LiDAR Derived T2 Inventory for the Romeo Malette Forest

KTTD Project # 20B-2021

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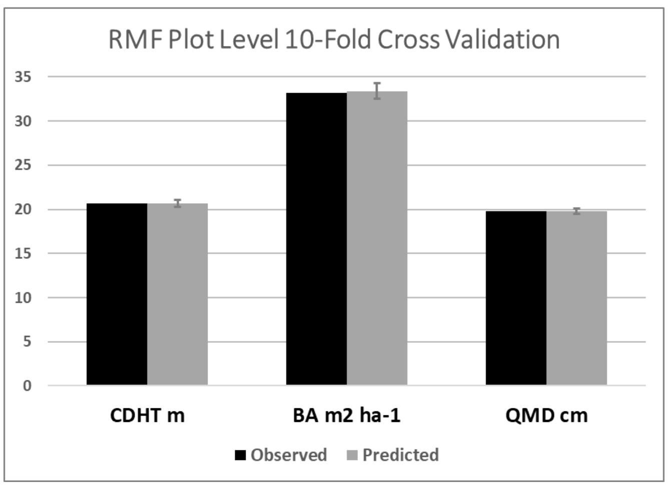
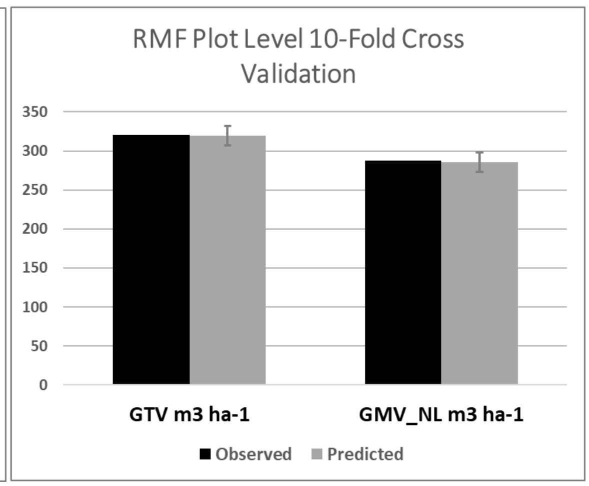
Executive Summary

Single Photon LiDAR (SPL) was acquired over the Romeo Malette Forest (RMF) during the summer of 2018. A total of 258 lidar calibration plots ($400m^2$ – 11.28m radius) were established and measured between June 18 and August 21, 2019. These plots were used to derive an inventory update ("T2") based on LiDAR models for Height (Dominant/Codominant, Lorey, Top Height), Basal Area (BA), Volumes (Gross Total (GTV), Gross Merchantable (GMV_NL and GMV_WL)), Quadratic Mean Diameter (QMD), Total Above Ground Biomass (Biomass), Stems, and Basal Area and Gross Merchantable volume by four-size classes. Merchantable volume predictions used the provincial scaling specifications for upper diameter limits along with a 30cm stump height. An additional set of predicted volume rasters were produced for GreenFirst Forest Products range of varied mill requirements.

Plot level Model Validation

A 10-Fold Cross Validation (CV) of plot level ($400m^2$) predictions were calculated as a measure of model performance. Root Mean Square Error (RMSE) of models for height varied from 8.9%, 8.0% for Dominant/Codominant and Top height respectively. BA had a 18.7% RMSE while volumes (GTV, GMV_NL, GMV_WL) had 20.4%, 23.0% and 23.8 % respectively. QMD reported an RMSE of 15.6% and Biomass 19.2%. Stems resulted in an RMSE of 31.9%. Examples of mean observed and model predictions (along with standard error) of inventory attributes from cross validation are provided below.





Stand level Model Validation

Additional validation of the LiDAR predictions for 6 cruised harvest blocks was conducted. A stand (or harvest block) represents the scale inventory estimates will be used to support management decisions. The majority of inventory attribute RMSE's declined at the stand level from that reported via CV at the plot scale by an average of > 45% (with QMD and Stems improving the least). Height attributes are not significantly impacted by scale. However, attributes such as ones expressed per area (i.e., volume) are. CDht RMSE for the validation stands was 1.7%. RMSE for BA, GTV, GMV, and Biomass were reduced to 6.8%, 11%, 12.7% and 7.4%. RMSE for QMD and Stems were reduced to 12.6% and 25.4% respectively.

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 $\geq$ 20 years**. Stand level

QMD 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).

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

Study Site

The Romeo Malette Forest (RMF) (Figure 1) is located within the Timmins District in the Northeast Region of the Ministry of Northern Development, Mines and Natural Resources and Forestry (MNDMNRF). The Sustainable Forest Licence (SFL) is held by GreenFirst Forest Products. GreenFirst acquired the SFL from Rayonier Advanced Materials Canada G.P. (RYAM) in 2021.

The RMF lies entirely within the Boreal Forest Region, with one third in the Northern Clay Belt Section and two thirds in the Misinabi-Cabonga Section. The Clay Belt portion is dominated by large stands of black spruce which cover the poorly drained lowlands as well as gently rising upland areas. The Forest is characterized by the absence of exposed bedrock, extensive poorly drained flat areas, relatively few lakes, and clay-banked sluggish streams. The Central Transitional Section comprises the remaining area of the RMF, with stands that are generally more mixed and variable in size. The topography is moderately rolling with occasional ridges, and drainage is generally good.

The RMF encompasses an area of approximately 629,976 hectares (ha) of Crown managed land of which 87% is Crown managed forested land. Non-forested and non-productive land (i.e. water, grass, unclassified lands and agricultural land) comprise 13% (89,998 ha) of the land base. The managed forest contains a range of forest units (FU). The SB1 (16%) and SP1 (16%) represent the largest proportions as mixture and intolerant hardwoods make up the next largest potions. Figure 2 provides a detailed breakdown of the RMF by forest unit.

Data

Airborne LIDAR data

Single Photon LiDAR (SPL) was acquired over the Romeo Malette Forest during the summer of 2018. The SPL100 sensor was flown aboard a Piper–PA–31–350 at an average altitude of 3760m. More details of acquisition parameters are provided in Table 1.

Table 1 - Lidar acquisition specifications for 2018–SPL mission

Parameter	2018 –SPL Description
Pulse repetition rate	6000 KHz
Frequency	21Hz
Scan Angle	+/– 15 Degrees
FOV	30 Degrees
Swath Width	2000m

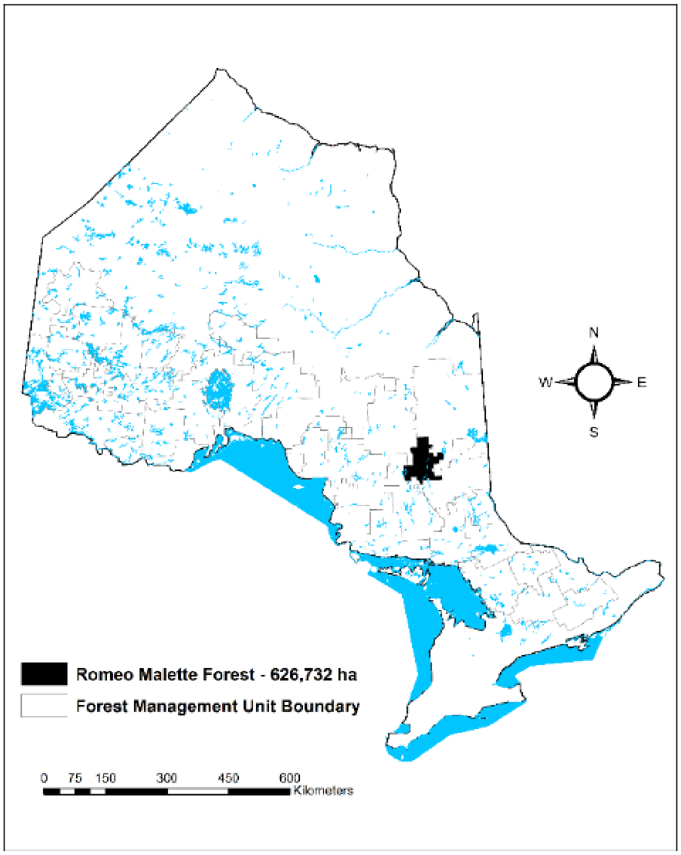


Figure 1 - Romeo Malette Forest Study Location

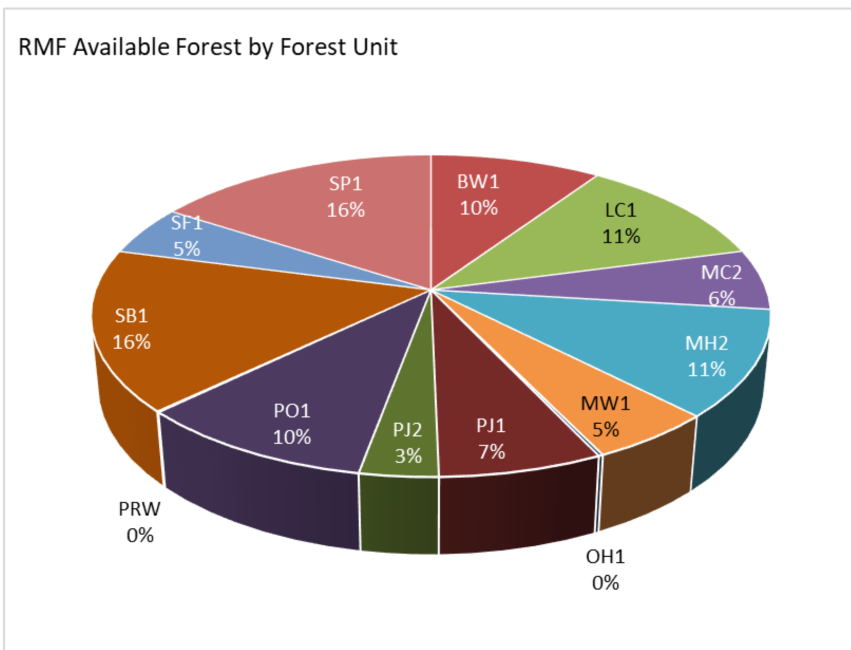


Figure 2 - Percent area by Northeast Forest Unit for the RMF.

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 258 lidar calibration plots (400m^2 – 11.28m radius) were established and measured between June 18 and August 21, 2019. Calibration plots were selected using a "structurally guiding" 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.

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 $\geq$ 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.

An approved provincial standard set of inventory attributes were summarized for model prediction. In addition to these, staff managing the RMF requested some additional volume summarizations (based on destination mill requirements) of the calibration data and subsequent modeling products. **Error! Reference source not found.**All plots were spatially located with a survey grade GNSS system. Data was post–processed to meet required sub–metre positional requirements.

Table 2 lists the inventory attributes that were summarized for modeling (live trees with DBH $\geq$ 7.1cm unless noted) on the RMF. Individual tree volumes were calculated using Zakrzewski and Penner (2014) taper models developed for Ontario. No height estimation was required for the RMF dataset as each tree had a measured height

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

All plots were spatially located with a survey grade GNSS system. Data was post–processed to meet required sub–metre positional requirements.

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.

Inventory Attribute	Units	Description
Stems	Stems ha^{-1}	Number of live trees
BasalArea	$m^2\ ha^{-1}$	Basal Area
CDHt	m	Average CoDominant-Dominant height
LoreyHeight	m	Lorey's Height. Mean height weighted by basal area
TopHt	m	Top Height defined as height of the 100 largest DBH trees per hectare (irrespective of species)
QMD	cm	Quadratic mean diameter
GTV	$m^3\ ha^{-1}$	Gross Total Volume (includes stump and top)
GMV_NL	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement. Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
GMV_WL	$m^3\ ha^{-1}$	• t
BA_SmP [9 < Dbh ≤ 16 cm]	$m^2\ ha^{-1}$	Basal Area for the Small Pole size class.
BA_LgP [16 < Dbh ≤ 25 cm]	$m^2\ ha^{-1}$	Basal Area for the Large Pole size class.
BA_SmS [25 < Dbh ≤ 37 cm]	$m^2\ ha^{-1}$	Basal Area for the Small Sawlog size class.
BA_LgS [Dbh > 37 cm]	$m^2\ ha^{-1}$	Basal Area for the Large Sawlog size class.
GMV_NL_SmP [9 < Dbh ≤ 16 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Small Pole size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
GMV_NL_LgP [16 < Dbh ≤ 25 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Large Pole size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
GMV_NL_SmS [25 < Dbh ≤ 37 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Small Sawlog size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
GMV_NL_LgS [Dbh > 37 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Large Sawlog size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
Biomass	Tonnes ha^{-1}	Total above ground biomass (wood + bark + branches + foliage)
GMV_GF	$m^3\ ha^{-1}$	Gross merchantable volume to Green First specifications for their mills (Appendix B)
GMV_Eac16	$m^3\ ha^{-1}$	Gross merchantable volume to Green First Forest Products specifications for Eacom mill (Appendix B))
GMV_GP	$m^3\ ha^{-1}$	Gross merchantable volume to Green First Forest Products specifications for Georgia Pacific (Appendix B))
GMV_Rock	$m^3\ ha^{-1}$	Gross merchantable volume to Green First Forest Products specifications for Rockshield (Appendix B))
RBA_SmP [9 < Dbh ≤ 14.9 cm]	$m^2\ ha^{-1}$	Basal Area for the Small Pole size class – Green First Size Class Specification.
RBA_LgP [14.9 < Dbh ≤ 25 cm]	$m^2\ ha^{-1}$	Basal Area for the Large Pole size class – Green First Size Class Specification.
RBA_SmS [25 < Dbh ≤ 37 cm]	$m^2\ ha^{-1}$	Basal Area for the Small Sawlog size class – Green First Size Class Specification.
RBA_LgS [Dbh > 37 cm]	$m^2\ ha^{-1}$	Basal Area for the Large Sawlog size class – Green First Size Class Specification.
RMV_SmP [9 < Dbh ≤ 14.9 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Green First Small Pole size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3) -
RMV_LgP [14.9 < Dbh ≤ 25 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Green First Large Pole size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
RMV_SmS [25 < Dbh ≤ 37 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Green First Small Sawlog size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)
RMV_LgS [Dbh > 37 cm]	$m^3\ ha^{-1}$	Gross Merchantable Volume with no minimum piece length requirement for the Green First Large Sawlog size class. • Stump height 30cm and upper diameter as per Ontario Scaling Manual (Table 3)

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

Species	Minimum Diameter Outside Bark (DOB)
Hardwoods (except poplar/white birch)	18cm class, 17.1 cm
Conifers (except White and Red Pine, Hemlock	10cm class, 9.1 cm

White & Red Pine Hemlock	14cm class, 13.1 cm
Poplar, White Birch	14cm class, 13.1 cm
Source: OMNRF. 2020. Scaling Manual, Toronto. Queen's Printer for Ontario. 169 pp ISBN:978-1-4868-4495-1	

Exclusion of Calibration Plots

As noted earlier, LiDAR was acquired during the summer of 2018 and plot measurements were started and completed during the summer of 2019 (June 18 – August 21). The intent of the calibration plots is to capture vegetation conditions that match the LiDAR measurements. However, a range of natural and anthropogenic activities on the RMF occurred during the one-year period between acquisition and plot establishment/measurement and as a result some plots were excluded from the analysis. Table 4 identifies the 15 plots excluded from the calibration of the lidar and their reason for removal. A total of 243 calibration plots were used in the production of the lidar inventory.

Table 4 - RMF calibration plots excluded from analysis

Plot Number	Reason for Exclusion
RMF3	Burned in 2012 - no live trees measured in plot
RMF8	Only Dead trees >= 7.1cm
RMF20	Burned
RMF21	Burned
RMF37	Burned 2012 - No Live trees >= 7.1cm
RMF141	Harvested since LiDAR capture
RMF182	Burned 2012 - No Live trees >= 7.1cm
RMF185	Burned 2012 - No Live trees >= 7.1cm
RMF214	Harvested 2012 - no live trees >= 7.1cm
RMF273	Harvested after LiDAR acquisition
RMF350	Harvested 2013 - no live trees >= 7.1cm
RMF375	Large Single Aspen blown down
RMF421	Clearcut since LiDAR flown in 2018
RMF445	Burned 2012 - no live trees >= 7.1cm
RMF446	Burned 2012 - no live trees >- 7.1cm

A summary of the calibration plots by Northeast standard Forest Units (FUs) (Yietagesu *et al.* 2016) is provided in Table 5. Of note is the number of calibration plots per FU. Some conditions seem under sampled (SB1) while others appear oversampled (PO1). This disparity in sample size by FU 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., mixedwoods) were sampled more than more "simple" structures often found in pure black spruce stands.

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 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

Table 5 – Statistics – Mean (range) of calibration plots by standard NE Forest Units on the RMF used for LiDAR modeling

NE-Forest Unit	No Plots	Breast Height Age (yrs)[1]	TopHt (m)	CDHT (m)	Lorey Ht (m)	Stems (ha)	Basal Area (m^2 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})
BW1	13	55 (N=11) (16 - 80)	19.6 (10.6 - 26.2)	18.3 (9.9 - 23.1)	17.9 (10.3 - 22.3)	1015 (75 - 2575)	24.1 (2.6 - 41.6)	18.4 (8.6 - 25.4)	198.1 (11.9 - 400.7)	147.7 (0.5 - 361.7)	138.3 (0.4 - 349.2)	129.3 (8.9 - 244.8)
LC1	33	81 (N=27) (18 - 135)	17.4 (8.8 - 24)	15.0 (7.9 - 22.2)	14.8 (8.1 - 21.6)	1377 (75 - 2850)	24.9 (2.5 - 56.3)	15.7 (10 - 20.6)	169.1 (22.6 - 343.5)	136.5 (11.6 - 295.6)	127.6 (9.0 - 284.5)	99.2 (12.1 - 182.3)
MC2	7	71 (N=6) (18 - 92)	24.5 (15.2 - 29.8)	21.0 (8.9 - 25.3)	20.2 (10.2 - 24)	954 (450 - 1300)	32.1 (11.3 - 42.9)	21.3 (10.5 - 27)	294.6 (51.6 - 455.2)	264.0 (21.6 - 420)	255.3 (15.9 - 410.2)	160.5 (36.9 - 240.6)
MH1	11	61 (N=9) (29 - 89)	18.4 (6.3 - 22.7)	16.8 (6 - 21.1)	16.0 (6.0 - 19.8)	1543 (250 - 3550)	30.2 (2.9 - 43.6)	16.8 (11.6 - 21.5)	216.3 (8.1 - 329.1)	151.0 (4.1 - 269.5)	137.5 (3.5 - 252.9)	138.8 (12.7 - 200.9)
MH2	23	84 (N=17) (44 - 115)	25.9 (18 - 35.7)	23.5 (15.7 - 35.5)	22.1 (16 - 29.6)	1140 (225 - 2225)	41.3 (27.1 - 59.2)	23.0 (15 - 41.3)	406.3 (213.2 - 722.6)	357.6 (141.2 - 678.3)	346.0 (126.8 - 663.5)	219.9 (137.6 - 362)
PJ1	33	54 (N=23) (9 - 96)	18.5 (4.4 - 28.4)	17.2 (4.4 - 26)	16.7 (4.4 - 23.2)	1420 (25 - 3025)	26.3 (0.2 - 43.4)	15.9 (7.4 - 22.7)	216.1 (0.4 - 452.6)	180.8 (0 - 408.1)	170.2 (0.0 - 395.8)	119.5 (0.4 - 239.7)
PJ2	12	70 (N=10) (30 - 111)	21.0 (14.4 - 26.8)	19.5 (13.5 - 25.3)	17.9 (12.8 - 22.3)	1554 (625 - 2875)	31.8 (14.9 - 42.3)	17.2 (13.1 - 21.5)	250.4 (125.9 - 352)	205.9 (111.9 - 310.2)	194.7 (107.5 - 302.2)	139.3 (69.6 - 190.7)
PO1	85	78 (N=82) (21 - 125)	27.7 (8.4 - 38.5)	26.2 (8.2 - 36)	24.6 (8.2 - 33.6)	1041 (200 - 2825)	42.3 (9.3 - 86.3)	24.0 (8.2 - 38.2)	487.8 (28.5 - 1044.8)	437.6 (0 - 992.3)	425.0 (0.0 - 980.8)	252.8 (22.0 - 534)
PW1	1	113 (N=1) (113 - 113)	30.5 (30.5 - 30.5)	26.8 (26.8 - 26.8)	30.6 (30.6 - 30.6)	400 (400 - 400)	26.7 (26.7 - 26.7)	29.2 (29.2 - 29.2)	313.3 (313.3 - 313.3)	290.6 (290.6 - 290.6)	287.9 (287.9 - 287.9)	167.3 (167.3 - 167.3)
SB1	8	85 (N=5) (70 - 111)	14.7 (8.2 - 20.1)	12.8 (7.6 - 17.1)	12.5 (7.7 - 17.1)	1594 (400 - 3400)	20.9 (3.1 - 37)	13.2 (8.4 - 17.2)	131.0 (12.6 - 221)	95.0 (2.6 - 179.4)	85.3 (2.1 - 167.6)	80.9 (10.2 - 138.5)
SF1	12	51 (N=11) (25 - 97)	15.5 (7.8 - 25.2)	13.4 (6.9 - 21.5)	13.2 (7.2 - 21.7)	1267 (250 - 2575)	21.2 (2 - 37.9)	14.2 (9.1 - 21.3)	139.7 (7.0 - 298.2)	108.1 (2.7 - 261.3)	101.0 (2.0 - 254.4)	82.3 (5.1 - 164.1)
SP1	5	66 (N=4) (26 - 106)	19.6 (11.6 - 27.7)	17.4 (9.1 - 25.8)	17.5 (10.7 - 25.5)	1105 (325 - 3025)	23.7 (3.4 - 36.1)	18.3 (11.2 - 25.6)	192.7 (16.8 - 335.9)	160.7 (10.5 - 295.5)	153.5 (9.7 - 285.8)	110.6 (11.6 - 182)
All	**243**	**72 (N=206) (9 - 135)**	**22.4 (4.4 - 38.5)**	**20.6 (4.4 - 36)**	**19.7 (4.4 - 33.6)**	**1220 (25 - 3550)**	**33.1 (0.2 - 86.3)**	**19.7 (7.4 - 41.3)**	**319.1 (0.4 - 1044.8)**	**275.5 (0.0 - 992.3)**	**264.6 (0.0 – 981.0)**	**1723.3 (0.4 - 534)**

[1] 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.

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 RMF. 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 predictive models are also indicated.

Lidar Model Development

A non-parametric Random Forest 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 11 calibration plots from the modeling but ensured that only plots with predominantly merchantable sized trees were utilized in the models and the predictions made at the landscape level. In the prediction of merchantable volume attributes, calibration plots with Zq99 > 9m were used as plots with Zq99 ≤ 9m had little or no merchantable volume.

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 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.

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 very 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 as 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 GMV_SFL[2]) were constrained against GTV. Merchantable volumes (i.e., GMV_NL and GMV_WL) were not constrained to be greater or equal to each other.

Error! Not a valid bookmark self-reference. indicates which attributes were predicted directly from the statistical predictor summaries of the raw LiDAR point cloud. Table 7 indicates which inventory attributes are calculated as a fraction of another one to help ensure logical predictions.

Size class estimates of merchantable volume and basal area were constrained to always sum to either predicted GMV_NL or Basal Area. To ensure this was the case, size class attributes were modeled as a fraction (refer to Table 7 size class metrics and their method of calculation).

Table 6 - Inventory attributes predicted directly from the point cloud predictors.

Inventory Attribute
TopHt
CDHt
LoreyHeight
BasalArea
QMD
Biomass

Lidar Model Results

Species/forest type and age were not used in the modeling. All LiDAR predictions are based on the LiDAR structure statistics and the field plot measurement summaries only[3]. Figure 3 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 available were used in model training and prediction. As a result, no independent

[2] GMV_SFL refers to the additional summaries for Resolute specific volumes GMV_TL_IGN_TBY , GMV_CTL_ATK, GMV_CTL_IGN_TBY, GMV_Norbord_Hwd and GMV_Kenora_Hwd

[3] The field measurement summaries include species composition and age. However, they were not used in modeling.

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

Inventory Attribute	Calculation
Stems	Stems = (P_BasalArea / P_QMD^2) / 0.00007854
GTV	GTV = P_BasalArea * P_VBAR_GTV
GMV_NL	GMV_NL = P_GTV * P_GMV_NL_ratio
GMV_WL	GMV_WL = P_GTV * P_GMV_WL_ratio
BA_SmPoles [9 < Dbh ≤ 16 cm]	BA_SmPoles_frac = BA_SmPoles/BasalArea (>9cm) BA_SmPoles = (P_BasalArea (>9cm) * P_BA_SmPoles_frac)
BA_LgPoles [16 < Dbh ≤ 25 cm]	BA_LgPoles_frac = BA_LgPoles/(BasalArea (>9cm) – BA_SmPoles) BA_LgPoles = P_BA_LgPoles_frac * ((P_BasalArea (>9cm) -_P_BA_SmPoles)
BA_SmSaw [25 < Dbh ≤ 37 cm]	BA_SmSaw_frac = BA_SmSaw/(BasalArea (>9cm) - BA_SmPoles – BA_LgPoles) BA_SmSaw = P_BA_SmSaw_frac * (P_ BasalArea (>9cm) -_P_BA_SmPoles - P_ BA_LgPoles)
BA_LgSaw [Dbh > 37 cm]	BA_LgSaw = ((P_ BasalArea (>9cm) -_P_BA_SmPoles - P_BA_LgPoles – P_BA_SmSaw)
GMV_NL_SmPoles [9 < Dbh ≤ 16 cm]	GMV_NL_SmPoles_frac = GMV_NL_smPoles/GMV_NL GMV_NL_SmPoles= (P_GMV_NL * P_GMV_NL_smPoles_frac)
GMV_NL_LgPoles [16 < Dbh ≤ 25 cm]	GMV_NL_LgPoles_frac = GMV_NL_LgPoles/(GMV_NL – GMV_NL_SmPoles) GMV_NL_LgPoles = P_GMV_NL_LgPoles_frac * (P_GMV_NL -_P_GMV_NL_SmPoles)
GMV_NL_SmSaw [25 < Dbh ≤ 37 cm]	GMV_NL_SmSaw_frac = GMV_NL_SmSaw/(GMV_NL – GMV_NL_SmPoles – GMV_NL_LgPoles) GMV_NL_SmSaw = P_GMV_NL_SmSaw_frac * (P_GMV_NL -_P_GMV_NL_SmPoles - P_ GMV_NL_LgPoles)
GMV_NL_LgSaw [Dbh > 37 cm]	GMV_NL_LgSaw = (P_GMV_NL -_P_GMV_NL_SmPoles - P_GMV_NL_LgPoles - P_GMV_NL_SmSaw)
GMV_GF	GMV_GF = P_GTV * P_GMV_GF_ratio
GMV_Eacom16	GMV_Eacom16 = P_GTV * P_GMV_Eacom16_ratio
GMV_GP	GMV_GP = P_GTV * P_GMV_GP_ratio
GMV_Rockshield	GMV_Rockshield = P_GTV * P_GMV_Rockshield_ratio
RMF_BA_SmPoles[4]	RMF_BA_SmPoles_frac = RMF_BA_SmPoles/BasalArea (>9cm)

[4] RMF_BA …size class indicates RMF specific size class distribution ranges for the pole class. The small, and large sawlog size class are identical to the provincial classes.

[9 < Dbh < 14.9 cm]	RMF_BA_SmPoles = (P_BasalArea (>9cm) * P_RMF_BA_SmPoles_frac)
RMF_BA_LgPoles [14.9 < Dbh < 25 cm]	RMF_BA_LgPoles_frac = RMF_BA_LgPoles/(BasalArea (>9cm) - RMF_BA_SmPoles) RMF_BA_LgPoles = P_RMF_BA_LgPoles_frac * (P_BasalArea (>9cm) -_P_RMF_BA_SmPoles)
RMF_BA_SmSaw [25 < Dbh < 37 cm]	RMF_BA_SmSaw_frac = RMF_BA_SmSaw/(BasalArea (>9cm) - RMF_BA_SmPoles - RMF_BA_LgPoles) RMF_BA_SmSaw = P_RMF_BA_SmSaw_frac * (P_BasalArea (>9cm) -_P_RMF_BA_SmPoles - P_ RMF_BA_LgPoles)
RMF_BA_LgSaw [Dbh > 37 cm]	RMF_BA_LgSaw = (P_BasalArea (>9cm) -_P_RMF_BA_SmPoles - P_RMF_BA_LgPoles – P_RMF_BA_SmSaw)
RMF_GMV_NL_SmPoles[5] [9 < Dbh < 14.9 cm]	RMV_NL_SmPoles_frac = RMV_NL_smPoles/GMV_NL RMV_NL_SmPoles= (P_GMV_NL * P_RMV_NL_smPoles_frac)
RMF_GMV_NL_LgPoles [14.9 < Dbh < 25 cm]	RMV_NL_LgPoles_frac = GMV_NL_LgPoles/(GMV_NL- RMV_NL_SmPoles) RMV_NL_LgPoles = P_RMV_NL_LgPoles_frac * (P_GMV_NL -_P_RMV_NL_SmPoles)
RMF_GMV_NL_SmSaw [25 < Dbh < 37 cm]	RMV_NL_SmSaw_frac = RMV_NL_SmSaw/(GMV_NL - RMV_NL_SmPoles - RMV_NL_LgPoles) RMV_NL_SmSaw = P_RMV_NL_SmSaw_frac * (P_GMV_NL -_P_RMV_NL_SmPoles - P_ RMV_NL_LgPoles)
RMF_GMV_NL_LgSaw [Dbh > 37 cm]	RMV_NL_LgSaw = (P_GMV_NL -_P_RMV_NL_SmPoles - P_RMV_NL_LgPoles – P_RMV_NL_SmSaw – P_RMV_NL_MedSaw)

plots were available to test model prediction error with. Two methods, “Out of Bag” (OOB) and “Cross Validation” (CV) can be used to estimate prediction error at the plot scale (20m x 20m) in the absence of a validation data set.

OOB error is generated by measuring the prediction error of random forest models utilizing bagging (bootstrap aggregation). Bagging uses subsampling with replacement of a subset of the data (the “in the bag” dataset) to create training samples for the model to learn from. The model is then used to predict the reserved or “out of bag” samples. OOB error is the mean prediction error on each training sample x_i, using only the trees that did not have x_i in their bootstrap sample. Since each out-of-bag set is not used to train the model, it is a good test for the performance of the model. A general calculation method is outlined below:

- Find all models (or trees, in the case of a random forest) that are not trained by the OOB instance.

[5] RMF_GMV_NL …size class indicates RMF specific size class distribution ranges for the pole class. The small and large sawlog size class are identical to the provincial classes.

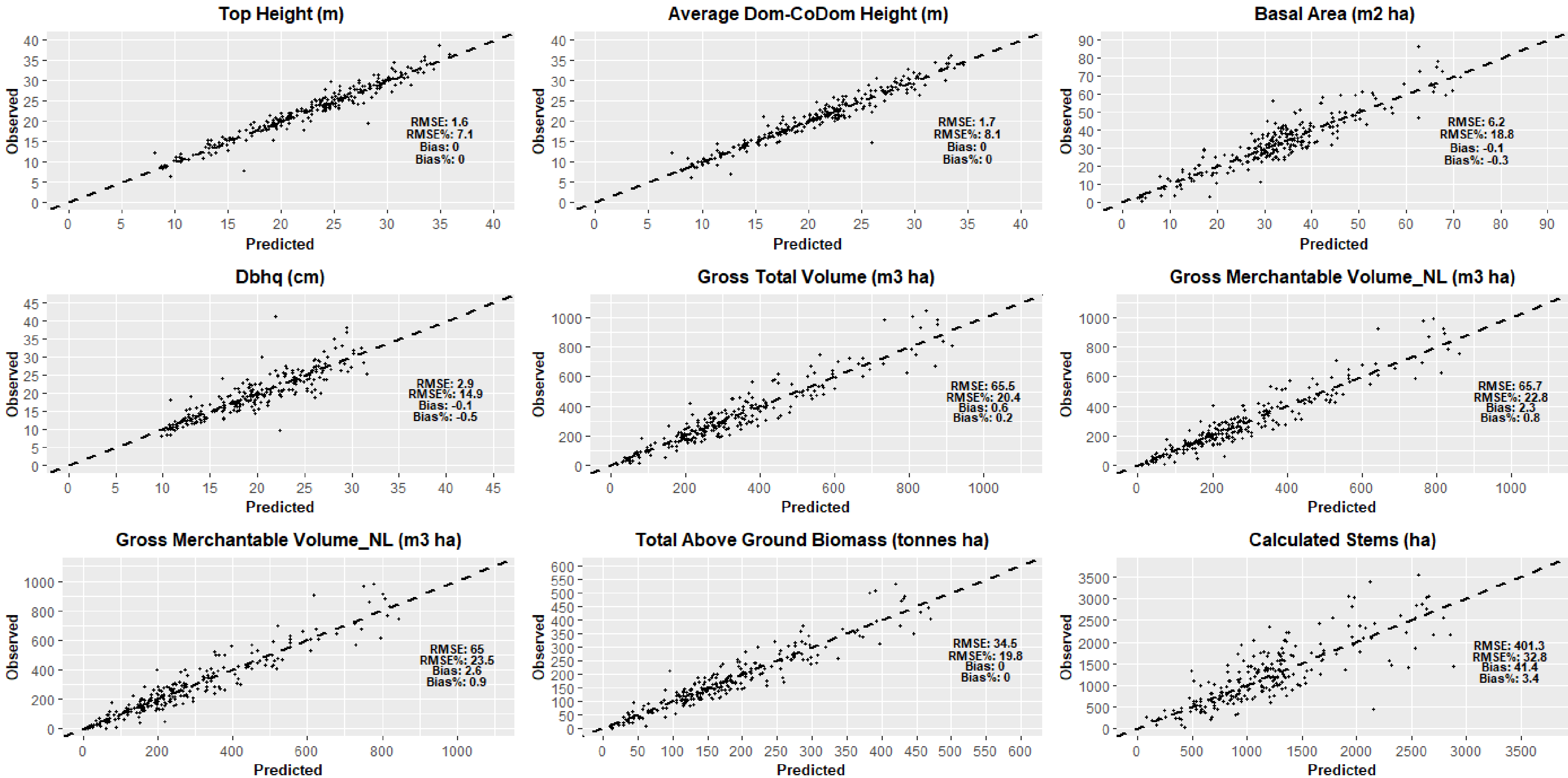


Figure 3 - Modeling results of Observed versus Predicted for selected inventory attributes on the RMF. Error statistics are based on OOB sample.

- Take the majority vote of these models' result for the OOB instance, compared to the true value of the OOB instance.
- Compile the OOB error for all instances in the OOB dataset.

V-fold CV error is generated by dividing the data set randomly into *V* equal parts. Training for the model is done on one of the *V* 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:

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

$$\text{RELATIVE RMSE} = \frac{\text{RMSE}}{\bar{Y}},$$

$$\text{BIAS} = \frac{\sum_{i=1}^{n}(\hat{Y}_i - Y_i)}{n},$$

$$\text{RELATIVE BIAS} = \frac{\text{BIAS}}{\bar{Y}}.$$

Plot level OOB and a 10-fold CV comparisons of root mean square error (RMSE) and bias are presented by inventory attributes in **Error! Reference source not found.**. OOB and CV RMSE (%) AND bias (%) are graphically presented in Figure 4. These results reflect modeling of all species/silviculture/origin based solely on LiDAR point cloud structure and at the plot or 20 x 20m pixel 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 pixel scale how a model is performing overall. Figure 5 provides CV comparisons of RMSE (%) by FU and by inventory attribute. **Note, the number of plots by forest type varies and the results should be viewed in that light.** Appendix C provides a tabular summary of OOB and CV plot level predictions by forest types on the RMF forest.

LiDAR Prediction Raster Surface Adjustments

Predicted raster products were modified to align pixel predictions with the limitations of the calibration

Table 8 - Plot level validation statistics using OOB and 10-fold Cross Validation methods

	Observed				Out Of Bag (OOB) Validation						10-Fold Cross Validation (CV)					
Inventory Metric	N	Mean	Min	Max	P_Mean	P_SE	RMSE	% RMSE	BIAS	% BIAS	P_Mean	P_SE	RMSE	RMSE %	BIAS	BIAS%
CDHT m	243	20.6	6.0	36.0	20.6	0.4	1.8	8.7	0.0	-0.1	20.7	0.4	1.8	8.9	-0.1	-0.2
TOPHT m	243	22.4	6.2	38.5	22.5	0.4	1.8	8.0	0.0	-0.1	22.5	0.4	1.8	8.0	-0.1	-0.3
LoreyHt m	243	19.7	6.0	33.6	19.7	0.4	1.5	7.8	0.0	0.0	19.7	0.4	1.6	7.9	0.0	0.0
BA m^2 ha^{-1}	243	33.1	0.5	86.3	33.1	0.9	6.1	18.6	0.0	0.0	33.1	0.9	6.2	18.7	0.0	0.0
QMD cm	243	19.7	8.2	41.3	19.8	0.3	3.1	15.6	-0.1	-0.5	19.8	0.3	3.1	15.6	-0.1	-0.5
GTV m^3 ha^{-1}	243	319.1	1.9	1044.8	317.6	12.6	64.1	20.1	1.4	0.4	318.0	12.6	65.1	20.4	1.1	0.3
GMV_NL m^3 ha^{-1}	233	286.7	0.8	992.3	283.6	12.4	64.9	22.6	3.1	1.1	283.6	12.4	66.0	23.0	3.1	1.1
GMV_WL m^3 ha^{-1}	233	275.5	0.5	980.8	272.2	12.3	64.1	23.3	3.3	1.2	272.4	12.3	65.6	23.8	3.1	1.1
GMV_GreenFirst m^3 ha^{-1}	233	264.6	0.7	800.2	263.2	9.8	51.9	19.6	1.4	0.5	263.7	9.8	52.7	19.9	0.9	0.3
GMV_Eacom16 m^3 ha^{-1} [6]	233	255.6	0.0	953.7	253.4	12.6	58.3	22.8	2.1	0.8	253.6	12.6	59.3	23.2	2.0	0.8
GMV_GP m^3 ha^{-1}	233	268.7	0.0	982.0	266.2	12.8	60.4	22.5	2.5	0.9	266.9	12.8	61.4	22.8	1.8	0.7
GMV_Rockshield m^3 ha^{-1}	233	158.6	0.0	870.5	155.3	11.5	56.0	35.3	3.3	2.1	154.9	11.4	56.7	35.8	3.8	2.4
Biomass T ha^{-1}	243	173.3	1.3	534.0	172.9	6.2	33.3	19.2	0.5	0.3	172.2	6.2	33.4	19.2	1.2	0.7
Stems ha^{-1}	243	1220	25	3550	1174	36.0	395.9	32.5	45.3	3.7	1173.7	36.0	388.6	31.9	45.9	3.8

Note- “P_Mean” indicates Predicted Mean “P_SE” indicates Predicted Standard Error

[6] GMV_Eacom8 was not modeled separately as it is equivalent to specifications of GMV_WL x SPF fraction

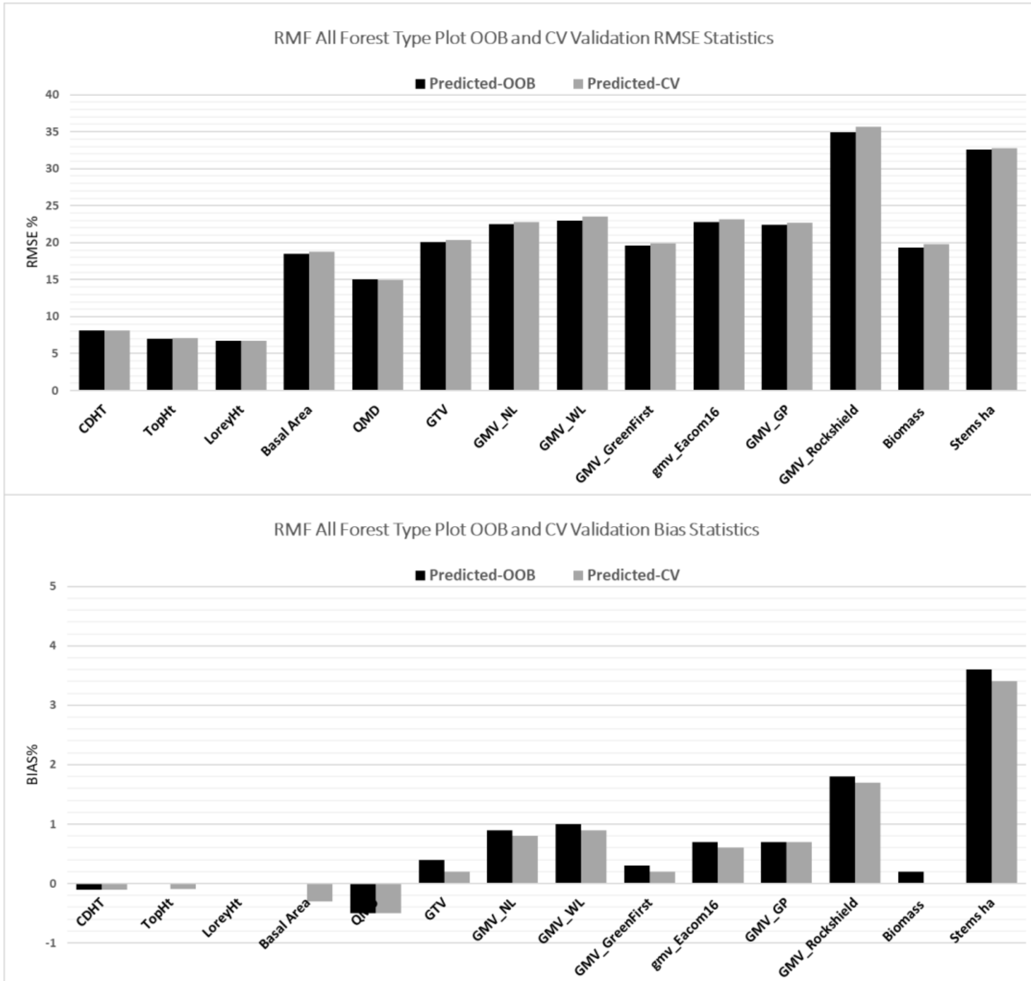
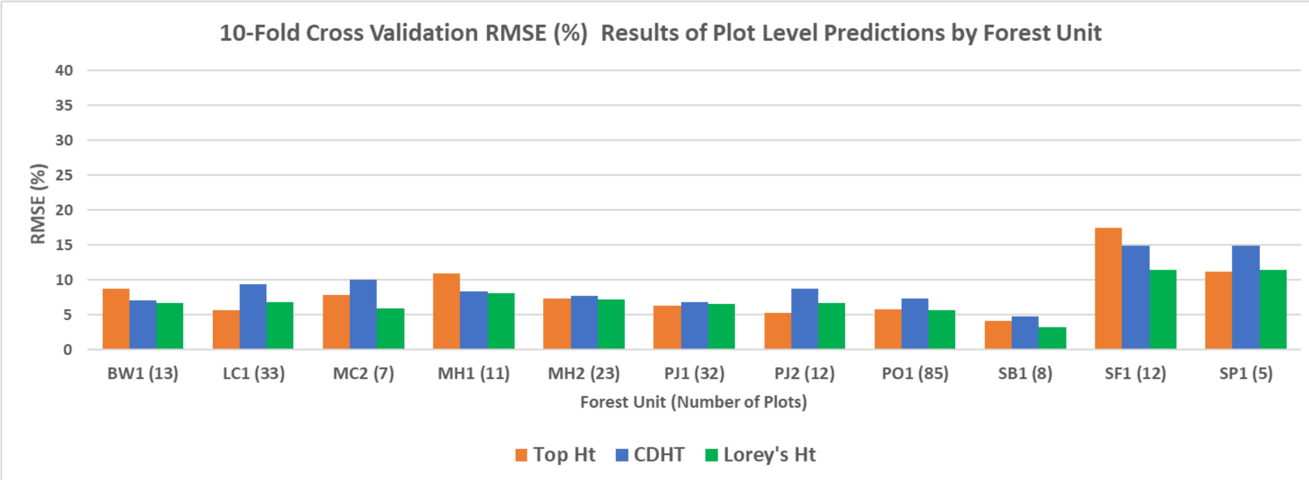
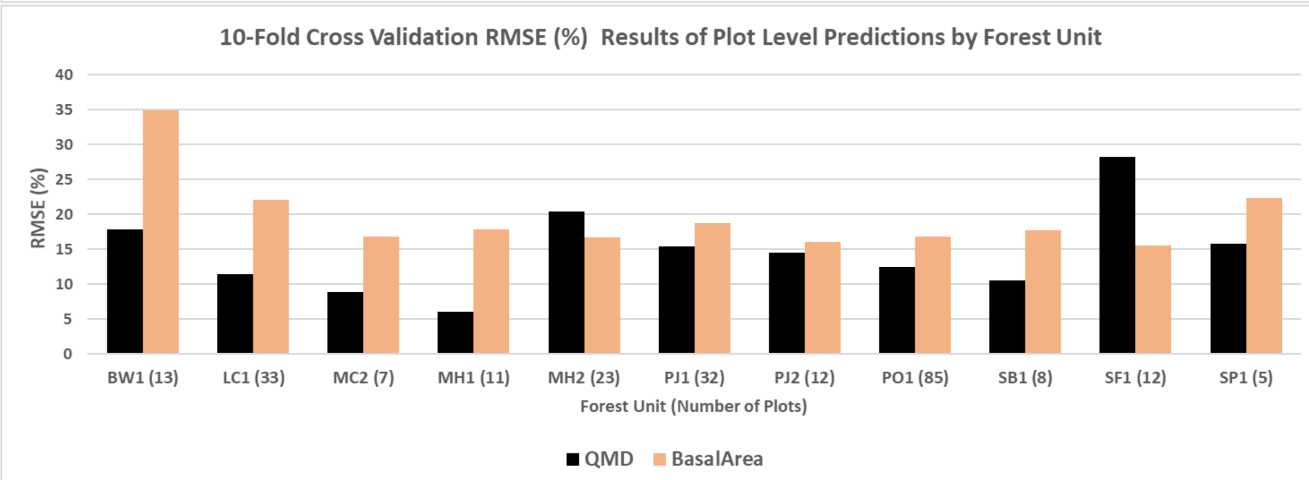


Figure 4 - RMSE (%) and Bias (%)for inventory attribute validation using OOB and a 10-fold Cross Validation

plot network (DBH > 7.1 cm). Table 9 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.

The LiDAR derived CDHT raster for the RMF is provided in (Figure 6). Additional examples of derived inventory raster outputs are provided in Appendix D





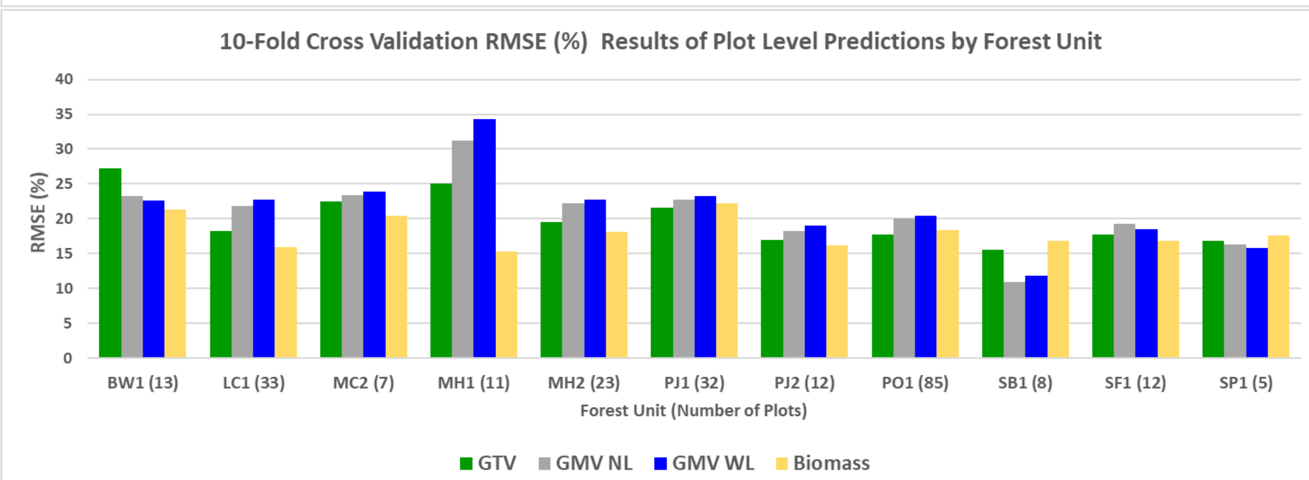


Figure 5 - 10-Fold cross validation RMSE (%) results of plot level predictions by NE Forest Unit. The PW1 Forest Unit was not displayed as it only had one plot.

Table 9 - Adjustments to LiDAR raster predictions based on zq99 thresholds.

Raster Surface	Zq99 Threshold	Adjustment of Raster Predictions
CDHT	5 m	CDHT predictions replaced with zq99 value where zq99 < 5 m
TOPHT	5 m	TopHt predictions set to **NULL** where zq99 < 5 m
LoreyHt	5 m	LoreyHt predictions set to **NULL** where zq99 < 5 m
Basal Area	5 m	Basal Area predictions set to 0 where zq99 < 5 m
QMD	5 m	QMD predictions set to **NULL** where zq99 < 5 m
GTV	5 m	GTV predictions set to 0 where zq99 < 5 m
Biomass	5 m	Biomass predictions set to 0 where zq99 < 5 m
Stems	5 m	Stems calculation set to 0 where zq99 < 5 m
BA_SmPoles	9 m	BA_SmPoles predictions set to 0 where zq99 < 9m
BA_LgPoles	9 m	BA_LgPoles predictions set to 0 where zq99 < 9 m
BA_SmSaw	9 m	BA_SmSaw predictions set to 0 where zq99 < 9 m
BA_LgSaw	9 m	BA_LgSaw predictions set to 0 where zq99 < 9 m
GMV_NL	9 m	GMV_NL predictions set to 0 where zq99 < 9 m
GMV_WL	9 m	GMV_WL predictions set to 0 where zq99 < 9 m
GMV_SFL[1]	9 m	GMV_SFL predictions set to 0 where zq99 < 9 m
GMV_SmPoles	9 m	GMV_NL_SmPoles predictions set to 0 where zq99 < 9 m
GMV_LgPoles	9 m	GMV_NL_LgPoles predictions set to 0 where zq99 < 9 m
GMV_SmSaw	9 m	GMV_NL_SmSaw predictions set to 0 where zq99 < 9 m
GMV_LgSaw	9 m	GMV_NL_LgSaw predictions set to 0 where zq99 < 9 m
RMV_BA_SmPoles	9 m	RMF_BA_SmPoles predictions set to 0 where zq99 < 5m
RMF_BA_LgPoles	9 m	RMF_BA_LgPoles predictions set to 0 where zq99 < 5 m
RMF_BA_SmSaw	9 m	RMF_BA_SmSaw predictions set to 0 where zq99 < 5 m
RMF_BA_LgSaw	9 m	RMF_BA_SmSaw predictions set to 0 where zq99 < 5 m
RMV_SmPoles	9 m	RMV_NL_SmPoles predictions set to 0 where zq99 < 9 m
RMV_LgPoles	9 m	RMV_NL_LgPoles predictions set to 0 where zq99 < 9 m
RMV_SmSaw	9 m	RMV_NL_SmSaw predictions set to 0 where zq99 < 9 m
RMV_LgSaw	9 m	RMV_NL_LgSaw predictions set to 0 where zq99 < 9 m

Stand Level Validation

Most forest management decisions are not made at a raster pixel (20 m x 20 m) scale. Usually, decisions are made on an aggregation of pixels within a forest stand or harvest block. Six harvest blocks were cruised by GFFP staff and (Ministry of Northern Mines Natural Resources and Forestry) MNDMNRF staff on the RMF to measure of model performance at the scale decisions are usually made. The six blocks were linked to another ongoing KKTD study looking at the automation of vertical structure characterization and as such, were chosen to represent a range for forest types and vertical structures. As a result, these validation stands may not represent common conditions on the RMF forest.

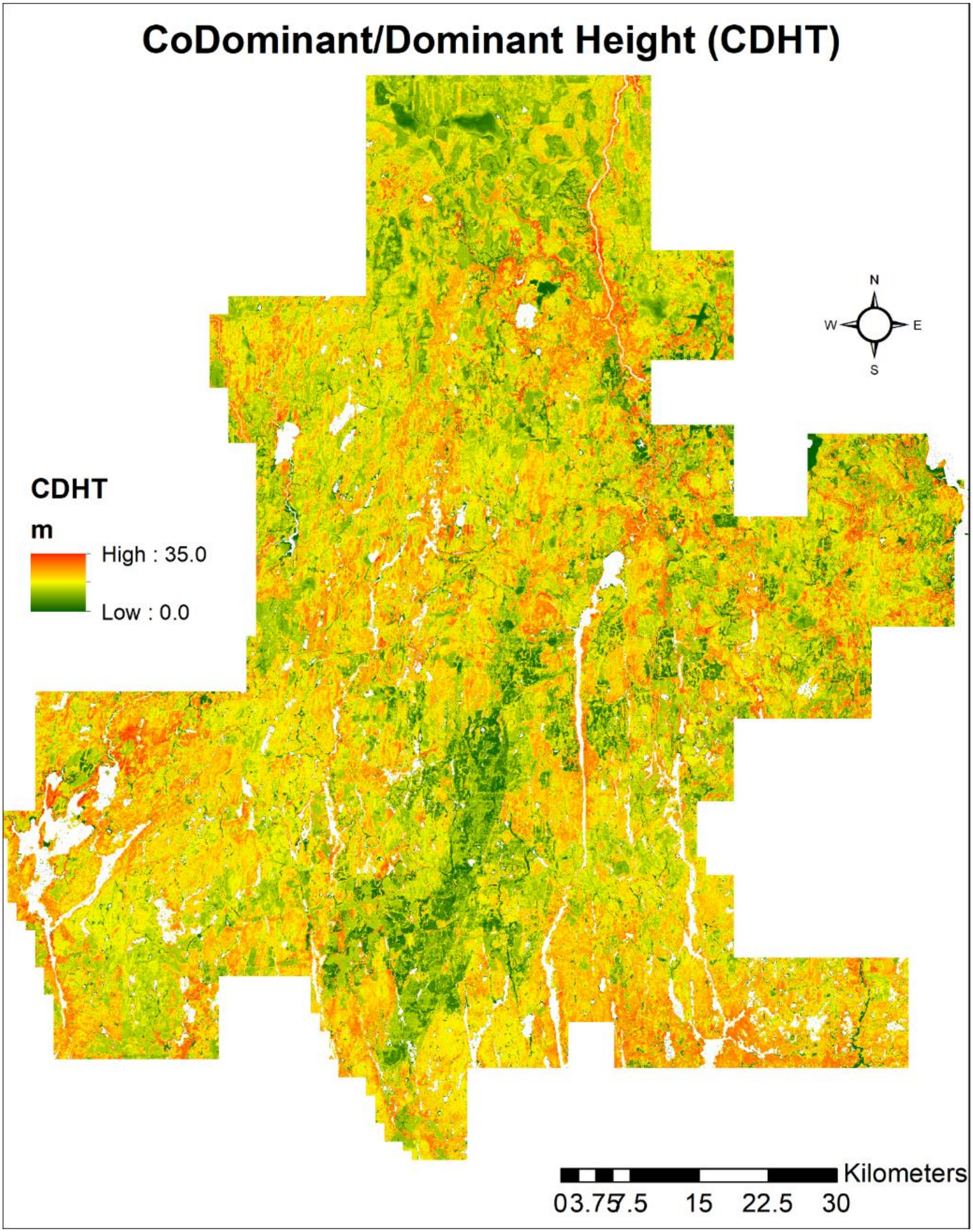


Figure 6 - Lidar derived RMF Dominant/CoDominant Height raster

Validation Sampling

A minimum of 20 stations spaced on a 100m grid covering the entire polygon was targeted. Ideally this would be about 1 plot/ha or sample on a 100m x 100m grid. Depending on stand size and shape, 20 sampling points were not always possible.   Harvest blocks were also buffered by –20m to ensure that plot centres are at least 20m from a stand boundary (Figure 7). A range of forest types were sampled. At each station, a BAF2 prism was used to determine “in” trees > 7cm. Each “in” tree was assessed for species, dbh, crown status (superstory, overstory, understory) and measured for height. Some stations had only every other tree measured for height if the prism identified a high number of trees. Table 10 provides a description of the 6 stands cruised. It should be noted that all 6 of these stands are considered mixed with only Block 446 coming close to being considered “pure” in a Forest Unit context.

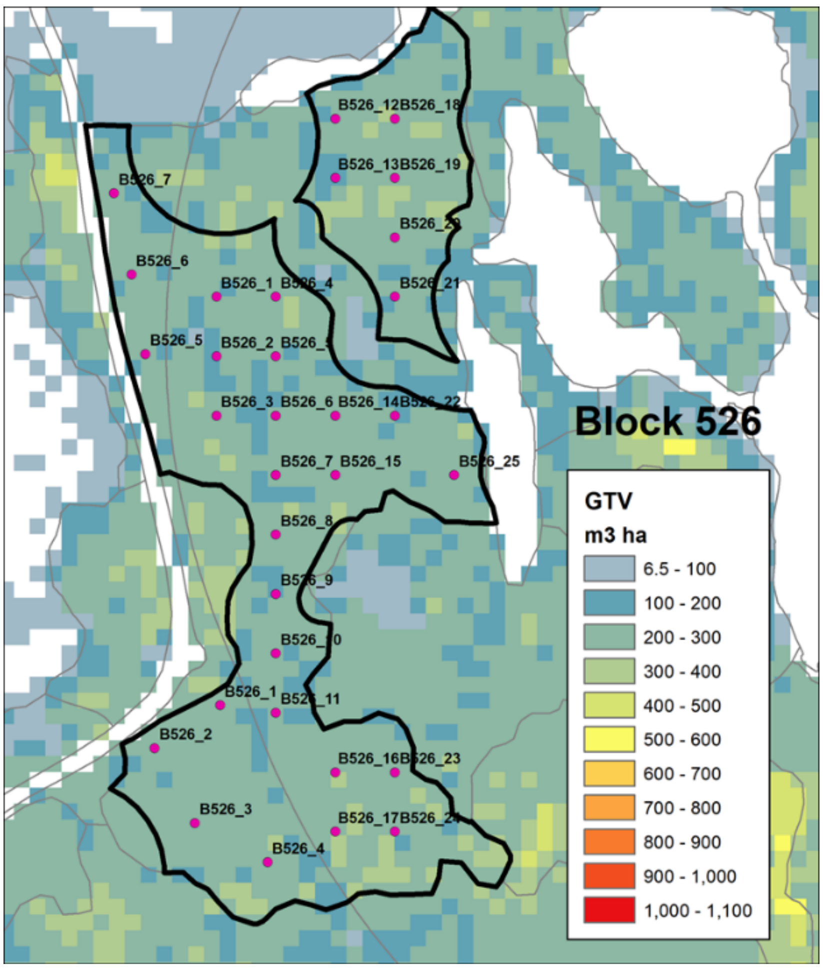


Figure 7 - Example of sampling stations established in a validation block.

Validation Results

Results for the 6 validation blocks are presented in Table 11. Seven key attributes were possible to report on based on the field data collected during the validation cruise. Figure 8 provides a comparison of measured block mean observed and predicted attributes. An additional comparison of predicted BA and GMV by 4 size classes are presented in Figure 9.

Table 10 - Description of validation stands and number of BAF2 stations sampled

Block	Cruised Species Composition	Stations
436	Sb 47 Bf33 Pt8 Pb4 Bf8	19
446	Sb 67 Bf17 Bw10 La6	11
499	Pj 52 Pt29 Bf7 Bw5 Sb7	20
500	Sb 40 Bf26 Bw17 Ce7	17
526	Pj 51 Sb19 Pt10 Sw8	26
527	Bw 37 Sw30 Bf14 Pt6	20

Table 11 - Validation RMSE and Bias results for the 6 cruised validation blocks.

	CDHT	BA	QMD[7]	GTV	GMVnl	Biomass	Stems
RMSE	0.28	1.77	2.18	20.82	19.17	8.26	293.18
RMSE %	1.7%	6.8%	12.6%	11.0%	12.7%	7.4%	25.4%
MeanBias	0.00	-1.33	0.81	-14.88	-14.23	-7.17	-115.48
Bias %	0%	-5%	5%	-8%	-9%	-6%	-10%
N	6	6	6	6	6	6	6

T2 Inventory Updating

The T2 inventory polygon update is comprised of Lidar predictions and calculated attributes based on LiDAR predictions and T1 polygon age and T1 polygon species composition.

Mean raster values by T1 polygon are provided for the following attributes:

- **Heights** - TopHt, CDHT, LoreysHt
- Basal Area,
- Stems
- QMD
- **Volumes** – GMV_NL, GMV_WL, GMV_NL
- **By Size Class** – Basal Area, GMV_NL

For the RMF, additional volumes and size class summaries were also produced:

- **Volumes** – GMV_GF, GMV_GP, GMV_Eacom8, GMV_Eacom16, GMV_Rockshield
- **By Size Class** – RMF_Basal Area, RMV_NL

[7] QMD = Calculated QMD from predicted stand basal area and predicted stems.

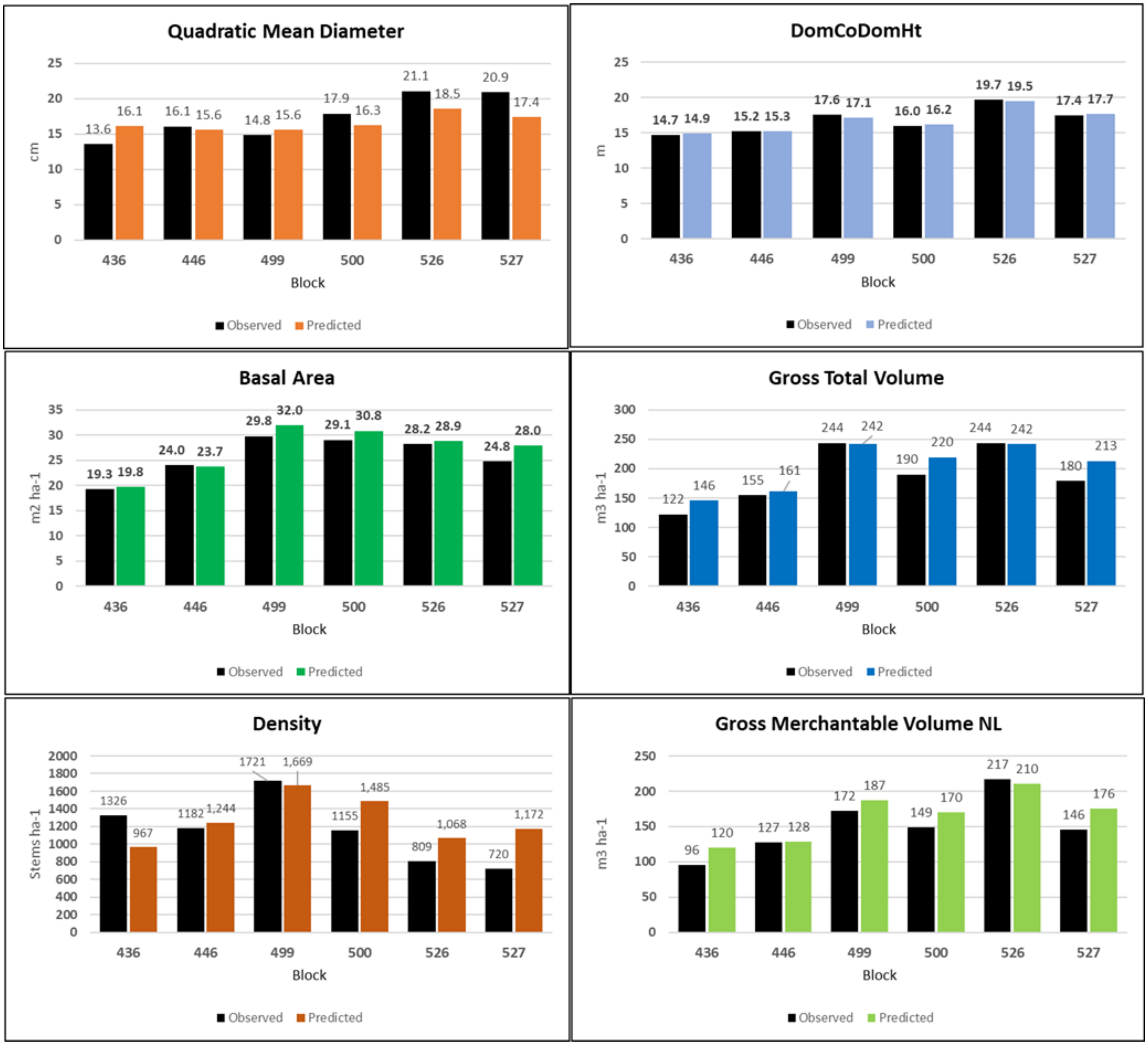


Figure 8 - Validation comparison by block of inventory observed and predicted attributes.

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

- 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 **Error! Reference source not found.**. 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 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 .

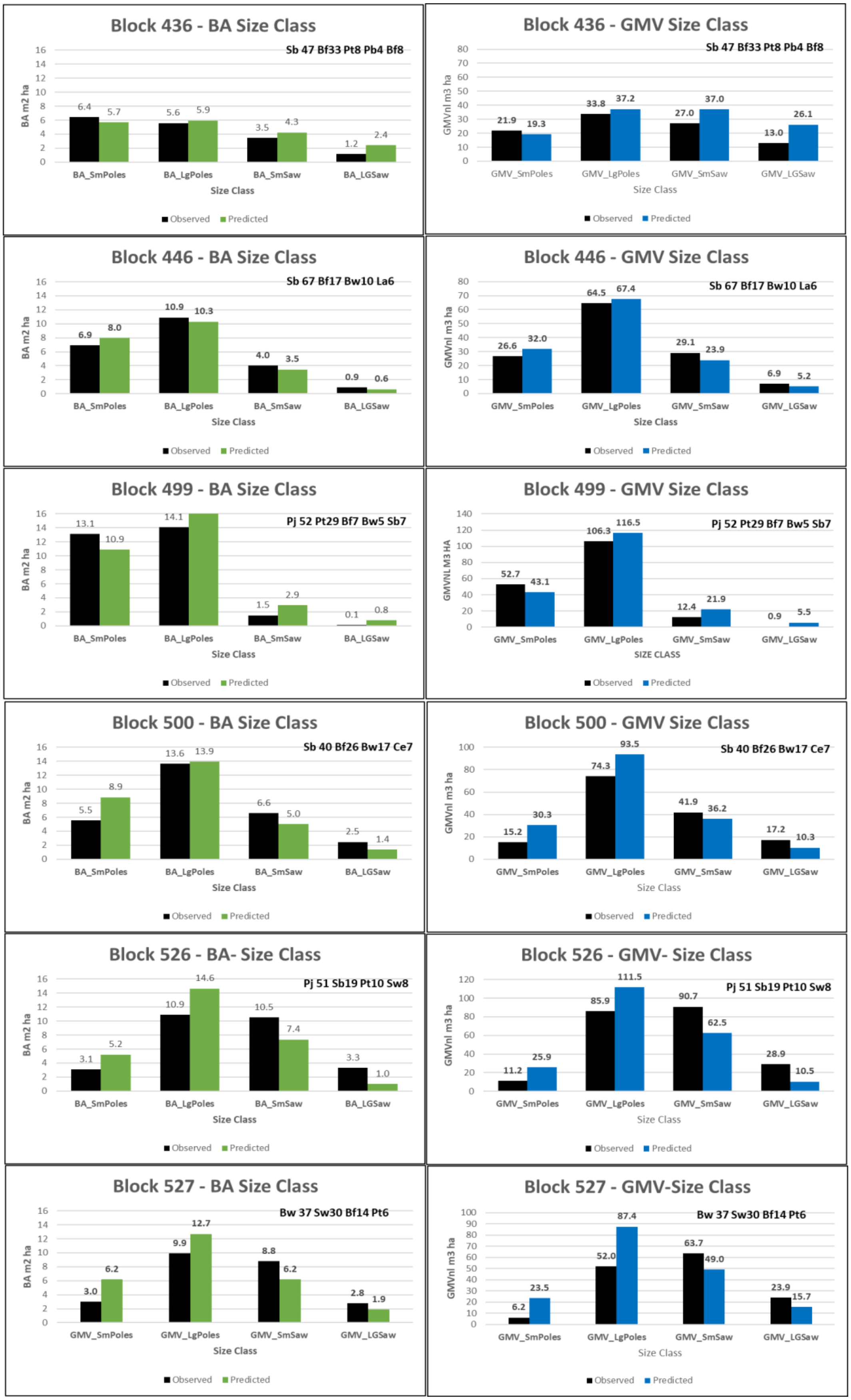


Figure 9 - Observed and predicted basal area and gross merchantable volume by size class.

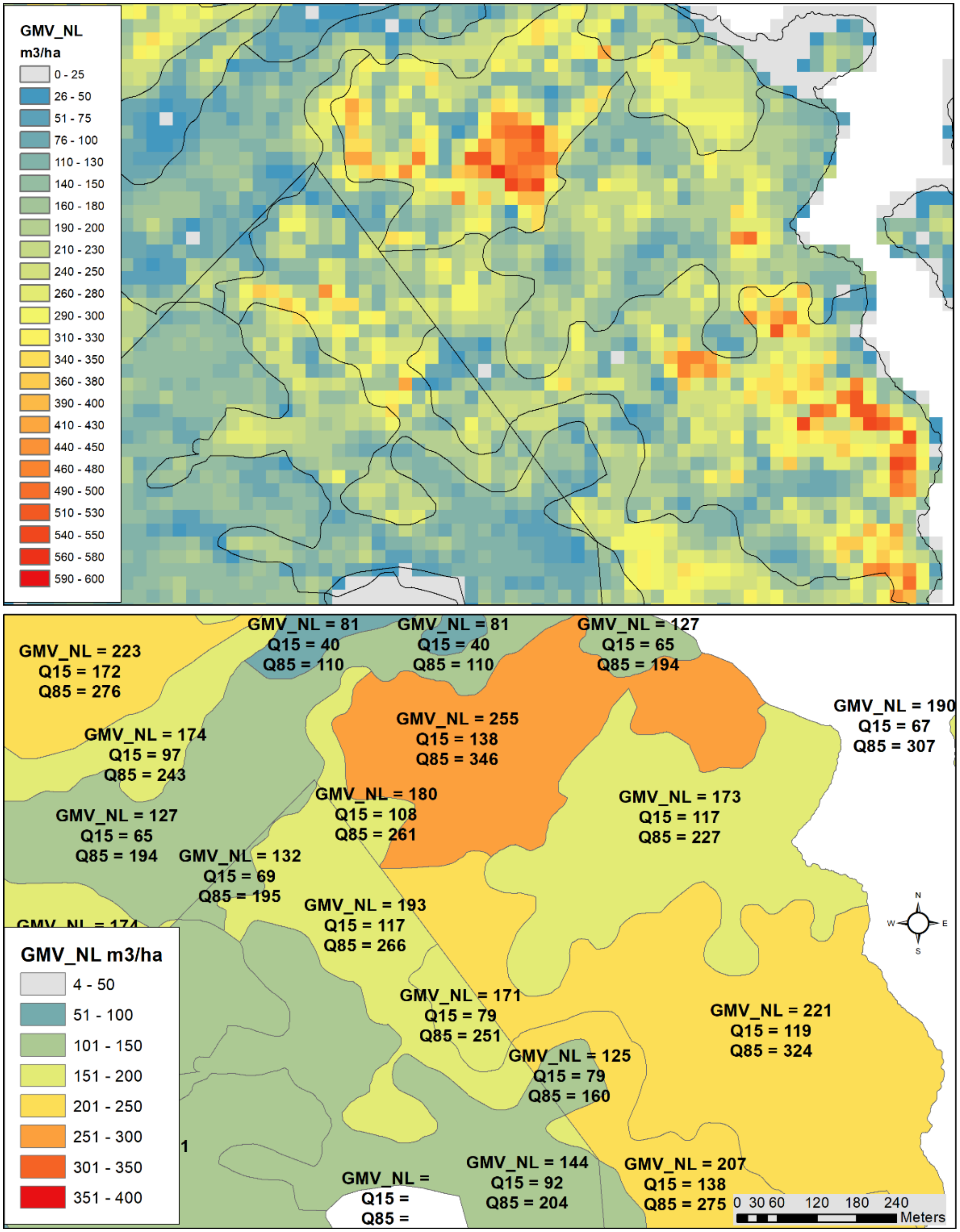


Figure 10 - Example of a GMV_NL raster prediction and mean T2 Polygon summary. Mean GMV_NL is labeled in each polygon along with the 15th and 85th quantile value.

Green First requested SFL volumes were adjusted for combinations of T1 polygon Spruce-Pine-Fir (SPF) or Poplar-White Birch stand content based on T1 species information (**Error! Reference source not found.**). Refer to Appendix B for all specific log size specifications.

Table 12 - RMF specific volumes adjustments by T1 polygon species composition

Volume	Stump height	Species	Multiply by
GMV_NL	30 cm	All	
GMV_WL	30 cm	All	
GMV_GF	30 cm	Applied to SPF	SPF_pct/100
GMV_Eacom_Timmins 8'	30 cm	Applied to SPF	SPF_pct/100
GMV_Eac16	30 cm	Applied to SPF	SPF_pct/100
GMV_GP	30 cm	Applied to Po/Bw	PoBw_pct/100
GMV_Rock	30 cm	Applied to Po/Bw	PoBw_pct/100

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 13 for a list of attributes and their source.

Table 13 - Additional T2 calculated inventory attributes and their source.

Attribute	LiDAR Derived	Calculated	T1 Polygon Information	Literature Source
Site Index	CDHt		Age, Leading Species	Various (refer to Appendix E)
Stocking	Basal Area	Site Index	Age, Leading Species	Plonski 1974
Cull Fraction	GMV		Age, Species Composition	Basham 1991
Net Merchantable Volume	Basal Area , GMV_NL	Cull Fraction Species VBAR[8]	Age, species composition	

[8] Species vbar are calculated from a combination of calibration plots for the SFL and provincial monitoring plots

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 11). 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 RMF Forest.

Based on Figure 11, the SI for ages < 20 was set to missing and the SI for ages >= 20 was capped at 35m. Figure 11 identifies issues with the available set of SI curves. The trend of SI with age is likely partly an artefact of the SI curves and partly an issue of the ages for older polygons not corresponding to the height. For older stands, the age is likely the age since disturbance and the heights are likely from younger trees.

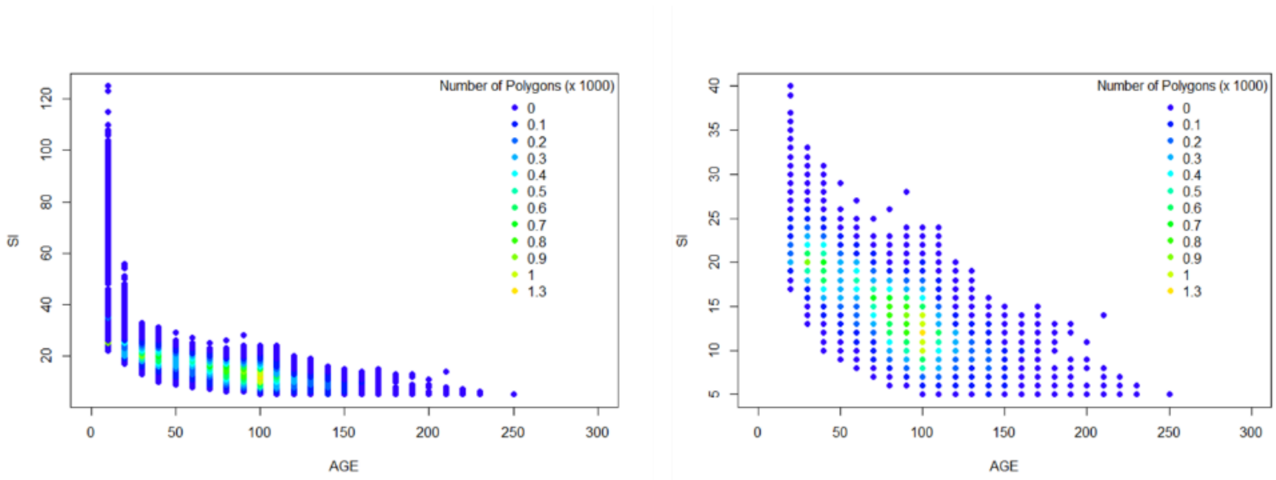


Figure 11 - Site index is plotted against age for ages 10+ and for ages 20+ for the RMF. Note the minimum SI is set to 5m

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 12 provides a graphic of the number of DRM polygons by Stocking and age. Note that stands less than 20 years old are not presented.

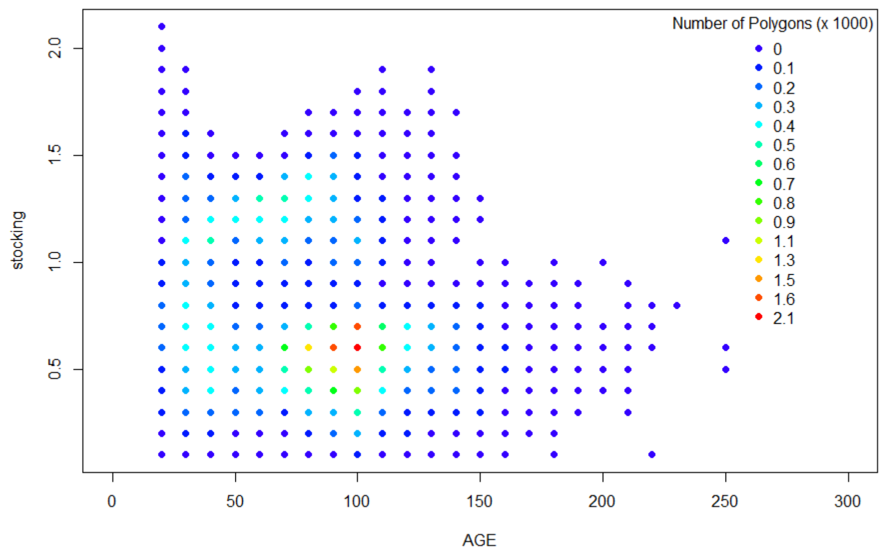


Figure 12 - Calculated Plonski stocking by polygon for the RMF. Note: no stocking estimates for stands < 20 years old.

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)) was fit, by species, using published data (see Table 14). 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, $\widehat{cull}$ 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)) by species using the provincial PSP/PGP database (gyPSPPGP_2021_10_04.bak).

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

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.

$$(3) \qquad mvol\ frac_i = \frac{species\ fraction_i \cdot vbar_i}{\sum species\ fraction_i \cdot vbar_i}$$

Table 14 - The sources for the cull estimates are given. The table references are from Basham (1991) except for red pine.

Species	Table	Comment
Hemlock	Table 7	
Sugar Maple	Table 13	
Yellow birch	Table 12	
Red pine		Source unknown. Basham (1991) reports an average of 1% for the 141-160 age class.
White pine	Table 1	
Cedar	Table 8	
White birch	Table 11	
Trembling aspen	Table 9	
Ironwood	Table 20	
Basswood	Table 16	
Balsam fir	Table 6	
White elm	Table 19	
Red oak	Table 18	
Black ash	Table 17	
Beech	Table 15	
Red maple	Table 14	
White spruce	Table 5	Note that the data for age 170 was taken from Table 6 of OMNR (1978)
Jack pine	Table 2	
Black spruce	Table 4	Note that data from ages 200+ were not used

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

$$(4) \qquad cull = \sum mvol\ frac_i \cdot spp\ cull\ est_i$$

Sample calculations are given in Table 15. An example of vbar estimates by age and species is presented in Figure 13.

Table 15 - 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.

	Spp	Vbar coefficient					Cull coefficient			Mvol	weighted
Spp	frac	V0	V1	V2	V3	Vbar	D0	D1	cull	frac	cull
Pj	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

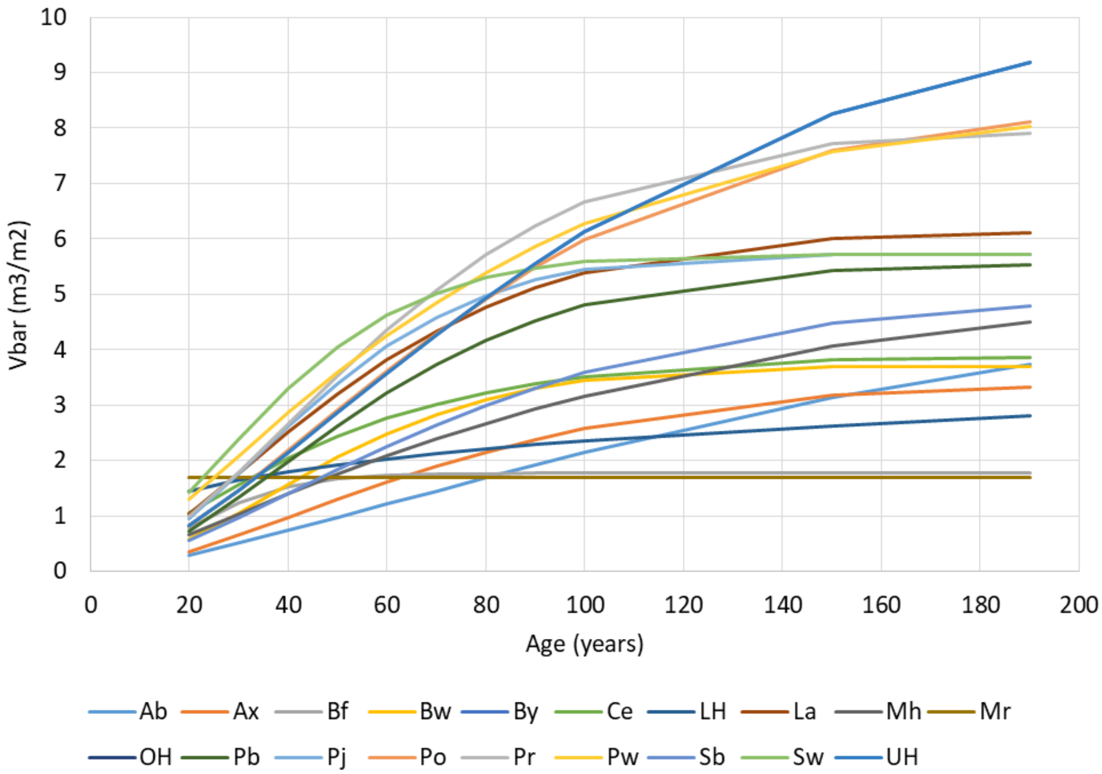


Figure 13 - The vbar estimates are given by age and species, for SI = 20

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.

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

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.** In addition, different polygon CDHT thresholds were used to constrain provided inventory attributes (Table 16). Crown Closure (CC2m) was retained all stands.

Discussion

Plot Level Model Validation (OOB and CV)

Overall, the RMF pixel level predictions are similar whether using the OOB or CV validation methods and the results are similar to those reported in other studies in Ontario.

Table 16 - T2 polygon inventory attributes and instituted constraints for all stands with age ≥ 20 years

Inventory Attribute	Polygon CDHT <5m	Polygon 5m > CDHT <9m	Polygon CDHT >9m
CC2m			
TOPHT	NULL		
CDHT			
LoreyHT	NULL		
BA	NULL		
Stems	NULL		
QMD	NULL		
GTV	NULL	NULL	
GMV_NL	NULL	NULL	
GMV_WL	NULL	NULL	
NMV_NL	NULL	NULL	
NMV_WL	NULL	NULL	
Biomass	NULL	NULL	
BA_SmPoles	NULL	NULL	
BA_LgPoles	NULL	NULL	
BA_SmSaw	NULL	NULL	
BA_LgSaw	NULL	NULL	
GMV_SmPoles	NULL	NULL	
GMV_LgPoles	NULL	NULL	
GMV_SmSaw	NULL	NULL	
GMV_LgSaw	NULL	NULL	
Site Index[9]	NULL		
Stocking	NULL		
Cull Fraction	NULL	NULL	

Woods et al. 2011, on an earlier project with more traditional NIR LiDAR on the Romeo Malette Forest reported GTV RMSEs ranging from 17–24% for a range of forest types. This study reports an OOB RMSE of 20.1% and a CV RMSE of 20.4%. Similarly, GMV RMSE was reported in Woods et al. 2011 to range from 19–24% by forest conditions. This study reported 23% for all forest types with an expanded list of forest types sampled in this study. Woods et al (2011) reported a range of basal area RMSEs from 16 – 19% by forest type and this study found 18.6% (OOB) and 18.7% (CV) for all forest types. In work conducted on the Hearst Forest using Seemingly Unrelated Regression (Penner et al. 203), RMSEs for basal area were reported at 27.6% for all forest types.

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.

[9] Maximum capped at SI 35

Although a validation sample of 6 harvest blocks/stands is small, they give a sense of the expected model performance at that scale. Overall, RMSEs for the stand level predictions were less than reported through the OOB or CV plot level testing (Figure 14) for most inventory attributes. In many cases the difference was near or greater than 50% (CDHT, BA, GTV, Biomass).

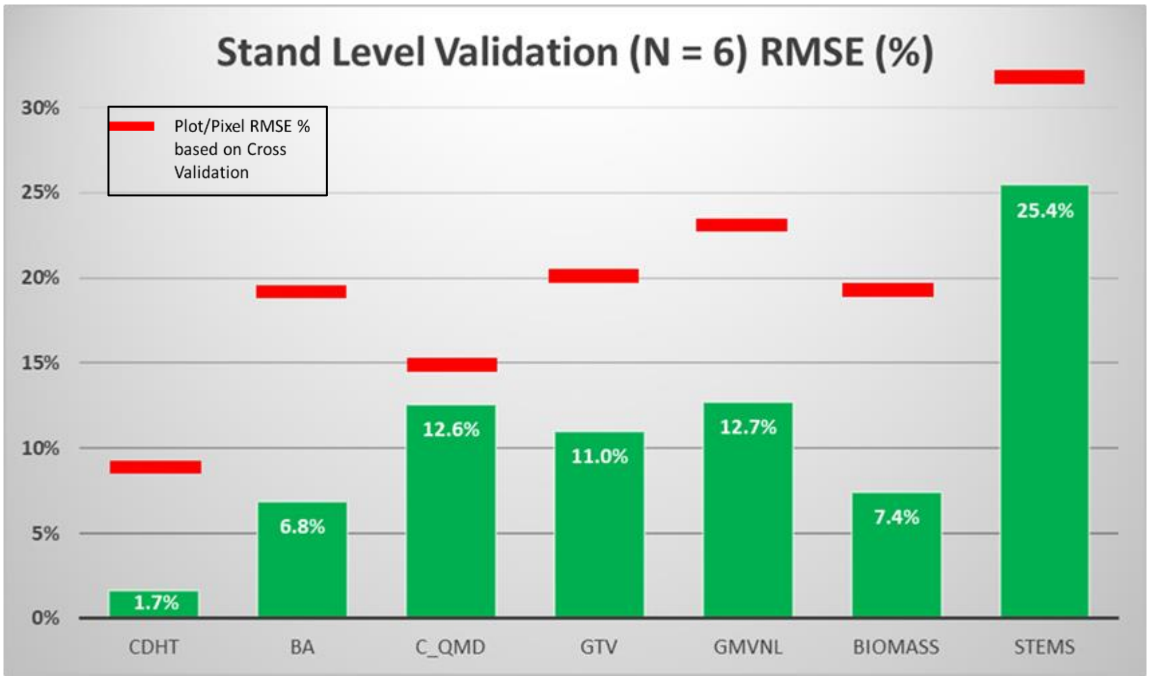


Figure 14 - Comparison of Stand/Block level validation RMSE with Cross Validation at the plot/pixel scale.

Note the 6 validation stands sampled would be generally described as having “mixed- species” composition. Each stand has a mix of conifer and hardwood species. In addition, these stands do not exhibit simple single-tier structure conditions; often used to characterize these natural fire-origin derived stands. Even with the range of species (Table 10)and structure (Figure 15), the inventory models performed well.

Vertical structure can make it much more of a challenge to predict size class attributes from LiDAR point clouds. Block 446 is the closest stand condition example of a purer species composition (Table 10) and single tier structure (Figure 15). Not surprisingly, it also resulted in a very acceptable modeling result of BA and GMV by size class (Figure 9). Block 436 contained portions of the stand that could be considered two-tiered and as a result the predicted BA/GMV by size class predictions were poorer for the larger Sawlog size classs. The LiDAR derived model predicts more BA or GMV in the large size classes than was observed during cruising. It should be noted that the crusing sample portions of the stand while the LiDAR measrued 100% of the area wtihn the polygon. In some cases the LiDAR estimates may be closer to reality than the cruise summary.

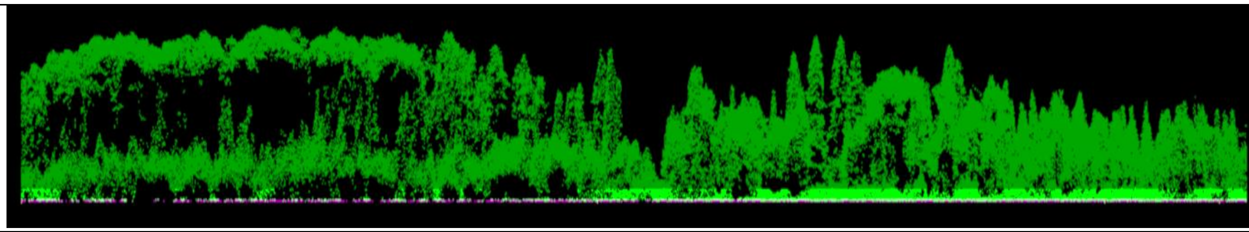
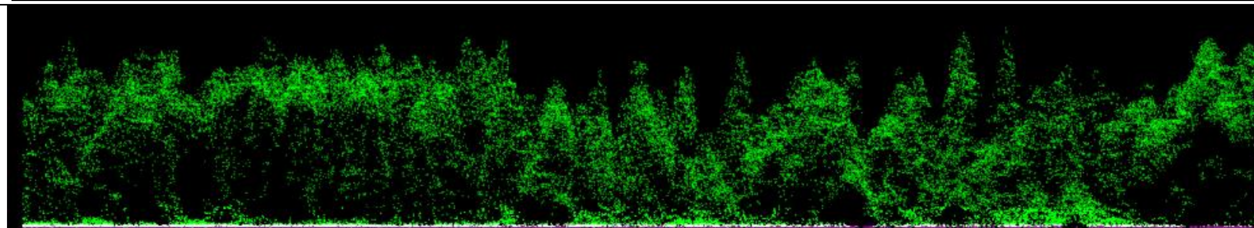
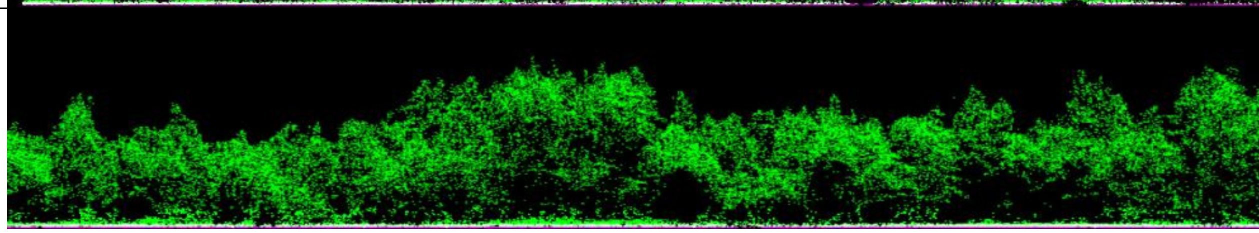
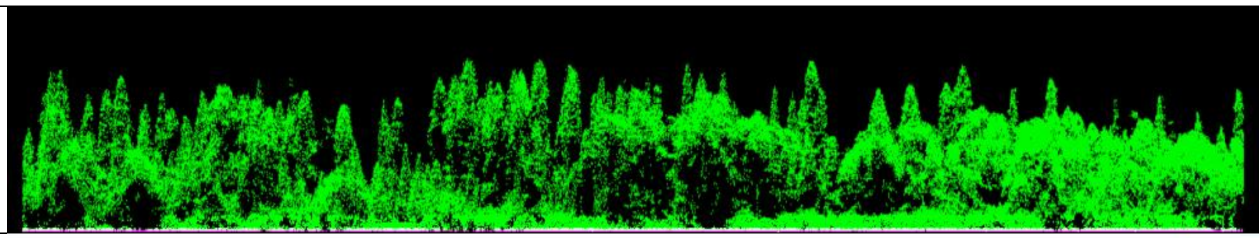
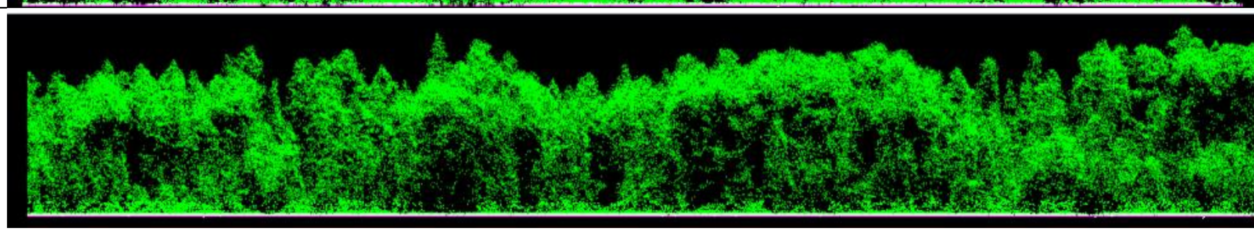
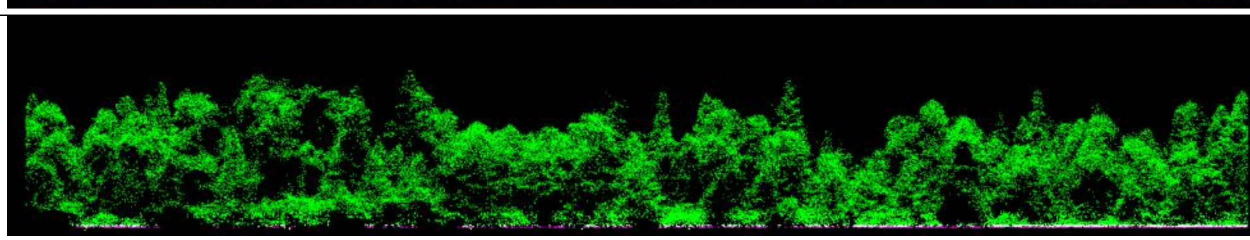
Block	LiDAR Profile
436	
446	
499	
500	
526	
527	

Figure 15 -Profile sample of the 6 validation blocks/stands.

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

Many tools available to conduct raster summation with a polygon work via selecting raster pixels to include based on their centroid occurring within the polygon. This can result in many edge raster pixels being excluded due to factors such as: irregular shaped polygon boundaries, bordering linear features such as roads/rivers, water bodies (Figure 16). In addition, where polygons bisect raster pixels, only one polygon is assigned the value of the raster pixel (Figure 17). The issue is particularly problematic for small polygons (< 1 ha). In the RMF PCI, there were approximately 5,500 polygons with area < 0.5 ha, accounting for about 1,400 ha (out of a forested area of approximately 550,000 ha with approximately 65,000 polygons). There were about 1,400 polygons with area < 0.1 ha (covering a total of 44 ha).

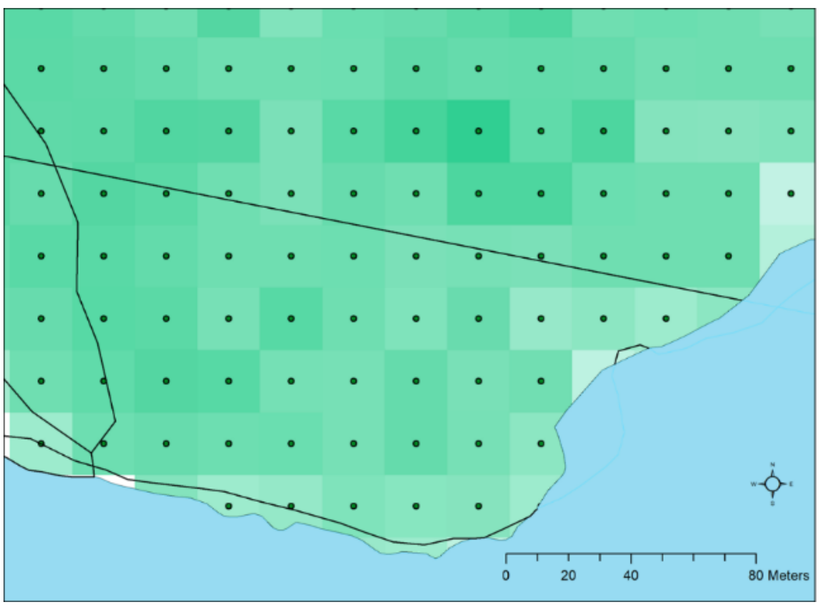


Figure 16 - Example of centroid selection or raster cells excluding raster values for narrow polygons along waterbodies.

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.

Figure 17 - Example of a raster pixel being bisected into 4 by polygon boundaries with only one polygon including the centroid value.

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.

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Appendix A - Lidar predictors for RMF 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 indicated.

Attribute	Threshold	Description	Model Predictor
zmax	>0m	max height of z	
zmean	>0m	mean height of z	
zsd	>0m	standard deviation of z	
zskew	>0m	skewness of z	
zkurt	>0m	kurtosis of z	
zentropy	>0m	entropy of height distribution (z)	
pzabovezmean	>0m	percentage of returns above zmean	
pzabove0	>0m	percentage of returns above threshold	
zq5	>0m	height of the 5th percentile of z	
zq10	>0m	height of the 10th percentile of z	
zq15	>0m	height of the 15th percentile of z	
zq20	>0m	height of the 20th percentile of z	
zq25	>0m	height of the 25th percentile of z	
zq30	>0m	height of the 30th percentile of z	
zq35	>0m	height of the 35th percentile of z	
zq40	>0m	height of the 40th percentile of z	
zq45	>0m	height of the 45th percentile of z	
zq50	>0m	height of the 50th percentile of z	
zq55	>0m	height of the 55th percentile of z	
zq60	>0m	height of the 60th percentile of z	
zq65	>0m	height of the 65th percentile of z	
zq70	>0m	height of the 70th percentile of z	
zq75	>0m	height of the 75th percentile of z	
zq80	>0m	height of the 80th percentile of z	
zq85	>0m	height of the 85th percentile of z	
zq90	>0m	height of the 90th percentile of z	
zq95	>0m	height of the9 5th percentile of z	
zq99	>0m	height of the 99th percentile of z	
zpcum1	>0m	percent of z returns below the 1st decile	
zpcum2	>0m	percent of z returns below the 2nd decile	
zpcum3	>0m	percent of z returns below the 3rd decile	
zpcum4	>0m	percent of z returns below the 4th decile	
zpcum5	>0m	percent of z returns below the 5th decile	
zpcum6	>0m	percent of z returns below the 6th decile	
zpcum7	>0m	percent of z returns below the 7th decile	
zpcum8	>0m	percent of z returns below the 8th decile	
zpcum9	>0m	percent of z returns below the 9th decile	
zsd95	>0m	standard deviation of z trimmed to 95%	
zskew95	>0m	skewness of z trimmed to 95%	
zkurt95	>0m	kurtosis of z trimmed to 95%	
zmin	>0m	minimum height of z returns	
allpts	>=0m	count of all points > Threshold (2,3,4,5)	
allptsAT	>0m	count of all points (2,3,4,5)	
vegcnt	>=0m	count of vegetation points (3,4,5)	
firstveg	>=0m	count of first return points of vegetation (3,4,5)	
firstcnt	>=0m	count of first returns	
firstonlycnt	>=0m	count of first and ONLY return points of vegetation (3,4,5)	
groundcnt	>=0m	count of f=ground returns (2)	
vegratio	>=0m	vegetation ratio (vegetation points (vegcnt) / all points (allpts))	
da	>=0m	percentage of First Returns / all returns (firstcnt / allpts) *100	
db	>=0m	percentage of "First & Only" Returns / all returns (firstonlycnt	
dv	>=0m	percentage of "Vegetation & Only" Returns / all returns	
vdr	>0m	Vertical Distribution Ratio (max-median)/max	
cv	>0m	coefficient of variation of z returns	
vci_1m	>0m	vegetation complexity index - 1m bins (Van Ewijk 2011)	

cov_2m	NA	canopy cover % above 2m (number of first returns above 2m / number of first returns) * 100	
cov_4m	NA	canopy cover % above 4m (number of first returns above 4m / number of first returns) * 100	
cov_6m	NA	canopy cover % above 6m (number of first returns above 6m / number of first returns) * 100	
cov_8m	NA	canopy cover % above 8m (number of first returns above 8m / number of first returns) * 100	
cov_10m	NA	canopy cover % above 10m (number of first returns above 10m / number of first returns) * 100	
cov_12m	NA	canopy cover % above 12m (number of first returns above 12m / number of first returns) * 100	
cov_14m	NA	canopy cover % above 14m (number of first returns above 14m / number of first returns) * 100	
cov_16m	NA	canopy cover % above 16m (number of first returns above 16m / number of first returns) * 100	
cov_18m	NA	canopy cover % above 18m (number of first returns above 18m / number of first returns) * 100	
cov_20m	NA	canopy cover % above 20m (number of first returns above 20m / number of first returns) * 100	
cov_22m	NA	canopy cover % above 22m (number of first returns above 22m / number of first returns) * 100	
cov_24m	NA	canopy cover % above 24m (number of first returns above 24m / number of first returns) * 100	
cov_26m	NA	canopy cover % above 26m (number of first returns above 26m / number of first returns) * 100	
cov_28m	NA	canopy cover % above 28m (number of first returns above 28m / number of first returns) * 100	
cov_30m	NA	canopy cover % above 30m (number of first returns above 30m / number of first returns) * 100	
dns_2m	NA	canopy cover % above 2m (number of all returns above 2m / number of all returns) * 100	
dns_4m	NA	canopy cover % above 4m (number of all returns above 4m / number of all returns) * 100	
dns_6m	NA	canopy cover % above 6m (number of all returns above 6m / number of all returns) * 100	
dns_8m	NA	canopy cover % above 8m (number of all returns above 8m / number of all returns) * 100	
dns_10m	NA	canopy cover % above 10m (number of all returns above 10m / number of all returns) * 100	
dns_12m	NA	canopy cover % above 12m (number of all returns above 12m / number of all returns) * 100	
dns_14m	NA	canopy cover % above 14m (number of all returns above 14m / number of all returns) * 100	
dns_16m	NA	canopy cover % above 16m (number of all returns above 16m / number of all returns) * 100	
dns_18m	NA	canopy cover % above 18m (number of all returns above 18m / number of all returns) * 100	
dns_20m	NA	canopy cover % above 20m (number of all returns above 18m / number of all returns) * 100	
dns_22m	NA	canopy cover % above 22m (number of all returns above 18m / number of all returns) * 100	

dns_24m	NA	canopy cover % above 24m (number of all returns above 24m / number of all returns) * 100	
dns_26m	NA	canopy cover % above 26m (number of all returns above 26m / number of all returns) * 100	
dns_28m	NA	canopy cover % above 28m (number of all returns above 28m / number of all returns) * 100	
dns_30m	NA	canopy cover % above 30m (number of all returns above 30m / number of all returns) * 100	
vegden_0_2	>=0m	Percent vegetation returns between 0 and 2m	
vegden_2_4	>=0m	Percent vegetation returns between 2 and 4m	
vegden_4_6	>=0m	Percent vegetation returns between 4 and 6m	
vegden_6_8	>=0m	Percent vegetation returns between 6 and 8m	
vegden_8_10	>=0m	Percent vegetation returns between 10 and 10m	
vegden_10_12	>=0m	Percent vegetation returns between 10 and 12m	
vegden_12_14	>=0m	Percent vegetation returns between 12 and 14m	
vegden_14_16	>=0m	Percent vegetation returns between 14 and 16m	
vegden_16_18	>=0m	Percent vegetation returns between 16 and 18m	
vegden_18_20	>=0m	Percent vegetation returns between 18 and 20m	
vegden_20_22	>=0m	Percent vegetation returns between 20 and 22m	
vegden_22_24	>=0m	Percent vegetation returns between 22 and 24m	
vegden_24_26	>=0m	Percent vegetation returns between 24 and 26m	
vegden_26_28	>=0m	Percent vegetation returns between 26 and 28m	
vegden_28_30	>=0m	Percent vegetation returns between 28 and 30m	
L1	NA	L1 moment of vegetation points (3,4,5)	
L2	NA	L2 moment of vegetation points (3,4,5)	
L3	NA	L3 moment of vegetation points (3,4,5)	
L4	NA	L4 moment of vegetation points (3,4,5)	
Lskew	NA	L Skewness of vegetation points (3,4,5)	
Lkurt	NA	L Kurtosis of vegetation points (3,4,5)	
Lcoefvar	NA	L Coeficient of Variation of vegetation points (3,4,5)	
ngrcnt	-0.15	count of all points (2,3,4,5) between -0.15 and 0.15 for LPI	
allptscnt_ngr	-0.15	Count of all points (2,3,4,5) between -0.15 and 48m for LPI	
lpi	-0.15	Lidar penetration index - count of returns between (-0.15 - 0.15)/all points (-.15 to 30m) * 100 [Uses Class 2,3,4,5]	
ri_pts	NA	rumple index GMV_NLsed on Lidar points - 1m DSM	

Appendix B – Requested Green First Forest Products volume specifications

Species Percentage Calculation for Requested RMF Volume Rasters

SPF is the percent of basal area in black spruce, white spruce, red spruce, jack pine and balsam fir. PoBw is the percent of basal area in white birch and any poplar (tree_spec = 70 – 75). If SPF + PoBw > 100 (due to round), PoBw was set to 100 - SPF

Only GMV_NL and GMV_WL are delivered as a raster product. The other volumes are provided as a polygon product as they require T1 species composition information to calculate the appropriate volume.

Volume	Stump height	Minimum top diameter (inside bark)	Minimum length	Maximum length	Species
GMV_NL	30 cm	Table 4	None	None	All
GMV_WL	30 cm	Table 4	8’ 4” (2.54 m)	8’ 4”	All
GMV_GF	30 cm	9.1 cm	10‘ 4”	52’	Applied to SPF
GMV_Eacom_Timmins 8’ [10]	30 cm	Applied to SPF	8’ 4” (2.54 m)	8’ 4”	Applied to SPF
GMV_Eacom_Timmins 16’	30 cm	16.1 cm	16’ 6”	16’ 6”	Applied to SPF
GMV_Georgia_Pacific	30 cm	12.1 cm	8’ 4”	14‘ 6”	Applied to Po/Bw
GMV_Rockshield	30 cm	21.1 cm	8’ 10”	8’ 10”	Applied to Po/Bw

[10] GMV_Eacom_Timmins 8’ = GMV_WL raster values X SPF percentage

Appendix C – Plot level validation statistics by OOB and CV methods

Out of Bag (OOB) Plot level model statistics by Forest Unit

Top Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	19.6	10.6	26.2	19.6	1.3	1.7	8.7	0.0	0.0
LC1	33	17.4	8.8	24.0	17.1	0.6	1.0	5.7	0.3	1.7
MC2	7	24.5	15.2	29.8	23.9	1.9	1.9	7.8	0.6	2.4
MH1	11	18.4	6.2	22.6	19.4	1.3	2.1	11.4	-0.9	-4.9
MH2	23	25.9	18.0	35.6	26.1	0.8	1.9	7.3	-0.1	-0.4
PJ1	32	19.0	9.9	28.4	18.6	0.8	1.2	6.3	0.4	2.1
PJ2	12	21.0	14.3	26.8	20.9	1.1	1.2	5.7	0.2	1.0
PO1	85	27.7	8.4	38.5	27.8	0.5	1.6	5.8	0.0	0.0
PW1	1	30.5	30.5	30.5	31.8		1.3	4.3	-1.3	-4.3
SB1	8	14.7	8.2	20.1	14.4	1.3	0.6	4.1	0.2	1.4
SF1	12	15.5	7.8	25.1	16.5	1.4	2.4	15.5	-1.0	-6.5
SP1	5	19.6	11.6	27.7	19.6	2.8	2.3	11.7	0.0	0.0

CDHT Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	18.3	9.9	23.1	18.0	1.2	1.3	7.1	0.3	1.6
LC1	33	15.0	7.9	22.2	14.9	0.6	1.4	9.3	0.1	0.7
MC2	7	21.0	8.9	25.3	21.1	1.9	2.1	10.0	-0.1	-0.5
MH1	11	16.8	6.0	21.1	17.6	1.2	1.3	7.7	-0.8	-4.8
MH2	23	23.5	15.7	35.5	23.7	0.8	1.9	8.1	-0.2	-0.9
PJ1	32	17.6	9.3	26.0	17.1	0.8	1.2	6.8	0.5	2.8
PJ2	12	19.5	13.5	25.2	19.0	1.1	1.7	8.7	0.4	2.1
PO1	85	26.2	8.2	36.0	26.3	0.5	1.8	6.9	-0.1	-0.4
PW1	1	26.8	26.8	26.8	29.6		2.8	10.4	-2.8	-10.4
SB1	8	12.8	7.6	17.1	13.0	1.3	0.8	6.2	-0.2	-1.6
SF1	12	13.4	6.9	21.5	14.3	1.2	1.9	14.2	-0.9	-6.7
SP1	5	17.4	9.1	25.8	17.1	2.4	2.6	14.9	0.2	1.1

Lorey's Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	17.9	10.3	22.3	17.4	1.2	1.1	6.1	0.5	2.8
LC1	33	14.8	8.1	21.6	14.6	0.6	1.0	6.8	0.2	1.4
MC2	7	20.2	10.2	24.0	20.4	1.7	1.2	5.9	-0.2	-1.0
MH1	11	16.0	6.0	19.8	16.9	1.0	1.3	8.1	-0.9	-5.6
MH2	23	22.1	16.0	29.6	22.5	0.7	1.5	6.8	-0.3	-1.4
PJ1	32	17.0	9.4	23.2	16.6	0.7	1.2	7.1	0.4	2.4
PJ2	12	17.9	12.8	22.3	18.3	1.0	1.2	6.7	-0.5	-2.8
PO1	85	24.6	8.2	33.6	24.5	0.4	1.4	5.7	0.1	0.4
PW1	1	30.6	30.6	30.6	27.6		3.0	9.8	3.0	9.8
SB1	8	12.5	7.7	17.1	12.7	1.2	0.4	3.2	-0.2	-1.6
SF1	12	13.2	7.2	21.7	13.9	1.1	1.7	12.9	-0.8	-6.1
SP1	5	17.5	10.7	25.5	16.8	2.5	2.1	12.0	0.7	4.0

BasalArea		Observed			Prediction					
$m^2 ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	24.1	2.6	41.6	30.3	3.3	8.5	35.3	-6.2	-25.7
LC1	33	24.9	2.5	56.3	23.4	1.6	5.4	21.7	1.5	6.0
MC2	7	32.1	11.3	42.9	32.0	3.0	5.2	16.2	0.1	0.3
MH1	11	30.2	2.9	43.6	32.8	3.0	5.3	17.5	-2.6	-8.6
MH2	23	41.3	27.1	59.2	40.4	1.6	6.8	16.5	0.9	2.2
PJ1	32	27.1	0.6	43.4	26.2	1.5	5.0	18.5	0.8	3.0
PJ2	12	31.8	14.9	42.3	29.1	1.4	4.9	15.4	2.7	8.5
PO1	85	42.3	9.3	86.3	42.1	1.5	7.0	16.5	0.1	0.2
PW1	1	26.7	26.7	26.7	31.9		5.2	19.5	-5.2	-19.5
SB1	8	20.9	3.1	37.0	20.2	3.7	3.5	16.7	0.7	3.3
SF1	12	21.2	2.0	37.9	22.4	3.6	3.2	15.1	-1.3	-6.1
SP1	5	23.7	3.4	36.1	27.1	4.5	5.1	21.5	-3.4	-14.3

GTV		Observed			Prediction					
$m^3 ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	198.1	11.9	400.7	242.4	34.5	54.7	27.6	-44.2	-22.3
LC1	33	169.1	22.6	343.5	160.5	14.1	30.2	17.9	8.6	5.1
MC2	7	294.6	51.6	455.2	299.8	39.8	65.0	22.1	-5.2	-1.8
MH1	11	216.3	8.1	329.1	254.9	26.7	54.5	25.2	-38.5	-17.8
MH2	23	406.3	213.2	722.6	405.0	26.3	79.0	19.4	1.3	0.3
PJ1	32	222.8	3.5	452.6	206.4	14.7	47.9	21.5	16.4	7.4
PJ2	12	250.4	125.9	352.0	233.4	13.3	40.5	16.2	16.9	6.7
PO1	85	487.8	28.5	1044.8	480.2	21.9	84.6	17.3	7.6	1.6
PW1	1	313.3	313.3	313.3	397.7		84.4	26.9	-84.4	-26.9
SB1	8	131.0	12.6	221.0	129.3	29.2	19.5	14.9	1.7	1.3
SF1	12	139.7	7.0	298.2	154.0	31.2	23.4	16.8	-14.4	-10.3
SP1	5	192.7	16.8	335.9	216.8	56.7	32.4	16.8	-24.1	-12.5

GMV NL		Observed			Prediction					
$m^3 ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	12	159.9	6.4	361.7	182.1	30.6	39.0	24.4	-22.2	-13.9
LC1	31	144.0	20.8	295.6	131.6	12.2	31.4	21.8	12.3	8.5
MC2	7	264.0	21.6	420.0	262.9	38.8	60.8	23.0	1.0	0.4
MH1	10	165.7	84.6	269.5	201.7	20.1	53.3	32.2	-36.0	-21.7
MH2	23	357.6	141.2	678.3	354.1	28.1	79.3	22.2	3.4	1.0
PJ1	28	210.1	64.6	408.1	187.8	11.3	47.3	22.5	22.3	10.6
PJ2	12	205.9	111.9	310.2	191.4	16.4	36.6	17.8	14.5	7.0
PO1	84	442.8	48.3	992.3	439.4	21.2	86.7	19.6	3.4	0.8
PW1	1	290.6	290.6	290.6	377.1		86.5	29.8	-86.5	-29.8
SB1	7	108.2	5.4	179.4	109.9	27.1	12.1	11.2	-1.7	-1.6
SF1	12	108.1	2.7	261.3	119.0	27.9	21.2	19.6	-10.9	-10.1
SP1	5	160.7	10.5	295.5	177.4	57.8	26.7	16.6	-16.7	-10.4

GMV WL		Observed			Prediction					
$m^3 ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	12	149.8	5.0	349.2	170.9	29.8	36.6	24.4	-21.2	-14.2
LC1	31	134.8	20.4	284.5	122.2	11.7	30.2	22.4	12.6	9.3
MC2	7	255.3	15.9	410.2	252.0	38.0	60.0	23.5	3.3	1.3
MH1	10	151.0	64.9	252.9	187.0	21.0	52.7	34.9	-36.1	-23.9
MH2	23	346.0	126.8	663.5	341.9	28.2	78.1	22.6	4.1	1.2
PJ1	28	198.3	62.6	395.8	175.3	11.3	46.7	23.6	23.0	11.6
PJ2	12	194.7	107.5	302.2	181.3	17.1	34.6	17.8	13.5	6.9
PO1	84	430.1	37.9	980.8	427.1	21.1	85.6	19.9	3.0	0.7
PW1	1	287.9	287.9	287.9	369.7		81.8	28.4	-81.8	-28.4
SB1	7	97.2	4.4	167.6	101.0	25.6	11.0	11.3	-3.8	-3.9
SF1	12	101.0	2.0	254.4	111.1	27.0	19.5	19.3	-10.1	-10.0
SP1	5	153.5	9.7	285.8	169.3	57.1	25.8	16.8	-15.7	-10.2

QMD		Observed			Prediction					
cm	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	18.4	8.6	25.4	16.9	1.1	3.4	18.5	1.5	8.2
LC1	33	15.7	10.0	20.6	15.2	0.5	1.8	11.5	0.4	2.5
MC2	7	21.3	10.5	27.0	20.7	1.6	2.0	9.4	0.6	2.8
MH1	11	16.8	11.6	21.5	16.5	1.0	0.9	5.4	0.3	1.8
MH2	23	23.0	15.0	41.3	22.4	0.7	4.7	20.4	0.7	3.0
PJ1	32	16.2	9.8	22.7	16.4	0.7	2.6	16.0	-0.3	-1.9
PJ2	12	17.2	13.1	21.5	18.8	1.2	2.5	14.5	-1.6	-9.3
PO1	85	24.0	8.2	38.2	24.3	0.4	3.1	12.9	-0.3	-1.2
PW1	1	29.2	29.2	29.2	29.6		0.5	1.7	-0.5	-1.7
SB1	8	13.2	8.4	17.2	13.8	1.0	1.4	10.6	-0.6	-4.5
SF1	12	14.2	9.5	21.3	15.5	1.2	3.9	27.5	-1.3	-9.2
SP1	5	18.3	11.2	25.6	17.7	2.5	2.7	14.8	0.7	3.8

Biomass		Observed			Prediction					
$T ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	129.3	8.9	244.8	142.0	18.6	27.8	21.5	-12.7	-9.8
LC1	33	99.2	12.1	182.3	95.4	7.6	15.6	15.7	3.8	3.8
MC2	7	160.5	36.9	240.6	161.9	19.4	32.4	20.2	-1.4	-0.9
MH1	11	138.8	12.7	200.9	149.5	14.6	21.2	15.3	-10.7	-7.7
MH2	23	219.9	137.6	362.0	213.9	12.7	39.5	18.0	6.0	2.7
PJ1	32	123.2	2.1	239.7	118.3	7.7	26.6	21.6	4.9	4.0
PJ2	12	139.3	69.6	190.7	129.3	6.8	22.3	16.0	10.0	7.2
PO1	85	252.8	22.0	534.0	252.7	10.7	45.1	17.8	0.1	0.0
PW1	1	167.3	167.3	167.3	199.8		32.5	19.4	-32.5	-19.4
SB1	8	80.9	10.2	138.5	79.6	16.1	13.8	17.1	1.3	1.6
SF1	12	82.3	5.2	164.1	90.4	16.7	13.8	16.8	-8.1	-9.8
SP1	5	110.6	11.6	182.0	120.2	30.3	18.9	17.1	-9.6	-8.7

Density		Observed			Prediction					
$Stems\ ha^{-1}$	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	1015	75	2575	1535	235	722.2	71.1	-519.2	-51.1
LC1	33	1377	75	2850	1345	94	365.0	26.5	31.6	2.3
MC2	7	954	450	1300	974	80	197.6	20.7	-20.2	-2.1
MH1	11	1543	250	3550	1612	240	428.8	27.8	-69.1	-4.5
MH2	23	1140	225	2225	1091	78	321.5	28.2	49.5	4.3
PJ1	32	1463	25	3025	1362	111	465.2	31.8	100.7	6.9
PJ2	12	1554	625	2875	1245	198	407.9	26.2	309.2	19.9
PO1	85	1041	200	2825	955	36	317.5	30.5	85.7	8.2
PW1	1	400	400	400	463		62.5	15.6	-62.5	-15.6
SB1	8	1594	400	3400	1290	204	617.0	38.7	304.0	19.1
SF1	12	1267	250	2575	1242	198	314.1	24.8	24.4	1.9
SP1	5	1105	325	3025	1263	353	438.8	39.7	-157.9	-14.3

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

Top Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	19.6	10.6	26.2	19.7	1.4	1.7	8.7	-0.1	-0.5
LC1	33	17.4	8.8	24.0	17.1	0.6	1.0	5.7	0.3	1.7
MC2	7	24.5	15.2	29.8	23.9	1.9	1.9	7.8	0.6	2.4
MH1	11	18.4	6.2	22.6	19.3	1.3	2.0	10.9	-0.9	-4.9
MH2	23	25.9	18.0	35.6	26.1	0.8	1.9	7.3	-0.2	-0.8
PJ1	32	19.0	9.9	28.4	18.6	0.8	1.2	6.3	0.4	2.1
PJ2	12	21.0	14.3	26.8	20.8	1.1	1.1	5.2	0.3	1.4
PO1	85	27.7	8.4	38.5	27.8	0.5	1.6	5.8	-0.1	-0.4
PW1	1	30.5	30.5	30.5	31.6		1.1	3.6	-1.1	-3.6
SB1	8	14.7	8.2	20.1	14.5	1.3	0.6	4.1	0.2	1.4
SF1	12	15.5	7.8	25.1	16.6	1.4	2.7	17.4	-1.1	-7.1
SP1	5	19.6	11.6	27.7	19.5	2.9	2.2	11.2	0.1	0.5

CDHT Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	18.3	9.9	23.1	18.1	1.3	1.3	7.1	0.3	1.6
LC1	33	15.0	7.9	22.2	14.9	0.6	1.4	9.3	0.1	0.7
MC2	7	21.0	8.9	25.3	21.2	1.9	2.1	10.0	-0.2	-1.0
MH1	11	16.8	6.0	21.1	17.6	1.2	1.4	8.3	-0.8	-4.8
MH2	23	23.5	15.7	35.5	23.6	0.8	1.8	7.7	-0.1	-0.4
PJ1	32	17.6	9.3	26.0	17.2	0.8	1.2	6.8	0.5	2.8
PJ2	12	19.5	13.5	25.2	19.0	1.1	1.7	8.7	0.5	2.6
PO1	85	26.2	8.2	36.0	26.3	0.5	1.9	7.3	-0.1	-0.4
PW1	1	26.8	26.8	26.8	29.3		2.5	9.3	-2.5	-9.3
SB1	8	12.8	7.6	17.1	13.1	1.3	0.6	4.7	-0.3	-2.3
SF1	12	13.4	6.9	21.5	14.3	1.2	2.0	14.9	-0.9	-6.7
SP1	5	17.4	9.1	25.8	17.1	2.4	2.6	14.9	0.2	1.1

Lorey's Ht		Observed			Prediction					
m	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	17.9	10.3	22.3	17.3	1.2	1.2	6.7	0.6	3.4
LC1	33	14.8	8.1	21.6	14.6	0.6	1.0	6.8	0.2	1.4
MC2	7	20.2	10.2	24.0	20.4	1.6	1.2	5.9	-0.2	-1.0
MH1	11	16.0	6.0	19.8	16.9	1.0	1.3	8.1	-0.9	-5.6
MH2	23	22.1	16.0	29.6	22.5	0.7	1.6	7.2	-0.3	-1.4
PJ1	32	17.0	9.4	23.2	16.6	0.7	1.1	6.5	0.4	2.4
PJ2	12	17.9	12.8	22.3	18.3	1.0	1.2	6.7	-0.4	-2.2
PO1	85	24.6	8.2	33.6	24.5	0.4	1.4	5.7	0.1	0.4
PW1	1	30.6	30.6	30.6	27.4		3.2	10.5	3.2	10.5
SB1	8	12.5	7.7	17.1	12.7	1.2	0.4	3.2	-0.2	-1.6
SF1	12	13.2	7.2	21.7	13.9	1.1	1.5	11.4	-0.7	-5.3
SP1	5	17.5	10.7	25.5	16.8	2.5	2.0	11.4	0.7	4.0

BasalArea		Observed			Prediction					
m^2 ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	24.1	2.6	41.6	30.3	3.4	8.4	34.9	-6.2	-25.7
LC1	33	24.9	2.5	56.3	23.6	1.6	5.5	22.1	1.3	5.2
MC2	7	32.1	11.3	42.9	32.3	3.0	5.4	16.8	-0.2	-0.6
MH1	11	30.2	2.9	43.6	32.7	2.9	5.4	17.9	-2.5	-8.3
MH2	23	41.3	27.1	59.2	40.2	1.6	6.9	16.7	1.1	2.7
PJ1	32	27.1	0.6	43.4	26.6	1.5	5.1	18.8	0.5	1.8
PJ2	12	31.8	14.9	42.3	29.1	1.4	5.1	16.0	2.7	8.5
PO1	85	42.3	9.3	86.3	42.2	1.5	7.1	16.8	0.1	0.2
PW1	1	26.7	26.7	26.7	31.4		4.7	17.6	-4.7	-17.6
SB1	8	20.9	3.1	37.0	20.4	3.6	3.7	17.7	0.5	2.4
SF1	12	21.2	2.0	37.9	22.6	3.6	3.3	15.6	-1.5	-7.1
SP1	5	23.7	3.4	36.1	27.3	4.5	5.3	22.4	-3.5	-14.8

GTV		Observed			Prediction					
m^3 ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	198.1	11.9	400.7	242.1	35.4	54.1	27.3	-44.0	-22.2
LC1	33	169.1	22.6	343.5	161.4	14.0	30.9	18.3	7.7	4.6
MC2	7	294.6	51.6	455.2	303.4	40.1	66.4	22.5	-8.8	-3.0
MH1	11	216.3	8.1	329.1	254.6	26.0	54.0	25.0	-38.2	-17.7
MH2	23	406.3	213.2	722.6	404.1	25.8	79.3	19.5	2.2	0.5
PJ1	32	222.8	3.5	452.6	208.2	14.4	48.2	21.6	14.6	6.6
PJ2	12	250.4	125.9	352.0	233.6	13.3	42.6	17.0	16.8	6.7
PO1	85	487.8	28.5	1044.8	480.6	22.0	86.9	17.8	7.2	1.5
PW1	1	313.3	313.3	313.3	390.6		77.2	24.6	-77.2	-24.6
SB1	8	131.0	12.6	221.0	129.7	28.4	20.5	15.6	1.3	1.0
SF1	12	139.7	7.0	298.2	155.2	30.8	24.9	17.8	-15.5	-11.1
SP1	5	192.7	16.8	335.9	217.8	56.0	32.6	16.9	-25.2	-13.1

GMV NL		Observed			Prediction					
m^3 ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	12	159.9	6.4	361.7	182.1	31.6	37.3	23.3	-22.2	-13.9
LC1	31	144.0	20.8	295.6	132.6	12.1	31.4	21.8	11.4	7.9
MC2	7	264.0	21.6	420.0	265.4	39.1	61.7	23.4	-1.4	-0.5
MH1	10	165.7	84.6	269.5	198.3	19.8	51.7	31.2	-32.6	-19.7
MH2	23	357.6	141.2	678.3	352.5	27.7	79.5	22.2	5.1	1.4
PJ1	28	210.1	64.6	408.1	188.9	11.0	48.0	22.8	21.2	10.1
PJ2	12	205.9	111.9	310.2	191.9	16.3	37.6	18.3	14.0	6.8
PO1	84	442.8	48.3	992.3	440.3	21.3	88.4	20.0	2.5	0.6
PW1	1	290.6	290.6	290.6	370.9		80.3	27.6	-80.3	-27.6
SB1	7	108.2	5.4	179.4	109.8	26.5	11.8	10.9	-1.6	-1.5
SF1	12	108.1	2.7	261.3	119.1	27.5	20.9	19.3	-11.0	-10.2
SP1	5	160.7	10.5	295.5	177.5	57.5	26.2	16.3	-16.8	-10.5

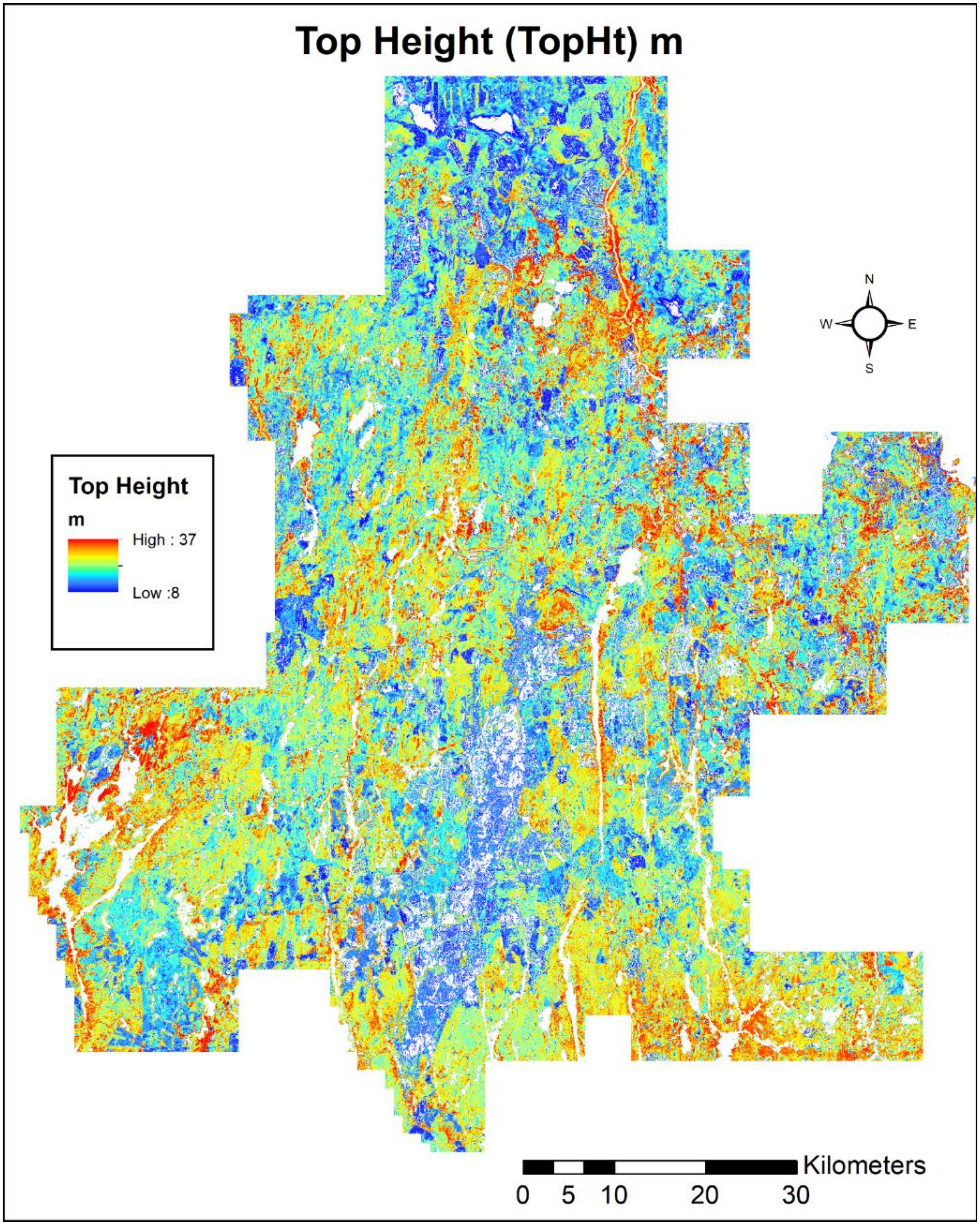
GMV WL		Observed			Prediction					
m^3 ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	12	149.8	5.0	349.2	169.1	30.9	33.8	22.6	-19.3	-12.9
LC1	31	134.8	20.4	284.5	123.1	11.6	30.8	22.8	11.7	8.7
MC2	7	255.3	15.9	410.2	255.1	38.2	61.1	23.9	0.2	0.1
MH1	10	151.0	64.9	252.9	186.1	20.0	51.8	34.3	-35.1	-23.2
MH2	23	346.0	126.8	663.5	340.6	27.7	78.7	22.7	5.4	1.6
PJ1	28	198.3	62.6	395.8	176.8	11.0	46.2	23.3	21.5	10.8
PJ2	12	194.7	107.5	302.2	181.0	16.6	36.9	19.0	13.7	7.0
PO1	84	430.1	37.9	980.8	427.2	21.1	88.0	20.5	2.9	0.7
PW1	1	287.9	287.9	287.9	364.1		76.2	26.5	-76.2	-26.5
SB1	7	97.2	4.4	167.6	101.9	24.8	11.5	11.8	-4.7	-4.8
SF1	12	101.0	2.0	254.4	110.8	26.5	18.7	18.5	-9.9	-9.8
SP1	5	153.5	9.7	285.8	169.2	56.5	24.3	15.8	-15.7	-10.2

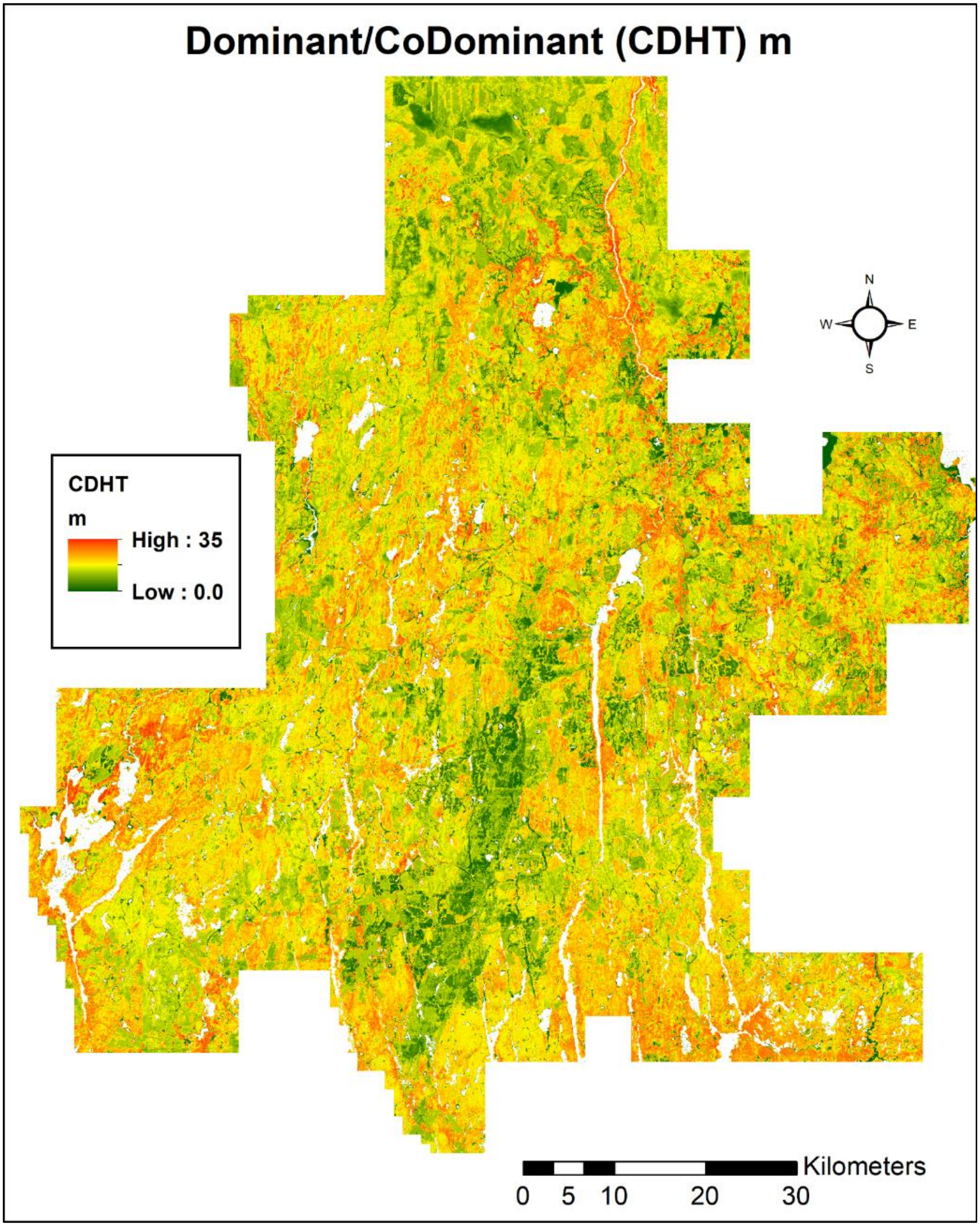
QMD		Observed			Prediction					
cm	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	18.4	8.6	25.4	17.1	1.1	3.3	17.9	1.3	7.1
LC1	33	15.7	10.0	20.6	15.3	0.5	1.8	11.5	0.3	1.9
MC2	7	21.3	10.5	27.0	20.8	1.6	1.9	8.9	0.4	1.9
MH1	11	16.8	11.6	21.5	16.6	1.0	1.0	6.0	0.1	0.6
MH2	23	23.0	15.0	41.3	22.4	0.7	4.7	20.4	0.6	2.6
PJ1	32	16.2	9.8	22.7	16.5	0.7	2.5	15.4	-0.3	-1.9
PJ2	12	17.2	13.1	21.5	18.6	1.2	2.5	14.5	-1.4	-8.1
PO1	85	24.0	8.2	38.2	24.3	0.4	3.0	12.5	-0.3	-1.2
PW1	1	29.2	29.2	29.2	29.0		0.2	0.7	0.2	0.7
SB1	8	13.2	8.4	17.2	13.8	1.0	1.4	10.6	-0.7	-5.3
SF1	12	14.2	9.5	21.3	15.6	1.2	4.0	28.2	-1.4	-9.9
SP1	5	18.3	11.2	25.6	17.8	2.6	2.9	15.8	0.5	2.7

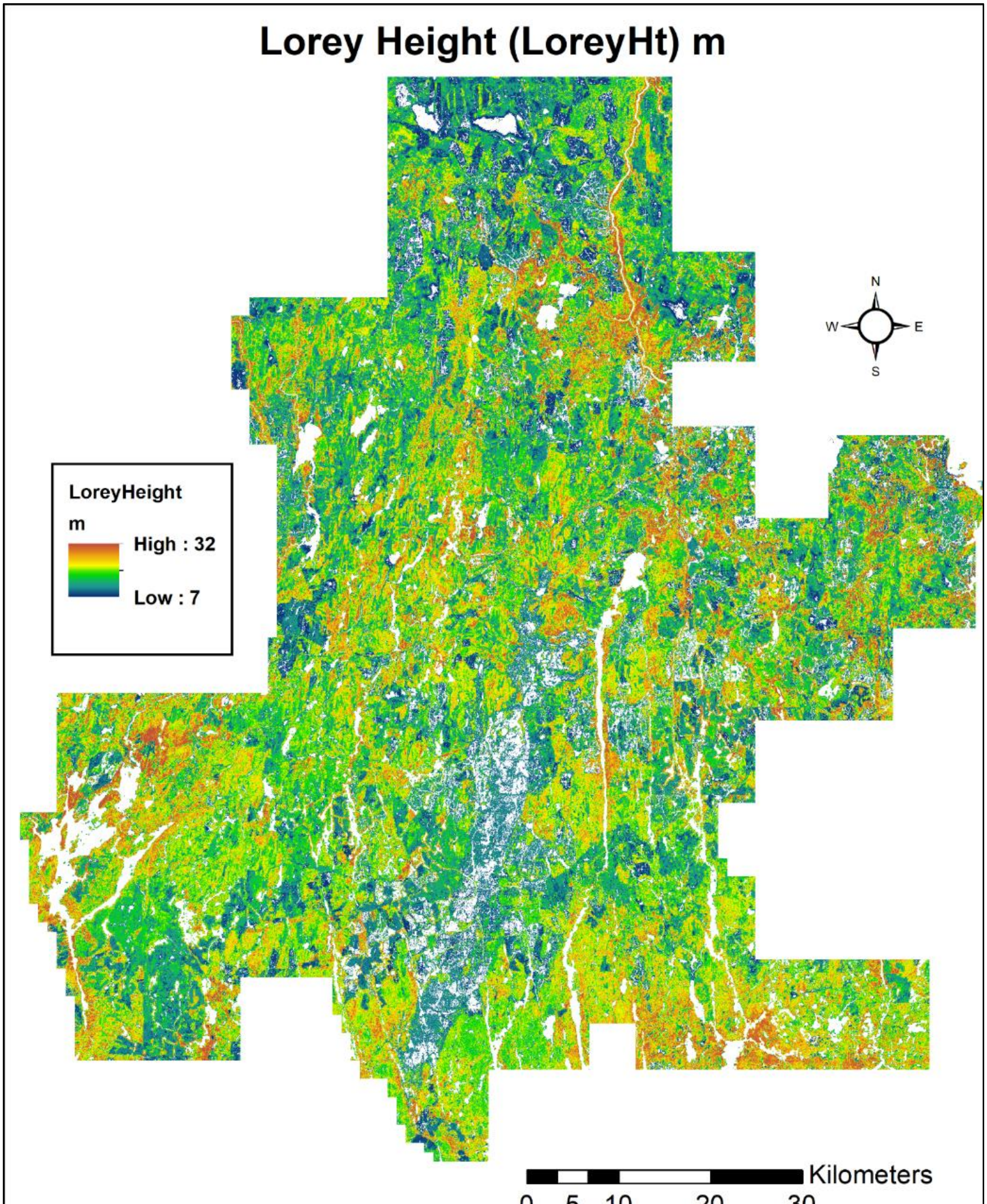
Biomass		Observed			Prediction					
T ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	129.3	8.9	244.8	142.1	18.8	27.5	21.3	-12.8	-9.9
LC1	33	99.2	12.1	182.3	95.2	7.7	15.8	15.9	4.0	4.0
MC2	7	160.5	36.9	240.6	163.3	19.7	32.9	20.5	-2.8	-1.7
MH1	11	138.8	12.7	200.9	149.8	14.9	21.2	15.3	-11.0	-7.9
MH2	23	219.9	137.6	362.0	216.2	13.3	39.8	18.1	3.7	1.7
PJ1	32	123.2	2.1	239.7	117.8	7.8	27.3	22.2	5.4	4.4
PJ2	12	139.3	69.6	190.7	129.0	7.0	22.6	16.2	10.3	7.4
PO1	85	252.8	22.0	534.0	253.3	10.7	46.5	18.4	-0.5	-0.2
PW1	1	167.3	167.3	167.3	198.3		31.0	18.5	-31.0	-18.5
SB1	8	80.9	10.2	138.5	79.6	16.1	13.6	16.8	1.3	1.6
SF1	12	82.3	5.2	164.1	90.3	16.7	13.9	16.9	-8.1	-9.8
SP1	5	110.6	11.6	182.0	122.0	30.7	19.5	17.6	-11.4	-10.3

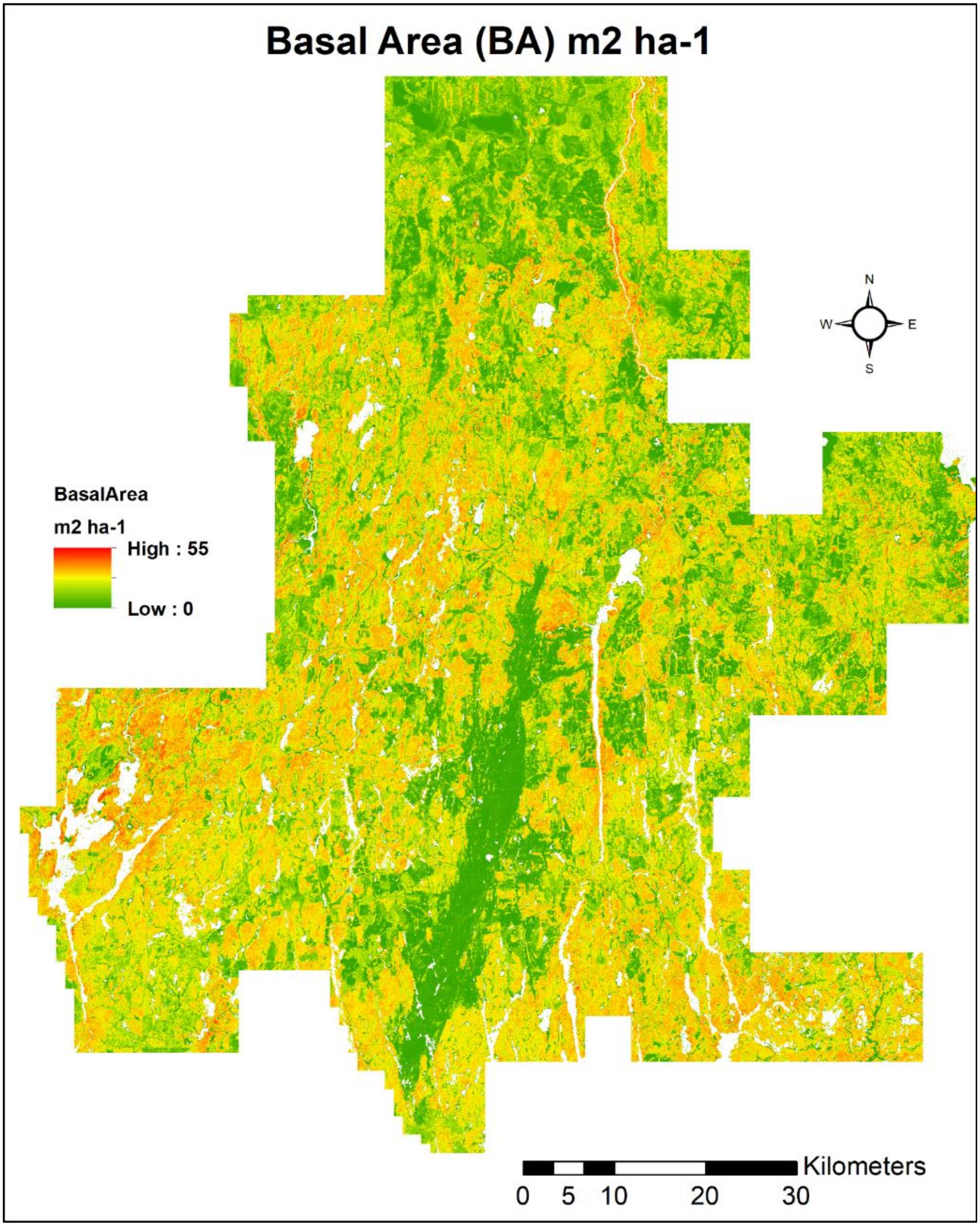
Density		Observed			Prediction					
Stems ha^{-1}	N	Mean	Min	Max	Mean	StdErr	RMSE	RMSE%	BIAS	BIAS%
BW1	13	1015	75	2575	1500	228	700.0	68.9	-484.8	-47.7
LC1	33	1377	75	2850	1348	97	374.4	27.2	29.0	2.1
MC2	7	954	450	1300	978	87	209.9	22.0	-24.5	-2.6
MH1	11	1543	250	3550	1591	237	447.0	29.0	-48.3	-3.1
MH2	23	1140	225	2225	1079	78	317.4	27.8	61.5	5.4
PJ1	32	1463	25	3025	1383	116	458.7	31.4	79.2	5.4
PJ2	12	1554	625	2875	1261	194	413.9	26.6	293.1	18.9
PO1	85	1041	200	2825	956	37	323.1	31.0	84.7	8.1
PW1	1	400	400	400	476		76.0	19.0	-76.0	-19.0
SB1	8	1594	400	3400	1300	191	632.5	39.7	293.5	18.4
SF1	12	1267	250	2575	1278	224	330.6	26.1	-11.4	-0.9
SP1	5	1105	325	3025	1253	357	440.1	39.8	-147.7	-13.4

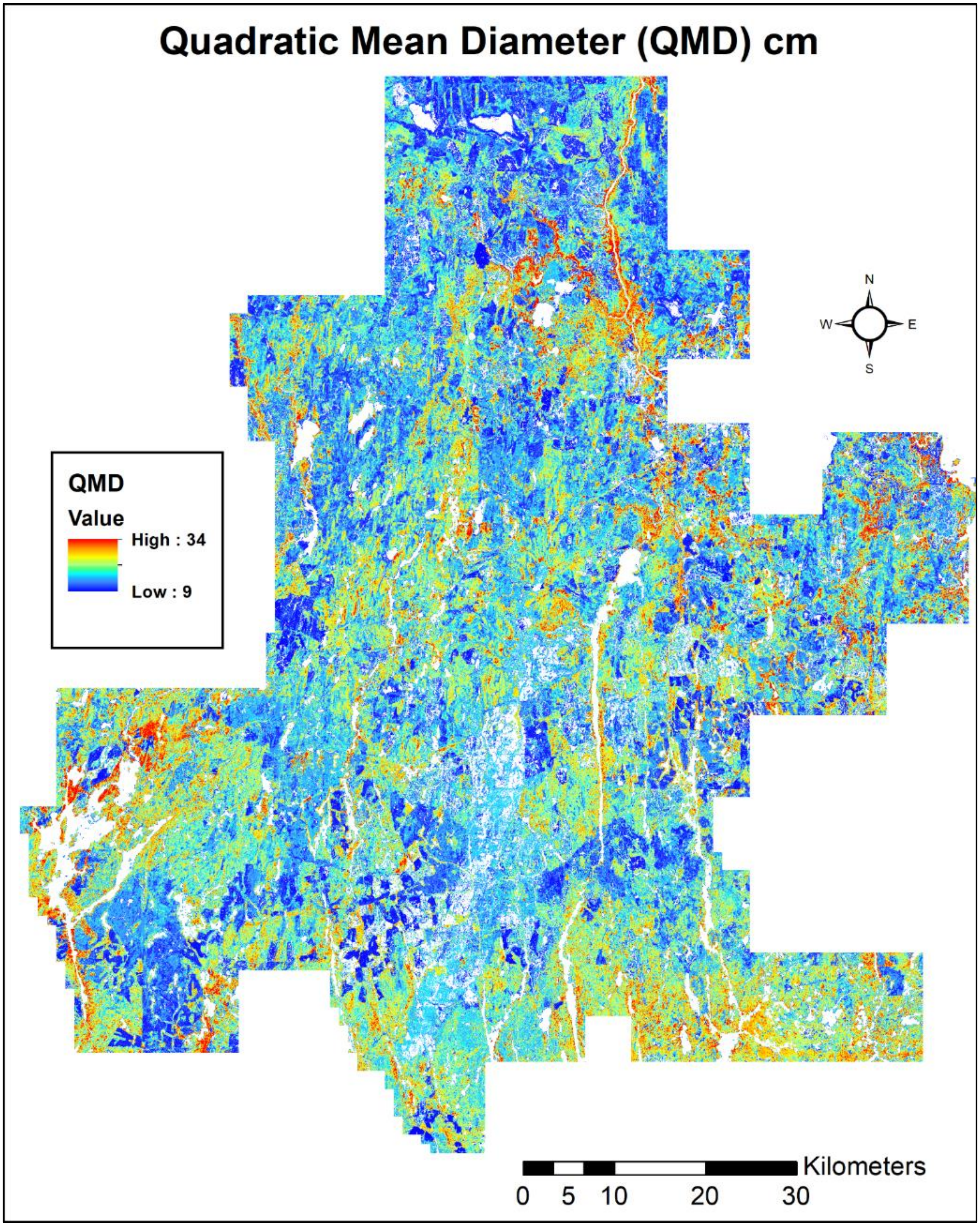
Appendix D - Examples of LiDAR derived Raster Outputs

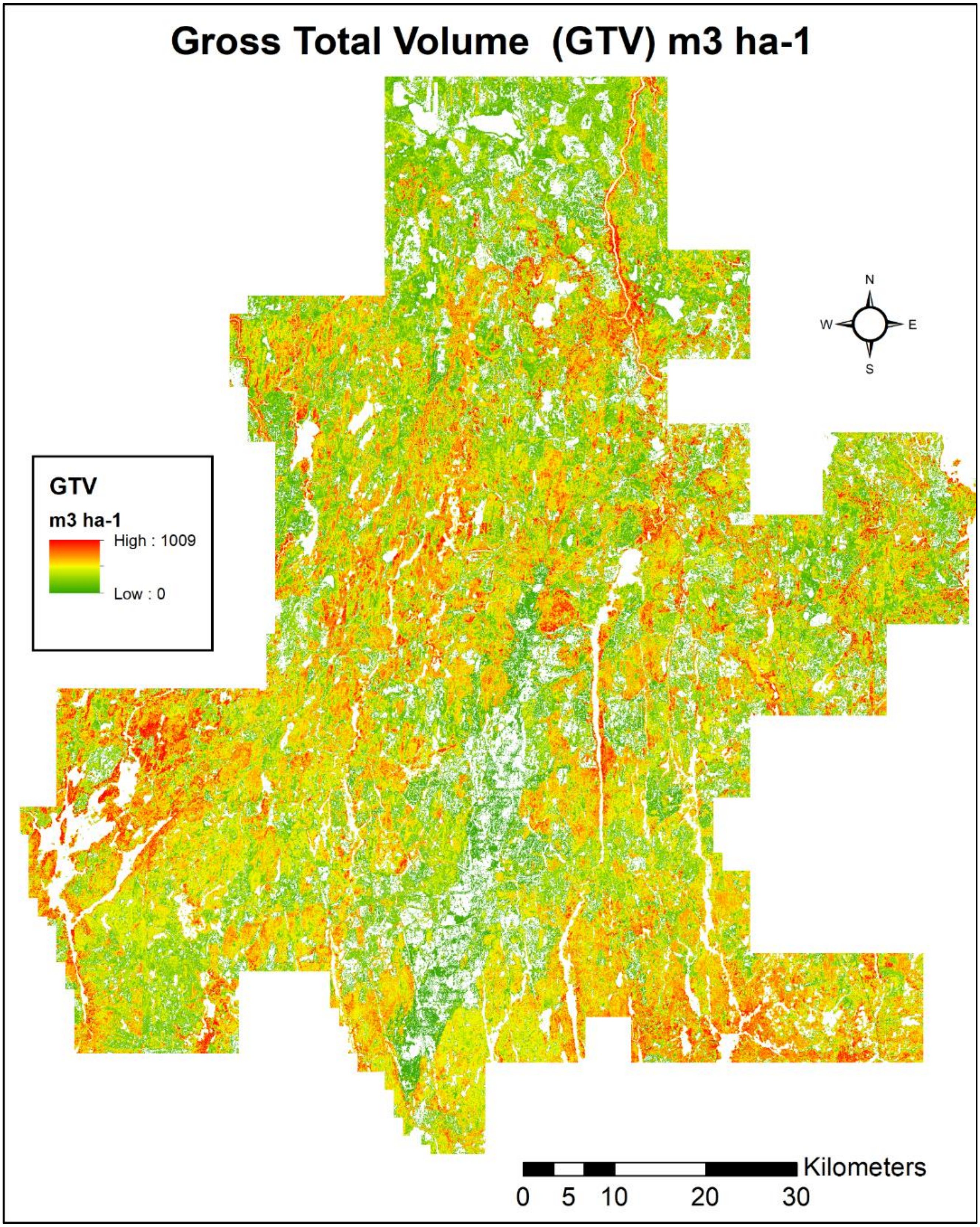


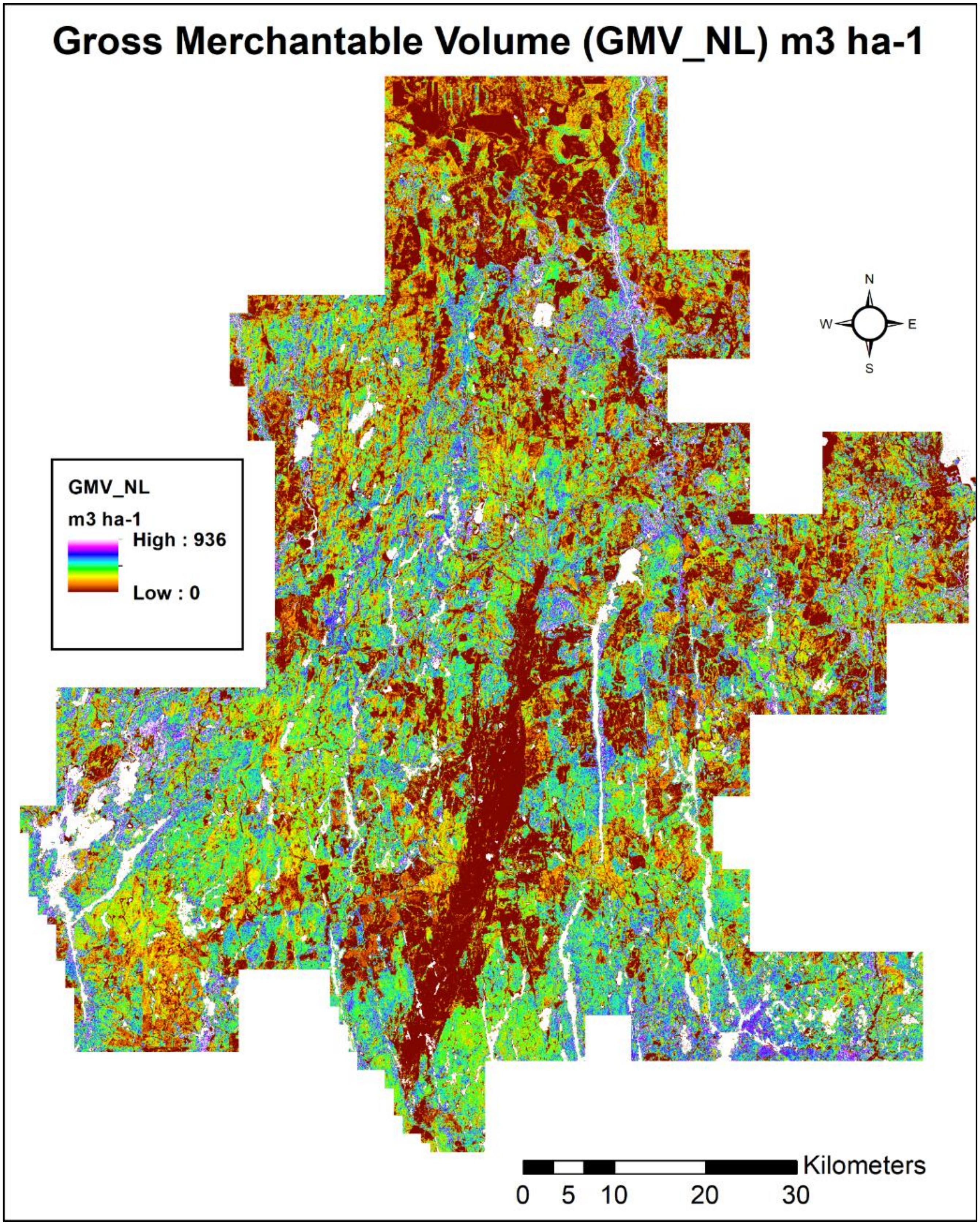

Dominant/CoDominant (CDHT) m
CDHT
m
High : 35
Low : 0.0
N
W
E
S
Kilometers
0
5
10
20
30


Lorey Height (LoreyHt) m
N
W
E
S
LoreyHeight
m
High : 32
Low : 7
Kilometers
0
5
10
20
30

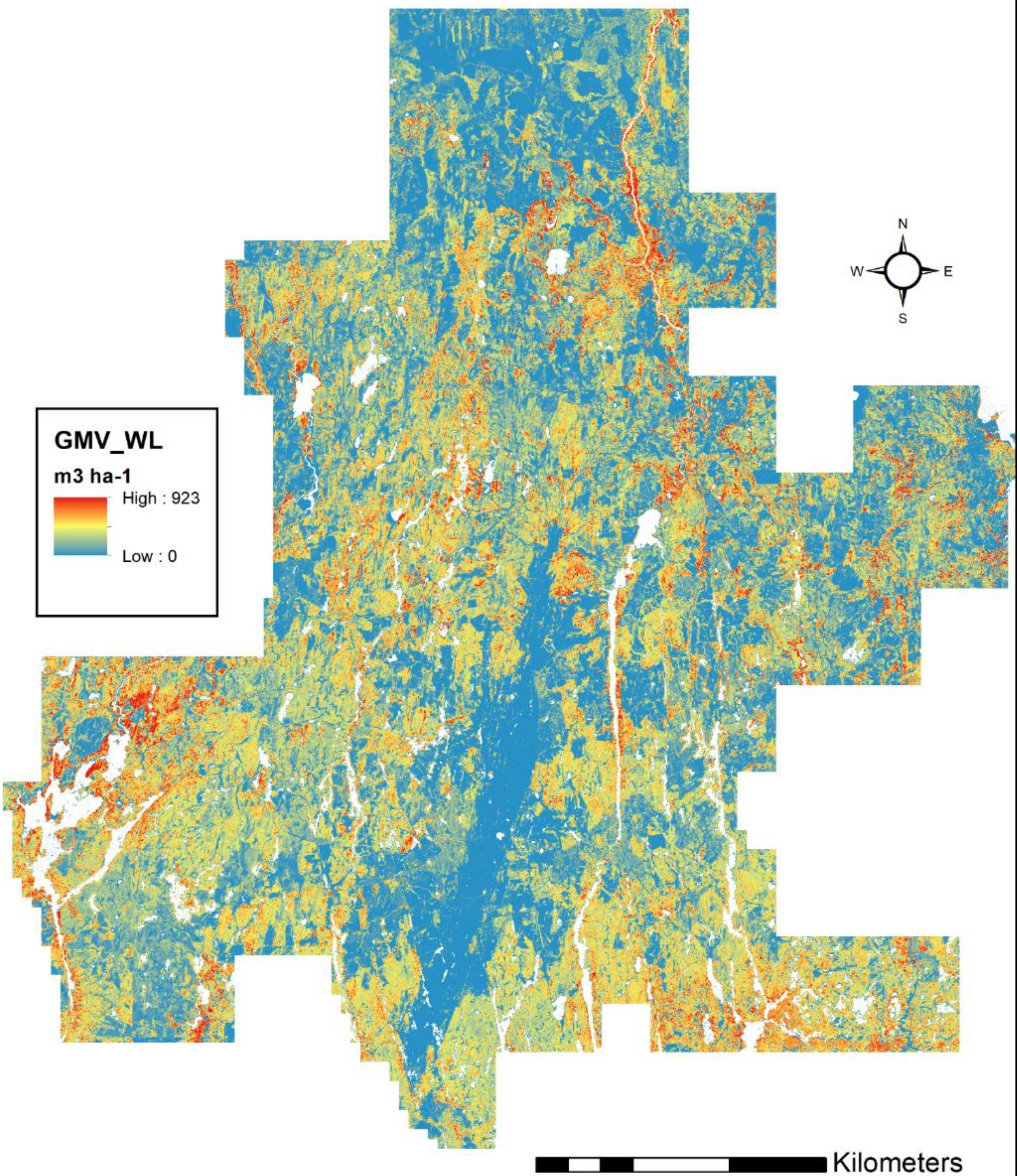

Basal Area (BA) m2 ha-1
BasalArea
m2 ha-1
High : 55
Low : 0
N
W
E
S
Kilometers
0
5
10
20
30

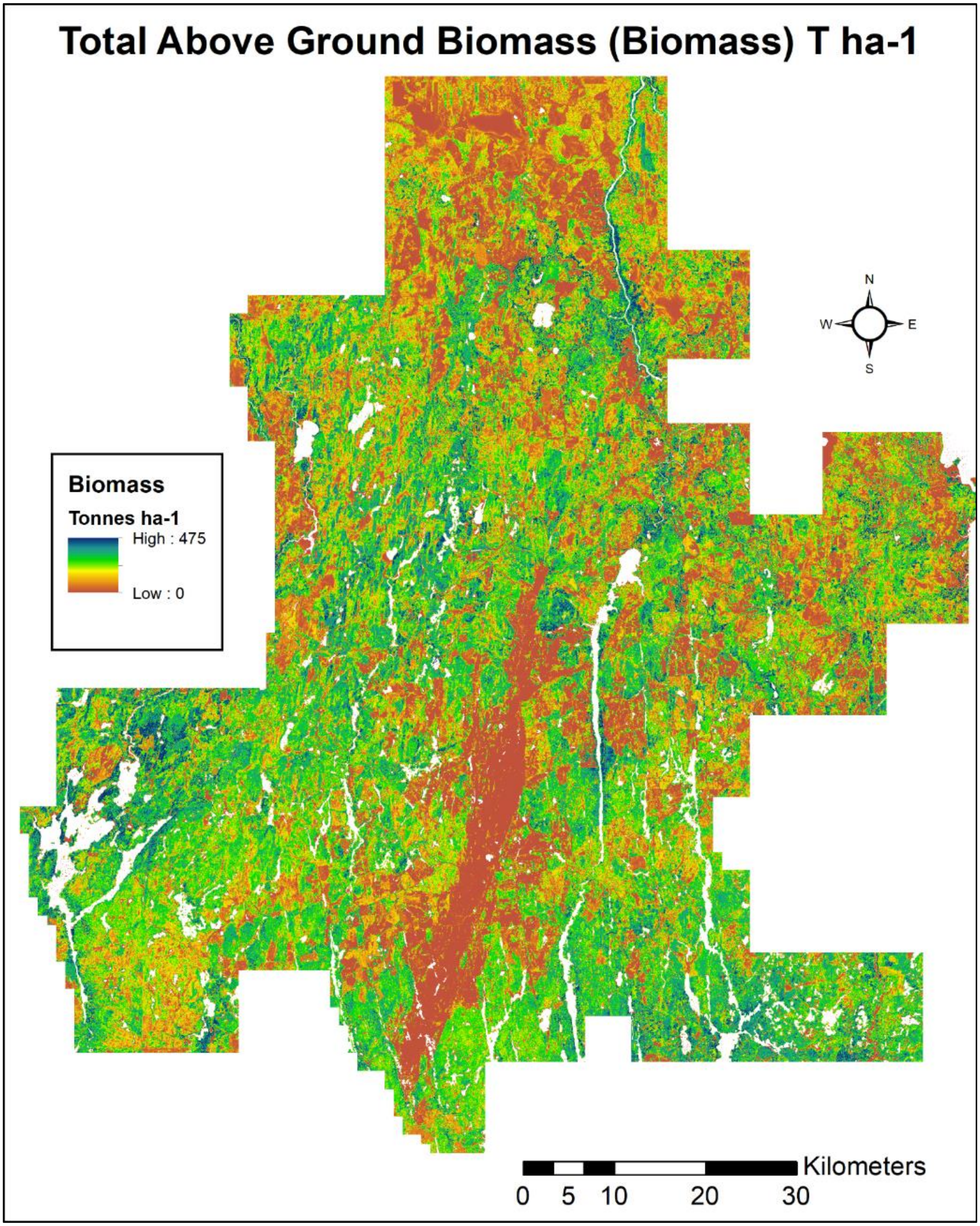

Quadratic Mean Diameter (QMD) cm
QMD
Value
High : 34
Low : 9
N
W
E
S
Kilometers
0
5
10
20
30


Gross Total Volume (GTV) m3 ha-1
GTV
m3 ha-1
High : 1009
Low : 0
N
W
E
S
Kilometers
0 5 10 20 30


Gross Merchantable Volume (GMV_NL) m3 ha-1
GMV_NL
m3 ha-1
High : 936
Low : 0
N
W
E
S
Kilometers
0
5
10
20
30

Gross Merchantable Volume (GMV_WL) m3 ha-1




Total Above Ground Biomass (Biomass) T ha-1
Biomass
Tonnes ha-1
High : 475
Low : 0
N
W
E
S
Kilometers
0 5 10 20 30

Appendix E – 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. The recommended equations are **bolded**. If there is only one reference, it is the curve used.

Species	Planted	Natural
White pine	**Sharma & Parton (2019) equation 1, table 2 no climate**	Parresol & Vissage (1998)
Red pine	**Sharma & Parton (2018b) equation 1, table 4 (no climate)**, Carmean & Thrower (1995)	**Buckmann et al. (2006)**
Jack pine	**Sharma et al. (2015) equation 1 (no climate)**, Guo and Wang (2006), Subedi & Sharma (2010)	**Sharma & Reid (2018), equation 3, table 4** Sharma (2021), Carmean et al. (2001) Goelz and Burk. (1998), Guo and Wang (2006)
White spruce	**Sharma & Parton (2018a) equation 1, table 2 (no climate)**	
Black spruce	**Sharma et al. (2015) equation 1 (no climate)**, Subedi & Sharma (2010)	**Sharma & Reid (2018), equation 3, table 4** Sharma (2021), Carmean et al. (2006)
Hemlock		Carmean et al. (1989) figure 127
Balsam fir		Carmean (1996) figure 18
Tamarack		Carmean (1996) figure 16
cedar		Carmean et al. (1989) figure 57
Sugar maple		Buda & Wang (2006)
Red maple		Carmean et al. (1989) figure 1
Yellow birch		Carmean et al. (1989) figure 6
White birch		Carmean (1996) figure 14
Poplar (all including Aspen, largetooth and balsam poplar)		Carmean et al. (2006), Sharma working on Po/Pj for Dec. 2021
White ash		Carmean et al. (1989) figure 13
Black ash		Carmean et al. (1989) figure 14
Red oak		Carmean et al. (1989) figure 48
Elm		Carmean et al. (1989) figure 53
Basswood		Carmean et al. (1989) figure 51
Beech		Carmean et al. (1989) figure 11
Black cherry		Carmean et al. (1989) figure 34
SI conversion	Carmean et al. (2013), Sharma (2021), working on Po,Pj for Dec 2021	
Northeastern US	Westfall et al. (2017)	