9 canopy density metrics (i.e., d1 … d9). The remaining two canopy density metrics were calculated as the number of first returns divided by all returns intersecting a sample plot (Da) and the number of first and only returns divided by all returns intersecting a sample plot (Db).

Statistical Analyses

Stepwise regression and a significance level of 0.05 were used for model building. A diagnosis of each model was performed to determine if parametric statistical assumptions were satisfied. The Shapiro-Wilk Test was used to determine if residuals were normally distributed, whereas the Brown-Forsythe Test was used to check for the presence of heteroschedasticity (i.e., unequal error variance).

As LIDAR predictors have been reported to be highly correlated, the variance inflation factors (VIF) for the predictors used in a model were examined (Neter *et al*., 1996). Candidate models where predictors exhibited VIF greater than 10 were discarded, as values above 10 suggest the presence of multi-collinearity in the predictor data (Neter *et al.*, 1996).

Repeated measures ANOVA was used to investigate the effect of decimation on predictions of forest variables. A repeated measures ANOVA is used when all members of a sample are measured repeatedly under a number of different conditions. Within the context of this study, it was a particular forest variable for a plot that was repeatedly predicted using LIDAR data of three varying point densities. Given repeated measurements, the use of a standard ANOVA is not appropriate (Popescu and Zhao, 2008). The hypothesis tested with repeated measures ANOVA was: Does point density (i.e., 3, 1.5 and 0.5 points/m^2) influence predictions of each of the forest variables considered in this study? This is referred to as a within-subjects test.

RESULTS

Swan Lake Research Reserve – Tolerant Hardwoods

The regression models at each decimation level by forest variable for the SLRR are reported in Table 3. An assessment of the percent root mean square error (RMSE) for each forest variable by decimation level shows little variability. With the exception of QMDBH, no decimation effect was found for any of the other forest variables considered for the SLRR (i.e., with the exception of QMDBH, Wilk's Lamda p values were greater than 0.195 for the other forest variables) (Table 4). For QMDBH at D0, the R^2 was 0.592 compared a R^2 of 0.702 and 0.703 for D1 and D2, respectively. This indicates that the model for the D0 dataset (high density) is accounting for less of the variability in the observations in comparison to the models derived for the D1 and D2 datasets (lower densities).

Table 3. Models developed for each decimation level by forest variable for SLRR – Tolerant Hardwoods

Variable	Dec. Level	Equation	R^2	R^2 (Adj.)	RMSE	RMSE (%)
SUMBA (m^2/ha)	D0	34.8 - 16.7 d7	0.262	0.237	3.17	12.64
	D1	35.2 - 17.4 d7	0.277	0.253	3.14	12.50
	D2	34.3 - 16.0 d7	0.245	0.220	3.20	12.78
SUMGTV (m^3/ha)	D0	84.8 + 7.63 p50 + 6.58 p10	0.458	0.420	29.18	12.92
	D1	198 - 201 d7 + 6.65 p10 + 4.69 Da	0.558	0.511	26.34	11.66
	D2	93.6 + 7.30 p10 + 7.08 p50	0.469	0.433	28.86	12.78
SUMGMV (m^3/ha)	D0	27.6 + 10.3 p50	0.375	0.354	28.93	14.77
	D1	28.4 + 10.3 p50	0.374	0.353	28.94	14.78
	D2	67.5 + 6.99 p50 + 6.07 p10	0.456	0.418	26.98	13.78
DENSITY (stems/ha)	D0	1518 - 111 stddev - 12.3 p10 - 10.9 Da	0.761	0.736	51.85	12.70
	D1	464 + 794 d8 + 27.8 p20 - 34.1 max	0.842	0.825	42.14	10.32
	D2	617 + 673 d8 + 26.3 p20 - 35.9 max	0.830	0.812	43.73	10.71
QMDBH (cm)	D0	6.33 + 2.26 stddev - 17.2 d7 + 0.600 Da	0.592	0.548	2.31	8.37
	D1	27.8 - 27.1 d8 + 64.6 d2 + 0.876 p10 + 0.331 Da	0.702	0.658	1.97	7.15
	D2	50.5 - 20.5 d8 + 62.0 d2 + 1.04 p10 - 0.281 Db	0.703	0.660	1.97	7.13
AVGHT (m)	D0	9.97 + 0.738 p50 - 0.0987 Db + 4.29 d8	0.837	0.820	0.62	3.36
	D1	10.1 + 0.746 p50 - 0.105 Db + 4.53 d8	0.836	0.819	0.62	3.37
	D2	- 0.43 + 0.744 p50 + 0.132 Da + 4.50 d8	0.850	0.834	0.59	3.23
TOPHT (m)	D0	6.44 + 0.889 p80	0.764	0.756	0.83	3.45
	D1	6.64 + 0.879 p80	0.758	0.749	0.84	3.50
	D2	6.97 + 0.865 p80	0.751	0.743	0.86	3.55
SUMBIO (kg/ha)	D0	208918 - 194385 d7 + 3821 Da	0.360	0.315	26,884	13.62
	D1	287254 - 156798 d7	0.279	0.255	28,532	14.46
	D2	182026 + 7783 p10	0.257	0.232	28,966	14.68

Table 4. Results from repeated measures ANOVA for the Tolerant Hardwoods

Variable	Decimation Effect?	MANOVA – Wilk's Lamda		
		Value	**F**	***p***
SUMBA	No	0.893	1.73	0.195
SUMGTV	No	0.894	1.71	0.199
SUMGMV	No	0.927	1.14	0.334
DENSITY	No	0.944	0.87	0.431
QMDBH	Yes	0.595	9.85	0.001
AVGHT	No	0.991	0.14	0.872
TOPHT	No	0.910	1.43	0.256
SUMBIO	No	0.935	1.01	0.376

Romeo Malette Forest

Intolerant Hardwoods. The regression models at each decimation level by forest variable for the intolerant hardwood forest grouping are reported in Table 5. It is interesting to note that in most instances, the same LIDAR predictors are selected during stepwise regression model building and again exhibit limited variability in percent RMSE. The repeated measures ANOVA results (Table 6) did not identify a decimation effect for any of the forest variables in the intolerant forest grouping (Wilk's Lamda p values > 0.32) for the RMF.

Jack Pine. The regression models at each decimation level by forest variable for the jack pine forest grouping are reported in Table 7. Similar to results reported for other sites and groupings, with the exception of DENSITY, the percent RMSE values for each variable by decimation level are very similar to each other. Excluding DENSITY, no decimation effect was found for any of the other forest variables in the jack pine forest grouping (i.e., Wilk's Lamda p values were greater than 0.37 for the other forest variables) (Table 8).

***Black Spruce*.** The regression models at each decimation level by forest variable for the black spruce forest grouping are reported in Table 9. The repeated measures ANOVA results (Table 10) did not identify a decimation effect for any of the forest variables in the black spruce forest grouping (Wilk's Lamda *p* values > 0.259) in the RMF.

Table 5. Models developed for each decimation level by forest variable for RMF-Intolerant Hardwoods

Variable	Dec. Level	Equation	R^2	R^2 (Adj.)	RMSE	RMSE (%)
SUMBA (m^2/ha)	D0	- 16.1 + 4.16 mean	0.837	0.831	4.45	14.12
	D1	- 16.1 + 4.15 mean	0.833	0.827	4.50	14.29
	D2	- 15.8 + 4.12 mean	0.823	0.817	4.62	14.68
SUMGTV (m^3/ha)	D0	- 175 + 30.0 p80 - 331 d2	0.880	0.872	42.17	15.76
	D1	- 261 + 45.6 p80 - 38.9 stddev	0.877	0.868	42.70	15.96
	D2	- 267 + 30.7 p80	0.860	0.855	45.52	17.01
SUMGMV (m^3/ha)	D0	- 310 + 30.3 p80	0.873	0.869	42.14	19.40
	D1	- 312 + 30.3 p80	0.871	0.867	42.55	19.59
	D2	- 308 + 30.1 p80	0.877	0.873	41.56	19.13
DENSITY (stems/ha)	D0	1875 - 2465 d3	0.239	0.214	272.68	22.78
	D1	1853 - 2413 d3	0.227	0.201	274.84	22.96
	D2	1867 - 2486 d3	0.248	0.223	271.06	22.65
QMDBH (cm)	D0	1.06 + 0.925 p90	0.842	0.837	1.50	8.21
	D1	1.05 + 0.925 p90	0.843	0.838	1.50	8.20
	D2	0.93 + 0.932 p90	0.840	0.834	1.51	8.28
AVGHT (m)	D0	8.01 + 0.498 p80	0.767	0.75	1.00	6.02
	D1	7.99 + 0.499 p80	0.764	0.756	1.01	6.05
	D2	8.03 + 0.496 p80	0.773	0.766	0.99	5.93
TOPHT (m)	D0	3.04 + 0.628 p90 + 0.356 max	0.941	0.937	0.89	3.95
	D1	3.03 + 0.627 p90 + 0.359 max	0.939	0.935	0.90	4.01
	D2	3.29 + 0.629 p90 + 0.351 max	0.943	0.939	0.87	3.87
SUMBIO (kg/ha)	D0	- 103147 + 20390 mean	0.788	0.781	25,562	19.68
	D1	- 103157 + 20351 mean	0.784	0.777	25,789	19.85
	D2	- 101819 + 20193 mean	0.775	0.767	26,332	20.27

Table 6. Results from repeated measures ANOVA for the intolerant hardwoods forest type grouping

Variable	Decimation Effect?	MANOVA – Wilk's Lamda		
		Value	F	*p*
SUMBA	No	0.972	0.42	0.660
SUMGTV	No	0.986	0.21	0.813
SUMGMV	No	0.975	0.37	0.696
DENSITY	No	0.978	0.32	0.727
QMDBH	No	0.995	0.08	0.927
AVGHT	No	0.924	1.19	0.320
TOPHT	No	0.993	0.10	0.908
SUMBIO	No	0.972	0.41	0.666

Table 7. Models developed for each decimation level by forest variable for RMF-Jack Pine

Variable	Dec. Level	Equation	R^2	R^2 (Adj.)	RMSE	RMSE (%)
SUMBA (m^2/ha)	D0	5.82 + 2.10 p60 - 28.4 p10 + 0.842 p40	0.803	0.784	4.29	13.73
	D1	0.17 + 4.21 mean - 5.94 p20	0.783	0.770	4.49	14.39
	D2	5.16 + 2.94 mean - 7.17 p20 + 1.07 p40	0.810	0.792	4.21	13.48
SUMGTV (m^3/ha)	D0	- 79.1 + 44.1 mean - 57.0 p20	0.891	0.884	31.11	12.50
	D1	- 74.1 + 43.2 mean - 51.3 p20	0.886	0.878	31.84	12.80
	D2	- 74.6 + 43.9 mean - 52.6 p20	0.887	0.880	31.64	12.71
SUMGMV (m^3/ha)	D0	- 156 + 20.4 p90 + 6.10 p40	0.856	0.847	33.63	17.21
	D1	- 69.5 + 20.9 p90 + 6.96 p40 - 3.14 Da	0.877	0.865	31.09	15.91
	D2	- 3.7 + 15.4 p90 + 8.05 p40 - 37.7 p20 - 4.98 Da + 7.95 p60	0.913	0.899	26.08	13.35
DENSITY (stems/ha)	D0	659 + 57.4 Da - 1604 p10 - 75.0 max + 96.4 p40	0.650	0.604	278.19	19.67
	D1	- 867 + 72.1 Da	0.372	0.353	372.74	26.35
	D2	- 475 + 61.1 Da	0.298	0.276	394.28	27.87
QMDBH (cm)	D0	- 8.17 + 0.805 max + 0.152 Db	0.713	0.695	1.48	8.66
	D1	9.24 + 0.703 max - 0.179 Da	0.732	0.715	1.43	8.37
	D2	3.99 + 0.701 max	0.671	0.661	1.58	9.27
AVGHT (m)	D0	12.9 + 0.471 p70 + 7.88 d2 - 9.31 d6	0.866	0.853	0.79	4.89
	D1	16.1 + 0.432 p70 - 10.7 d7 + 6.10 d2	0.857	0.844	0.81	5.05
	D2	10.3 + 0.525 p70 + 8.64 d2 - 7.87 d5	0.849	0.835	0.83	5.19
TOPHT (m)	D0*	14.3 - 0.182 p40 + 0.901 max - 6.66 d4 - 8.34 d8	0.981	0.979	0.42	2.08
	D1	3.91 + 0.557 p90 + 0.399 max	0.974	0.972	0.50	2.46
	D2	4.71 + 0.633 p90 + 0.305 max	0.967	0.965	0.56	2.75
SUMBIO (kg/ha)	D0	- 178881 + 24006 mean - 33568 p20 + 2033 Db	0.852	0.837	17,479	13.71
	D1	28639 + 21390 mean - 27034 p20 - 1902 Da	0.843	0.828	17.972	14.10
	D2	- 160390 + 24132 mean - 30628 p20 + 1745 Db	0.846	0.831	17,842	14.00

* Model developed using best subsets regression as regression modelling assumptions could not be met based on models developed using stepwise regression despite dependent and independent variable transformations.

Table 8. Results from repeated measures ANOVA for the jack pine forest type grouping

Variable	Decimation Effect?	MANOVA – Wilk's Lamda		
		Value	F	*p*
SUMBA	No	0.980	0.33	0.721
SUMGTV	No	0.992	0.12	0.885
SUMGMV	No	0.951	0.82	0.448
DENSITY	Yes	0.646	8.78	0.001
QMDBH	No	0.940	1.03	0.370
AVGHT	No	0.982	0.30	0.746
TOPHT	No	0.993	0.10	0.908
SUMBIO	No	0.993	0.12	0.888

Table 9. Models developed for each decimation level by forest variable for RMF-Black Spruce

Variable	Dec. Level	Equation	R^2	R^2 (Adj.)	RMSE	RMSE (%)
SUMBA (m^2/ha)	D0	58.9 - 20.2 d5 + 1.58 p50 - 0.379 Db	0.918	0.909	3.01	11.68
	D1	- 0.91 + 2.23 p50 + 0.622 Da	0.910	0.904	3.15	12.22
	D2	48.6 + 1.26 p60 + 1.27 p40 - 0.478 Db	0.935	0.929	2.66	10.33
SUMGTV (m^3/ha)	D0	- 702 + 32.1 mean - 210 d6 + 873 d9 - 110 p20	0.949	0.942	17.96	11.04
	D1	- 66.3 + 42.2 mean - 5.59 p30	0.927	0.922	21.52	13.23
	D2	268 + 23.5 mean - 3.30 Db + 4.95 p40	0.942	0.936	19.14	11.77
SUMGMV (m^3/ha)	D0	- 114 + 5.63 p40 + 17.4 p90	0.916	0.910	18.19	16.69
	D1	- 182 + 20.1 p80 + 7.02 p40 + 113 d4	0.915	0.907	18.25	16.74
	D2	- 195 + 41.5 mean + 164 d3 - 282 p10	0.939	0.933	15.46	14.18
DENSITY (stems/ha)	D0	- 112 - 4076 d3 + 3254 p10 - 159 p30 - 180 p80 - 56.4 Db + 106 p40 + 9705 d9	0.888	0.857	231.84	14.11
	D1	5380 - 4678 d4 + 5580 p10 - 134 p30 - 95.9 p90	0.794	0.766	313.83	19.10
	D2	11212 - 2363 d4 - 204 p90 - 80.4 Db + 70.5 p40	0.861	0.842	257.74	15.69
QMDBH (cm)	D0	8.03 + 1.18 p90 - 0.327 Da - 0.138 p40	0.838	0.822	0.82	5.80
	D1	8.58 + 1.07 p90 - 0.308 Da	0.783	0.769	0.95	6.72
	D2	2.44 + 1.12 p90 - 0.234 Da + 5.33 d6	0.863	0.850	0.76	5.34
AVGHT (m)	D0	2.41 + 0.948 p90 + 2.80 d1 - 0.0821 Da	0.951	0.946	0.49	3.81
	D1	1.73 + 0.836 p90 + 2.99 d2	0.941	0.938	0.53	4.16
	D2	2.34 + 0.802 p90 + 2.26 d3	0.936	0.932	0.56	4.34
TOPHT (m)	D0	2.32 + 0.547 max + 0.436 p90	0.923	0.918	0.69	4.10
	D1	2.10 + 0.578 max + 0.429 p90	0.927	0.922	0.66	3.98
	D2	3.79 + 0.577 max + 0.326 p90	0.903	0.897	0.77	4.58
SUMBIO (kg/ha)	D0	- 321894 + 15682 mean - 114298 d6 + 427669 d9	0.925	0.918	11,673	11.58
	D1	- 17265 + 21243 mean	0.905	0.902	13,199	13.09
	D2	157912 + 11931 mean - 1752 Db + 3131 p40	0.932	0.925	11,143	11.05

Table 10. Results from repeated measures ANOVA for the black spruce forest type grouping

Variable	Decimation Effect?	MANOVA – Wilk's Lamda		
		Value	F	***p***
SUMBA	No	0.984	0.25	0.784
SUMGTV	No	0.983	0.27	0.767
SUMGMV	No	0.985	0.23	0.795
DENSITY	No	0.935	1.08	0.354
QMDBH	No	0.916	1.41	0.259
AVGHT	No	0.982	0.29	0.752
TOPHT	No	0.987	0.21	0.811
SUMBIO	No	0.970	0.48	0.624

DISCUSSION AND CONCLUSION

With the exception of two cases, specifically QMDBH for SLRR and DENSITY for the jack pine grouping in RMF, predictions of forest variables were not influenced by decimation level. Comparisons between R^2, RMSE and percent RMSE show little deviation for the forest variables considered. The results indicating a decimation effect for DENSITY is not surprising since this forest variable is often the most difficult to predict using LIDAR data. In the case of QMDBH, further investigation is required for this deviation since this variable is most often predicted quite well from LIDAR data as illustrated by the other reported results in this study and others (e.g., Woods et al., 2008).

The results reported are promising and suggest that a point density of $0.5/m^2$ is sufficient for predicting forest variables at the plot and stand level and that the assumption that higher sampling point densities lead to better predictions needs to be challenged.

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