LiDAR Derived T2 Inventory for the French-Severn Forest

KTTD Project # 20B-2021

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FSF BasalArea $m2$ ha-1 $High:76$

 $Low: 0$

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LiDAR Derived T2 Inventory Technical Report for the French-Severn Forest

Executive Summary

Single Photon LiDAR (SPL) was acquired over the French-Severn Forest (FSF) during the summer of 2019. A total of 204 LiDAR field calibration plots (400 $m^2 - 11.28m$ radius) were established on the FSF and measured between June 25, 2020, and September 19, 2020, and an additional 8 Growth and Yield plots measured in September 2021. These plots were used to derive an inventory update ("T2") based on LiDAR models for Height (Dominant/Codominant, Lorey, Top Height), Basal Area (BA), Basal Area merchantable (BAmerch), Volumes (Gross Total (GTV), Gross Merchantable (GMV_NL and GMV_WL)), Quadratic Mean Diameter (QMD), Total Above Ground Biomass (Biomass), Stems, and BA and GMV_NL by four-size classes. Merchantable volume predictions used the provincial scaling specifications for upper diameter limits along with a 30cm stump height. One additional predicted volume raster was produced for the Westwind Forest Stewardship staff for a gross merchantable volume for smaller hardwood upper diameter specifications.

Plot level Model Validation

A 10-Fold Cross Validation (CV) of plot level (400m²) predictions were calculated as a measure of model performance. Root Mean Square Error (RMSE) was calculated on the results of the CV. RMSE is a measure of how close the predictions are to the actual values. The Smaller the RMSE, the better the predictions. RMSE of models for height were 9.7% and 6.9% for Dominant/Codominant and Top height respectively. BA had a 28.9% RMSE while volumes (GTV, GMV_NL, GMV_WL) had 32.6%, 39.0% and 40.5% respectively. QMD reported an RMSE of 22.9% and Biomass 29.6%. Stems resulted in an RMSE of 36.9%. Examples of mean observed and model predictions (along with standard error) of inventory attributes from cross validation are provided below.

The results for the FSF are generally comparable to those reported for the neighbouring Algonquin Park Forest (APF) with slightly higher RMSEs for BA and volume, likely due to fewer calibration plots (FSF n = 190 and APF n = 221).

Stand level Model Validation

Additional validation of the LiDAR predictions for 29 operational cruised stands was conducted. A stand (or harvest block) represents the scale inventory estimates will be used to support management decisions. The validation data was based on Sustainable Forest Licence (SFL) operational prescription development needs in Tolerant Hardwood and Pine stands and did not always cover the full range of stand species/site variability. The operational cruising only surveyed merchantable BA so that attribute is reported here.

For the tolerant hardwood polygons, BA was overestimated by approximately 6% compared to the cruise data while BA was overestimated by approximately 19% for the 6 managed pine stands. It should be emphasized that the cruise data is also an estimate of the polygon BA with 1 prism sweep for every 3 -4 ha.

Previous studies (White et al. (2021)) have documented the fact that the majority of inventory attribute RMSE's improved at the stand level compared to the CV at the plot scale. Height attributes are not significantly impacted by scale. However, attributes such as ones expressed per area (i.e., basal area, volume) are. Merchantable Basal Area (BAmerch) RMSE for All-Forest types on the FSF was reduced from 30% at the plot scale to 16% at the stand scale (N=29), a substantial improvement. By broad forest type the Pine stands were reduced to an RMSE of 22% (N=6) and the Tolhwd RMSE = 14% (N = 23).

T2 Polygon updating

Raster (20 x 20m) surfaces of the LiDAR predictions were created for the forest polygons. Polygon layers were created from the raster surfaces using the T1 (OPI) polygon layer. The polygon attributes were calculated as the mean of the raster predictions within the polygon **where age > 20 years**. Stand level QMD was calculated from polygon BA and Stems. These polygon-based estimates, were used in conjunction with T1 polygon age and species composition to calculate the following additional T2 inventory attributes:

- Site Index
- Stocking
- Cull Fraction
- Net Merchantable Volume (NMV).

Calibration Plot Data Quality

The quality of the field data on the FSF was found to be suspect. **Adjustments to field data measurements is something that should never be required**. However, it was clear that in most cases the field measurements of tree height seem to be higher than LiDAR measurements. Measured heights were adjusted based on LiDAR return information. Unfortunately, it is unknown whether additional measured parameters (DBH, borderline trees, etc.) were also done poorly and their potential impact on the LiDAR model outcomes.

Objective

The objective of this Forestry Futures Trust Knowledge, Transfer & Tool Development (KTTD) project is to develop open source (OS) software code for processing Ontario's Single Photon (SPL) Light Detection and Ranging (LiDAR) and to produce a raster-based product suite and an update for a new T2 polygon Forest Resources Inventory (FRI) for the French Severn Forest (FSF).

Study Site

The French-Severn Forest has a total area (all ownerships) of 1,281,677 ha [\(](#page-5-2) [Figure](#page-5-2) 1) and is located in the Great Lakes - St. Lawrence Forest Region. Crown land classification is broken down as 65% Production Forest, 23% Water, 10% Non-Productive Forest, 1% Other Land (agricultural, unclassified) and 1% Protection Forest.

The dominant forest species communities are tolerant hardwoods and white and red pine types Mixedwoods, Hemlock, Oak, Intolerant Hardwoods, Spruce Fir are more minor components (in the order they are presented) of the FSF. A range of silvicultural systems are employed to ensure a sustainable forest resource into the future. These include single-tree selection, uniform shelterwood and clear cutting. A detailed breakdown of the FSF Forest Units is presented i[n Figure 2.](#page-6-2) Additional detailed information about the FSF can be found in the 2019-2019 Forest Management Plan for the French Severn Forest [\(FMP Online \(gov.on.ca\)\)](https://nrip.mnr.gov.on.ca/s/fmp-online?language=en_US).

Figure 1 – French-Severn Forest Management Unit Location

Figure 2 - Percent area by Plan Forest Unit for the FSF.

Data

Airborne LIDAR data

Single Photon LiDAR (SPL) was acquired over the FSF during the summer of 2019. The SPL100 sensor was flown aboard a Piper–PA–31–350 at an average altitude of 3760m. More details of acquisition parameters are provided i[n Table 1.](#page-6-3)

Table 1 - LiDAR acquisition specifications for 2019–SPL mission

LiDAR Model Calibration Data

Calibration ground sample measurements followed the province of Ontario's Vegetation Sampling Network Protocol document *(Science and Research Technical Manual TM)*. The Vegetation Sampling Network (VSN) protocol consists of 3 potential plot measurement methodologies. "*A* modules" provide a base set of attributes for all plots. They include a range of stand attributes, tree attributes, and site and substrate attributes. "*B* modules" add in protocols for stem mapping and crown delineations and for assessing a smaller tree and shrub subplot, both of which support LiDAR diagnostics and development. When applied to the permanent subset of VSN plots, the smaller tree and shrub subplot module also supports tracking recruitment and succession. "*C* modules" apply only to the permanent plot subset and add some focus on understory vegetation (understory vegetation subplot) and down woody debris, as well as tree deformities and evidence of wildlife use. The A plot measurement thresholds, common to all protocols, were used to include as many plots as possible in this project.

A total of 212 LiDAR calibration plots $(400m^2 - 11.28m$ radius) were established and measured. Most of the plots were established between June 25, 2020, and September 19, 2020 (with a sub-set of 8 Growth and Yield plots being remeasured in September 2021). Calibration plots were selected using a "structurally guided" sampling approach. LiDAR structure measurements for the population were used to determine the full range of structural conditions. Calibration plots were then selected to sample the range of conditions. Where possible, existing provincial permanent sample plots were incorporated into the sampling framework where they met required structural conditions. These plots become the link between ground attributes (i.e., heights, volumes, etc.) and the LiDAR point cloud.

Data Quality

Initial data screening steps quickly identified some field measurement quality issues on the calibration plots established on the FSF. Tree heights measured by the field crew was often found to be higher than the maximum LiDAR return acquired for that plot. There were also some cases where field measured heights were lower than the Lidar returns. In some cases, the differences between the maximum LiDAR return and the measured heights were extreme.

Taking quality height measurements, especially during leaf-on periods of the year on these tall tree species requires extra time and care. Possible reasons for the field measured height issues:

- Some trees were very tall. For accurate height measurement, it is recommended the heights be measured from a distance as least as great as the height.
- In some cases, the canopy cover is dense, particularly in tolerant hardwoods when leaves are on. It may be difficult to see the top of the tree to get a good measurement. It may also be difficult to identify the top of the tree in tolerant hardwoods.
- There were issues with the height measurements. It appears the height measurements corresponded to the height above 1.3m, not the height above the ground. 1.3m was added to every height.

Additional complications and challenges of working with the FSF data set:

- There were no field audits, so data and measurement issues were not identified and corrected.
- There may be GPS errors leading to the field plots not lining up exactly with the LiDAR Point cloud.

[Figure 3](#page-8-0) provides some examples where field heights were found to exceed, or underestimate recorded maximum LiDAR returns.

- Some plots don't have many ground returns which can impact the LiDAR normalization (this is more likely seen in dense tolerant hardwood plots).
- Sometimes trees lean in or out of the plot.
	- \circ For leaning trees, it's not clear whether the crew measured the height of the tree tip above the ground (which seems to be the field manual procedure) or the length of the bole. No adjustments were made to height based on degree of lean.
- Some plot point clouds contain returns from crowns of trees outside the plot. These trees were not noted as leaning into the plot and therefore, have no mensuration information [\(Figure 4\)](#page-10-0)

Figure 3 - Examples of Field Height (FH) overestimating or underestimating Maximum LiDAR return.

• Also, in some cases there can be tall dead trees captured in the extracted point cloud [\(Figure 5\)](#page-10-1). These trees are not included in plot compilation but can impact modeling results.

[Figure 6](#page-11-0) provides a comparison on maximum LiDAR return versus maximum field height measured on each plot. The 1:1 line indicates identical measurements. It is clearly evident that a significant proportion of calibration plots over-estimated the largest tree height [\(Figure 6\)](#page-11-0) and the average of the 2 largest field measured heights [\(Figure 7\)](#page-11-1).

The issues with height measurement quality also raised suspicion on the care undertaken on using the GPS to identify the target plot location, DBH measurement or determination of what trees were within the 11.28m radius plot boundary. Unfortunately, there is no way with the LiDAR returns to evaluate this aspect of field collected data quality.

Calibration Plot Data Adjustment

Adjustments to field data measurements is something that should never be required. However, it was clear that the field measurements seem to be higher than LiDAR measurements. In some rarer cases, field heights were lower than the LiDAR measurements. Possible explanations for these differences have been discussed. It is critical that future field crews understand that the quality of the field data collection impacts the quality of the derived inventory product suite.

However, because tree height has a large impact on the calculation of tree volume, we felt that an adjustment was required for this.

A decision was made (in consultation and approval of MNRF FRI staff) to adjust the field heights using the relationship between the height of the tallest tree on the plot and the maximum LiDAR return. A "plot level ratio" adjustment was made to each plot for the FSF. Where no suitable height trees were available to make a plot level ratio adjustment, the population level adjustment was be used.

Examples of the adjustments to tree heights and the impact on gross total volume are presented in [Figure 8](#page-12-1) an[d Figure 9.](#page-12-2)

Similar issues were encountered on the Algonquin Park Forest (APF) and a similar "correction" applied.

Figure 4 - Example of a plot with crown returns from a tree outside and above the calibration plot.

Figure 5 - Example of a tall dead tree capturing LiDAR returns. This tree is not summarized as part of the plot compilation but impacts the model correlations with height-based predictors.

Figure 6 - The height of the tallest live tree on the plot is plotted against the maximum LiDAR return. The 1:1 line is given. Plots well below the 1:1 line (higher LiDAR MAX) are ones with tall dead trees (no field height) or overhanging trees outside the plot and not measured. There were a high number of plots where the tallest tree measured was quite a bit taller than the highest LiDAR return (above the 1:1 line).

Figure 7 - The same as [Figure 6](#page-11-0) except the average of the two tallest trees is plotted on the y-axis

Figure 8 - For this plot with a too high field height, both the population and plot adjustments are downward. The impact to GTV is Unadjusted GTV 189 m3/ha, adjusted GTV = 106 m3/ha.

Figure 9 - Here is an example where the field crew underestimated the heights. The population ratio adjusts height down while the plot ratio adjusts height higher. The impact to GTV is Unadjusted GTV = 217 increased to GTV = 233 m3/ha for the adjusted heights.

Plot Compilation

For all live trees with DBH \geq 7.1cm (common minimum DBH threshold for all VSN plot types) species, origin, Dbh, height, vigour and crown class were recorded. On some plots ages were recorded for a sample of trees. For dead trees > 10cm (and > 2m), species, Dbh, height, vigour and decay class were recorded. Trees that had crowns leaning in or out of the plot were noted as were broken top trees.

Plots were summarized to per hectare values for all live trees \geq 7.1cm. Dead trees were also summarized for their informational value in explaining potential differences noted between modeling results and plot summaries. However, dead trees were not used to calibrate the LiDAR models.

Table 2 - Inventory attributes summarized from calibration plots and predicted from LiDAR. Volume estimates came from Zakrzewski and Penner 1983. Biomass estimates came from Lambert et al. 2005.

An approved provincial standard set of inventory attributes were summarized for model prediction. [Table 2](#page-13-0) lists the inventory attributes that were summarized for modeling (live trees with DBH \geq 7.1cm unless noted) on the FSF. Individual tree volumes were calculated using Zakrzewski and Penner (2014) taper models developed for Ontario. No height estimation was required for the FSF dataset as each tree had a measured height. In the case of the FSF dataset, the "adjusted" height was used.

Table 3 - Minimum upper diameter limits for merchantable volume calculation by species group

Individual tree total above ground biomass was calculated by species using the equations published in Lambert et al. (2005). Individual species equations were used when available. When no species coefficients existed, broader "hardwood" or "softwood" model coefficients were used.

Calibration Plot Spatial Positioning

Once target plot locations were identified, all established plots were spatially located with a survey grade GNSS system. Data was post–processed to meet required sub–metre positional requirements.

Exclusion of Calibration Plots

As noted earlier, LiDAR was acquired for the bulk of the FSF forest during the summer of 2019 and the majority of plot measurements were occurred between June 25, 2020, till September 19, 2020. Eight provincial Growth and Yield program plots were remeasured in September 2021 and included. The intent of the calibration plots is to capture vegetation conditions that match the LiDAR measurements. However, some calibration plots sampled structural conditions made up of trees too small (minimum Dbh threshold of 7.1cm or < 5m in height) to provide opportunity for summarization and inclusion in the modeling. [Table 4](#page-15-0) identifies the 22 plots excluded from the calibration of the LiDAR and their reason for removal. A total of 190 calibration plots remained available to produce the LiDAR inventory. Further filtering of calibration plots for model construction is discussed later.

The FSF calibration plots were assigned a FSF Forest Unit (FSF FU) based on the SQL presented in Appendix E. Because not all attributes required (Site Class, Stocking) to implement the FSF FU SQL were available for each calibration plot and/or the number of observations by FU were too small to report statistics on, a broader aggregation of calibration plots to a forest type was carried out[. Table 5](#page-15-1) identifies the FSF FU assignment to FSF Forest Type (FT). A summary of the calibration plots by FT is provided in [Table 6.](#page-17-0) Of note is the number of calibration plots per FT. Some conditions seem under sampled while others appear oversampled. This disparity in sample size by FT is a function of the structural sampling approach adopted by the province of Ontario. Forest conditions with a wide range of vertical structures (i.e., pine shelterwoods) were sampled more than more "simple" structures often found in conditions like pure red pine plantations.

LiDAR Data Processing

Raw classified LiDAR LAS datasets were provided to the province by the vendor. Standard American Society for Photogrammetry and Remote Sensing (ASPRS) classification coding standards were used by

Table 4 - FSF calibration plots excluded from analysis

Table 5 - FSF Forest Type aggregation of FSF Forest Units used for calibration plot summaries.

the vendor. Classification codes (2) ground , (3) low vegetation , (4) medium vegetation and (5) high vegetation return data only were processed. LAStools (LAStools, 2021) was used to "normalize" the LiDAR returns to the terrain (converting "z" height from elevation to height above ground). An additional script was implemented to compress the LAS formatted files to a space efficient LAZ format.

A modeling predictor set on a 20m x 20m grid was created for the 2018 LiDAR data set using the lidR (Roussel and Auty 2020, Roussel et al. 2020) software package in R (R development Core Team 2020). A total of 112 potential LiDAR predictors were derived from structural statistical queries of all-return, normalized point cloud data. Following testing of predictive model performance from thresholding the returns at 0 m and 2.0 m, a decision was made to use all returns greater than 0 m for modeling inventory attributes on the FSF. This choice of threshold was also documented in other studies in Ontario (White *et al.* 2021, Woods *et al.* 2011). Data "z" spikes were removed by dropping any returns > 48m. A complete list and description of the LiDAR predictors created is provided in Appendix A. Predictors that were selected for use in the predictive models are indicated. LiDAR predictors that exhibiting artifacts of banding were not used in model development (i.e. counts of points).

LiDAR Model Development

A non-parametric Random Forest (RF) model (Liaw and Wiener 2002) solution via the statistical package R (R development Core Team 2020) was used for the prediction of inventory attributes. All model predictions were made at the plot scale and at a 20 m raster cell (matching the 400 m^2 plot size) with the model mtry parameter set to the default (number of predictors/3) and the parameter ntree (number of trees to construct) set to 1000. Only calibration plots with zq99 > 5m were used in the prediction of stand level metrics to better align with the calibration plot minimum DBH of 7.1 cm. This filter resulted in the dropping of an additional calibration plot from the modeling but ensured that only plots with at least some merchantable sized trees were utilized in the models and the predictions made at the landscape level. In the prediction of size class attributes and merchantable volume attributes, calibration plots with Zq99 > 9m were used as plots with Zq99 ≤ 9m had little or no merchantable volume.

Investigation of the initial modeling of specific inventory attributes of (BA, BA_merch, and QMD), identified that calibration plots consisting of tolerant and mid-tolerant hardwoods (> 50% hardwoods) were being generally overpredicted by a single un-stratified RF model intended to model All-Forest species conditions. The desire to utilize a nonparametric modeling approach like RF for the derivation of a LiDAR inventory is to eliminate the requirement for species information, usually only interpreted and provided at the polygon scale. In most situations, a dynamic RF modeling solution of matching pointcloud distribution statistical measurements at a grid cell level (20m x 20m) and a desired inventory attribute summaries, without any a priori knowledge of species, has resulted in flexible models (i.e., White et al. 2021) capable of predicting attributes a range of species conditions. However, it became clear for the FSF forest and this SPL dataset, that creating a stratified, 2 RF model solution resulted in better predictions for some of the inventory attributes (a basal area comparison of a single-strata vs 2 strata is presented i[n Figure 10\)](#page-18-0). The list of inventory attributes predicted by a single or stratified RF model approach and modeling strata description is presented i[n Table 7.](#page-18-1)

LiDAR predictions for each attribute were made independently. In most cases (e.g., DomCodom height, Top Height, Lorey Height) this works well. However, to ensure some logic and biological consistency in predictions, some attributes were predicted as a fraction of other attributes. An example of such an

Forest Type	No Plots	Breast Height Age $(yrs)^2$	TopHt (m)	CDHT (m)	Lorey Ht (m)	Stems (ha)	Basal Area $(m2 ha-1)$	QMD (cm)	GTV (m^3) ha ⁻¹)	GMV_NL (m^3) ha ⁻¹)	GMV_WL (m^3) ha ⁻¹)	Biomass (Tonnes ha^{-1})
BY	8	72 $(42 - 155)$	21.0 $(17.3 - 24.4)$	18.7 $(15.8 - 22.7)$	19.3 $(16.6 - 21.8)$	641 $(350 - 975)$	26.1 $(16.3 - 29.4)$	23.5 $(18.7 - 30.6)$	198 $(120 - 226)$	138 $(97 - 192)$	126 $(87 - 186)$	172 $(105 - 195)$
He	10		22.6	20.5	20.5	618	41.2	30.3	307	263	253	230
		$105 (N=8)$	$(15.3 - 28.8)$	$(13.9 - 24.1)$	$(13.3 - 25.4)$	$(300 - 1200)$	$(10.3 - 52.7)$	$(16.6 - 39.2)$	$(53 - 436)$			
		$(58 - 200)$								$(26 - 393)$	$(21 - 383)$	$(49 - 294)$
Intol	$\overline{2}$	$57(N=2)$	20.2	17.2	17.5	1263	29.0	19.9	214	144	134	160
		$(39 - 75)$	$(19.9 - 20.5)$	$(15.2 - 19.2)$	$(15.7 - 19.3)$	$(550 - 1975)$	$(27.8 - 30.2)$	$(13.4 - 26.4)$	$(189 - 239)$	$(97 - 192)$	$(86 - 182)$	$(113 - 207)$
Low	8	$70(N=8)$	15.6 (N=8)	14.0	14.4	694	16.2	16.7	100	78	73	59
		$(28 - 110)$	$(10.8 - 26.3)$	$(9.1 - 21.4)$	$(9.9 - 22.7)$	$(125 - 2100)$	$(1.2 - 39.8)$	$(9.3 - 25.1)$	$(6 - 267)$	(1 - 210)	$(1 - 200)$	$(4 - 173)$
MW	8	$60(N=7)$	19.7	17.4	16.2	1016	28.2	18.9	201	158	148	139
		$(23 - 136)$	$(12.3 - 22.9)$	$(9.5 - 20.8)$	$(10.6 - 19.7)$	$(650 - 1650)$	$(10.2 - 51.8)$	$(12.5 - 27.2)$	$(46 - 398)$	$(23 - 337)$	$(19 - 320)$	$(35 - 312)$
Oak	2	76	22.6	19.2	19.8	688	32.0	24.7	277	222	210	242
		$(54 - 98)$	$(21.5 - 23.8)$	$(18.4 - 20.0)$	$(17.5 - 22.1)$	$(575 - 800)$	$(24.4 - 39.6)$	$(19.7 - 29.6)$	$(185 - 368)$	$(138 - 307)$	$(123 - 297)$	$(148 - 336)$
Pine	46	93 (N=44)	26.2	24.2	23.3	566	27.5	27.7	276	247	242	145
		$(26 - 135)$	$(13.4 - 34.4)$	$(10.4 - 31.6)$	$(12.2 - 30.8)$	$(25 - 1475)$	$(2.2 - 96.4)$	$(14.2 - 69.3)$	$(16 - 1055)$	$(14 - 994)$	$(13 - 987)$	$(8 - 552)$
Ρj	2	54	11.8	10.8	10.7	775	12.9	14.6	61	45	40	39
		$(53 - 54)$	$(10.3 - 13.2)$	$(9.6 - 12)$	$(9.5 - 11.8)$	$(725 - 825)$	$(11.7 - 14.2)$	$(14.3 - 14.8)$	$(48 - 75)$	$(33 - 57)$	$(29 - 51)$	$(32 - 46)$
Pr	15	72 (N=14)	26.2	25.3	24.9	640	33.7	30.0	377	349	339	181
		$(24 - 126)$	$(17.3 - 33.5)$	$(17 - 32.9)$	$(17 - 31.5)$	$(25 - 1275)$	$(9.3 - 68.9)$	$(19.2 - 68.7)$	$(109 - 856)$	$(106 - 812)$	$(105 - 799)$	$(58 - 410)$
SF	14	59 $(N=13)$	18.9	$15.5 (N=13)$	15.7	1077	19.2	16.4	127	102	96	75
		$(22 - 93)$	$(9.5 - 27.6)$	$(8.4 - 24.1)$	$(8.6 - 27.6)$	$(25 - 2050)$	$(0.5 - 53.5)$	$(10.5 - 30.5)$	$(6 - 487)$	$(5 - 459)$	$(5 - 451)$	$(3 - 255)$
TolHwd	75	$80(N=68)$	21.9	19.7	19.8	636	23.9	23.1	189	139	130	162
		$(28 - 129)$	$(13.2 - 30.7)$	$(10.7 - 28.3)$	$(10.8 - 27.9)$	$(150 - 1700)$	$(9.5 - 45.6)$	$(12.6 - 37.9)$	$(50 - 444)$	$(14 - 395)$	$(8 - 387)$	$(47 - 385)$
All	190	80 (N=176)	22.6	20.5 (N=189)	20.3	675	26.1	24.1	222	184	176	151
		$(22 - 200)$	$(9.5 - 34.4)$	$(8.4 - 32.9)$	$(8.6 - 31.5)$	$(25 - 2100)$	$(0.5 - 96.4)$	$(9.3 - 69.3)$	$(6 - 1055)$	(1 - 994)	$(1 - 987)$	$(3 - 552)$

Table 6 – Statistics – Mean (range) of calibration plots by FSF Forest Type¹

¹ FSF Forest Unit syntax was used to assign FU. However, some information like Site Class (used in some FU assignment) was not available at the plot level so was not used. As a result, broader Forest Types were assigned.

² Breast height age is the average breast height age of dominant/codominant trees with measured ages. Trees were not measured for age on all plots and the sample sizes for age are less than the number of plots.

attribute is gross merchantable volume (GMV). Actual GMV is never larger than gross total volume (GTV). To constrain the prediction of GMV, the fraction of GMV/GTV was predicted. Different constraining approaches were tested and the rationale for the method chosen for the various volume predictions is described below.

Figure 10 - Comparison of a single RF model solution versus a stratified RF model solution for basal area on the FSF (units are m2 ha-1)

Table 7 - Modeling method adopted for the FSF.

Gross Total Volume (GTV)

Rather than predicting GTV directly, it was predicted as a function of basal area (BA) and the volume to basal area ratio (vbar). Both options were tested and resulted in similar RMSEs and biases. The vbar option to estimate GTV was chosen as it may help preserve a bit of the relationship between BA and GTV by ensuring the predicted vbar is always within the range observed in the calibration data.

- 1. BA is predicted directly.
- 2. vbar $GTV = GTV/BA$ is predicted directly.
- 3. GTV is calculated as predicted BA x predicted vbar_GTV

Gross Merchantable Volume (GMV)

All merchantable volumes are constrained to be less than or equation to the predicted GTV. This is accomplished through predicting the ratio GMV/GTV.

- 1. Predict GTV using the method described above
- 2. Predict ratio GMV = GMV/GTV directly
- 3. Calculate GMV as GTV x ratio GMV

This is mathematically equivalent to constraining the vbar_GMV to be less than or equal to vbar_GTV.

$$
ratio_{GMV} = \frac{GMV}{GTV} = \frac{vbar_GMV}{vbar_GTV} = \frac{GMV/_{BA}}{GTV/_{BA}}
$$

All merchantable volumes (GMV_NL, GMV_WL and FSF_Smlog) were constrained against GTV. Merchantable volumes (i.e., GMV_NL and GMV_WL) were not constrained to be greater or equal to each other.

Size Class estimates of Merchantable Basal Area and GMV_NL

Size class estimates of merchantable volume and basal area were constrained to always sum to either predicted GMV_NL or Basal Area_merch (BAmerch). An example of the method for basal area by size class is described below. First, the merchantable BA was split into BAMedLg and BASmPole. Then BAMedLg was split into BAmedium and BAlarge and BASmPole was split into BAsmall and BApole. Similar splits were made for GMV_NL

- 1. Calculate BAmerch = BaPoles + BAsmall + BAmedium + BAlarge from calibration plot data
- 2. Calculate a BAmedium + BAlarge fraction of plot BAmerch from calibration plot data i. BAMedLg frac <- (BAlarge + BAmedium)/BAmerch
- 3. Calculate fraction of Large BA in Medium and Large Sawlogs from calibration plot data i. BALg ratio <- BAlarge/(BAlarge + BAmedium)
- 4. Calculate fraction of Small BA in Small sawlogs and Poles from calibration plot data
	- i. BASm_ratio <- BAsmall/(BAsmall + BApoles)
- 5. Develop RF models for: BAmerch, BALg_ratio, BASm_ratio
- 6. Calculate basal area in medium and large sawlogs (BAMedLg)

BA_MedLg <- (BA_MedLgSawFrac * BAmerch)

7. Calculate the proportion of the predicted BA_MedLg is Large sawlog where P99 \geq 20 else be set to 0 & resulting in value moves to the Medium sawlog

BA_LgS <- ifel(zq99 >= 20, (BA_MedLg * BA_LgRatio), 0)

8. Calculate the BA_MedLg sawlog where P99 \geq 15 else be set to 0 & resulting in value moves to the small sawlog and pole basal area

BA_MS <- ifel(zq99 > 15, (BA_MedLg - BA_LgS),0)

9. Calculate the Basal area for SmallSawlog & Poles

BA_SmPl <- (BAmerch - BA_LgS - BA_MS)

10. Calculate the BA for Small Sawlogs

BA_SmS <- (BA_SmPl * BA_SmRatio)

11. Calculate Pole BA as the difference between predicted BAmerch and predicted Large, Medium and Small sawlog basal areas

BA_Pole <- (BAmerch - BA_LgS - BA_MS - BA_SmS)

[Table 8](#page-20-0) indicates which attributes were predicted directly from the statistical predictor summaries of the raw LiDAR point cloud[. Table 8](#page-20-0) indicates which inventory attributes are calculated as a fraction of another one to help ensure logical predictions.

Table 8- Inventory attributes predicted directly from the point cloud predictors.

Table 9 - Description of attributes and their calculations predicted indirectly. All attributes are summarized from > 7cm unless noted (P_ = Predicted)

LiDAR Model Results

All LiDAR predictions are based on the LiDAR structure statistics and the field plot measurement summaries only³. [Figure 11](#page-22-0) illustrates the observed versus the predicted estimate for each LiDAR model. The diagonal dashed line indicates a perfect match between the measured plot summary and the prediction.

Plot level Validation

All calibration plots were used in model training and prediction. As a result, no independent plots were available to test model prediction error with. A "Cross Validation" (CV) can be used to estimate prediction error at the plot scale (20m x 20m) in the absence of an independent validation data set. Vfold CV error is generated by dividing the data set randomly into *V* equal parts. Training for the model is done on *V-1* parts and testing is done on the remaining part. This is repeated many times (10 times in this study) and the error rate estimate is an average of the results.

RMSE and Bias were calculated using the following equations:

RMSE =
$$
\sqrt{\frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2}{n}}
$$
,
RELATIVE RMSE = $\frac{\text{RMSE}}{\bar{Y}}$,
BIAS = $\frac{\sum_{i=1}^{n} (\hat{Y}_i - Y_i)}{n}$,
RELATIVE BIAS = $\frac{\text{BIAS}}{\bar{Y}}$.

 3 The field measurement summaries include species composition and age. However, they were not used in modeling except to use a tolerant hardwood model vs. other as noted in [Table 6.](#page-17-0)

Figure 11 - Modeling results of Observed versus Predicted for selected inventory attributes on the FSF. Error statistics are based on a 10-fold Cross Validation sample.

Figure 11 continued - Modeling results of Observed versus Predicted for selected inventory attributes on the FSF. Error statistics are based on a 10-fold Cross Validation sample.

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Table 10 - Plot level validation statistics using a 10-fold Cross Validation methods for the FSF

Plot level 10-fold CV comparisons of root mean square error (RMSE) and bias are presented by inventory attribute in [Table 10.](#page-24-0) CV RMSE (%) AND bias (%) are graphically presented i[n Figure 12.](#page-25-0) These results reflect modeling of all species/silviculture/origin based solely on LiDAR point cloud structure and at the plot or 20 x 20m grid scale. The RMSE is a measure of how well the model performed. It is the square root of the average squared distance between the predicted values and the observed values in the dataset. The lower the RMSE, the better the modeling results. Bias is the difference between the average prediction and the correct value. Similarly, a lower bias is always preferred.

Although the LiDAR models were not fit by forest type, the results can be presented in that manner to get a sense at the 20m x20m grid scale how a model is performing overall[. Figure 13](#page-26-0) provides an example of 4 predicted inventory attributes by comparing the observed calibration plot mean and the CV mean prediction (along with standard error). **Note, the number of plots by forest type varies and the results should be viewed in that light. The percent of the managed forest land base that each forest type represents is also presented.**

Appendix B provides a tabular and graphical summary of CV plot level predictions by forest types on the FSF forest.

Figure 12 - RMSE (%) and Bias (%) for inventory attribute validation using a 10-fold Cross Validation.

Figure 13 - Comparison of CV observed and predicted means of four selected inventory attributes. Standard Error is presented for the predictions.

LiDAR Prediction Raster Surface Adjustments

Predicted raster products were modified to align pixel predictions with the limitations of the calibration plot network (DBH > 7.1 cm). [Table 11](#page-27-2) identifies the 99th percentile LiDAR height that was used as a threshold. Pixels with a Zq99 < 5m were not expected to have trees with DBH ≥ 7.1 cm. Pixels with a Zq99 < 9m were not expected to have merchantable sized trees.

Table 11 - Adjustments to LiDAR raster predictions based on zq99 thresholds.

The LiDAR derived CDHT raster for the FSF is provided in [\(Figure 14\)](#page-28-0). Additional examples of derived inventory raster outputs are provided in Appendix C.

Stand Level Validation

Most forest management decisions are not made at a raster grid cell (20 m x 20 m) resolution. Usually, decisions are made on an aggregation of grid cells within a forest stand or harvest block. Pre-harvest operational cruising (OPC) is conducted as part of planned forest management activities on the FSF. These OPC activities, although not intensive, provide a sample of planned harvest block conditions to support silvicultural prescription development. In these mixed species stand conditions, sometimes species, or areas, that are not going to be managed, are not sampled with cruising.

Figure 14 - LiDAR derived FSF Dominant/Codominant Height raster

OPC data for harvest blocks cruised in 2018 and 2019 and not harvested before the LiDAR was acquired were made graciously available by Westwind Forest Stewardship Inc. SFL. In many situations, harvest blocks were made up of multiple stands. To provide a validation dataset with enough cruising observations to be more confident in a comparison, the blocks were split back to the original stands and stands that had a minimum of 3 (only one stand had 3 with most having 4 or more) cruising stations were selected. The number of eligible validation stands was further refined for situations where portions of the stands containing pockets of species (i.e., hemlock) were not sampled at all by the OPC (as that species was not to be managed). Examples of cruised stands that were not included in the validation are presented in Appendix F.

A total of 29 stands were used for the validation exercise. These stands sampled a range of silvicultural conditions from hardwood selection, or uniform shelterwood first cut/seed cut scenarios to white/red pine uniform shelterwood seed cuts or last cuts. As is typical in the Great Lakes St. Lawrence Forest region, stand species and site conditions for most of these validation stands offer different levels of variable conditions (mixed-species, clumps of conifer in hardwood dominated stands, shallow sites over bedrock, exposed bedrock, linear features of trees due to site conditions, etc.). The required number of

cruising observations to provide estimates to some level of stated statistical rigour is usually way beyond what is operationally feasible. As a result, some validation stands are sampled at a low sampling intensity

OPC is intended to support silvicultural prescriptions development. Data collected consists of basal area by species, management size class and quality. Additional notes on levels of existing regeneration and presence of tree disease (Beech Bark Disease) are also included. Only stand merchantable basal area, and merchantable basal area for the poles and sawlog size-class can be compared against the LiDAR predictions[. Table 12](#page-30-1) provides a list of the validation stand conditions. They are presented by Foresttype-Silvicultural system. A pseudo-sampling intensity has been calculated to provide a sense of the "confidence" of the population observations. [Figure 15](#page-29-0) provides some examples of cruising station spatial distribution of some of the stands used in validation.

Figure 15 - Examples of sampling stations established in various OPC stand conditions (leaf-off imagery).

Table 12 - Description of FSF OPC validation stands. (Note – pseudo sampling intensity based on a station plot area = 0.04 ha).

Validation Results

[Figure 16](#page-31-0) graphically displays the average validation stand prediction results (N=29) for All-Forest types for three attributes: BAmerch, Pole basal area, and Sawlog basal area. [Figure 17](#page-32-0) provides the same information but separated by FT and silvicultural system. [Figure 18](#page-33-3) displays a more detailed comparison of individual validation stands observations and predictions for selected inventory attribute using a 1:1 line to represent agreement.

Figure 16 - Validation stand mean stand observed conditions and predictions. 95% Confidence intervals for observed and prediction are provided.

RMSE and Bias results for the 29 OPC cruised polygons (presented for All-Forest types and by Hardwood and by Pine) are presented in [Table 13.](#page-31-1)

Table 13 - Validation RMSE and Bias results for the 29 OPC cruised polygons.

Examples of individual hardwood and pine stand OPC observations and LiDAR predictions are presented in [Figure 19.](#page-34-0)

Figure 17 - - Validation stand mean stand observed conditions and predictions by forest type and silvicultural system. 95% Confidence intervals for observed and prediction are provided

Figure 18 - FSF OPC Validation stand predictions versus observed by forest type.

T2 Inventory Updating

LiDAR Raster updating

The T2 inventory polygon update began with the Operational Planning Inventory (OPI) provided by Westwind Forest Stewardship SFL. This was updated to 2019. The T1 polygon boundaries were used and mean raster values by T1 polygon are calculated and provided for the following attributes:

- **Heights** TopHt, CDHT, LoreyHt
- Basal Area,
- Stems
- **Volumes** GMV_NL, GMV_WL, GMV_NL , FSF_Smlog
- **By Size Class** Basal Area, GMV_NL
- QMD is calculated for each polygon based on mean stand Basal Area and Stems

Stand Level GMV_NL Quantiles

To provide a measure of stand level volume variation, the 15th and 85th quantiles of gross merchantable (NL) volume were also provided (GMV_NL_15 and GMV_NL_85).

An example of a raster prediction for GMV_NL and the corresponding mean polygon information are presented in [Figure 20.](#page-35-0) Note how within stand variation of GMV_NL predictions are lost when the rasters are summarized for their mean value by polygon. The addition of Q15 and Q85 values allows

Figure 19 - Examples of individual stand observations and predicted values of merchantable basal area and basal area by pole and sawlog size class. The 95th confidence interval of the OPC is included.

Figure 20 - Example of a GMV_NL (m3 ha-1) raster prediction and mean T2 Polygon summary. Mean GMV_NL (m3 ha-1) is labeled in each polygon along with the $15th$ and $85th$ quantile value. 70 percent of the GMV_NL is found between the quantile range.
The users of the inventory to also know that 70% of the GMV_NL pixels are between the Q15 and Q85 values for the polygon.

Huntsville Forest Products Gross Merchantable Volume (FSF_Smlog)

A request was made by Huntsville Forest Products (HFP) through Westwind Forest Stewardship Inc. for an additional gross merchantable volume calculation beyond the approved set of GMV_NL and GMV WL described earlier. This additional volume would present LiDAR predictions for tolerant hardwood species (not including Ironwood) with a smaller upper diameter limit. The parameters specified are listed below.

- All hardwood species except Ironwood
- Minimum top diameter outside bark: 15 cm (6")
- Maximum large end diameter outside bark: 60 cm (24")
- Lengths of 259 cm (8' 6")

Note: in rare situations that the large end diameter of the bottom bolt is > 60 cm (24"), it is removed and the volume of the bolts above is calculated.

NOTE: The provided FSF_Smlog raster must be multiplied by the species composition of the tolerant hardwood species (except Ironwood) to calculate the hardwood volume to the HFP mill specifications.

Additional Attributes Calculated for T2 Inventory

To provide further value to the T2 update of the inventory, polygon-based summation (mean) of LiDAR attributes, were used in conjunction with T1 polygon age and species composition to calculate the following additional T2 inventory attributes:

- Site Index
- Stocking
- Cull Fraction
- Net Merchantable Volume (NMV).

Refer to [Table 14](#page-36-0) for a list of attributes and their source.

Table 14 - Additional T2 calculated inventory attributes and their source.

Site Index

Site index is calculated using the leading species from the T1 species composition and the age from the T1 inventory updated to 2021 and the predicted LiDAR CDht. **For polygons with p99 < 5m, SI and stocking are not estimated.**

Most SI equations use breast height age. For young stands, small change in age result in large changes in SI. The SI estimates for young ages are unstable [\(Figure 21\)](#page-37-0). The inventory age, particularly for young stands, may come from supplementary information and may not correspond to the LiDAR heights. This issue is illustrated for the FSF.

Figure 21 - Site index is plotted against age for ages 10+ (upper graph) and for ages 20+ (lower graph) for the FSF. Note the minimum SI is set to 5m and maximum at 35m.

Based on Figure 21, the SI for ages < 20 was set to missing and the SI for ages >= 20 was capped at 35m. The minimum SI was set to 5m. There are some potential issues with SI. For older stands, there may be a mismatch with age and height. The age is likely the age since disturbance and the heights are likely from younger trees that may have been established years after the disturbance.

Stocking

Stocking was calculated from predicted LiDAR basal area and the T1 polygon age and leading species. Stocking is in reference to Plonski's Normal Yield Table (Plonski 1974). Stocking is also a challenge for young stands. Stocking requires SI and SI was set to missing for stands < 20 years old so stocking is also not calculated when age is < 20. Stocking was capped at 2. [Figure 22](#page-38-0) provides a graphic of the number of FSF polygons by stocking and age. Note that stands less than 20 years old are not presented.

Figure 22 - Calculated Plonski stocking by polygon for the FSF. Note: no stocking estimates for stands < 20 years old.

Cull and Cull Fraction

Cull as estimated following the procedure implemented in MIST. Gross merchantable volume is estimated without respect to species. However, Net merchantable volume (NMV) requires estimates of cull. Basham (1991) provides estimates of cull by species and age.

First, a cull model [\(\(1\)\)](#page-38-1) was fit, by species, using published data (see [Table 15\)](#page-39-0). The model predicts the cull fraction increases as a sigmoidal function of age.

$$
(1) \qquad \widehat{cull} = (1 - e^{-d_0 \cdot age})^{d_1}
$$

Where, \widehat{u} l is the estimate of cull as a percentage of tree volume at a given age.

To apply this to GMV, the GMV by species was estimated by fitting a volume to basal area ratio (vbar) prediction model [\(\(2\)\)](#page-39-1) by species using the provincial PSP/PGP database (gyPSPPGP_2021_10_04.bak).

(2) $vbar = (v_0 + v_1 \cdot SI) \cdot (1 - e^{-v_2 \cdot age^{v_3}})$

Where, *vbar* is the volume to basal area ratio for a species, *SI* is the site index, *age* is the Plot age and v_0 , v_1 , v_2 , and v_3 are coefficients.

The vbar estimate was used to estimate the relative GMV by species.

(3) *mvol frac_i =*
$$
\frac{species fractioni vbari}{\sum species fractioni vbari}
$$

Table 15 - The sources for the cull estimates are given. The table references are from Basham (1991) except for red pine.

Then the weighted cull estimate, all species combined, is estimated as follows.

(4) $\quad \textit{call} = \sum \textit{mvol} \textit{frac}_i \cdot \textit{spp} \textit{call} \textit{est}_i$

Sample calculations are given in [Table 16.](#page-40-0) An example of vbar estimates by age and species is presented in [Figure 23.](#page-40-1)

	Spp		Vbar	coefficient			Cull	coefficient		Mvol	weighted
Spp	frac	V0	V1	V2	V3	Vbar	D0	D1	cull	frac	cull
Pi	0.8	2.36509	0.54016	0.018021	1.01063	11.2	-0.01264	8.3752	0.062	0.79	0.049
Po	0.2	2.99849	0.50008	0.006109	1.30665	11.9	-0.00521	1.4052	0.282	0.21	0.059
All											0.108

Table 16 - Vbar and cull calculations are given for sample conditions. The age = 100 and SI = 20m. Poplar has a slightly higher vbar, giving slightly more weight to the poplar cull estimate.

Figure 23 - The vbar estimates are given by age and species, for SI = 20

Net Merchantable Volume

For the T1 polygons, cull was estimated at using the T1 age and species composition.

Net merchantable volume (NMV) is calculated as the GMV minus cull.

$$
(5) \qquad NMV = GMV \cdot (1 - \text{cull})
$$

Constraint of T2 Inventory Updates

Only trees \geq 7.1 cm were measured on all the calibration plots. As a result, shorter (and young) stands do not have any measured trees to support defensible LiDAR predictions. **Stands < 20 years are not being updated with LiDAR derived predictions and are set to <NULL>.** In addition, different polygon CDHT thresholds were used to constrain provided inventory attributes [\(Table 17\)](#page-41-0). Crown Closure (CC2m) was retained for all stands. If stand CDHT <5 m, zq99 replaced estimated CDHT value.

Table 17 - T2 polygon inventory attributes and instituted constraints for all stands with age > 20 years

Discussion

Calibration Plot Data Quality

Concern about calibration plot data quality has been expressed earlier. Although an attempt was undertaken to adjust tree heights due to observed field measurement errors, other potential sources of measurement error (i.e., target plot location not being achieved, DBH measurement, missed trees, etc.) could not be evaluated or adjusted for in compilation. The assumption had to be made that the other tree attributes were done well. However, a level of concern exists on the unknown impact of the field plot data quality and the results reported. **FRI quality is directly linked to field plot quality. Audits of field plots should occur as soon as data collection begins in order to identify and correct any data collection issues as quickly as possible.**

Plot Level Model Validation (CV)

Overall, the FSF pixel level predictions are like those reported in other studies in Ontario. White et al. (2021) reported results for similar forest types and SPL. In their work, larger calibration plots (625m2) were used and a lower Dbh measurement threshold (2.5cm vs. 7.1cm used in this study) was chosen. They reported RF Out-of-Bag (OOB) RMSE errors which are comparable to the CV RMSE error statistics reported here. White et al. (2021) reported RMSE of 15% for CDHT for All-Forest types. We report a similar RMSE of 10%. For volumes, White et al. (2021) reported 25.4% and 29.6% for basal area and GTV. This study reported slightly higher results of 29% and 33%. In White et al.'s (2021) work they reported a similar total above ground biomass RMSE of 25% vs our reported 30%. The work of White et al. (2021) had an additional 80 calibration plots versus what was available to use for modeling on the FSF.

Recent inventory efforts on the Algonquin Park Forest and SPL ABA estimates found comparable (but slightly higher) RMSE results. This may be partly due to the fact that the same contractor with the noted data quality issues was involved in collecting the calibration field data for both forests and the FSF being their first forest of their contract. Results from the APF reported RMSE's of 12%, 23%, 25% and 23% for All-Forest type CDHT, Basal Area, GTV and Biomass.

Where possible to broadly compare forest units (criteria differ but leading species is similar) we found the following. White et al. (2021) reported Tolerant Hardwood stand RMSEs for CDHT, Basal Area, GTV and biomass of 8%, 31%, 38% and 27% respectively. This study found similar or better results (likely partly due to a higher minimum Dbh threshold) in the Tolhwd of 10%, 29%, 29% and 27%. White pine was reported as managed/natural stands in the work of White et al. (2021). They reported 12%/19%, 20%/26%, 26%/ 27%, and 21%/26% for CDHT, Basal Area, GTV and biomass respectively. This study reported on a combined managed and natural Pine stand grouping at 9%, 30%, 35% and 33%. While the Tolhwd group performed better than the study of White et al. (2021) the Pine group generally performed poorer.

A comparison of the RMSE's between the APF and FSF results for these same two forest types found similar trends. RMSE's of 10%, 21%, 23%, and 23% were reported for APF Tolhwd CDHT, Basal Area, GTV and biomass. For Pine, RMSE's of 13%, 23%, 25% and 23% respectively were noted from the APF modeling results. Generally, FSF model RMSE results for Tolhwds were similar to those reported for APF.

However, RMSE results for the Pine forest type on the FSF were poorer than both the work of White et al (2021) and those found for the APF inventory effort. This finding may be a function of calibration data quality or the reduced number of Pine plot observations available to help train the model on the FSF (White et al. (2021) – 107 plots, APF – 82 plots, FSF – 46 plots).

Stand/Block Level Model Validation

As has been demonstrated in other published LiDAR inventory projects (White et al. 2021), validation of LiDAR predictions is more appropriately evaluated at the scale at which most management decisions are based. In Ontario, this is generally the harvest block or stand level.

Although the validation sample of 29 stands on the FSF is not large and only focuses on two forest types, it can still provide a sense of expected model performance at the appropriate scale for an inventory. It should be reiterated that the field validation sampling on the FSF was not an intensive (not a fixed grid of plots covering the extent of the stand) LiDAR validation effort but an opportunistic dataset representing OPC results of stands intended to develop harvesting prescriptions. As such, some of the plot locations were focused on the species or site conditions being managed and as a result, the OPC results too are also a stand level estimate of what and where they cruised. We are very grateful to the efforts of the Westwind Stewardship Forest staff for making these data available to this project.

Calculating the sampling intensity is challenging for variable radius plots but if the plots were 0.04ha, the approximate sampling intensity was 1.3% (range of 0.6% -3.4%) or 3.6 ha being sampled by each plot [\(Table 12\)](#page-30-0).

OPC data collection focused on the measurement and size-characterization of merchantable basal area. The All-Forest type RMSE for BAmerch dropped from 30% (at the plot/grid cell scale) to 16% at the stand scale. When analyzed by FT, Tolhwd (N=23) had better results (RMSE = 14%) when compared with the fewer Pine stands assessed (N=6) reporting an RMSE of 22%. [Figure 24](#page-44-0) graphically displays this comparison of 400 $m²$ scale error versus stand level. However, as expected RMSE at the stand scale decreased.

Challenges with aligning and summarizing vector data and raster data

T1 information in the inventory is polygon based, including species composition and forest classification (forest vs. non forest). LiDAR derived information in pixel based. An issue arises when aligning the two sources of information. T1 polygon boundaries do not follow raster edges and, as a result, bisect pixels.

Since, currently in Ontario, forests are managed at the polygon level, approaches to summarizing raster values within polygons was explored.

Two main approaches investigated for operational inventory production are discussed here.

- 1. Centroid based zonal summation
- 2. Area-weighted based summation

Figure 24 - Comparison of Stand level validation RMSE with Cross Validation RMSE at the plot/grid cell scale for All- Forest, Tolhwd and Pine BAmerch.

Some tools provide polygon summaries from raster layers by only selecting raster pixels with centroids within the polygon. This can result in edge raster pixels being excluded if they border linear features such as roads/rivers, water bodies [\(Figure 25\)](#page-45-0) and the centroid is in that feature. In addition, where polygons bisect raster pixels, only one polygon is assigned the value of the raster pixel [\(](#page-45-1)

[Figure 26\)](#page-45-1). The issue is particularly problematic for small polygons (< 1 ha).

In an area-weighted approach, the pixel's contribution to a polygon is weighted by the portion of the pixel falling within a polygon. This means a pixel can potentially be part of more than one polygon.

Pixels that fall entirely within the polygon will have a weight of one. If half of a pixels falls within a polygon, the pixel will be given a weight of 0.5.

The decision to implement the area-weighted approach to generating T2 polygon raster summaries was selected. This method ensured that each polygon benefits from an appropriately weighted proportion of each raster pixel covered by the polygon.

Figure 25 - Example of centroid selection or raster cells excluding raster values for narrow polygons along waterbodies.

Figure 26 - Example of a raster pixel being bisected into 4 by polygon boundaries with only one polygon including the centroid value.

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Appendix A - LiDAR predictors for FSF- SPL–2018

Full point cloud predictor suite derived from LidR software scripts from a threshold height > 0 m unless specified. Predictors selected for use in Random Forest modeling of inventory attributes are shaded.

Appendix B – Plot level validation statistics by CV methods

Ten-Fold Cross Validation Plot level model statistics by Forest Type

10-Fold cross validation RMSE (%) results of plot level predictions by AFA Forest Unit. Included are the number of calibration plots (in brackets) and % of forested landscape area the FU occupies.

Appendix C – FSF Inventory Rasters

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LiDAR Derived T2 Inventory Technical Report for the French-Severn Forest

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French-Severn Forest - Pole & Sawlog Basal Area (>9 cm) **BA_Sawlog BA_Pole** $m2$ ha-1 $m2$ ha-1 $High: 29$ **High: 68** $Low: 0$ Low: 0

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Kilometers

30 40

 20

0510

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Appendix D – Site Index Curve Sources

Sharma and Reid (2018) recommend that height and age be estimated from at least five independent sample within a stand and for trees that have at least 6 years of growth beyond breast height age.

Table 1. The available site index curves are listed by species and origin.
Appendix E – Implemented FSF Forest Unit SQL

Appendix F – Excluded OPC Cruised Stands from Validation

The following list of OPC cruised stands were excluded from the stand level validation exercise. The primary reasons for their exclusion were their lack of sampling for the full range of species (i.e. conifer portions) within the stands. Some examples are provided below.

