Projects Supporting Ontario's Forest Inventory Efforts

- Acceleration of LiDAR Enhanced Inventories
- Automated Characterization of Forest Vertical Structure
- Assessing Site Productivity from Remote Sensing & Historic Information
- + other KTTD Projects

Margaret Penner – Murray Woods – Alex Bilyk

Accelerating the Implementation of Enhanced Forest Inventories in Ontario

Project Team
Murray Woods
Margaret Penner

FORESTRY FUTURES TRUST ONTARIO

Government of Canada / Gouvernement du Canada

Ontario
Ministry of Natural Resources and Forestry

resolute Forest Products

Westwind
WESTWIND FOREST STEWARDSHIP INC.

GREENFIRST FOREST PRODUCTS

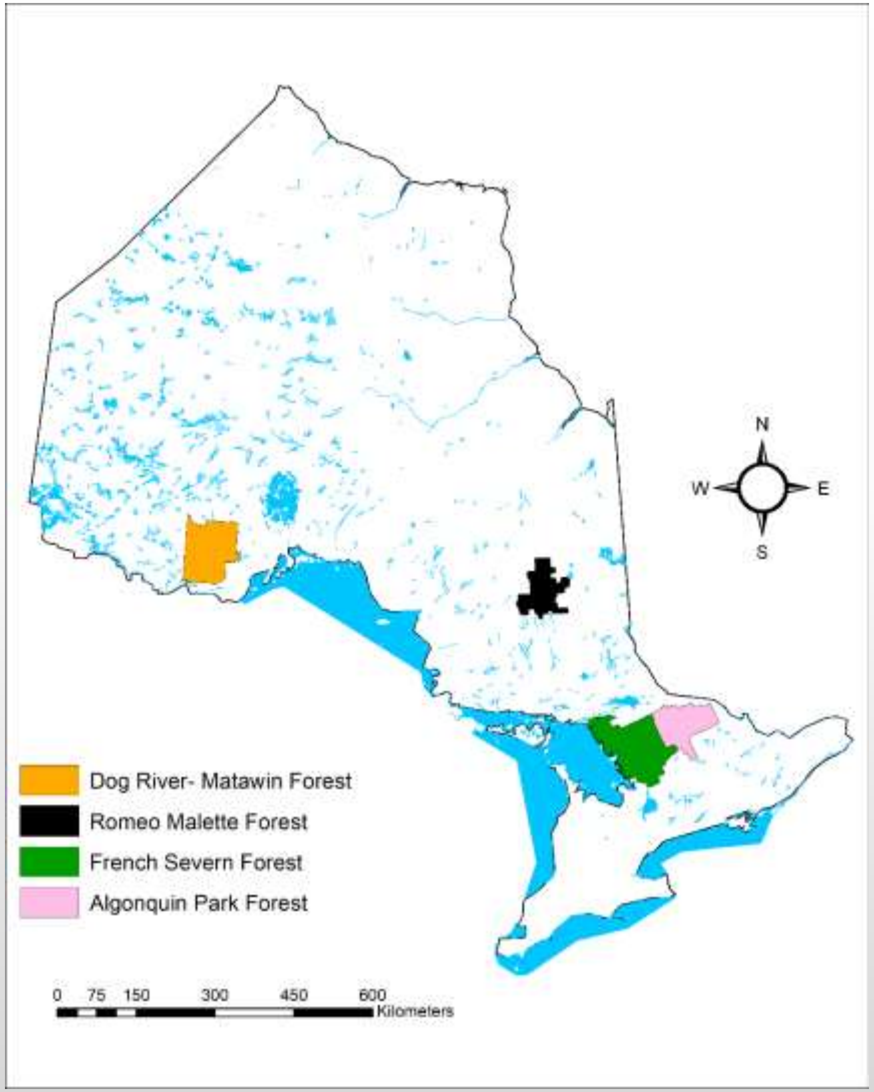
ALGONQUIN FORESTRY AUTHORITY

Accelerating the Implementation of Enhanced Forest Inventories in Ontario (KTTD 20B-2021)

- Romeo Malette Forest (RMF)
- Dog River-Matawin Forest (DRM)
- Algonquin Park Forest (APF)
- French-Severn Forest (FSF)

Boreal: Romeo Malette Forest (RMF), Dog River-Matawin Forest (DRM)

Great Lk St. Lawrence: Algonquin Park Forest (APF), French-Severn Forest (FSF)



Accelerating the Implementation of Enhanced Forest Inventories in Ontario (KTTD 20B-2021)

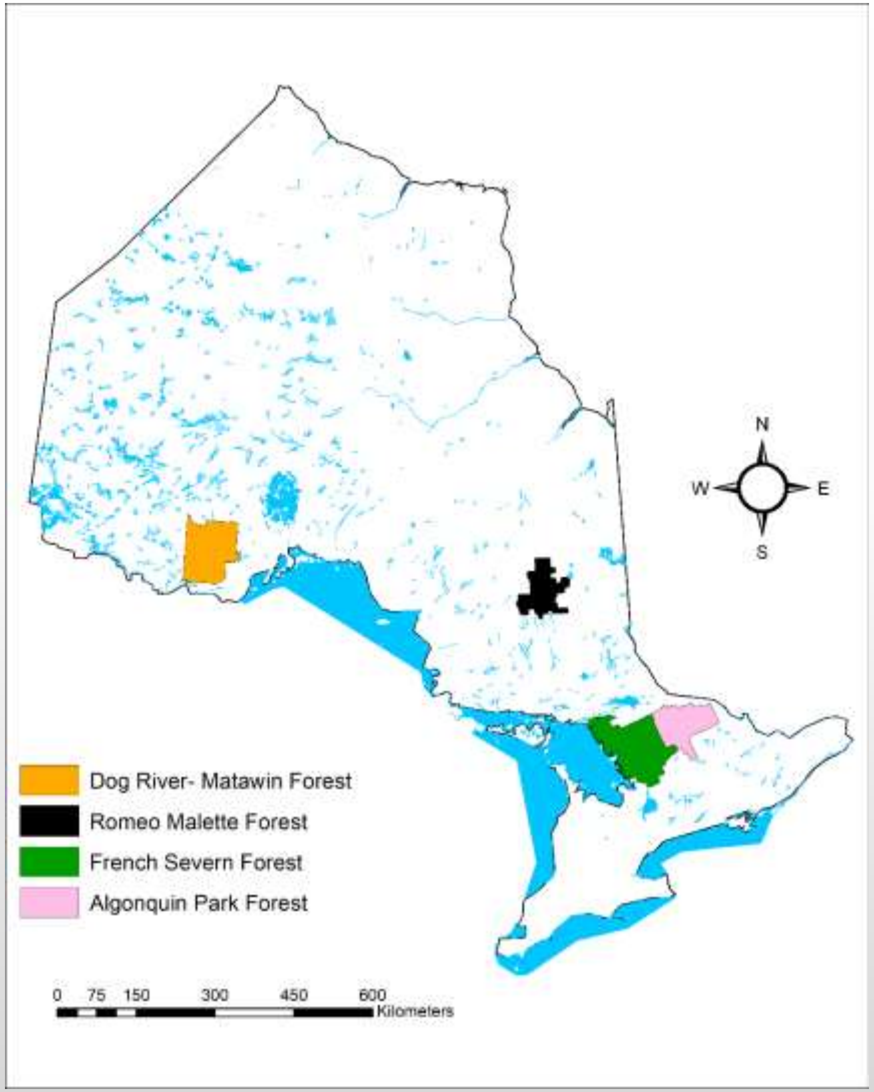
- **Romeo Malette Forest (RMF)**
- **Dog River-Matawin Forest (DRM)**

Boreal

- **Algonquin Park Forest (APF)**
- **French-Severn Forest (FSF)**

Great Lk St. Lawrence

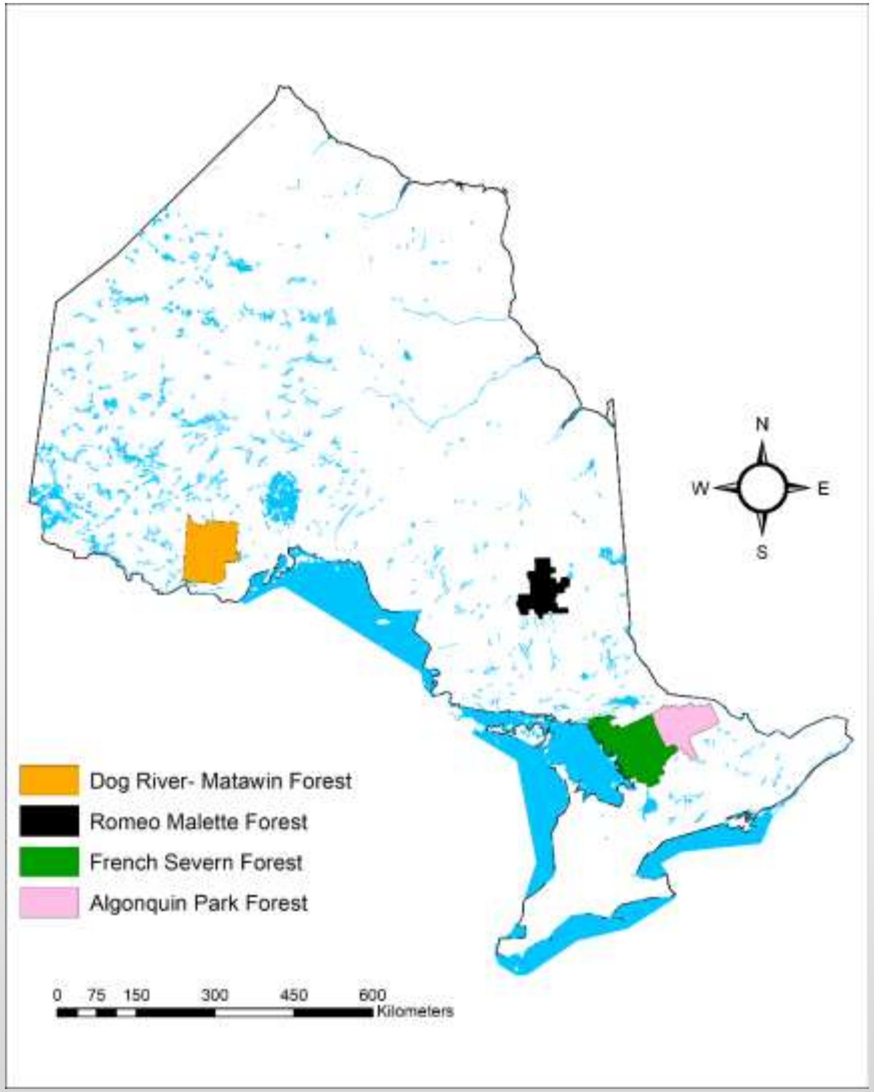
- **Using open-source software and sharing developed code.**
- **Using a cloud-based solution**
- **Communicate with clients (SFLs and Crown) through entire project**



Accelerating the Implementation of Enhanced Forest Inventories in Ontario (KTTD 20B-2021)

Project Flow

- create project teams
- Screen calibration plots
- summarize calibration plots
- generate prediction rasters
- Develop LiDAR models
- Integrate predictions with existing T1 inventory



Plot Compilation

- Compilation software written in R – Open Source
- Accesses Provincial VSN Database structure
- Utilizes Ontario/Canada published sources
  - Height diameter equations (Sharma & Parton 2007)
  - Volume – (Zakrzewski & Penner 2013)
  - Biomass – (Lambert et al. 2005)
- Using a Dbh ≥ 7.1 cm threshold

```
•       #
•#  Callibration plot compiler
•#
•#  Read in Plot file and tree file
•#
•#  For live trees
•#    do basic data cleaning
•#    estimate missing heights
•#    estimate tree volume
•#
•# Produce plot level estimates of
•#    basal area, QDBH, volume, heights, stems/ha
•#
•# by Margaret Penner (mpenner@forestanalysis.ca)
•#
•# clean slate - assign working directory and delete all objects currently in memory
•rm(list=ls(all.names=TRUE))


•# Set working directory
•rdir <- "c:/ForestAnalysis/on/2021/FRI_Acceleration/Rscripts"
•setwd(rdir)

•# Load the height estimation function
•source(paste(rdir,"/Functions/Ht_Est_FUN.R",sep=""))
•# Load the function that converts numeric species codes to alpha species codes
•source(paste(rdir,"/Functions/Spp_Alpha_FUN.R",sep=""))
•# Load the function that converts numeric species codes to alpha species codes
•source(paste(rdir,"/Functions/NE_FU_FUN.R",sep=""))

•# Set error directory & file
•# Output will be directed to thie error file as well as the screen
•ErrDir <- "./Error"
•error_file <- paste(ErrDir,"/Error_File.txt",sep="")
•sink(error_file,append=FALSE,split=TRUE)
•sink()
•sink(error_file,append=TRUE,split=TRUE)
•cat("This file contains the results of error checking \n",file=error_file, append=TRUE)

•Forest <- "RMF"
•MU <- 930
•InputDir <- paste("c:/forestanalysis/on/2021/FRI_Acceleration/Sascode/RMF_DR/",sep="")


•# get the plot data
•Plot_Data <- read.table(paste(InputDir,"/Plot.csv",sep=""),sep = ',',header=TRUE)

•# get plot data for RMF
•Plot_Data <- Plot_Data[Plot_Data[,"MU"]==MU, ]
```

Plot Compilation – grid cell/plot attributes

Unless otherwise noted, the following summaries are for live trees with Dbh ≥ 7.1 cm

<u>Tree level</u>

- Height – top height, dom/codom height, Lorey’s height
- Quadratic mean Dbh

<u>Area level</u>

- Basal area
- Volume - GTV, GMV_NL, GMV_WL
- Biomass

Plot Compilation – BA / Volume by size class

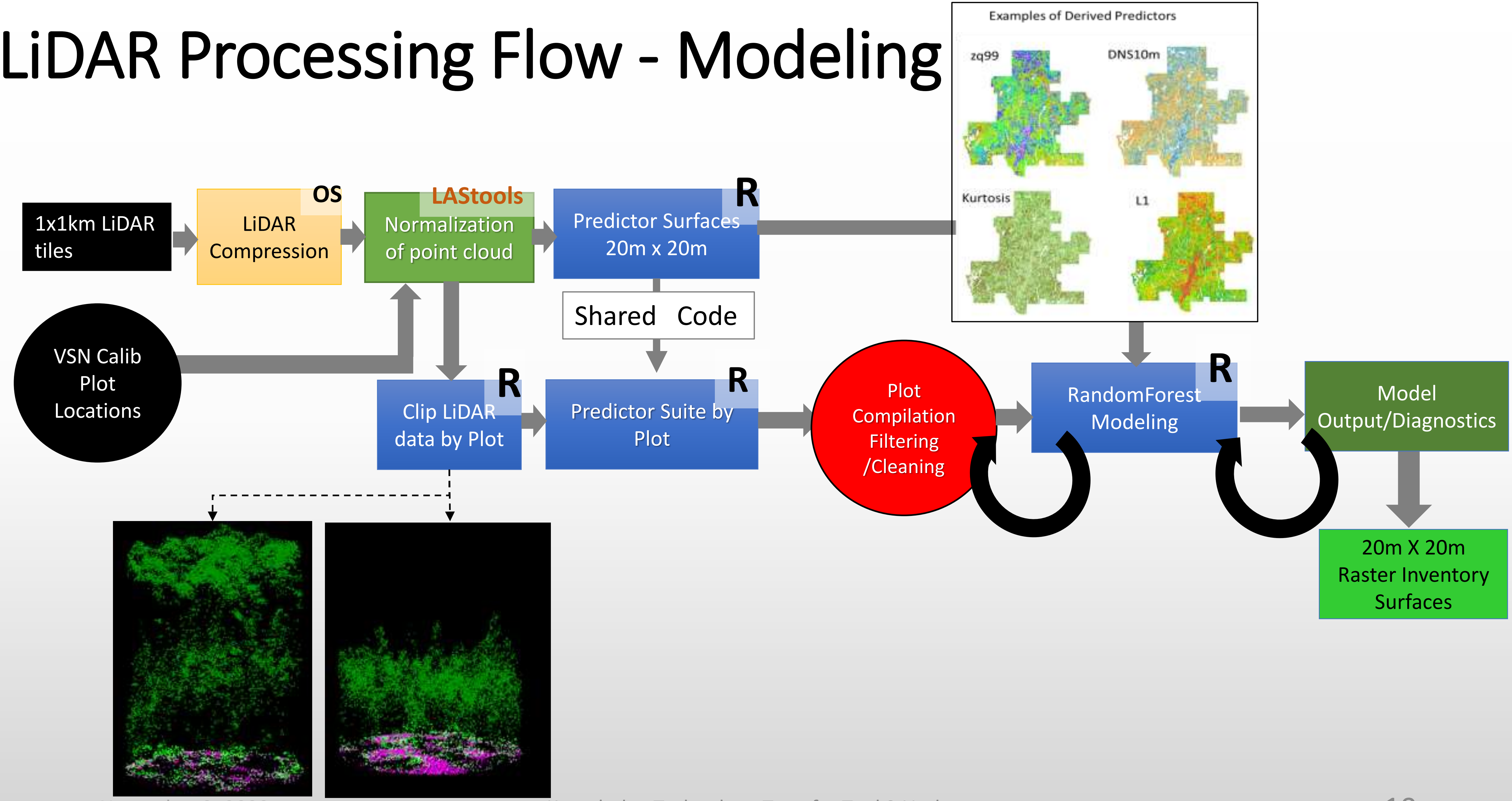
Standard Deliverable Boreal	Standard Deliverable Great Lakes St. Lawrence
• Only one GMV being modeled (GMV_nl) • 4 Size classes **SmPoles [9 < Dbh ≤ 16 cm]** **LargePoles [16 < Dbh ≤ 25]** **Small Sawlogs [25 < Dbh ≤ 37]** **Large Sawlogs [37cm+]** • 9m threshold for GMV and size class predictions	• Only one GMV being modeled (GMV_nl) • 4 Size classes **Poles [9 < Dbh ≤ 25 cm]** **Small Sawlogs [25 < Dbh ≤ 37]** **Medium Sawlogs [37 < Dbh ≤ 49]** **Large Sawlogs [49 cm+]** • 9m threshold for GMV and size class predictions

** Some SFL managers requested additional size-class aggregations to better align with their operational decision making

LiDAR Derived ABA Inventory

- Area-Based-Approach (ABA)-20m raster inventory product
- All raster cell vertical structures are treated the same way with a total BA/Volume predicted
- Calibration plot summary only considers ALL live trees and sums their contribution to total per ha values
- This has been the default prediction method for Ontario (and other jurisdictions)

LiDAR Processing Flow - Modeling



LiDAR - Modeling

Model Output/Diagnostics

Predicted Directly

Inventory Metric
TopHt
CDHT
LoreyHeight
BA
QMD
Biomass

Logical Calculation of Attributes

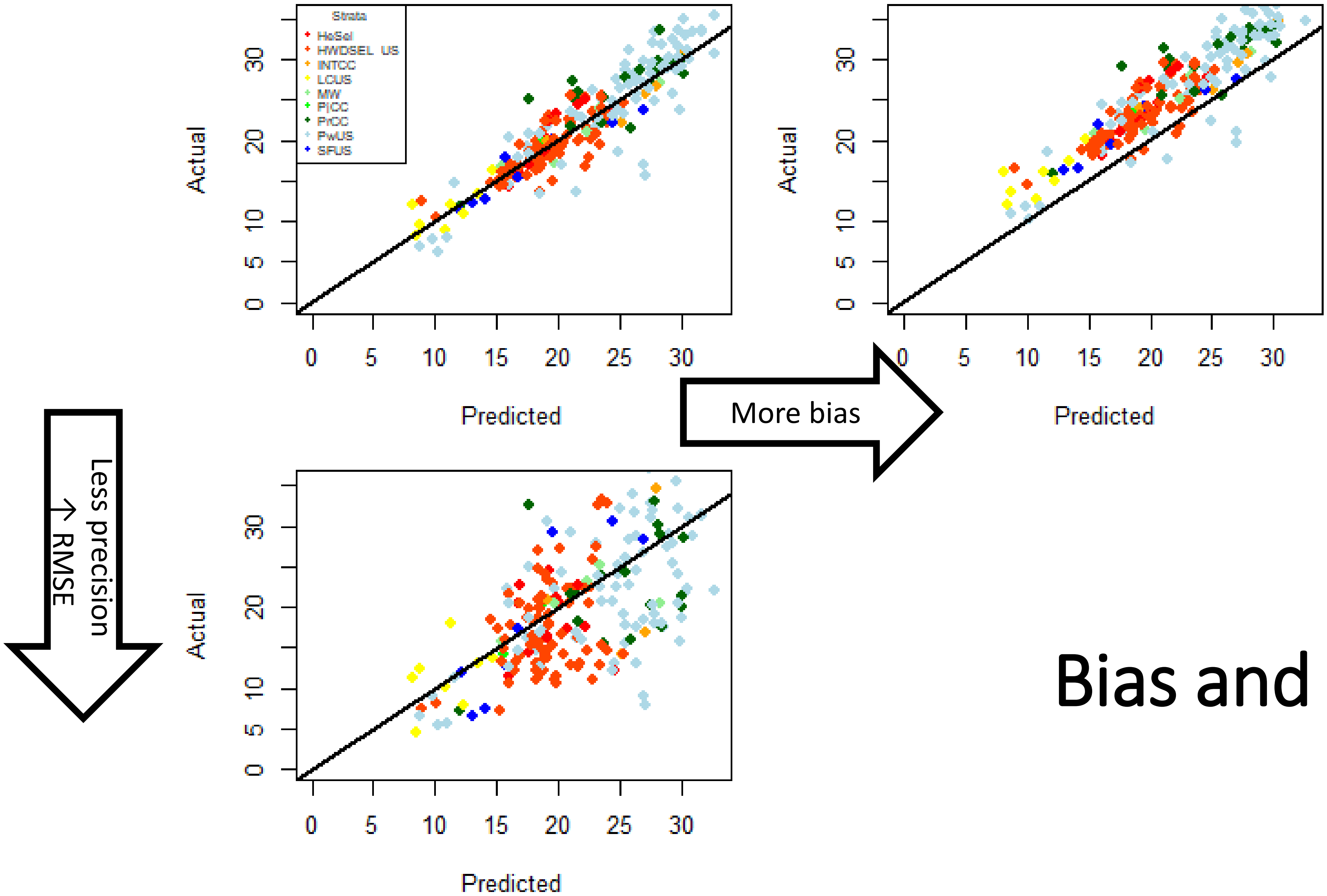
- GTV = Predicted VBAR * Predicted BA
- GTV >= GMV_NL >= GMV_WL

- BA_smallpoles + BA_largepoles + … + BA_largesawlogs = Predicted BA
- GMV_smallpoles + GMV_largepoles + … + GMV_largesawlogs = Predicted GMV

- Stems = (BA/ QMD^2) / 0.00007854

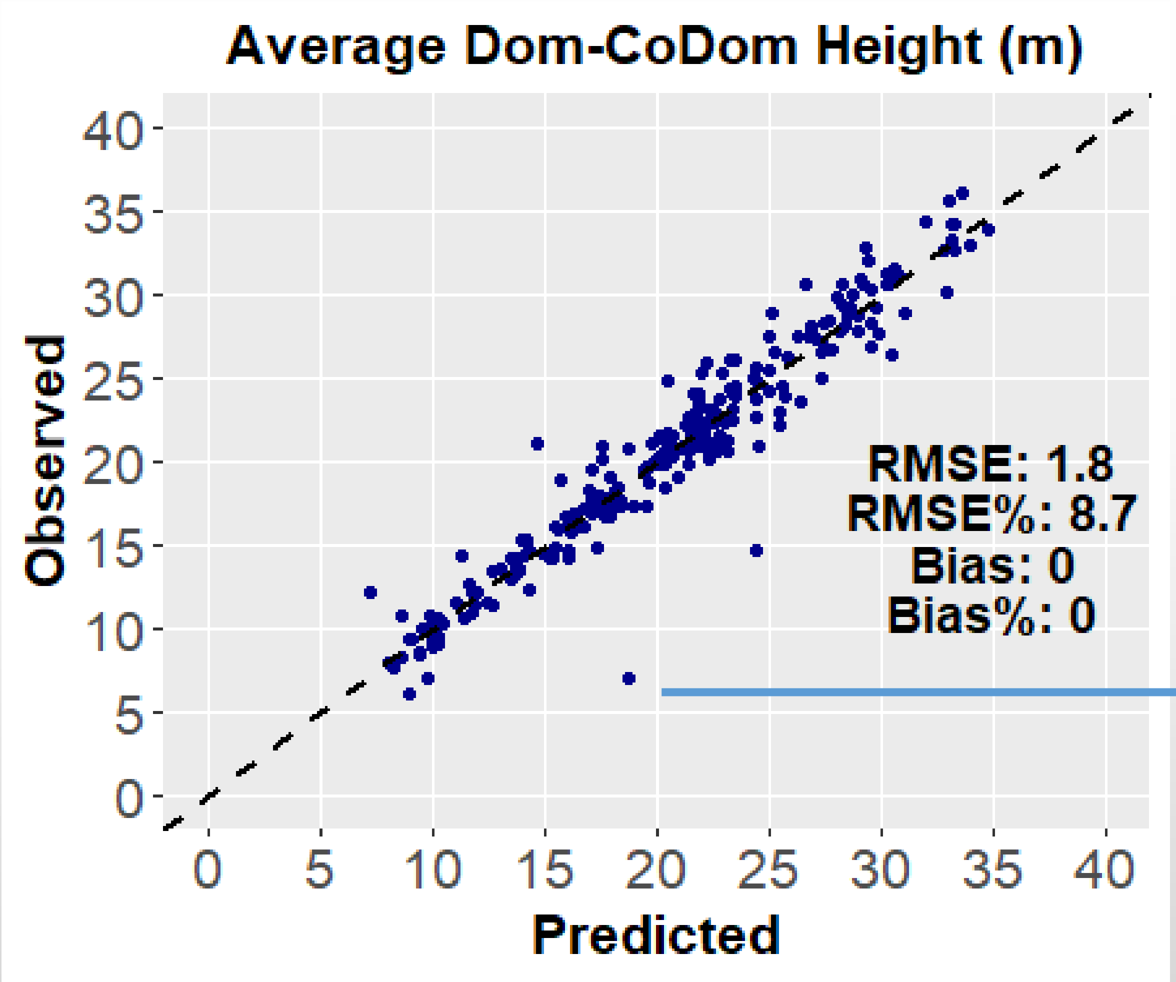
Additional T2 Attributes Not Directly Predicted from LiDAR

- Site Index is calculated from Topht & T1 Age & T1 Leading Species)
- Stocking is calculated from Site Index, BA ,T1 Age & T1 Leading Species)



Bias and Precision

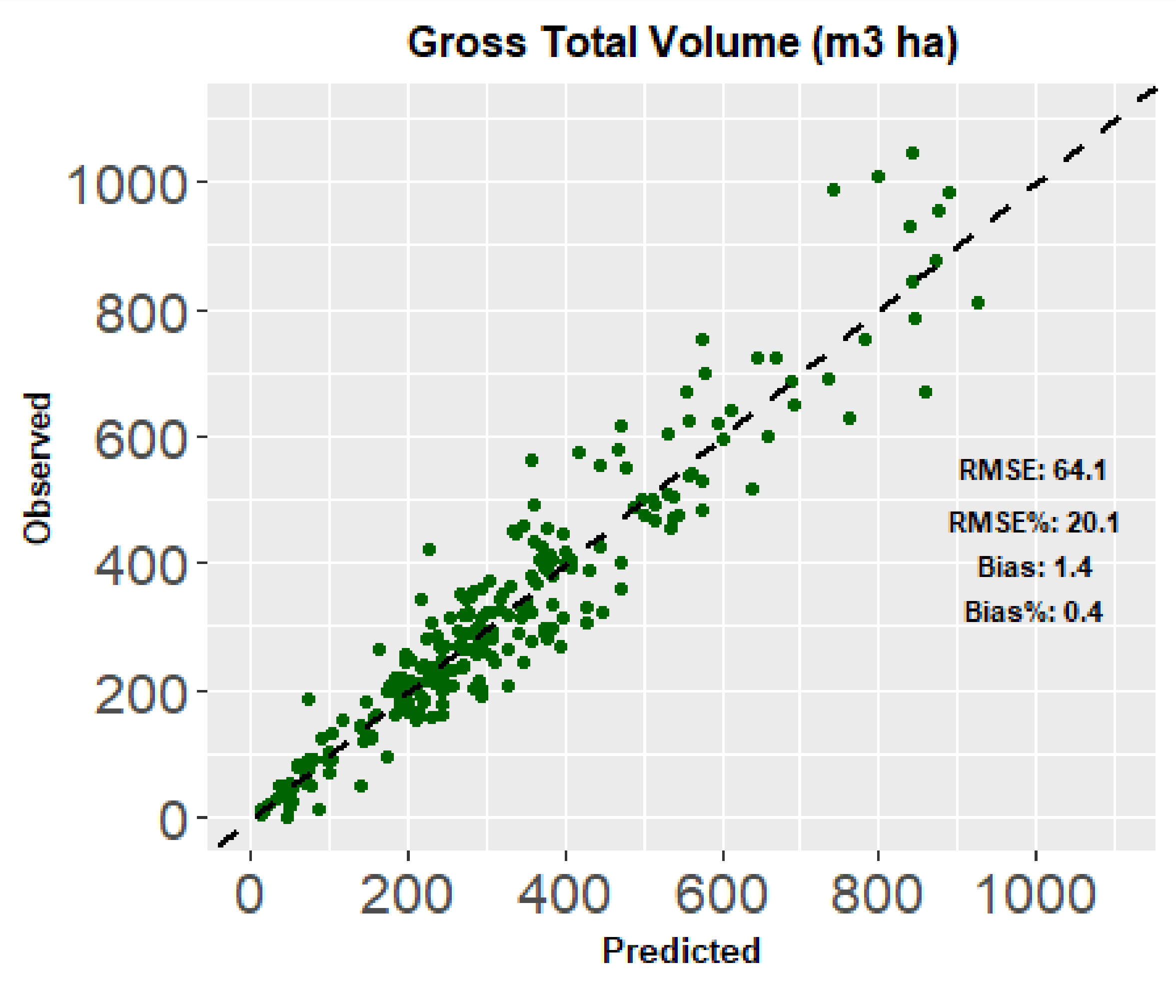
LiDAR Modelling – RMF Dom/CoDom Ht



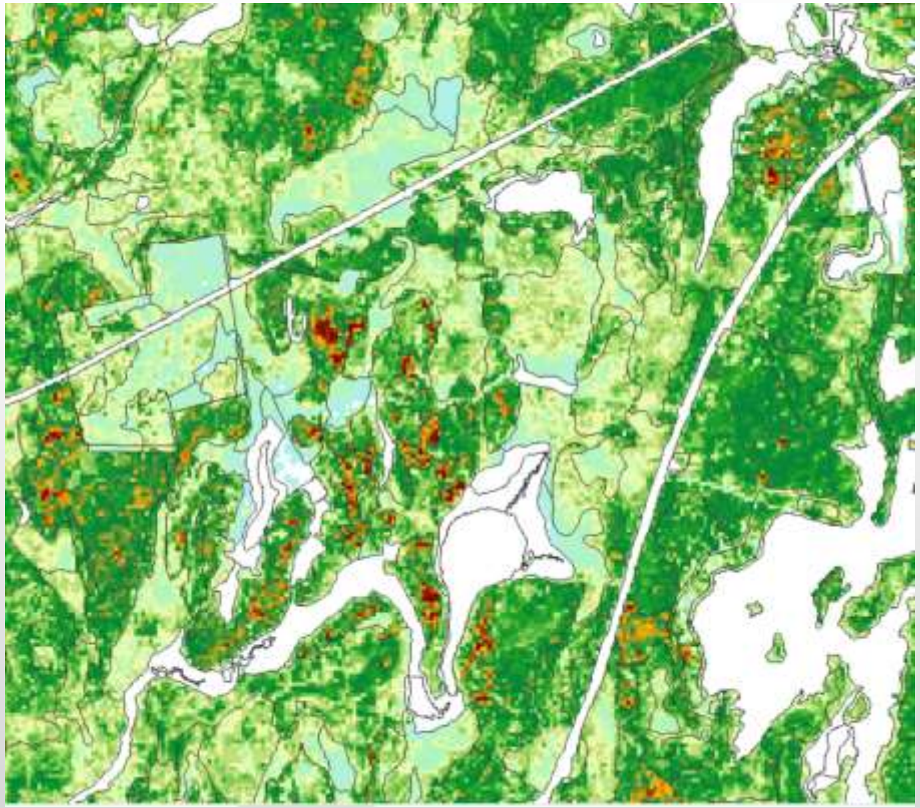
RMF375

Pt is outside field measured plot

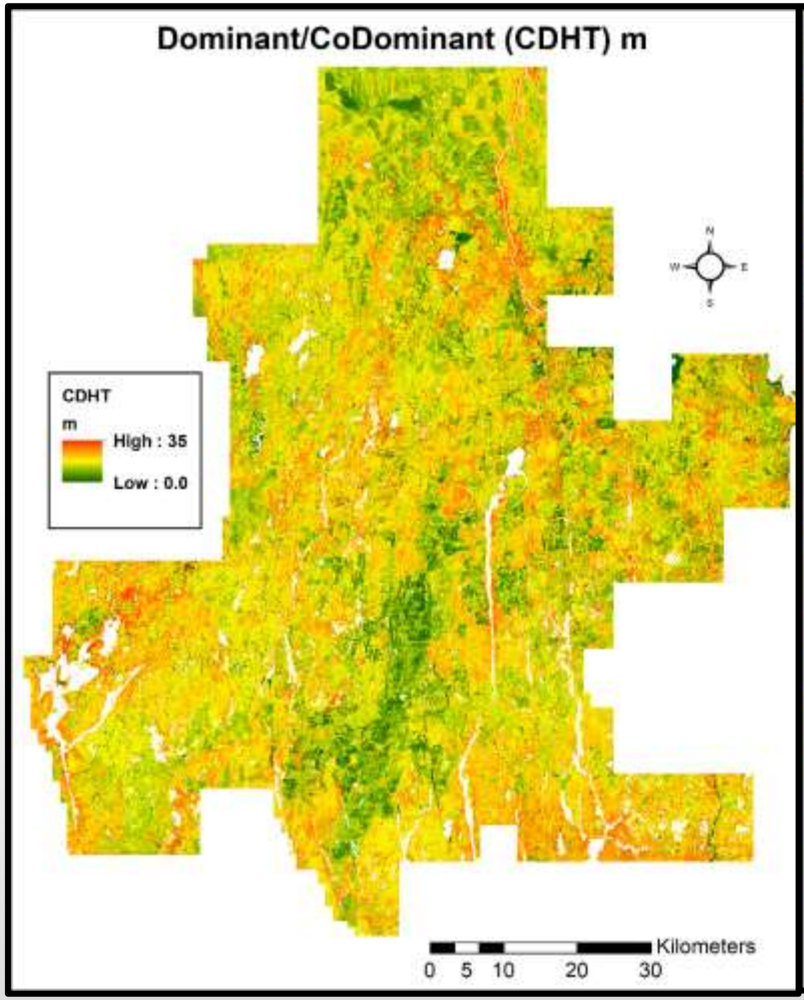
LiDAR Modelling – RMF Gross Total Volume



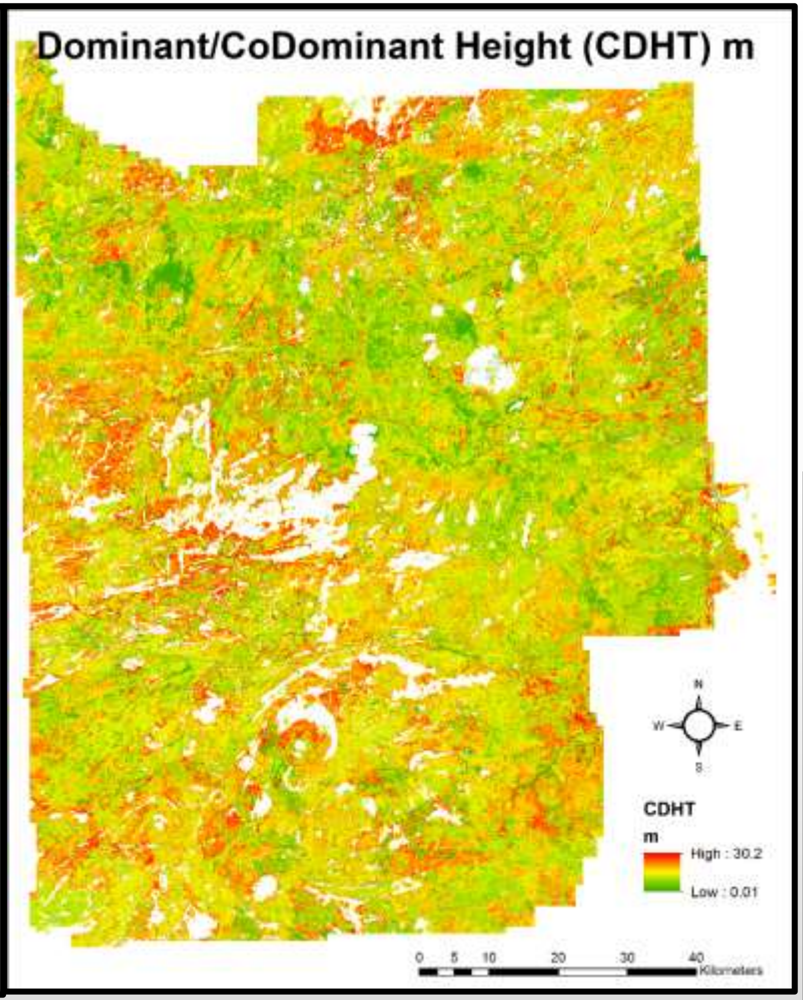
- Calculated from:
  - predicted Basal Area &
  - predicted VBAR [GTV/BA ratio]

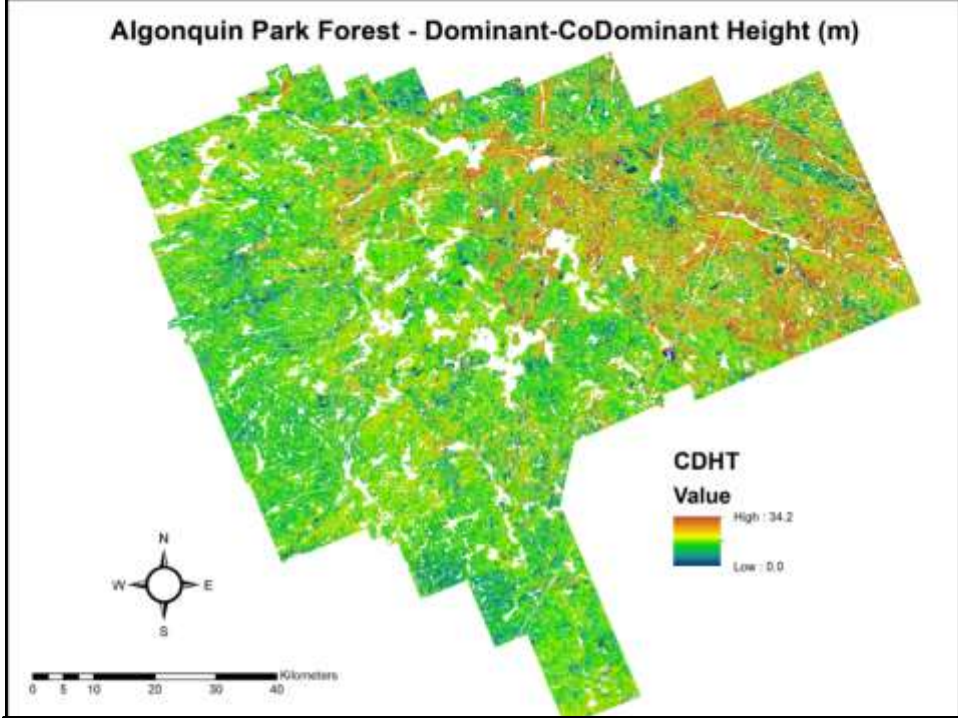


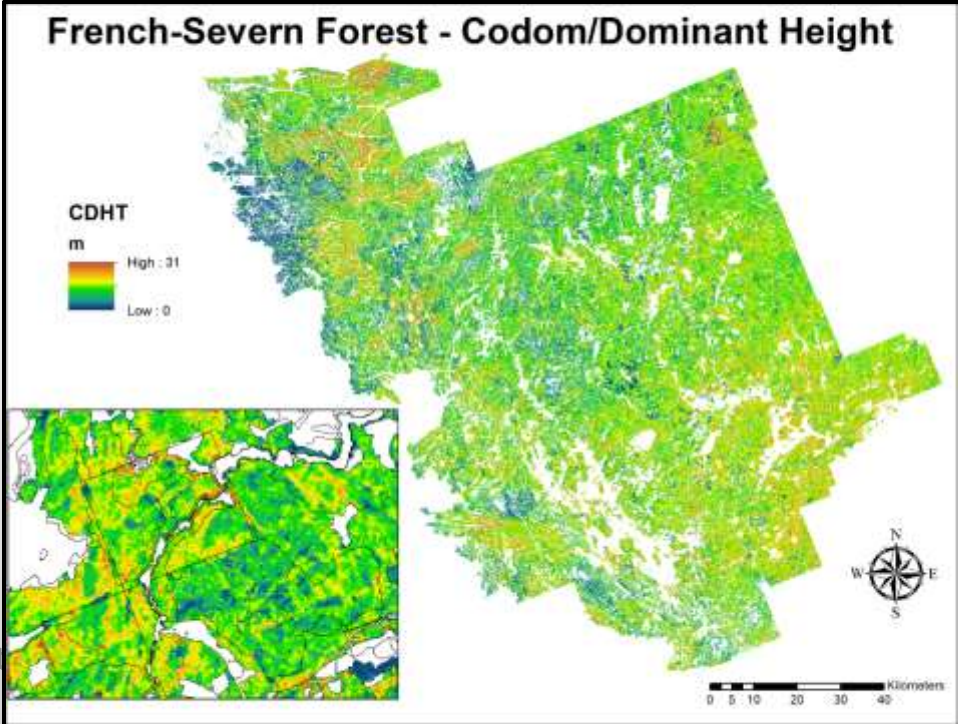
Romeo Malette Forest



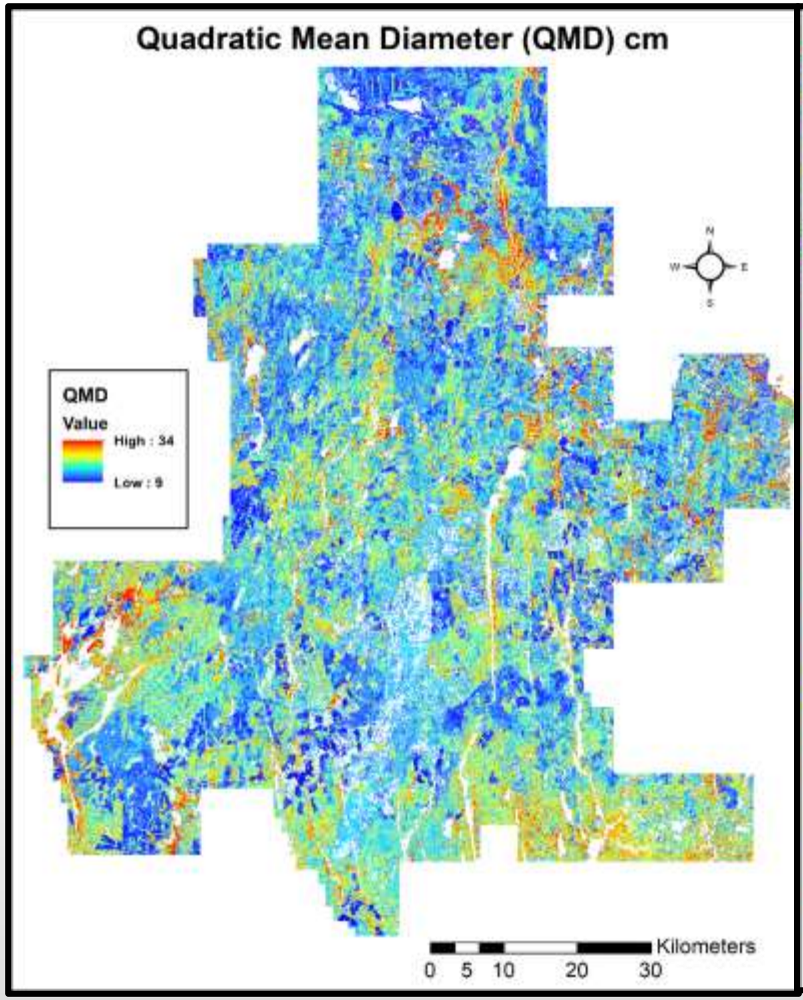
Dog River-Matawin Forest



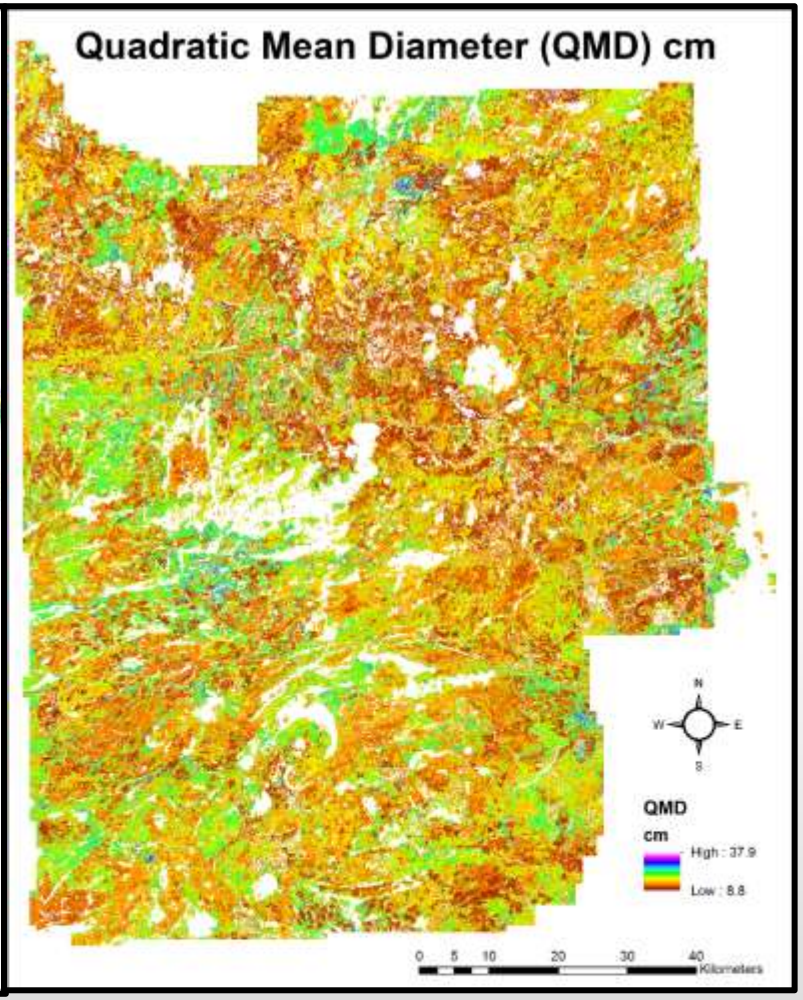


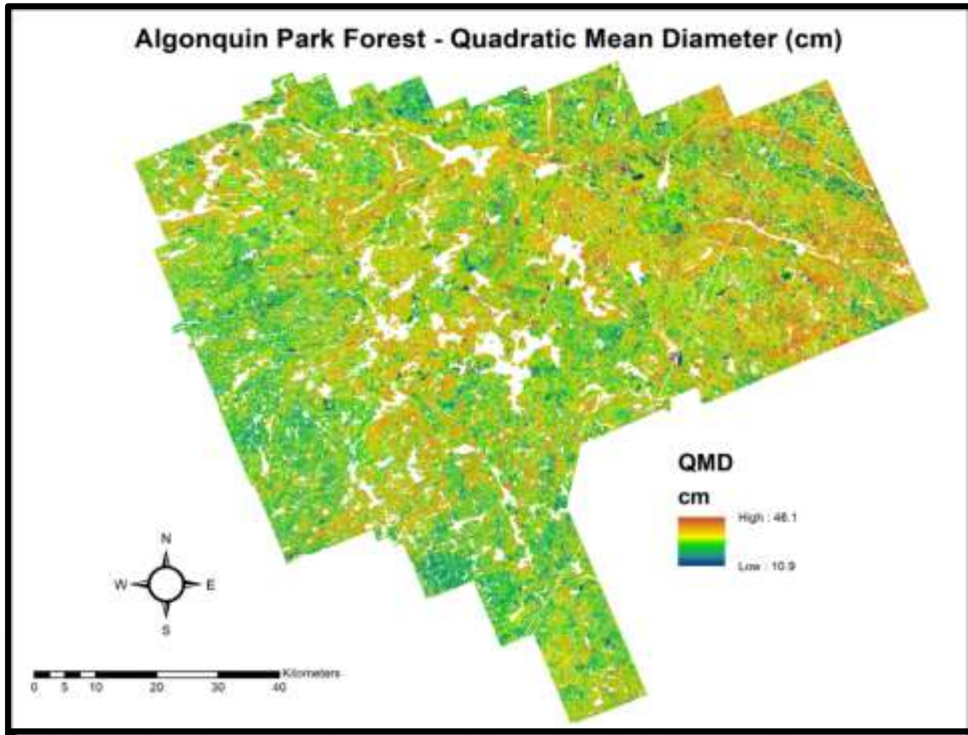


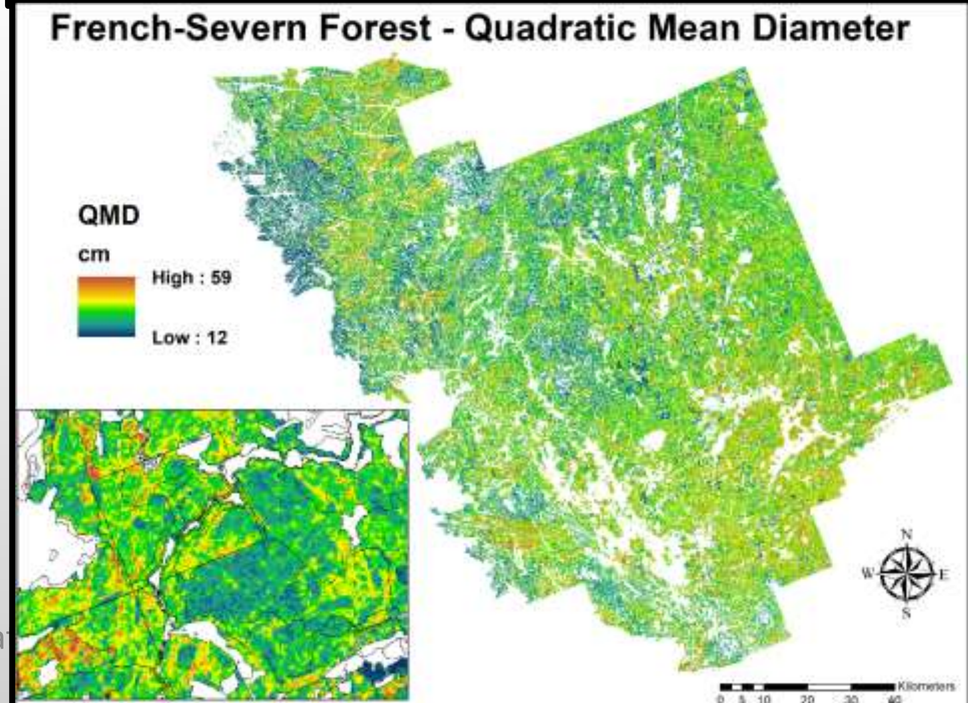
Romeo Malette Forest



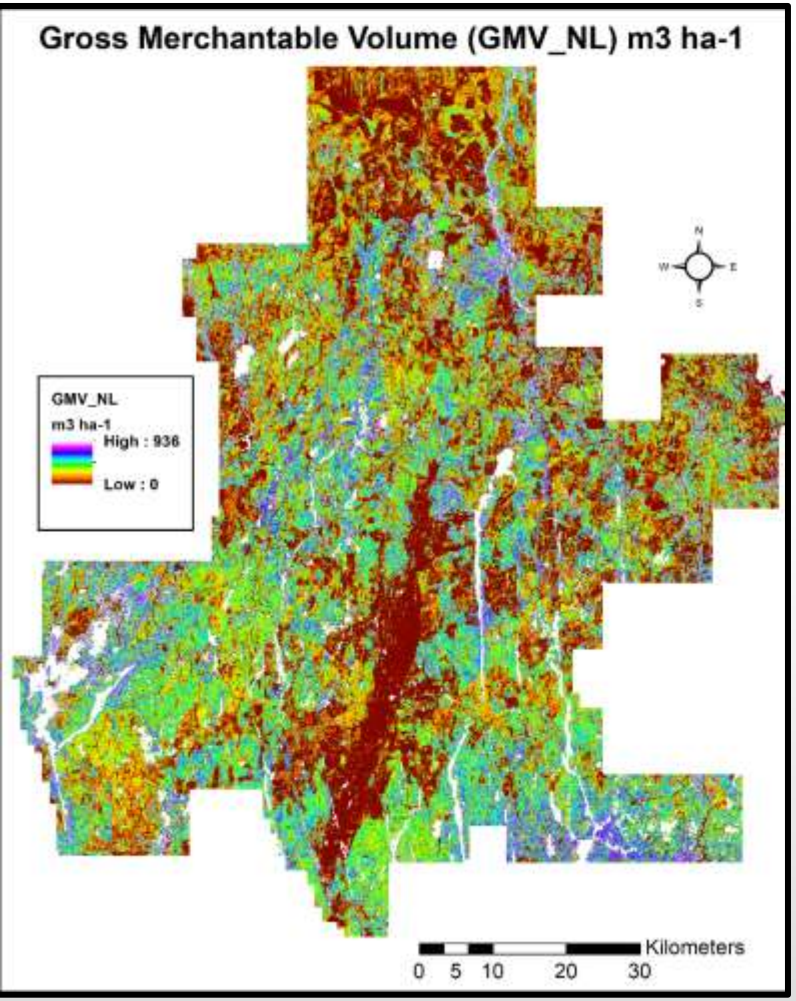
Dog River-Matawin Forest



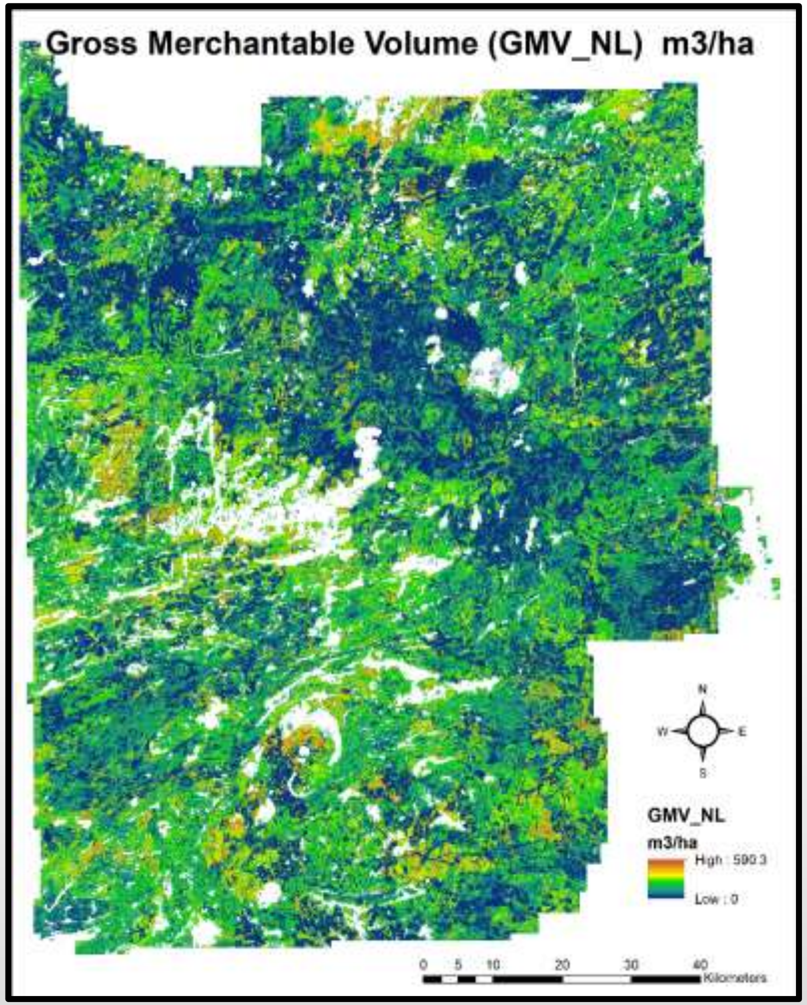


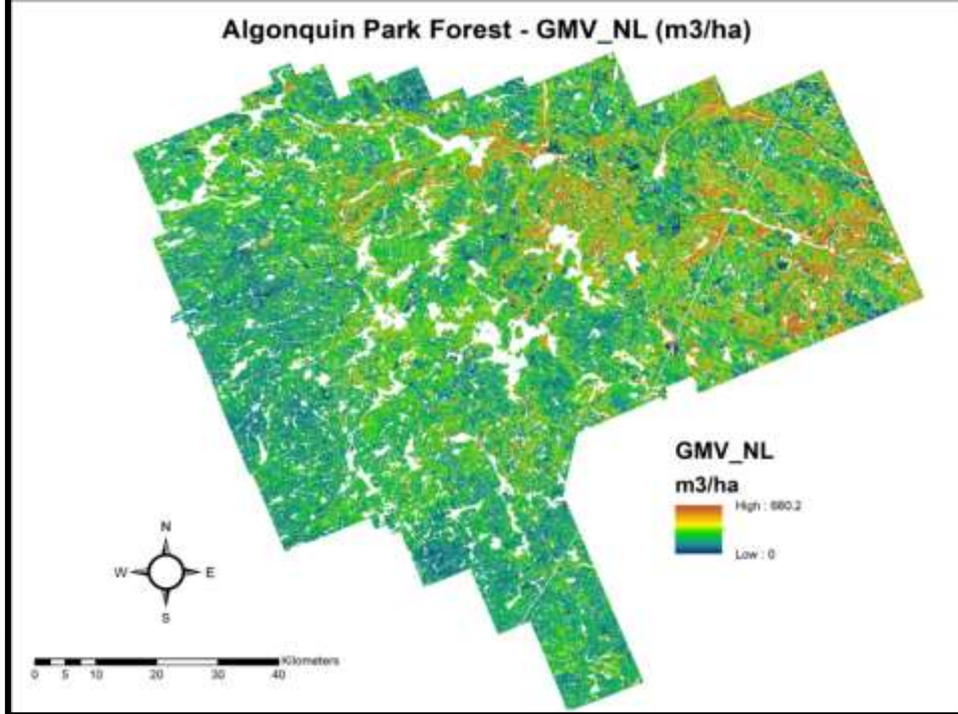


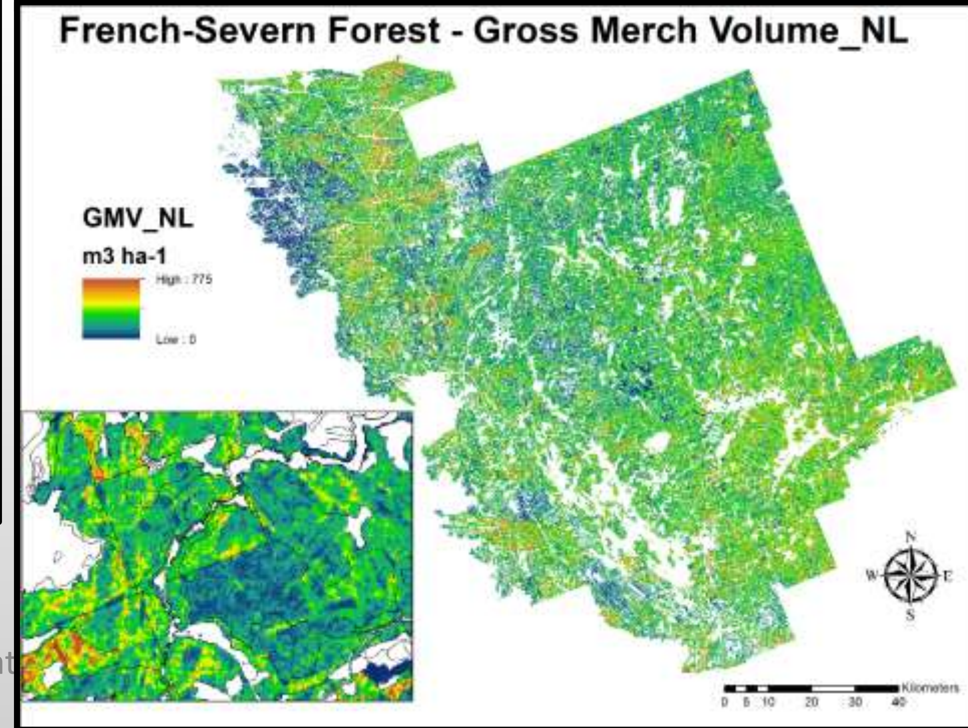
Romeo Malette Forest



Dog River-Matawin Forest



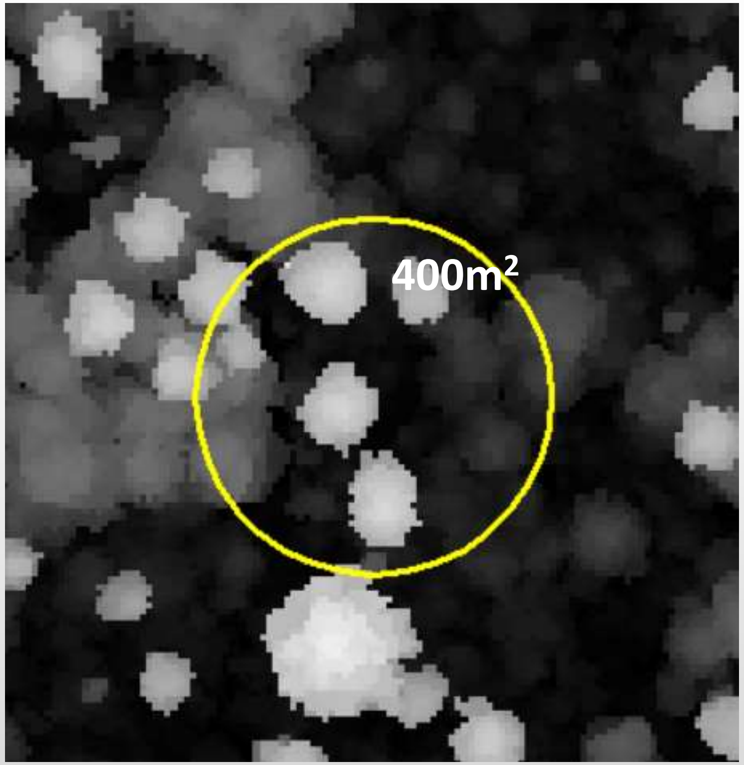


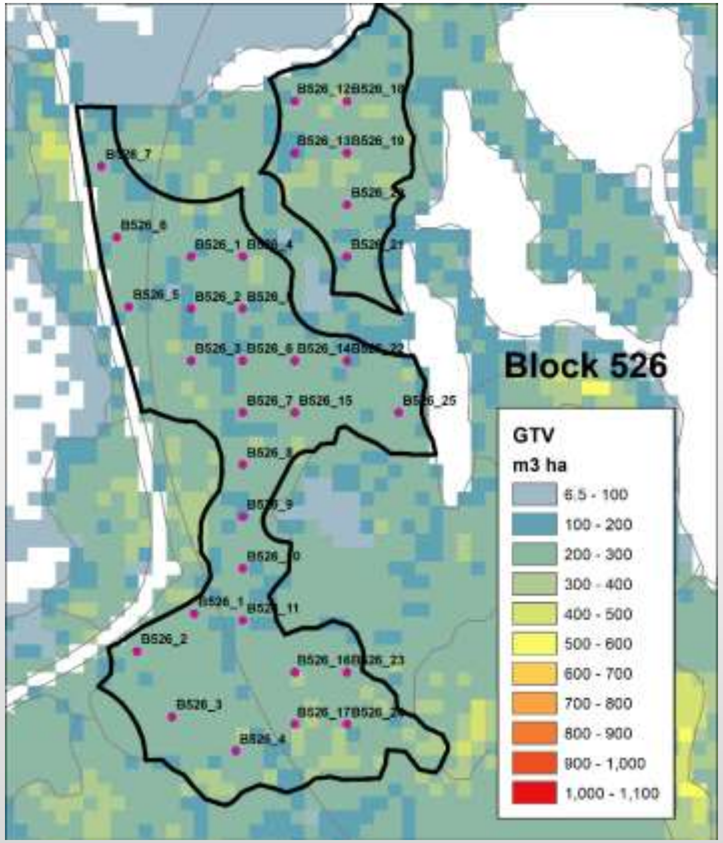


LiDAR Model Performance at 2 Scales

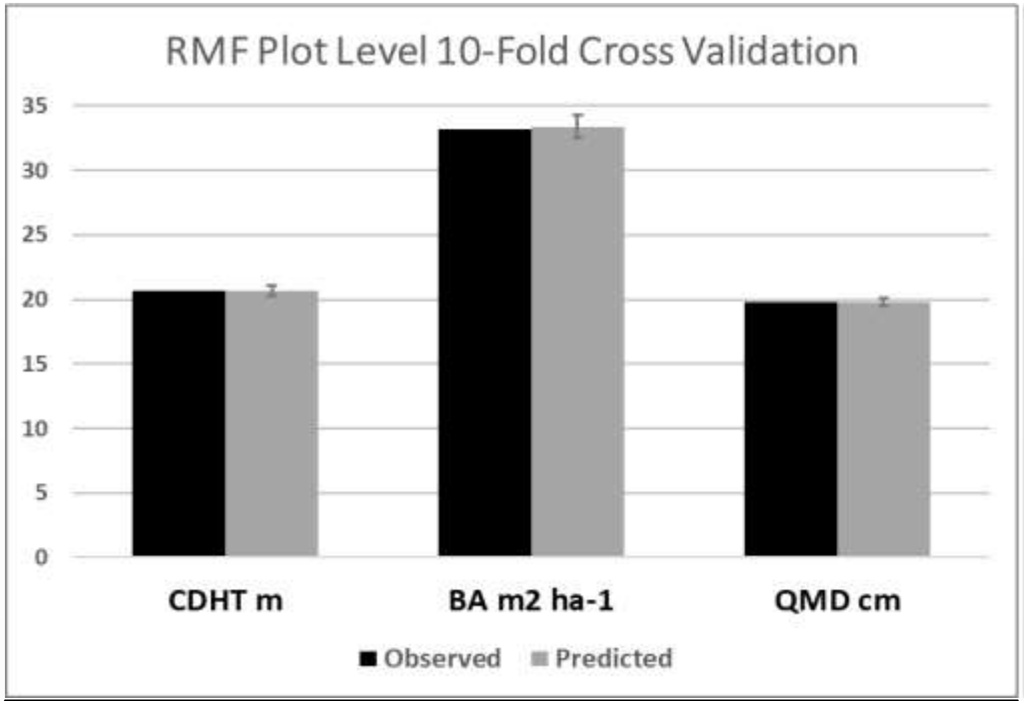
- Plot (cross-validation)
- Polygon*

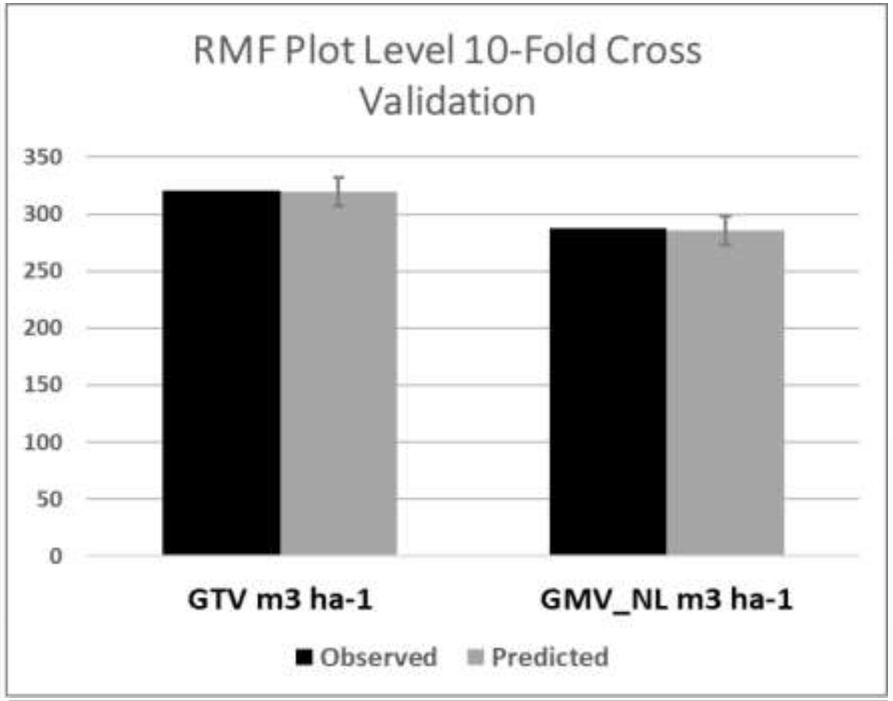
*Sample Size & Sampling Intensity Varied by Forest



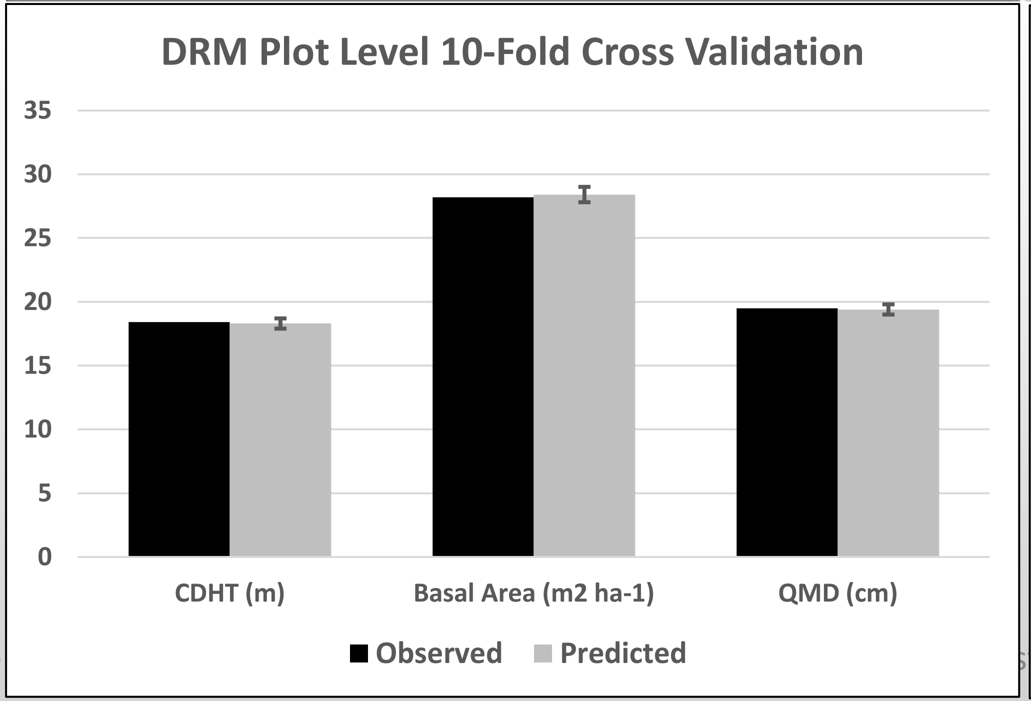


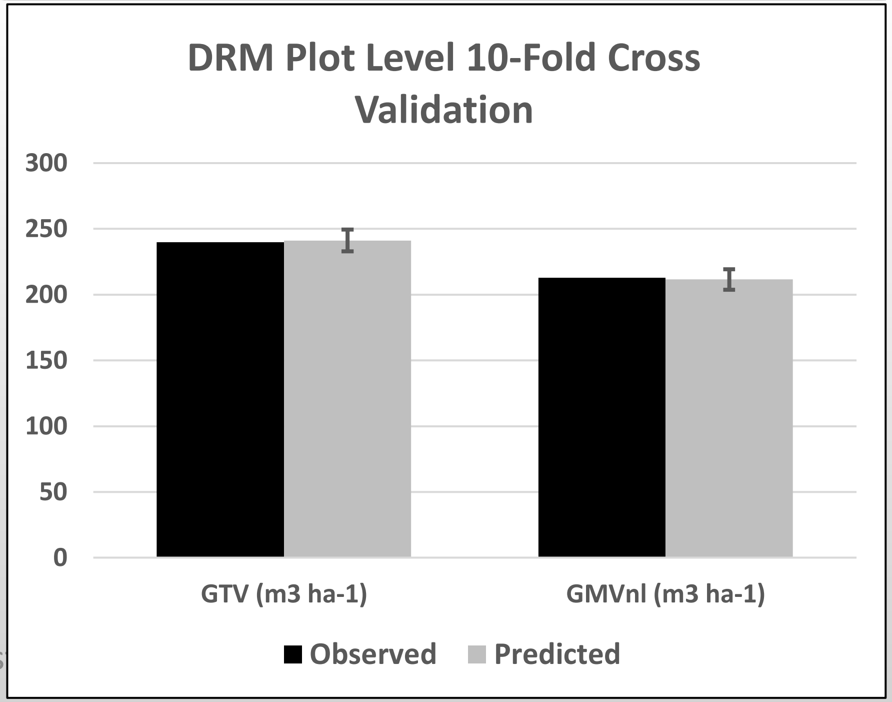
RMF





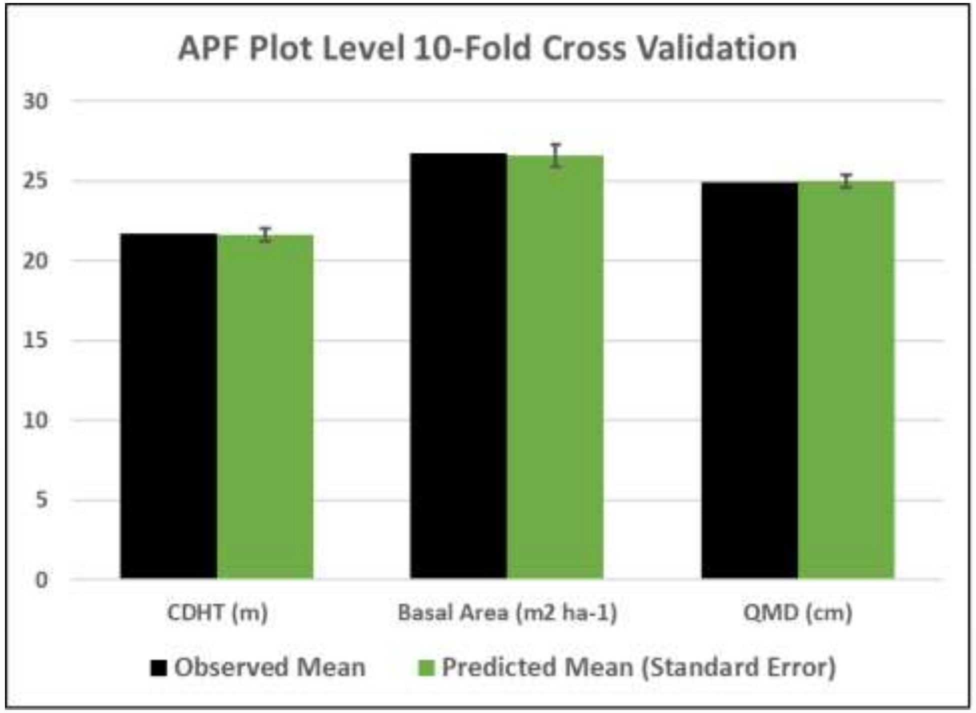
DRM

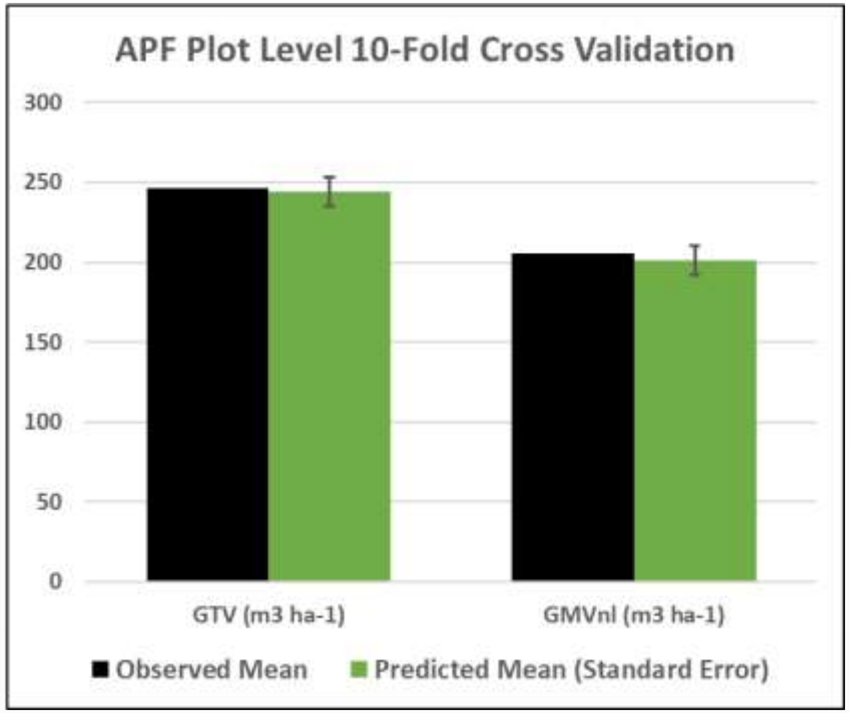




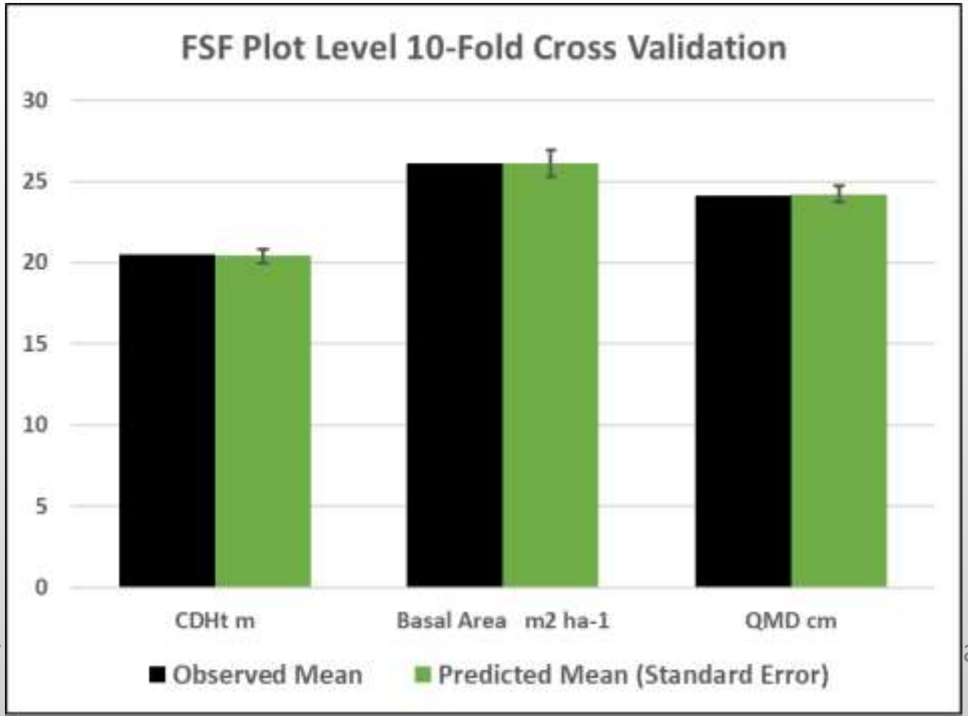
Standard Error

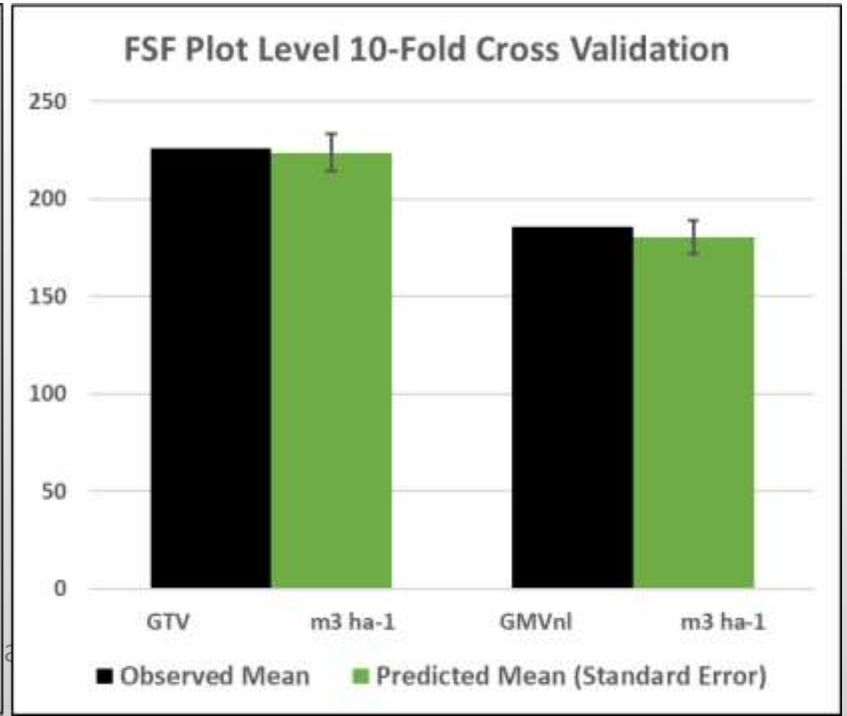
APF





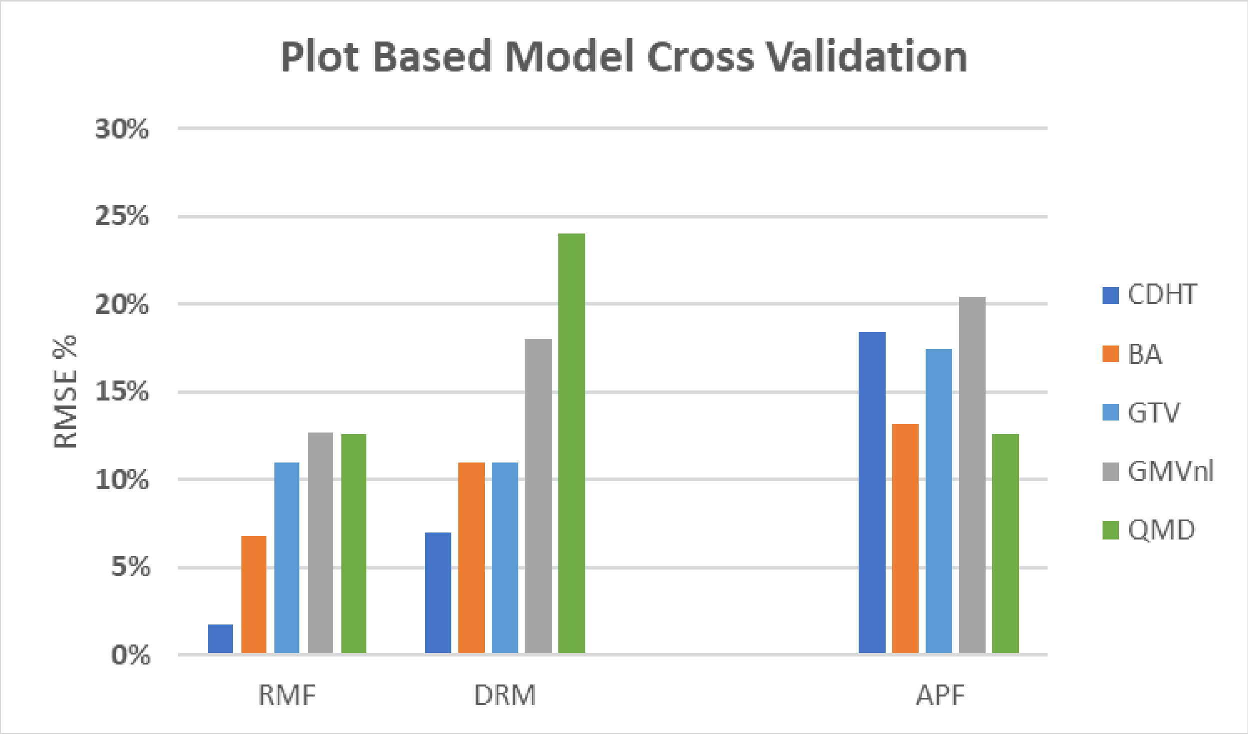
FSF

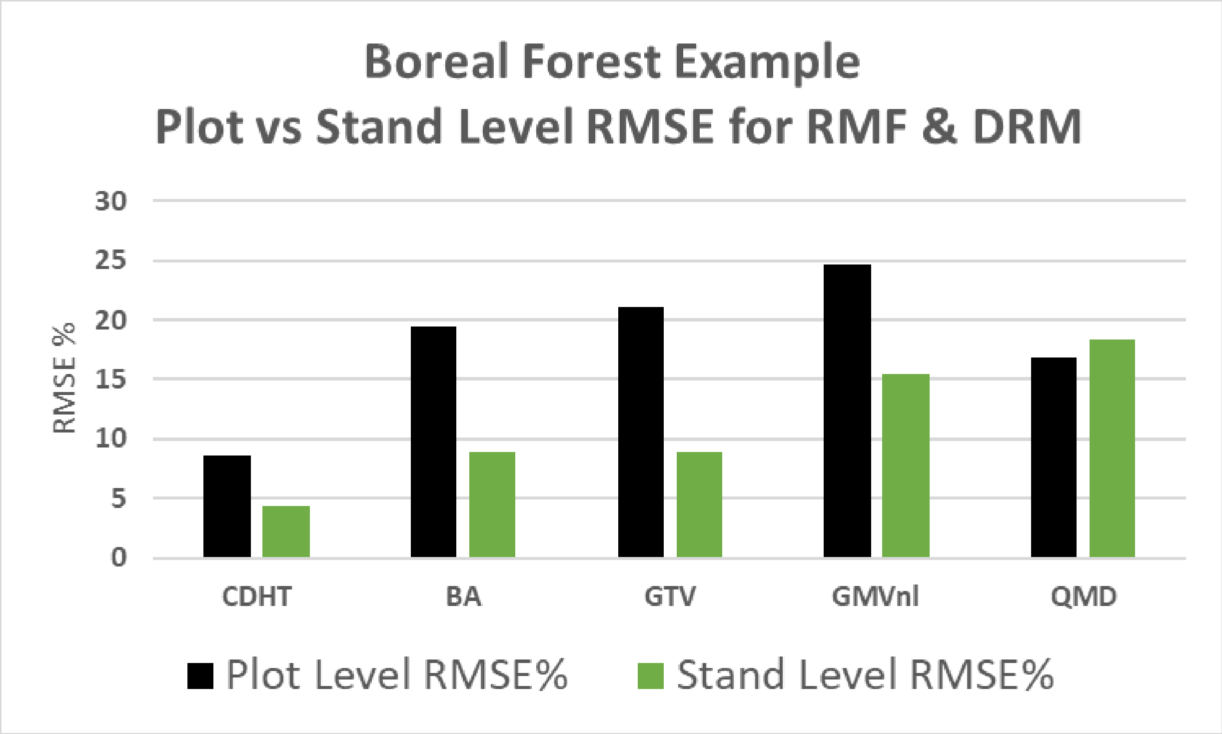




Standard Error

LiDAR model Validation – Plot vs Stand





RMF – 5 Stands
DRM – 9 Stands

Polygon

LiDAR Profile

103

107

114

116

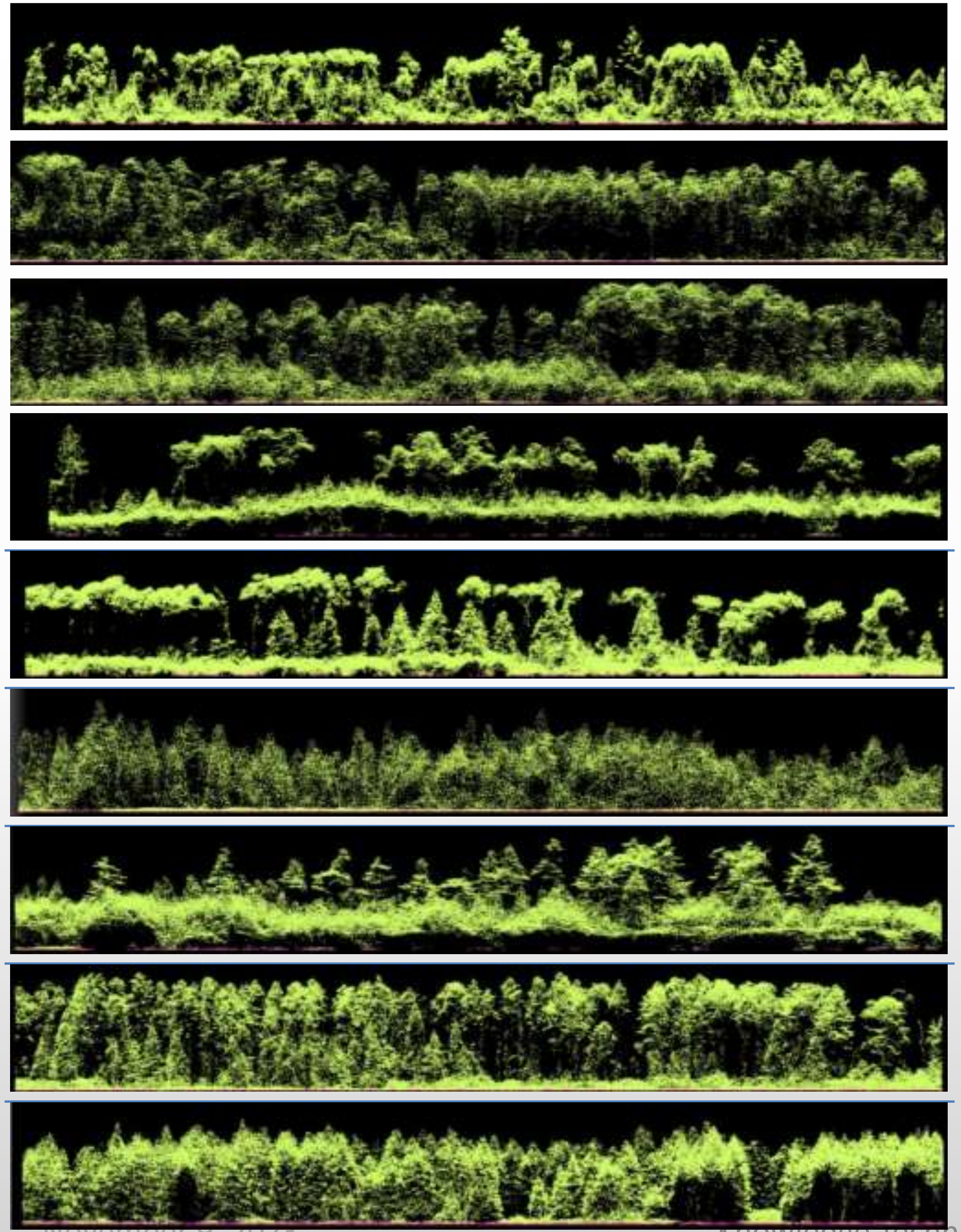
117

119

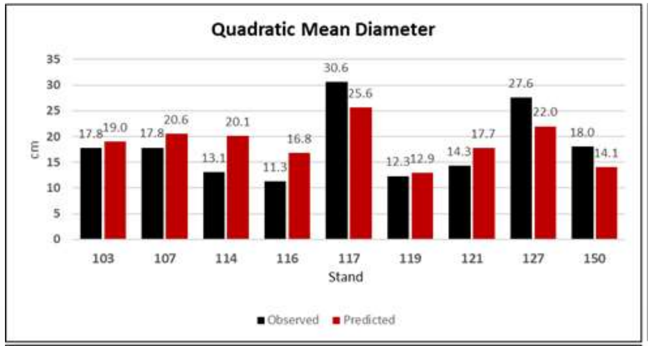
121

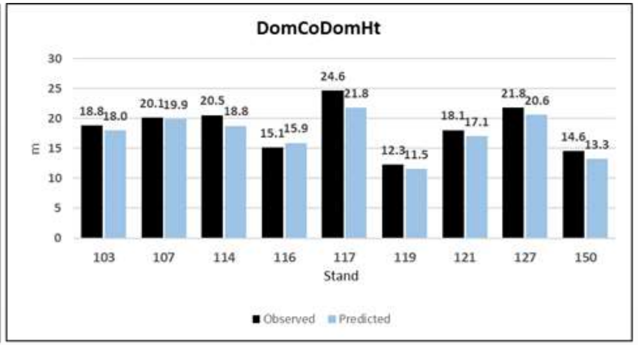
127

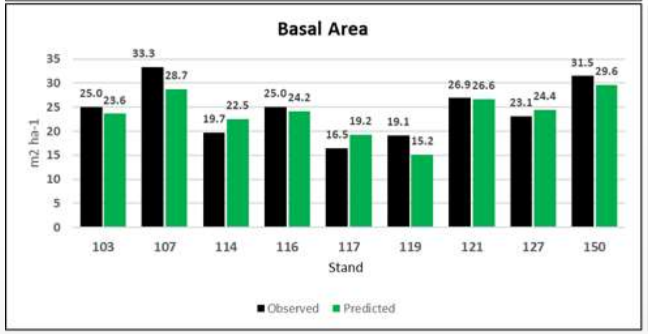
150

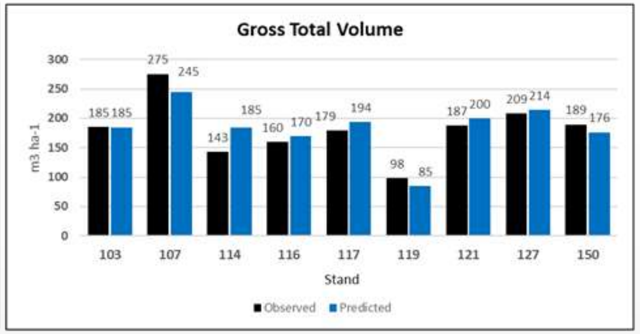


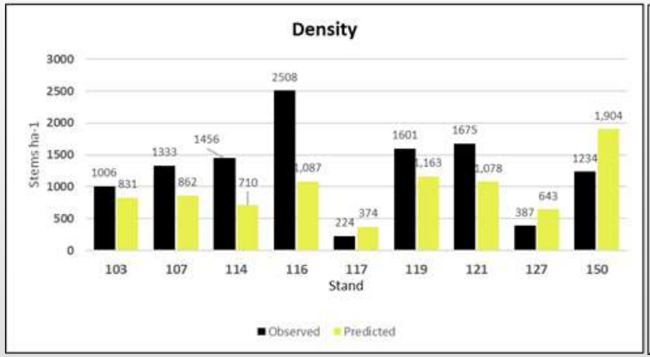
DRM Validation Stand Structure

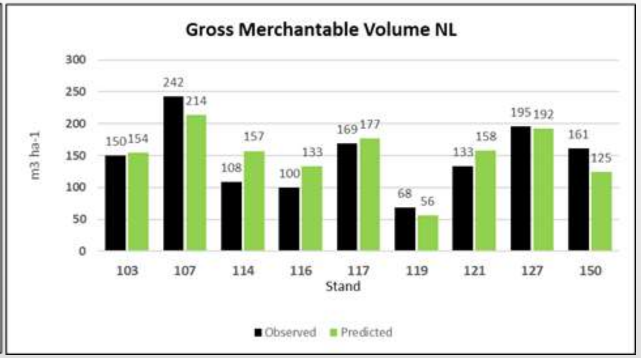




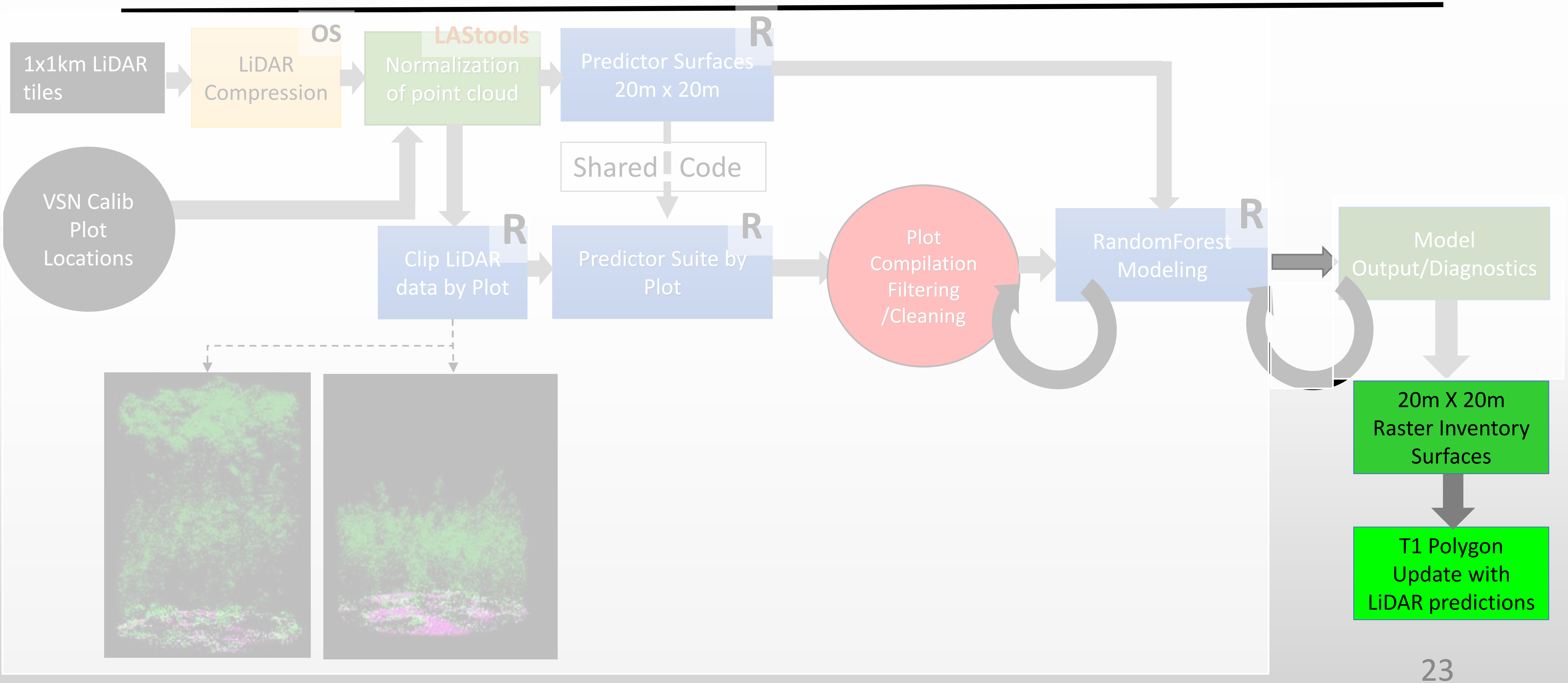








Updating T1 Inventories to T2 with LiDAR



Producing T2 – Raster summarized to Polygon Mean

Value for Biologists

Site Index = ƒ(Lead Spec, Age, Topht)

From T1 Inventory

POLYID	SPCOMP	AGE	CC2m	CC10m	SI	stocking	TOPHT	CDHT	LoreyHT	BA	BAmerch	Stems	QMD	GTV	GMV_NL	GMVnlQ15	GMVnlQ85	GMV_WL	Biomass
201	Mh 40Mr 20He 20By 10Be 10	97	95.1	86.7	13.1	0.9	21.5	19.2	19.5	24.7	24.0	610	22.7	189	144	109	183	136	173
202	He 40Mh 30By 10Sw 10Be 10	152	82.8	64.1	9.6	1	22.1	19.9	19.9	28.5	27.8	636	23.9	225	180	128	240	170	134
203	He 60By 20Pw 10Sw 10	132	98	84.5	10	1.2	22.1	19.4	19.7	32.5	31.9	723	23.9	253	192	134	255	182	161
204	He 70Mh 20By 10	107	85.6	70.4	10.6	1.2	20.5	18.5	18.3	29.5	28.8	692	23.3	215	160	130	197	149	132
205	Mh 50Mr 20By 20Pt 10	97	92.5	81.7	13.3	0.9	21.3	19.5	19.5	22.6	22.1	522	23.5	177	136	106	175	128	168
206	Mh 70By 10He 10Be 10	92	80.7	66.7	13.6	0.8	21.7	19.5	19.4	19.7	19.1	597	20.5	152	119	95	143	113	132
207	By 60Mh 20Mr 10He 10	92	92.8	78.5	14	0.8	21.8	19.5	19.6	21.8	21.1	567	22.1	169	131	98	171	123	157
73231	Pr 60Pj 20Pw 20	87	78.9	53	12.2	0.6	19.9	17.6	17.2	23.8	22.8	698	20.8	168	123	99	145	114	102

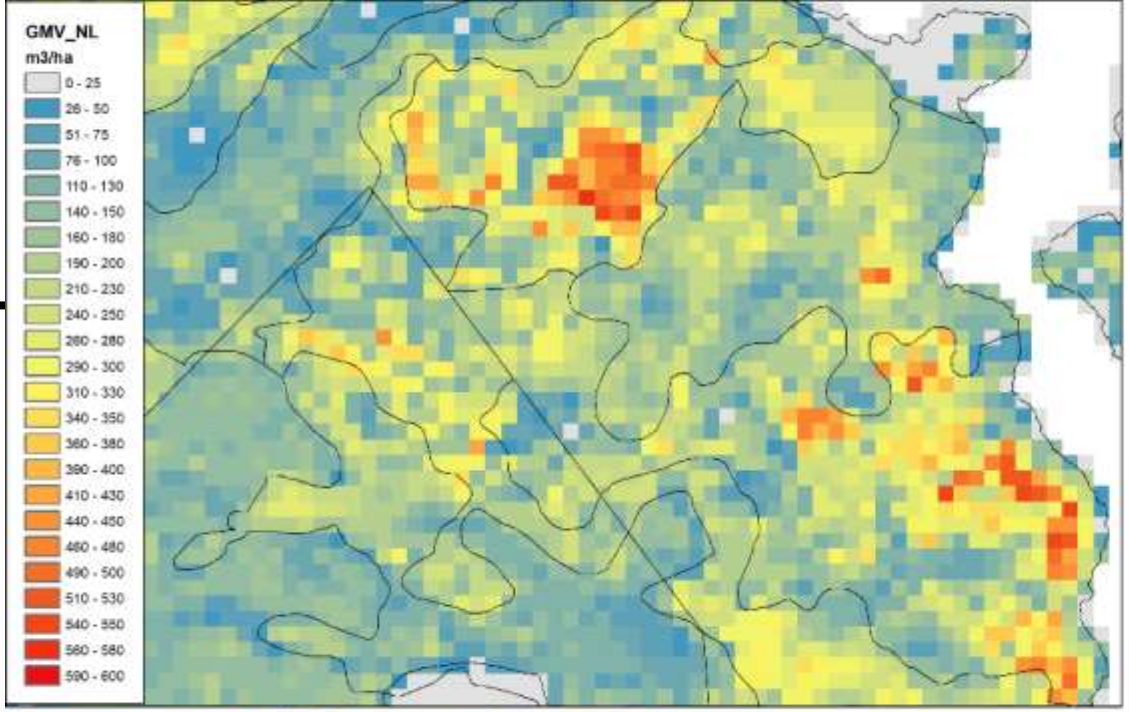
Size Class Predictions & NMV

Stocking = ƒ(Lead Spec, Age, BA, SI)

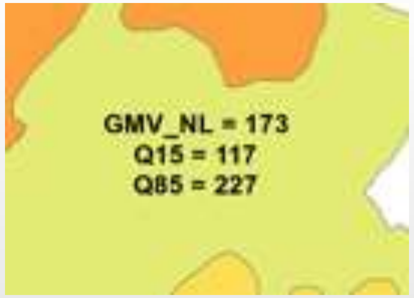
POLYID	SPCOMP	AGE	BA_Pole	BA_SmS	BA_MedS	BA_LgS	GMV_Pole	GMV_SmS	GMV_MedS	GMV_LgS	GMV_Util	Cull_frac	NMV_NL	NMV_WL	NMV_Util
201	Mh 40Mr 20He 20By 10Be 10	97	6.6	7	7	3.4	17.9	46.7	53.7	26.1	0	0.2	114	107	0
202	He 40Mh 30By 10Sw 10Be 10	152	8.3	6.5	9.2	3.8	27.6	45.1	75.2	31.6	0	0.2	144	136	0
203	He 60By 20Pw 10Sw 10	132	9.7	8.7	8.6	4.9	28.5	58.5	66	39.4	0	0.1	164	155	0
204	He 70Mh 20By 10	107	10.2	7.8	8.3	2.5	29.3	51.6	60.4	18.3	0	0.1	138	129	0
205	Mh 50Mr 20By 20Pt 10	97	6.1	7.2	6.7	2.1	17.2	49.4	52.4	17.2	0	0.3	101	95	0
206	Mh 70By 10He 10Be 10	92	6.3	4.2	6	2.6	20.3	29.7	47.6	21.6	0	0.2	93	88	0
207	By 60Mh 20Mr 10He 10	92	6.1	6.1	6.3	2.7	18.2	41.1	49.5	22	0	0.2	102	96	0
73231	Pr 60Pj 20Pw 20	87	10.6	5.5	5.1	1.6	36.7	35.8	38.1	12.4	13	0.0	120	112	13

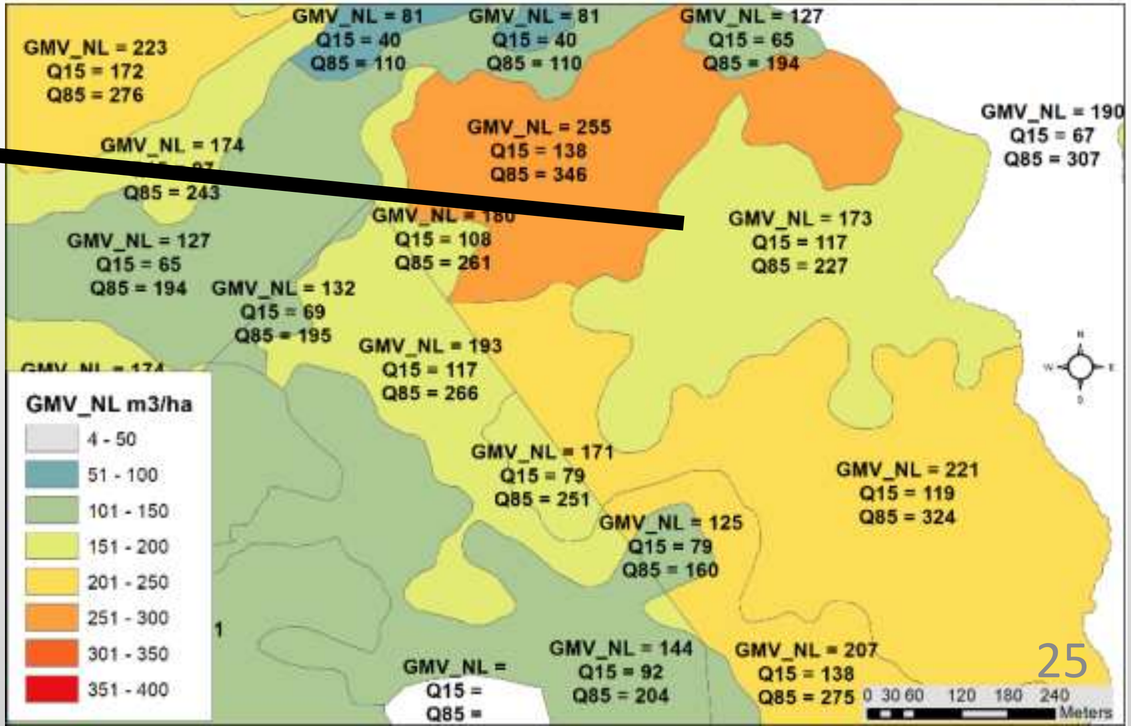
New GMV information

- Mean GMV
- Q15 GMV
- Q85 GMV



Example





Mean Stand GMV = 173 m^2 ha^{-1}

With 70% of grid cell GMV being between 117 & 227 m^2 ha^{-1}

T2 LiDAR Stand Constraints

Each polygon has full suite of inventory attributes **except:**

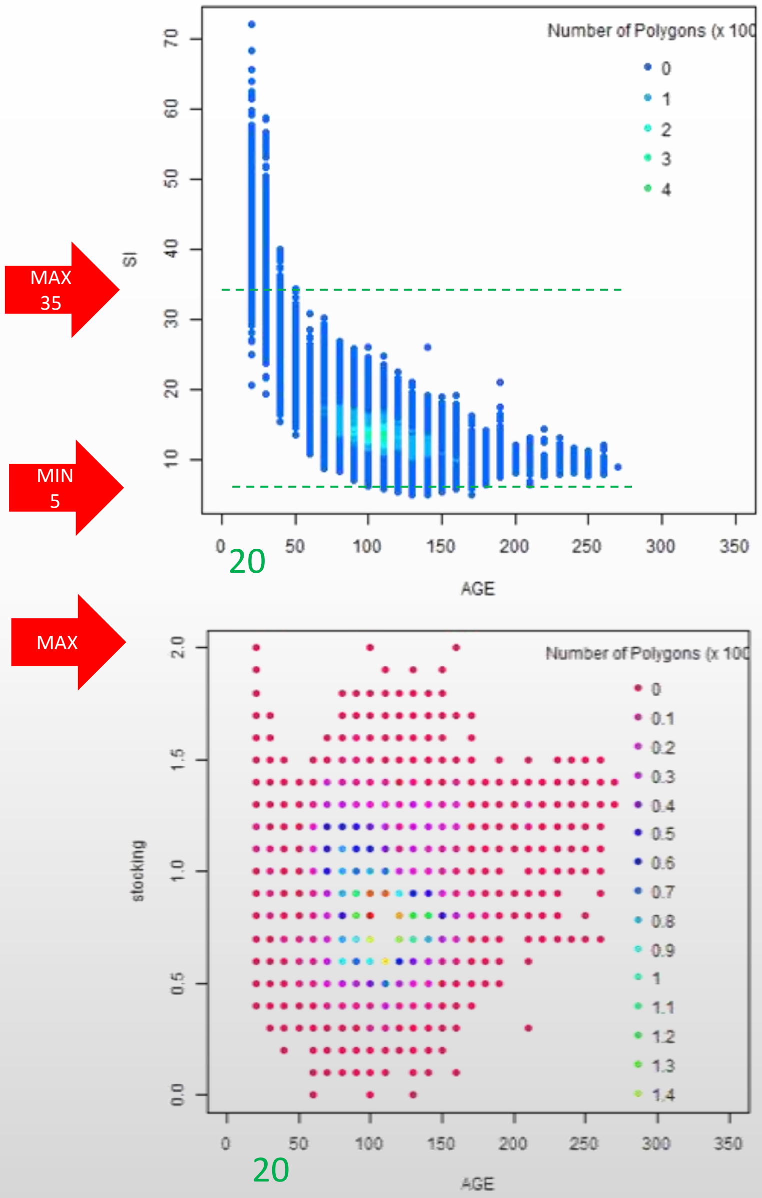
- If Stand age < 20 years old – No LiDAR derived attributes
- If zq99 < 5m, only CDht is replaced by zq99 ht and CC2 provided
- If zq99 < 9m, no merchantable volumes are estimated – or Ba/GMV by size classes are provided

	Polygon CDHT <5m	Polygon 5m > CDHT <9m	Polygon CDHT >9m
CC2m			
TOPHT	NULL		
CDHT	Zq99		
LoreyHT	NULL		
BA	0		
BAmerch	0	0	
Stems	0		
QMD	NULL		
GTV	0	0	
GMV_NL	0	0	
GMV_WL	0	0	
GMV_Util	0	0	
NMV_NL	0	0	
NMV_WL	0	0	
NMV_Util	0	0	
Biomass	0	0	
BA_Poles	0	0	
BA_SmSaw	0	0	
BA_MedSaw	0	0	
BA_LgSaw	0	0	
GMV_Poles	0	0	
GMV_SmSaw	0	0	
GMV_MedSaw	0	0	
GMV_LgSaw	0	0	
Site Index	NULL		
Stocking	NULL		
Cull Fraction	NULL	NULL	

Producing T2 – Challenges

- **SI calculation**
  - challenging with young stands
  - issue when interpreted age is low and LiDAR height is high

- **Stocking calculation**
  - Issue for young stands – requires BA – we have a 7.1cm min threshold



Project Reports/Presentations for each Forest available at http://www.forestryfutures.ca

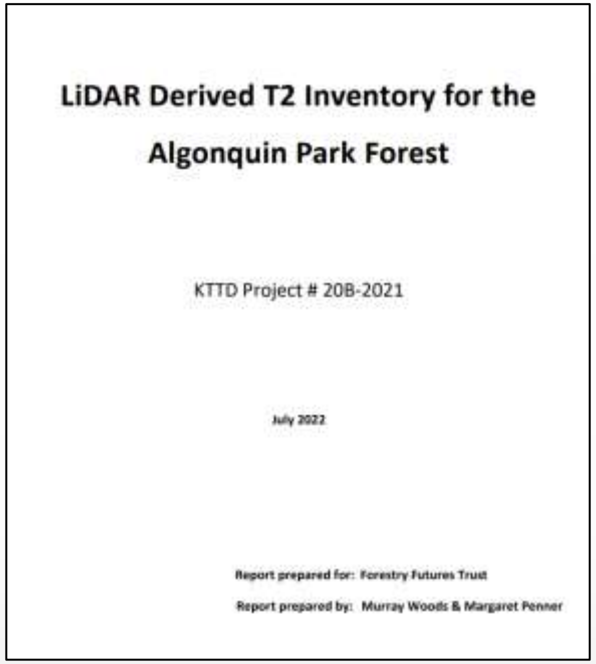

LiDAR Derived T2 Inventory for the Romeo Malette Forest

KTTD Project # 20B-2021

March 2022

Report prepared for: Forestry Futures Trust

Report prepared by: Murray Woods & Margaret Penner

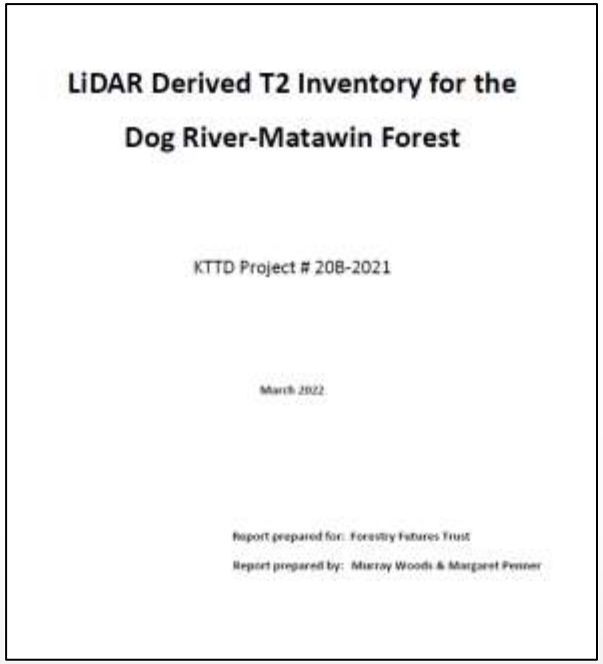

LiDAR Derived T2 Inventory for the Algonquin Park Forest

KTTD Project # 20B-2021

July 2022

Report prepared for: Forestry Futures Trust

Report prepared by: Murray Woods & Margaret Penner


LiDAR Derived T2 Inventory for the Dog River-Matawin Forest

KTTD Project # 20B-2021

March 2022

Report prepared for: Forestry Futures Trust

Report prepared by: Murray Woods & Margaret Penner

- R Code for Open-Source processing has been provided to FFT/FRI program for incorporation/sharing

Automated characterization of forest vertical structure using single photon LIDAR KTTD 10B-2021

Project Team
Margaret Penner
Joanne White
Murray Woods

GREENFIRST FOREST PRODUCTS

FORESTRY FUTURES TRUST ONTARIO

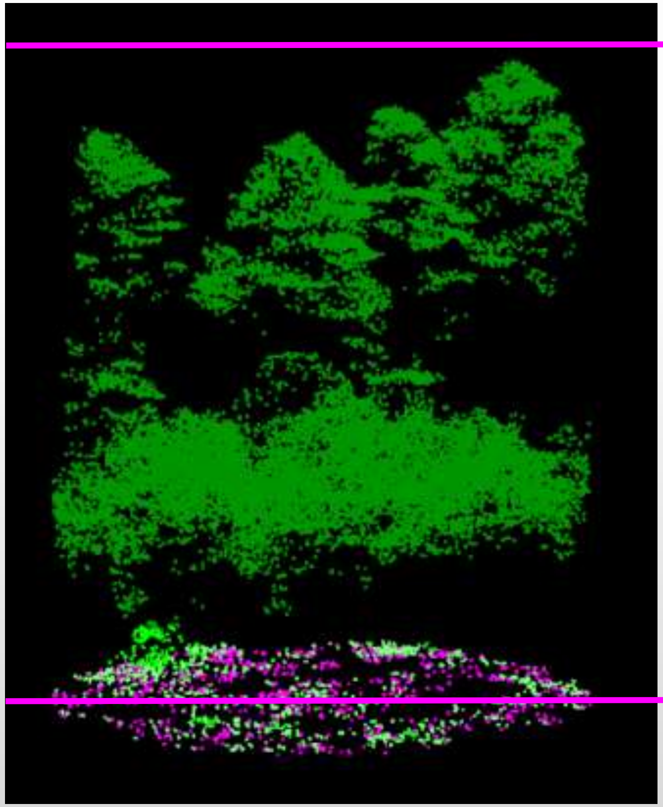
Government of Canada Gouvernement du Canada

ALGONQUIN FORESTRY AUTHORITY

Ontario
Ministry of Natural Resources and Forestry

ABA Enhancements Going Forward

Automated Characterization of Forest Vertical Structure

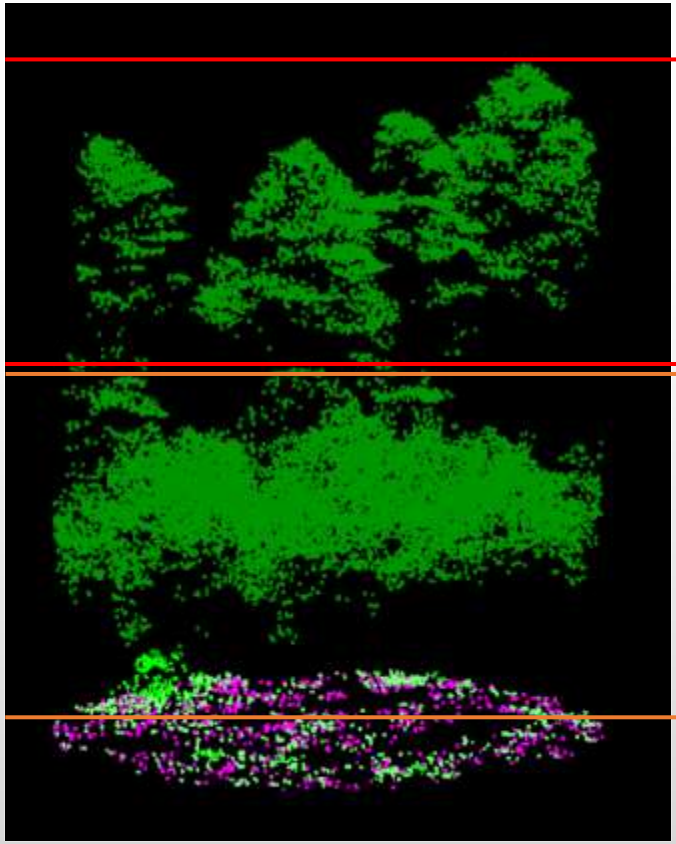


Current ABA Method

Single "Total" prediction of inventory Attributes

40.0 m

0.0 m

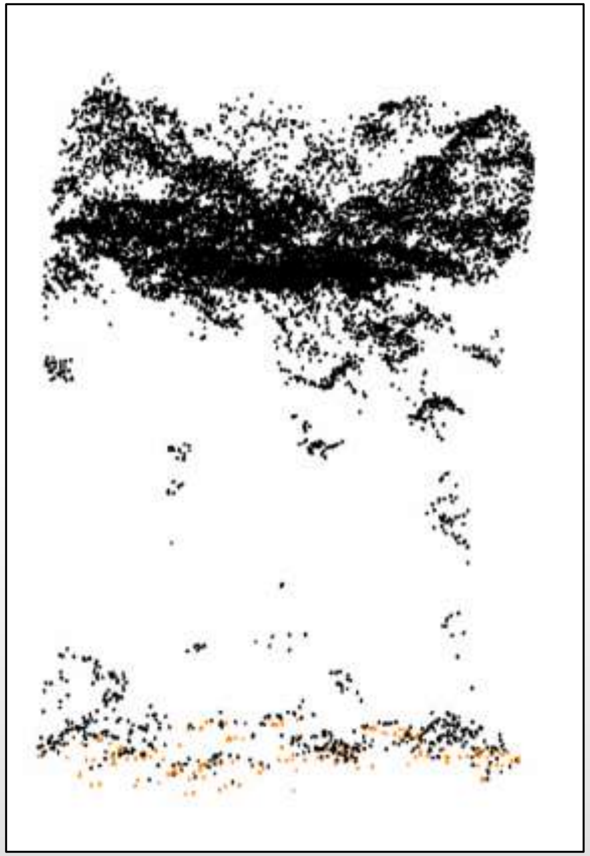


Layer 1 & Attributes

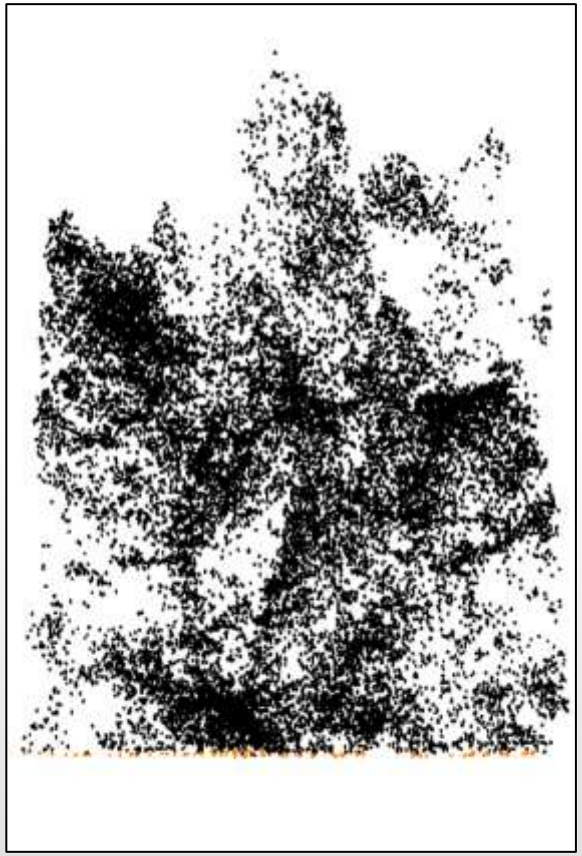
Layer 2 & Attributes

Structure Examples

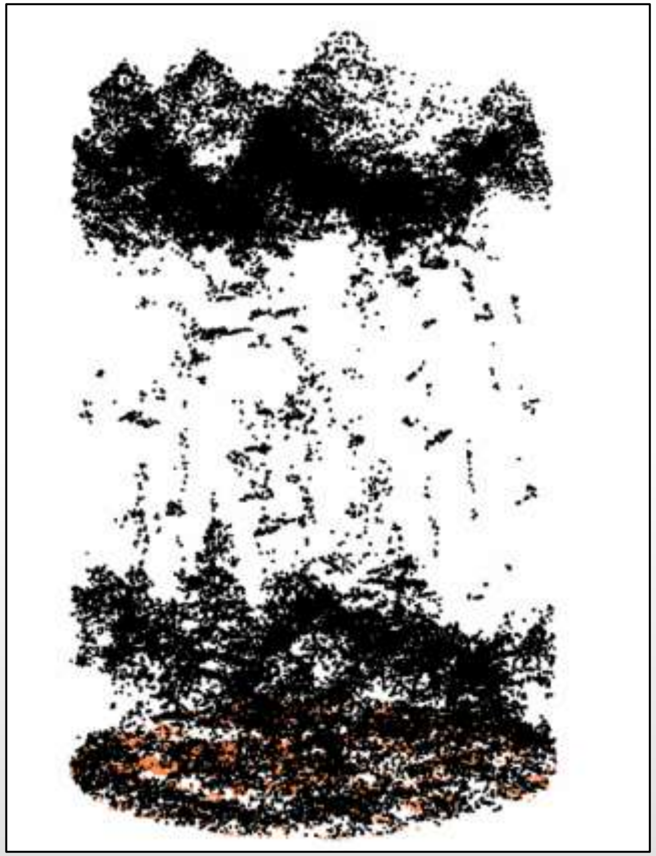
APF008
Mh82 CB18 BF1
Single



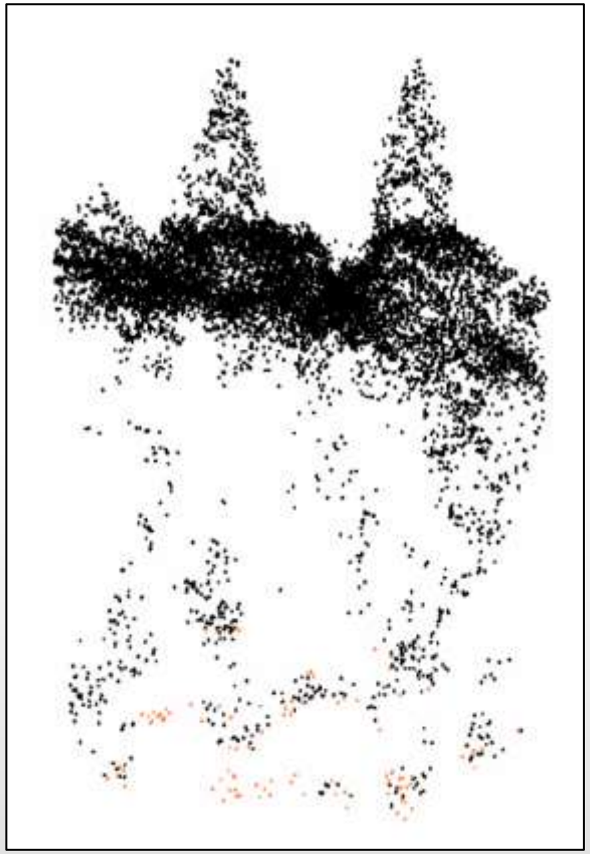
APF004
Cw83 Bf10 Bw4 Sw3
Complex



APF012
Pr88 Pw12 Mr0 Bf0
Two-Tiered

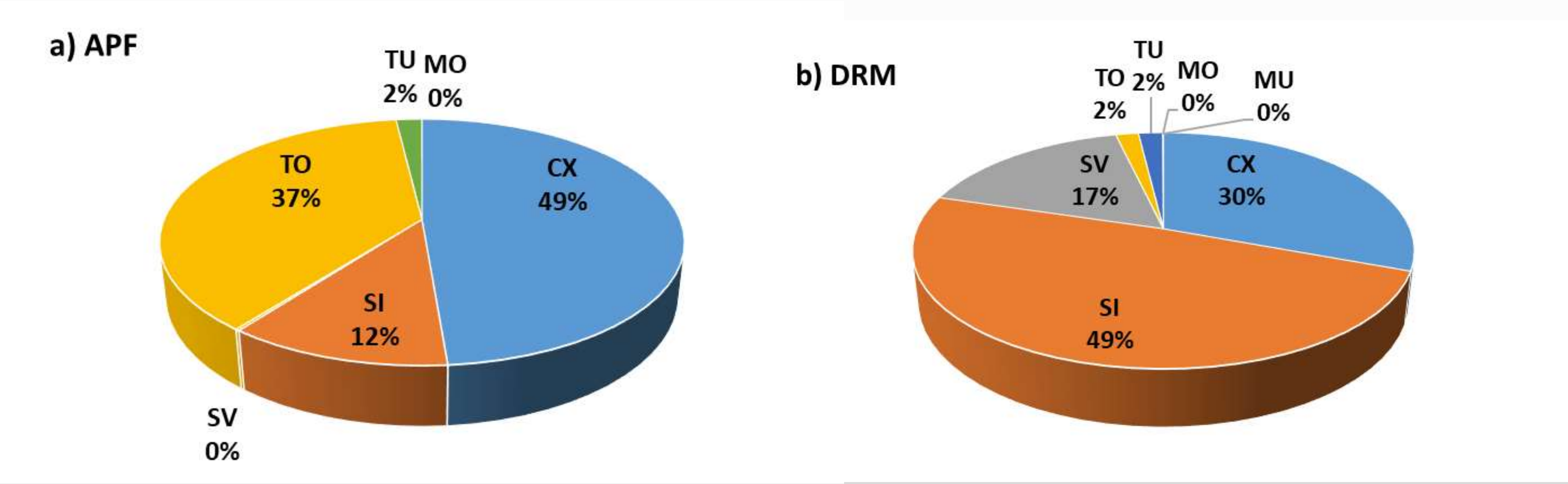


APF178
Mh56 Ce29 Sw14 By1 Be1
Single with Veterans



ABA Enhancements Going Forward

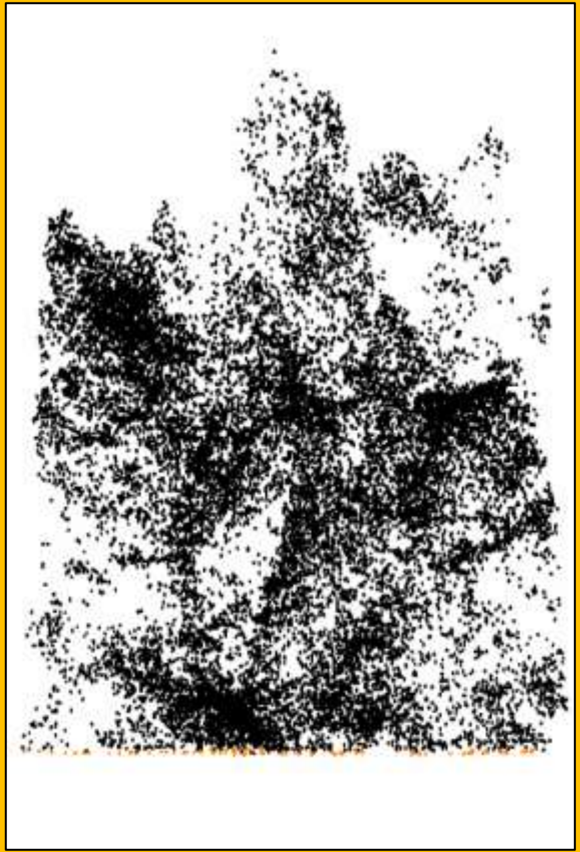
Automated Characterization of Forest Vertical Structure



Structure Examples

APF008
Mh82 CB18 BF1
Single

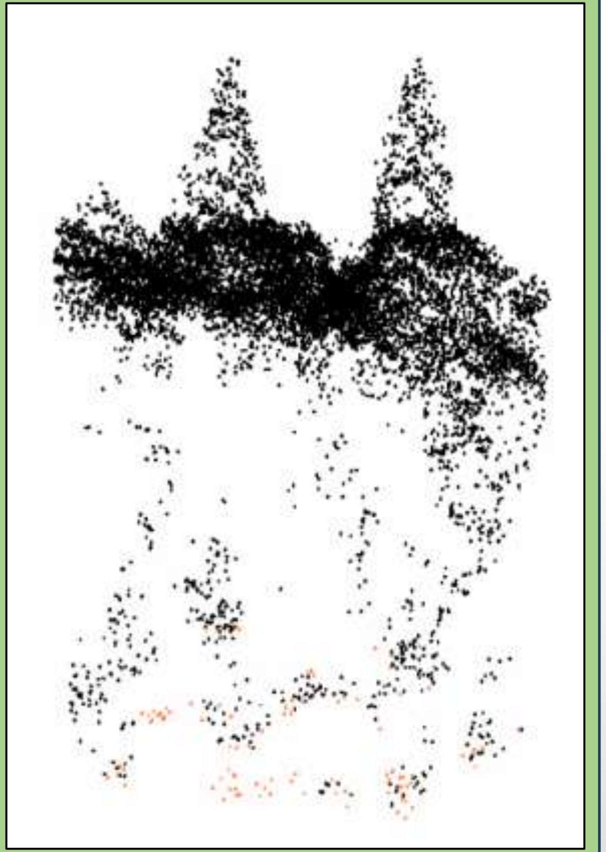
APF004
Cw83 Bf10 Bw4 Sw3
Complex



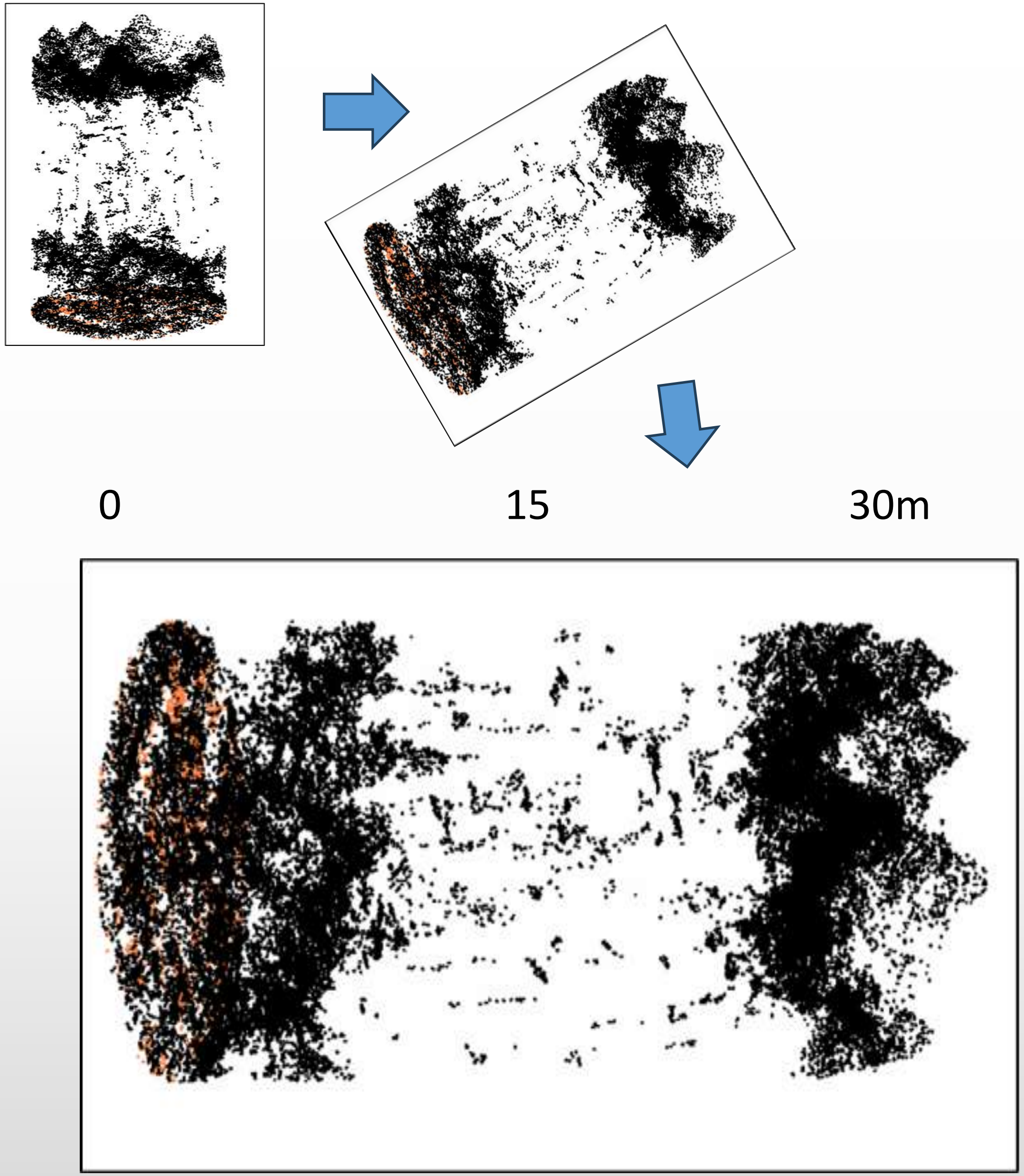
Treated as a Single Layer Prediction

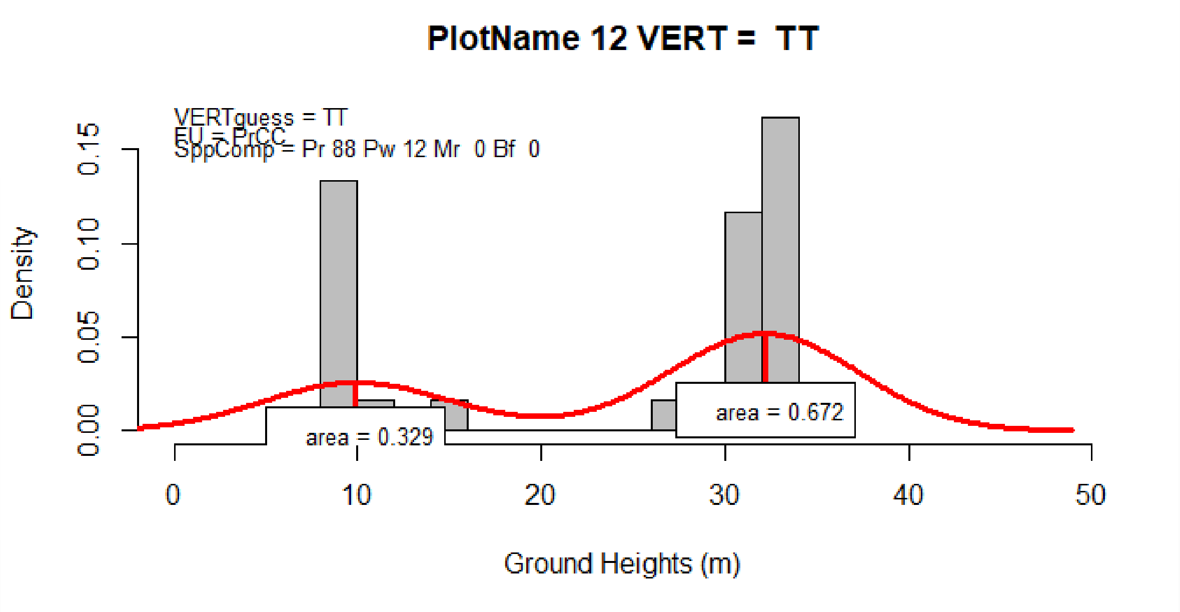
APF012
Pr88 Pw12 Mr0 Bf0
Two-Tiered

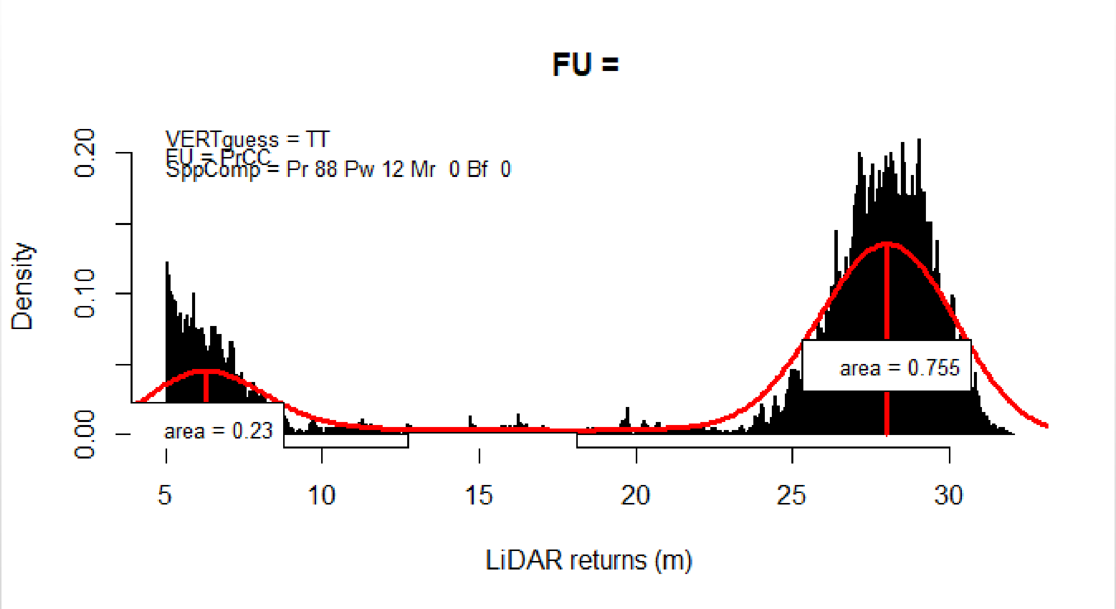
APF178
Mh56 Ce29 Sw14 By1 Be1
Single with Veterans



Predictions by Layer


0
15
30m


PlotName 12 VERT = TT
VERTguess = TT
EU = PrCC
SppComp = Pr 88 Pw 12 Mr 0 Bf 0
Density
0.00
0.05
0.10
0.15
area = 0.329
area = 0.672
0
10
20
30
40
50
Ground Heights (m)

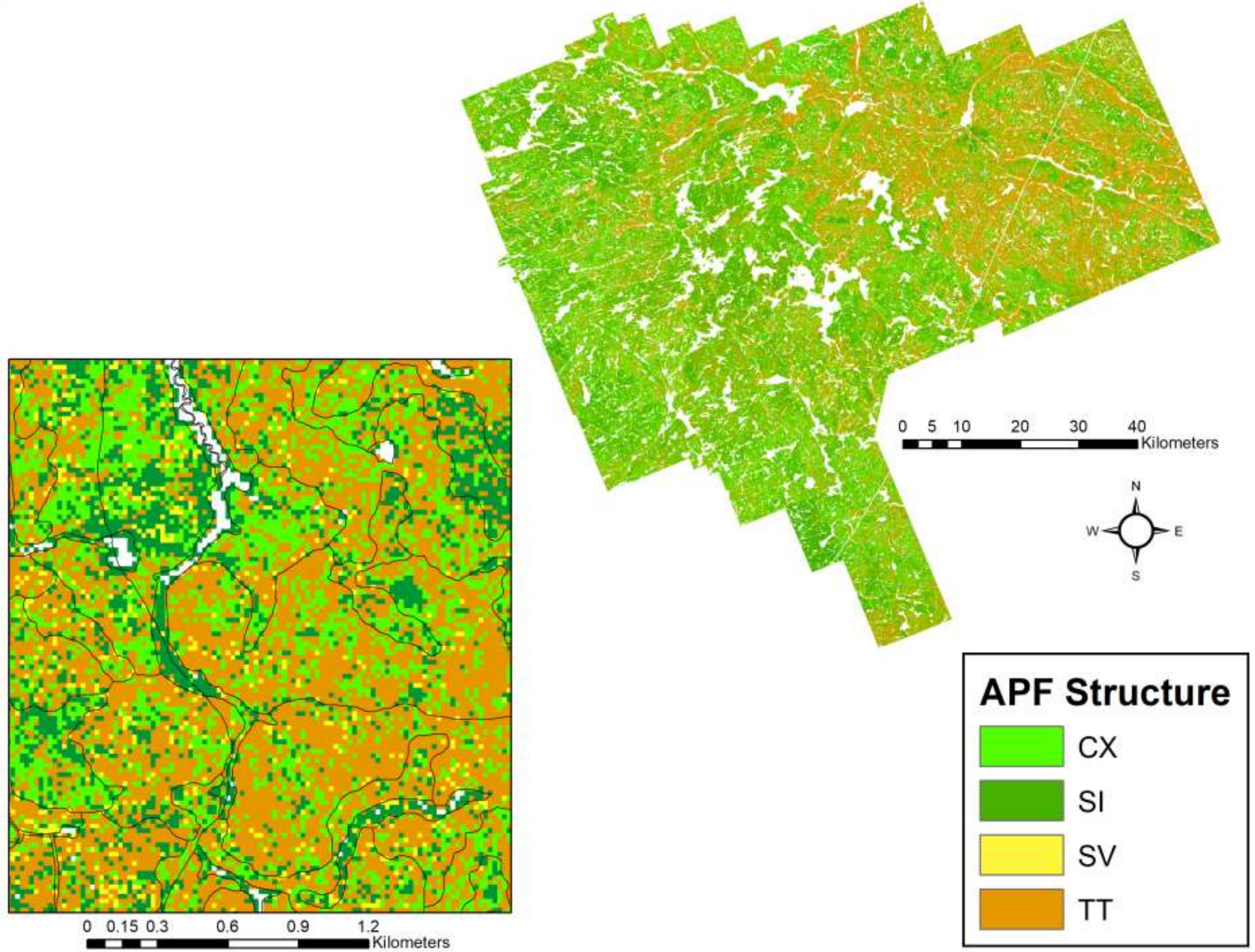

FU =
VERTguess = TT
EU = PrCC
SppComp = Pr 88 Pw 12 Mr 0 Bf 0
Density
0.00
0.10
0.20
area = 0.23
area = 0.755
5
10
15
20
25
30
LiDAR returns (m)

Predicting 20m x 20m Structure Classes for Algonquin Park Forest

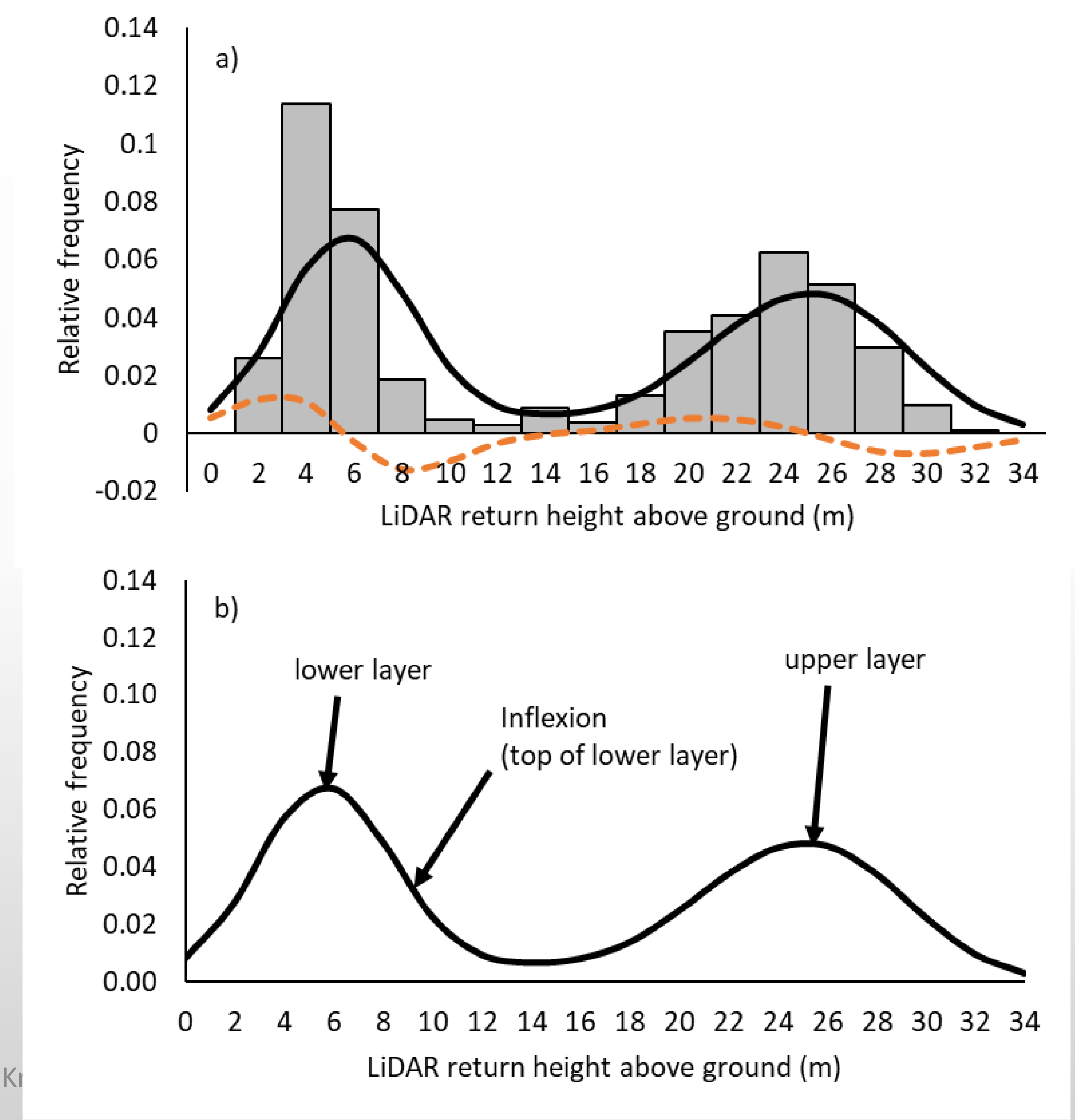
4-class system					
	Predicted				User Accuracy
Reference	CX	SI	SV	TO	
CX	14	5	2	16	38%
SI	2	63	2	17	75%
SV	3	4	9	6	41%
TO	10	15	3	95	77%
Producer Accuracy	48%	72%	56%	71%	OA 68%

2-class system			
	Predicted		User Accuracy
Reference	CX or SI	SV or TO	
CX or SI	84	37	69%
SV or TO	32	113	78%
Producer Accuracy	72%	75%	OA 74%

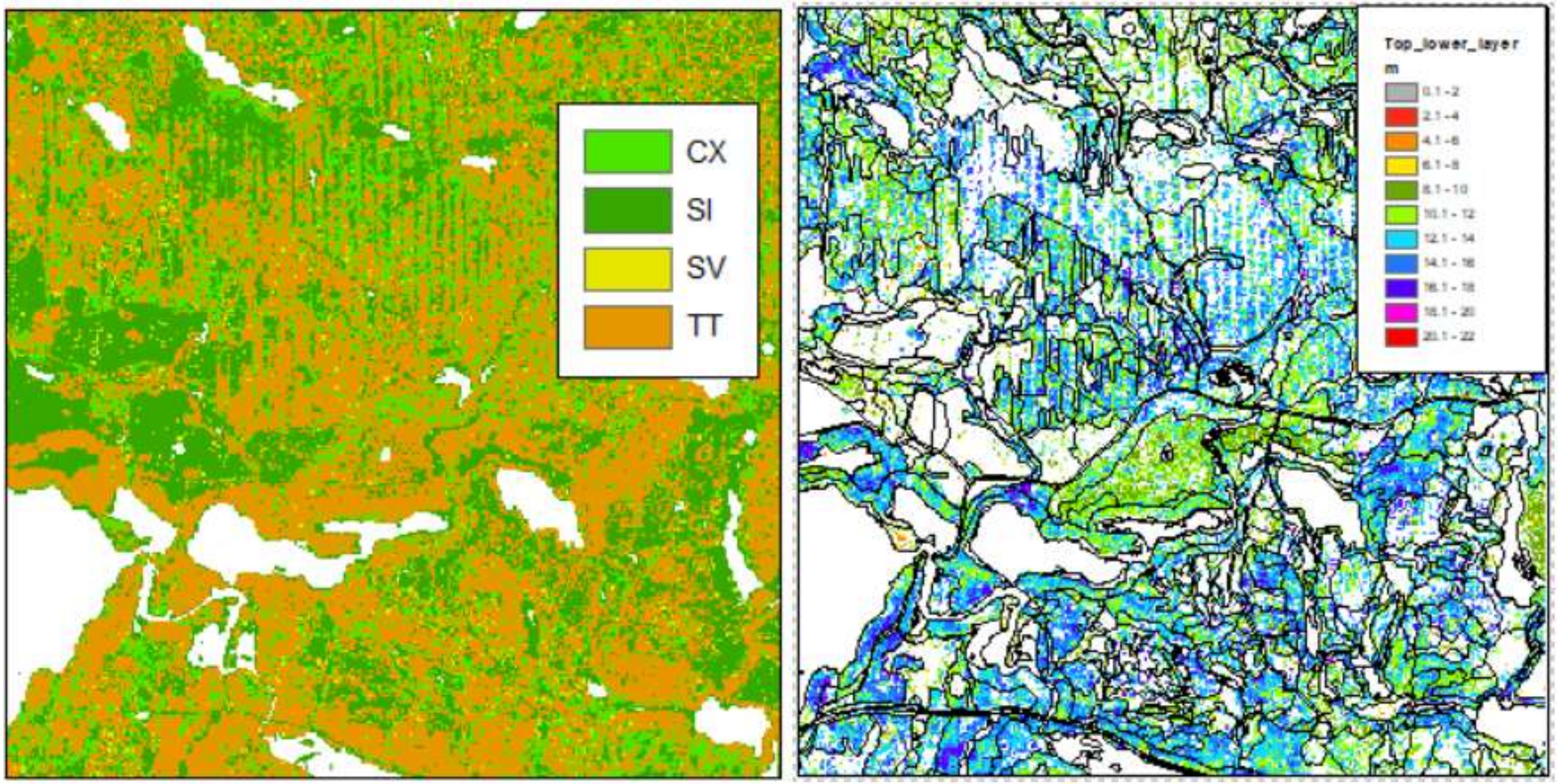
20m x 20m Prediction of Vertical Structure for the Algonquin Park Forest



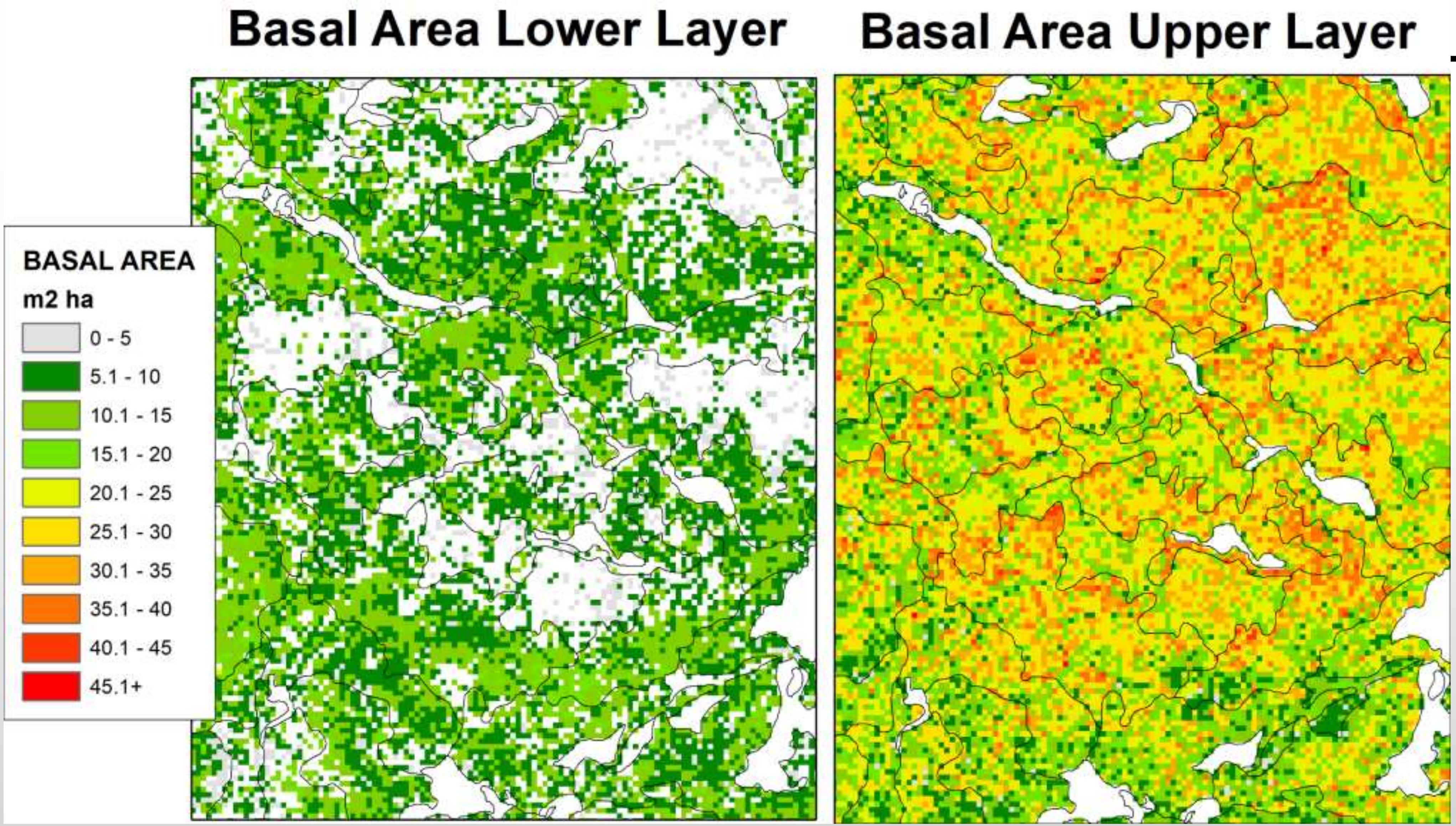
Determination of Layer Height Thresholds



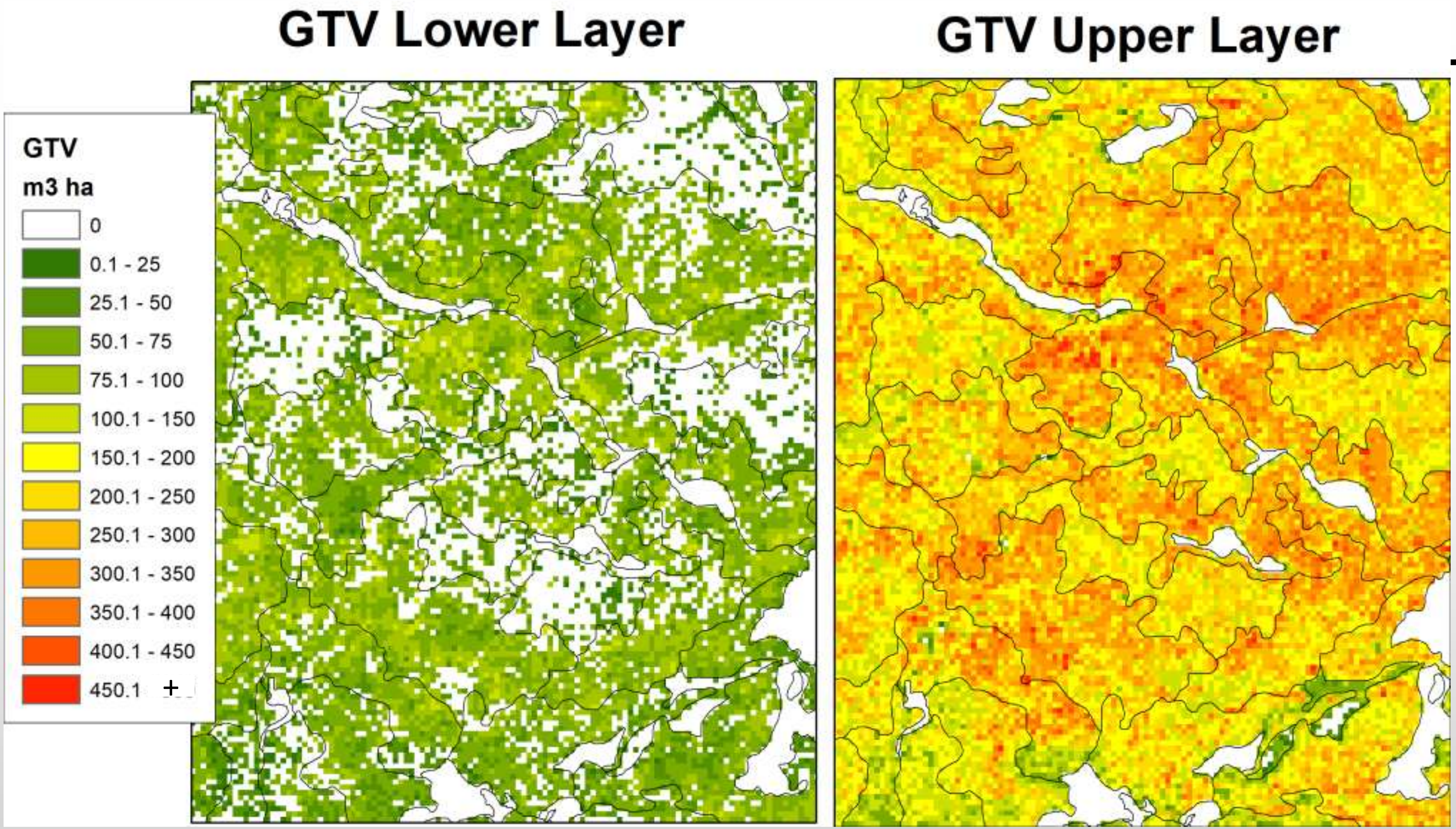
Top of Lower Layer Raster prediction for Two-Tier Conditions



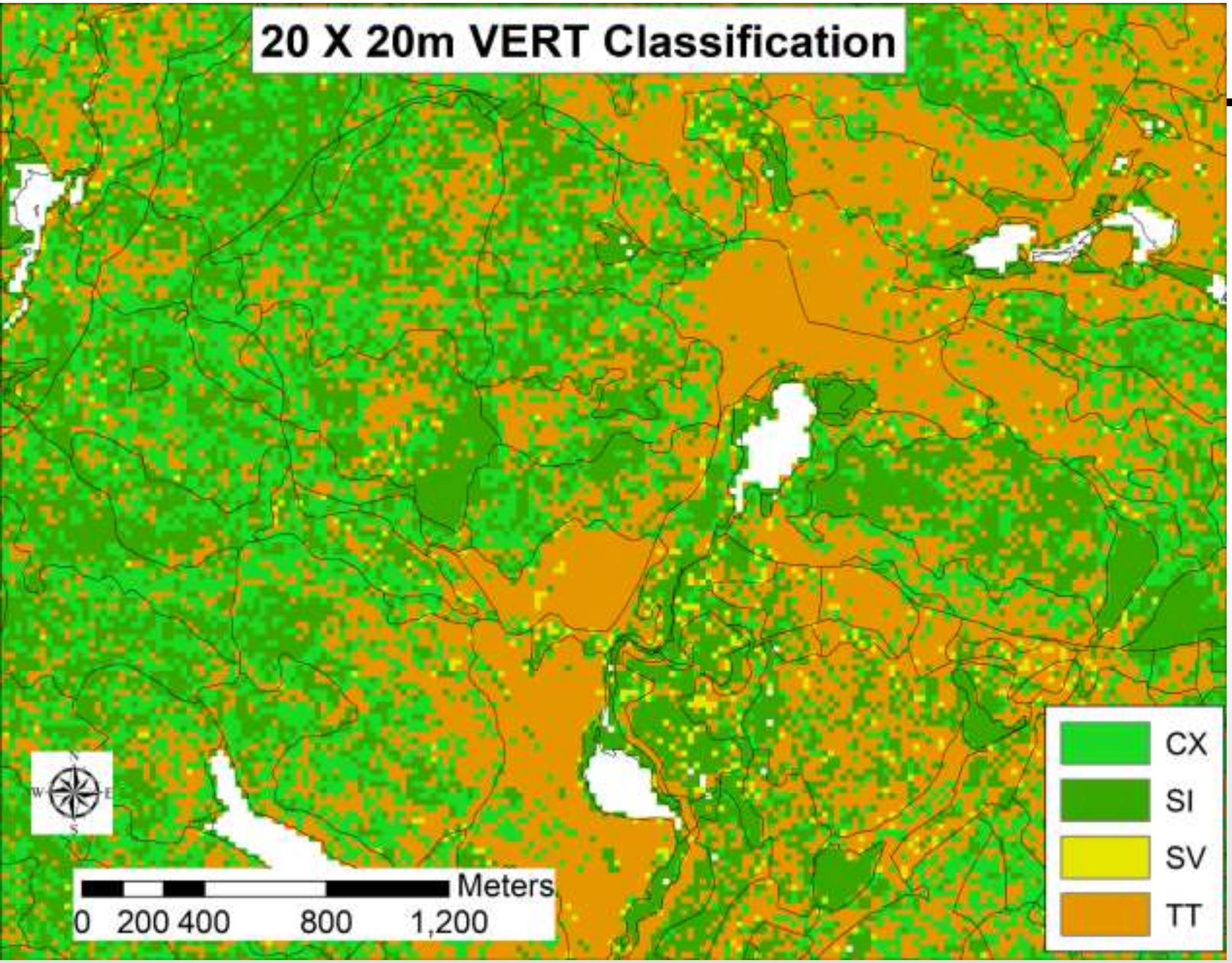
Layer Prediction of Basal Area (m2 ha)

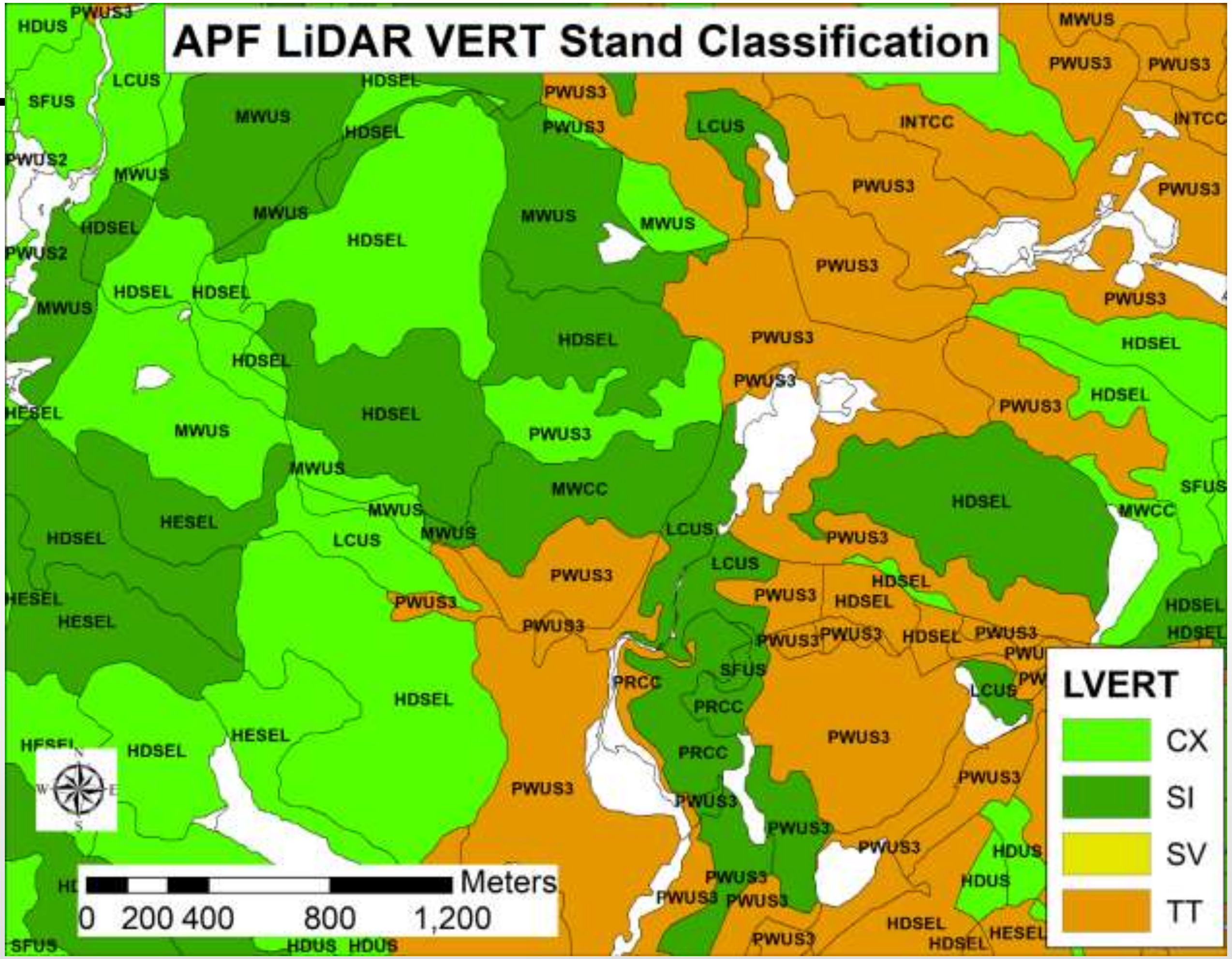


Layer Prediction of Gross Total Volume (m3 ha)



Assigning 20m x 20m Predictions of VERT Structure to Polygons





VERT assigned by the majority of 4-Class predictions within a polygon

APF Stand: 026847

T2 Photo Interpretation

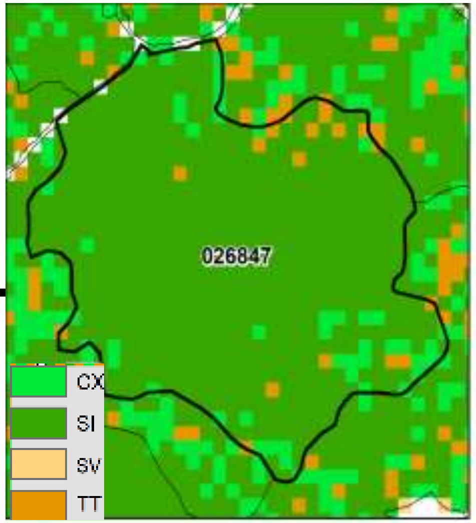
026847	
FID	3
POLYID	026847
OSPCOMP	Mh70Be20Cb10
OAGE	80
OHT	22
OSTK	1
USPCOMP	
UAGE	0
UHT	0
USTK	0
Notes	He incid almost enough for comp,
VERT	SV
INCID	He

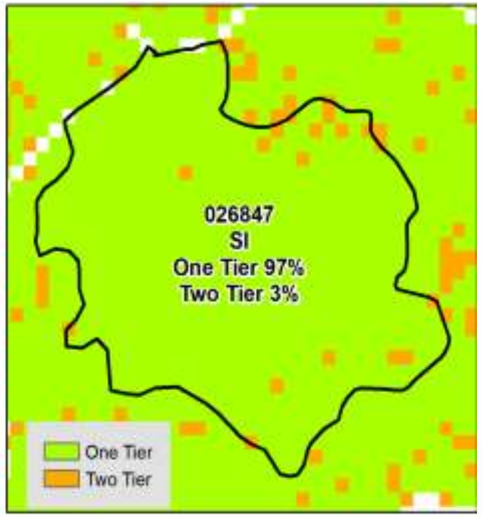
T2 LiDAR Summary

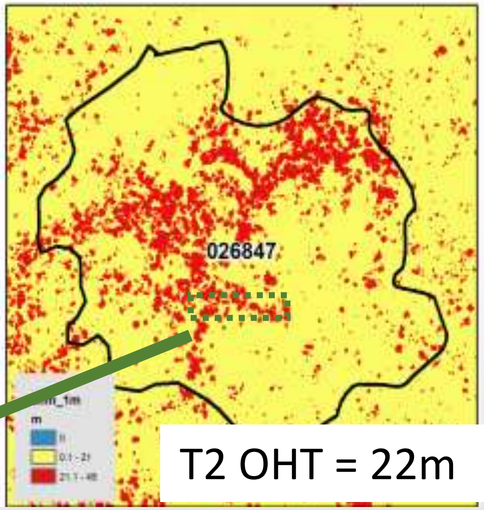
CC2m	98.1
CC10m	94.5
TOPHT	20.5
CDHT	18.2
LoreyHT	18.6
BA	28.8
BAmerch	28.3
Stems	753.5
GTV	214.9
GMV_NL	151
GMVnlQ15	115.1
GMVnlQ85	183.2
GMV_WL	139.3
Biomass	185.1
BA_Pole	9.6
BA_SmS	9.5
BA_MedS	6.7
BA_LgS	2.5
GMV_Pole	24.9
GMV_SmS	59.9
GMV_MedS	47.5
GMV_LgS	18.8
QMD	22.1
GMV_Util	0
SI	12
stocking	1.1
PrPj_frac	0
Cull_frac	0.2
NMV_NL	115.9
NMV_WL	106.9

Automated LiDAR Structure
One Tier - SI

TLL	0
LVERT	SI
Pct_OT	97
Pct_TT	3
BA_LL	0
BA_UL	28.8
GTV_LL	0
GTV_UL	214.9
TPH_LL	0
TPH_UL	753.5
QMD_LL	0
QMD_UL	22.1



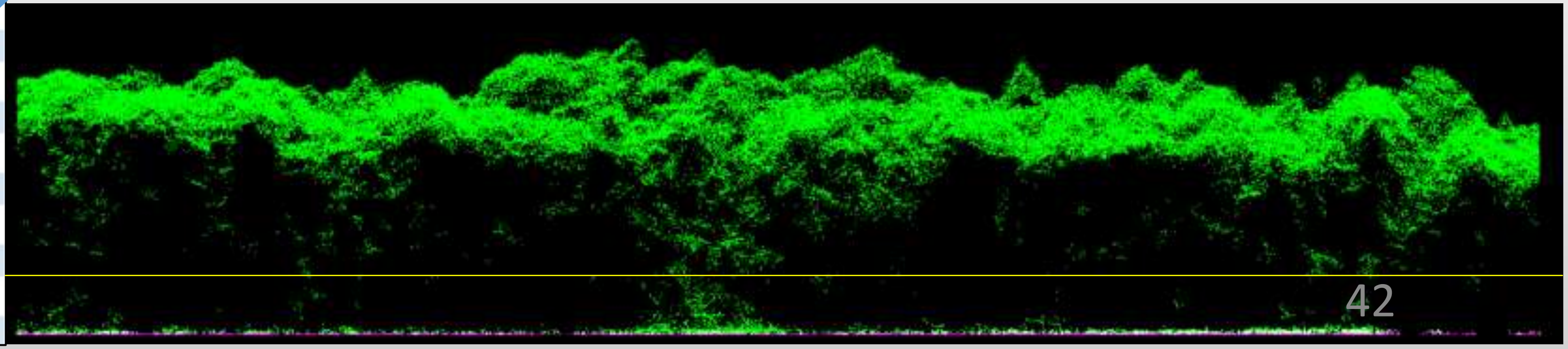




T2 OHT = 22m

From T1 FRI

DEVSTAGE	SELECT
YRDEP	1995
DEPTYPE	HARVEST



APF Stand: 090147

T2 Photo Interpretation

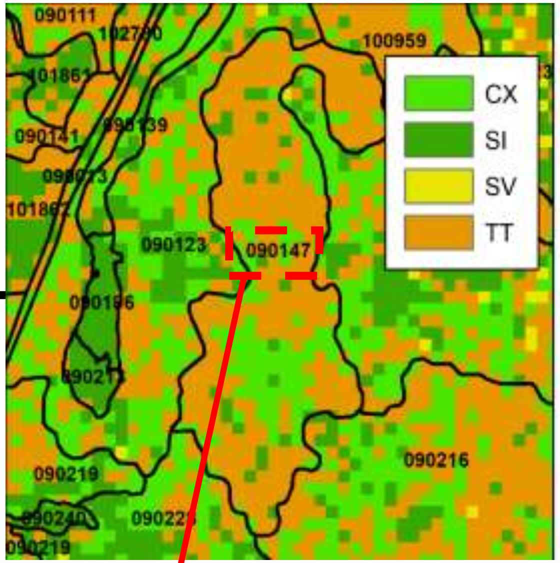
090147	
FID	14
POLYID	090147
OSPCOMP	Pr50Pt40Sw10
OAGE	85
OHT	24
OSTK	0
USPCOMP	
UAGE	0
UHT	0
USTK	0
Notes	INCID=Pw, Mr
VERT	CX
INCID	

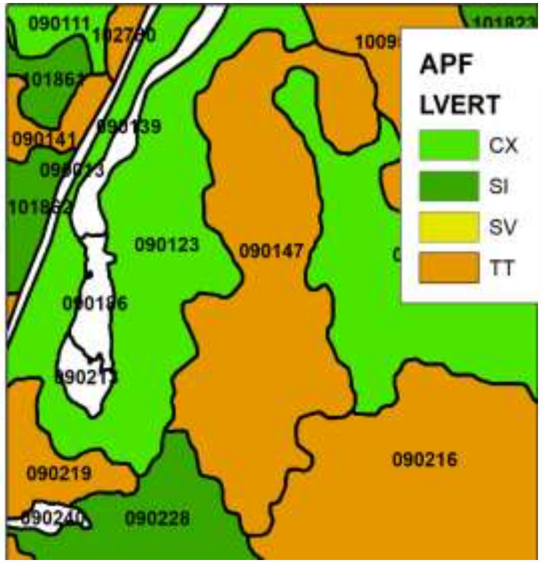
T2 LiDAR Summary

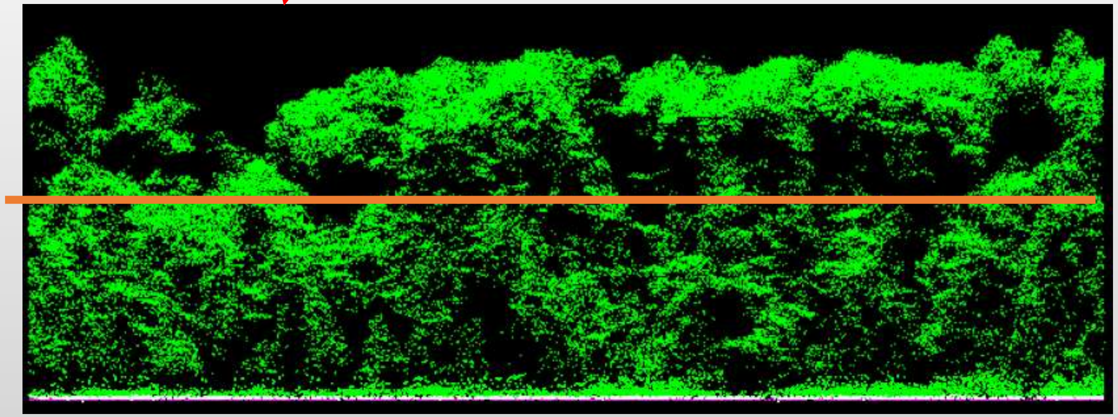
CC2m	92.4
CC10m	75.6
TOPHT	24.6
CDHT	22.1
LoreyHT	21.8
BA	32.3
BAmerch	31.5
Stems	680.1
GTV	286.2
GMV_NL	237.5
GMVnIQ15	155.4
GMVnIQ85	312.5
GMV_WL	227.9
Biomass	157.6
BA_Pole	8.2
BA_SmS	7.5
BA_MedS	11
BA_LgS	4.8
GMV_Pole	28.8
GMV_SmS	62.3
GMV_MedS	100.5
GMV_LgS	45.9
QMD	24.6
GMV_Util	15.2
SI	15.6
stocking	1.2
PrPj_frac	0.5
Cull_frac	0.1
NMV_NL	207.1
NMV_WL	198.7
NMV_Util	13.2

Automated LiDAR Structure Two Tier - TT

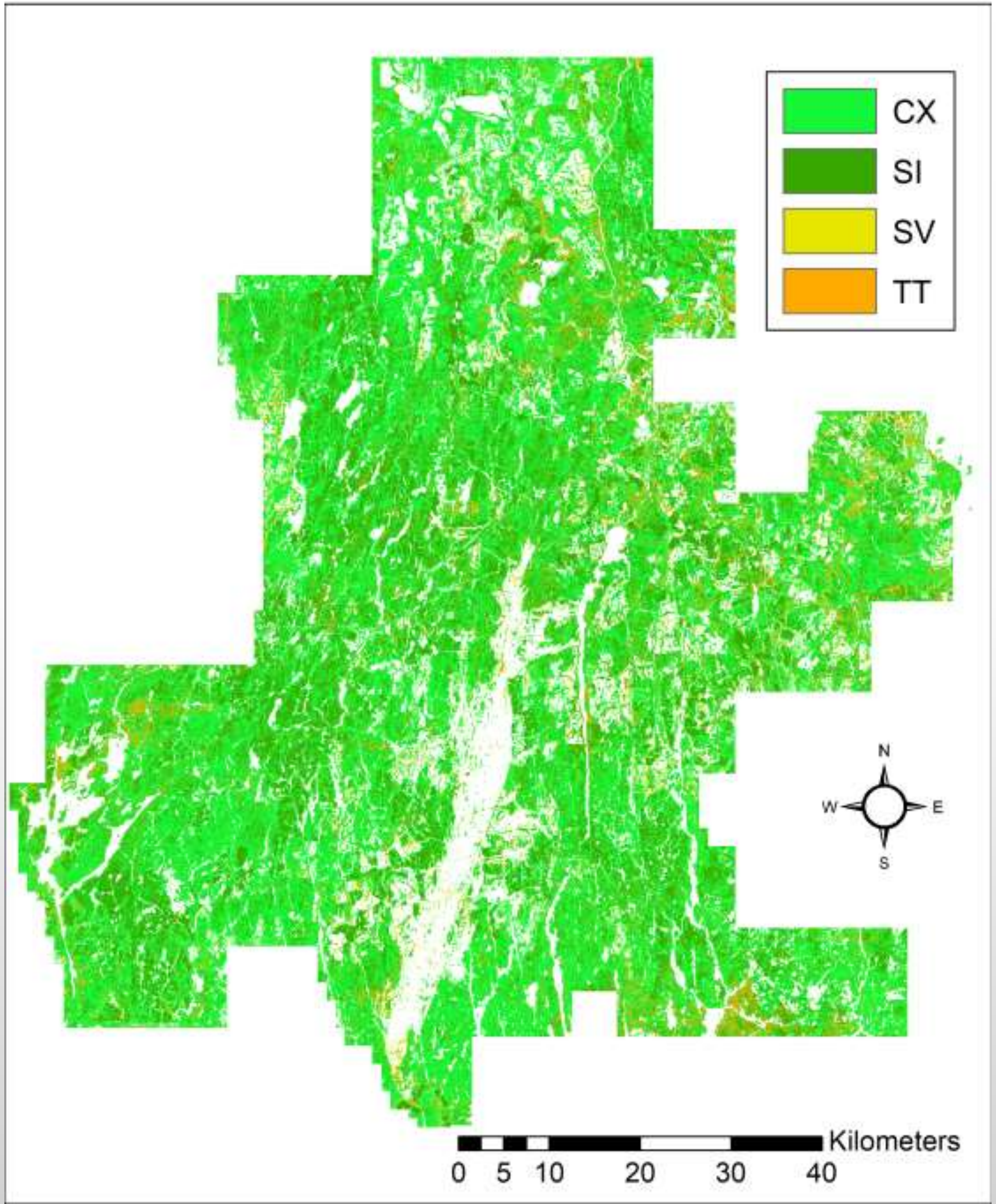
TLL	12.542113
LVERT	TT
Pct_OT	30
Pct_TT	70
BA_LL	5.4
BA_UL	26.9
GTV_LL	37.3
GTV_UL	248.9
TPH_LL	233.2
TPH_UL	446.9
QMD_LL	17.2
QMD_UL	27.7



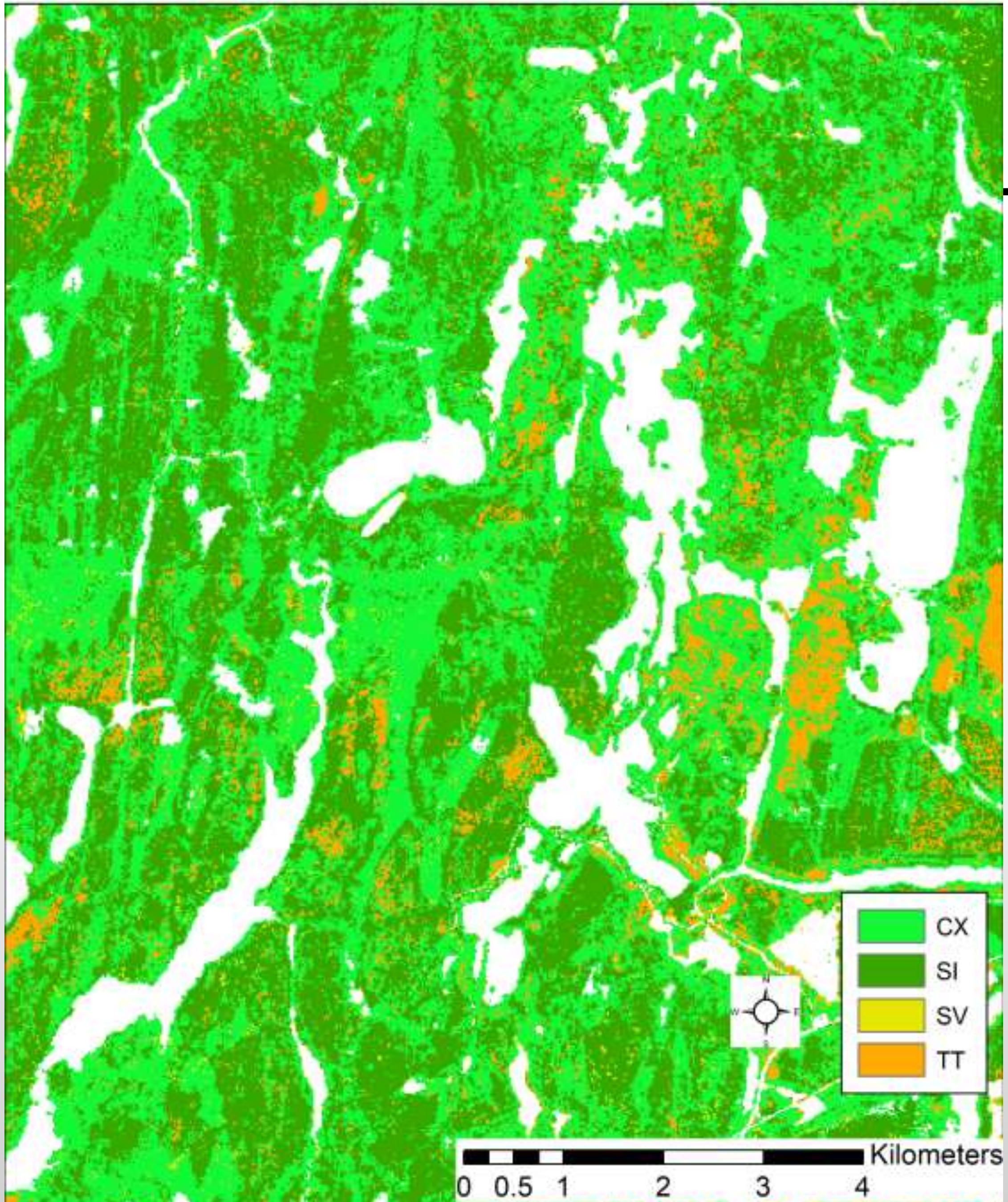




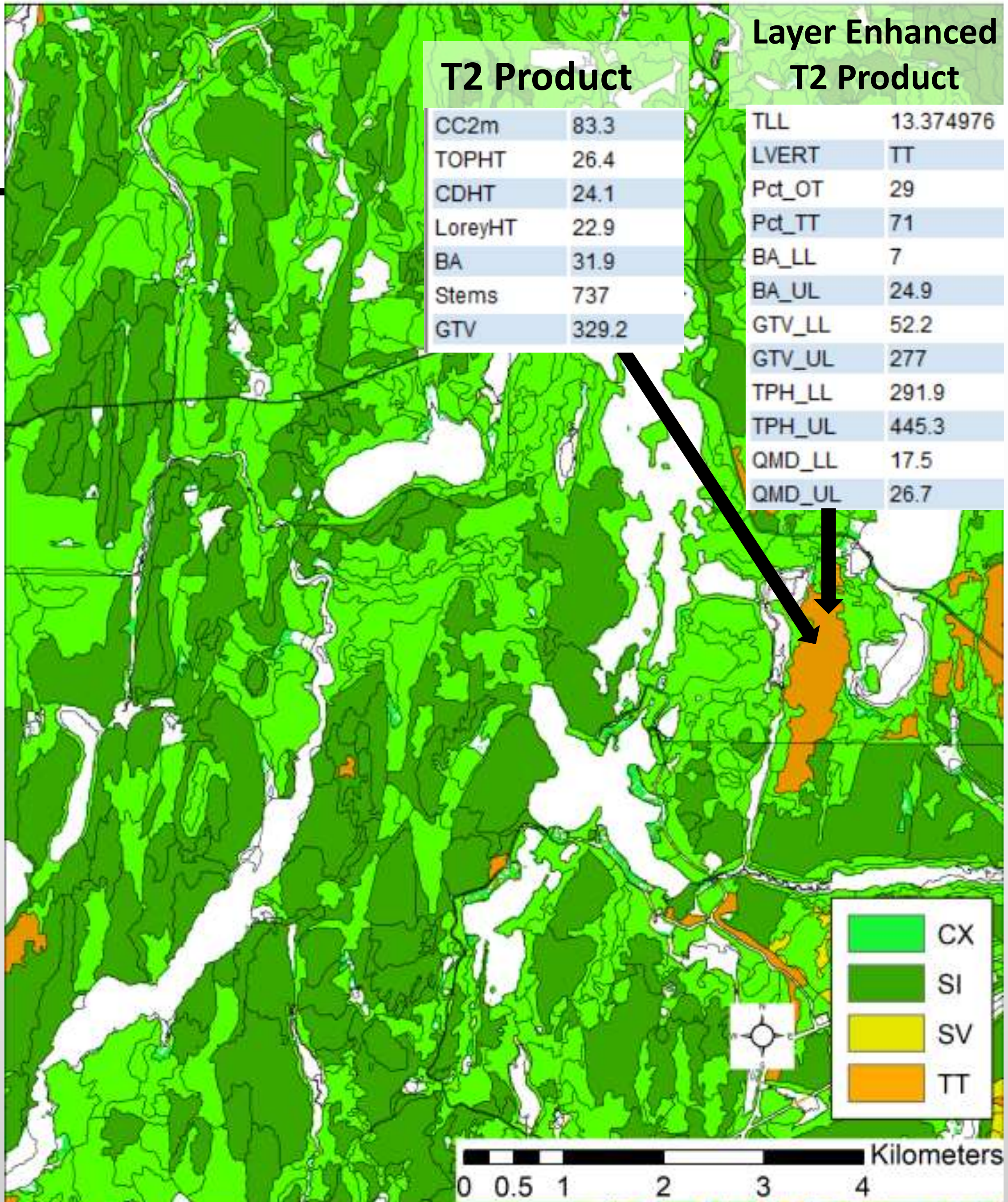
RMF 20m x 20m VERT Prediction



RMF 20m x 20m VERT Prediction



RMF Polygon VERT



Conclusions – Vertical Structure

Promising results for

- Predicting structure
- Partitioning FRI attributes by layer

Limitations

- Species and age come from T1 and may not be available by layer
- Structure is subjective

Vertical structure is likely less of an issue in the boreal. Horizontal structure appears to be an issue.

Forestry: An International Journal of Forest Research, 2023, 1–17
https://doi.org/10.1093/forestry/cpad033
Original Article

OXFORD Institute of Chartered Foresters

Automated characterization of forest canopy vertical layering for predicting forest inventory attributes by layer using airborne LiDAR data

Margaret Penner[1,*], Joanne C. White[2] and Murray E. Woods[3]

[1]Forest Analysis Ltd, 1188 Walker Lake Dr., Huntsville, ON P1H 2J6, Canada
[2]Canadian Forest Service (Pacific Forestry Centre), Natural Resources Canada, 506 West Burnside Road, Victoria, BC V8Z 1M5, Canada
[3]Retired—Natural Resources Information Section, Science and Research Branch, Ontario Ministry of Natural Resources and Forestry, 875 Gormanville Rd., North Bay, ON P1A 4L7, Canada
*Corresponding author Tel: +1(705)6351314; E-mail: mpenner@forestanalysis.ca

Abstract

Forest canopy vertical layering influences stand development and yield and is critical information for forest management planning and wood supply analysis. It is also relevant for other applications including habitat modelling, forest fuels management and assessing forest resilience. Forest inventories that use coincident airborne Light Detection and Ranging (LiDAR) data and field plots (i.e. area-based approach) to predict forest attributes generally do not consider the multi-layer canopy structure that may be found in many natural and managed forest stands. With airborne LiDAR, it is possible to separate single-layer and multi-layer stands. This information can be used to allocate predictions of forest attributes such as timber volume (m^3 ha^{-1}), by canopy layer. In this study, we used single-photon LiDAR data to automate the mapping of vertical stand layering in a temperate mixedwood forest with a variety of forest types and vertical complexities. We first predicted whether each 25 × 25 m grid cell had one or two canopy layers, and then partitioned inventory attributes (e.g. basal area (BA), gross total stem volume (GTV)) by canopy layer. We compared two methods for estimating attributes by layer at the stand level using nine independent validation stands. Overall agreement between the reference and predicted structure for the calibration plots was 74% ($n = 266$). At the grid-cell level, attributes were generally underestimated for the upper layer and overestimated for the lower layer. For the validation stands, the relative height of the lower layer was under-predicted compared to the reference data (46–52% versus 57%), while the proportion of BA and GTV in the lower layer were very similar to the reference values (17–19% versus 18% for BA and 12–15% versus 12% for GTV). Overall, the approach showed promise in distinguishing single- and two-layered stand conditions and partitioning estimates of inventory attributes such as BA and GTV by layer—both for grid cells and at the stand level. The inclusion of forest information by canopy layer enhances the utility of LiDAR-derived forest inventories for forest management in forest areas with complex, multi-layer stand conditions.

Forestry: An International Journal of Forest Research, 2023, 1–17
https://doi.org/10.1093/forestry/cpad033

Assessing Site Productivity from Remote Sensing and historic information KTTD 1B-2021

Project Team
Alex Bilyk
Margaret Penner
Murray Woods

resolute
Forest Products

GREENFIRST
FOREST PRODUCTS

Government of Canada / Gouvernement du Canada
Petawawa Research Forest

FORESTRY FUTURES TRUST ONTARIO
FORESTRY FUTURES TRUST ONTARIO

Ontario
Ministry of Natural Resources and Forestry

Project overview

Forests

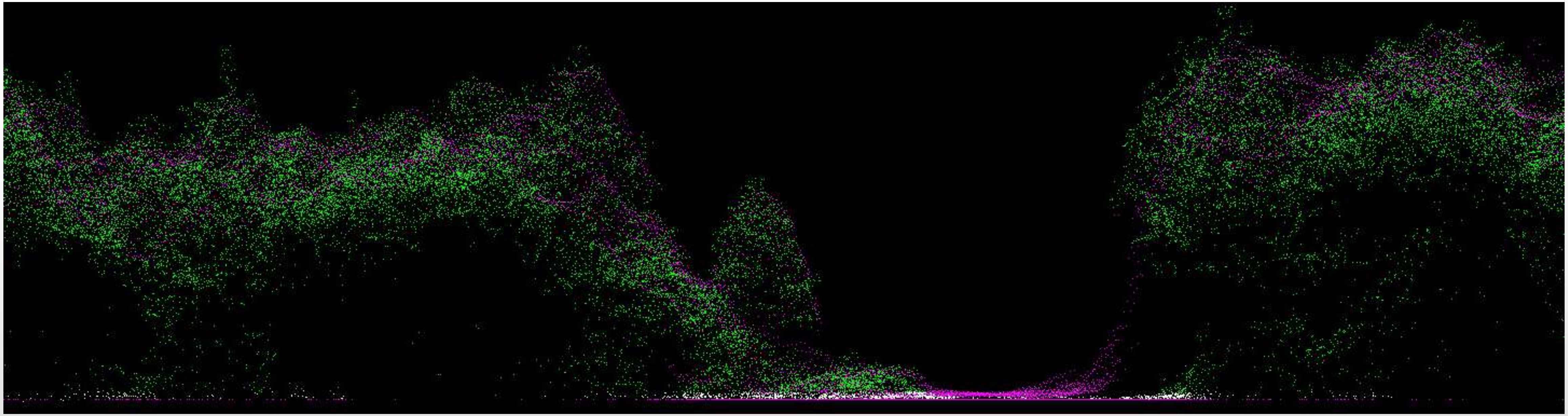
- Petawawa Research Forest – Great Lakes/St. Lawrence (2005, 2012, 2018 LiDAR)
- Dog River/Matawin – Boreal (2008 LiDAR/SGM, 2018 LiDAR)
- Romeo Malette Forest River – Boreal (2005, 2018 LIDAR)

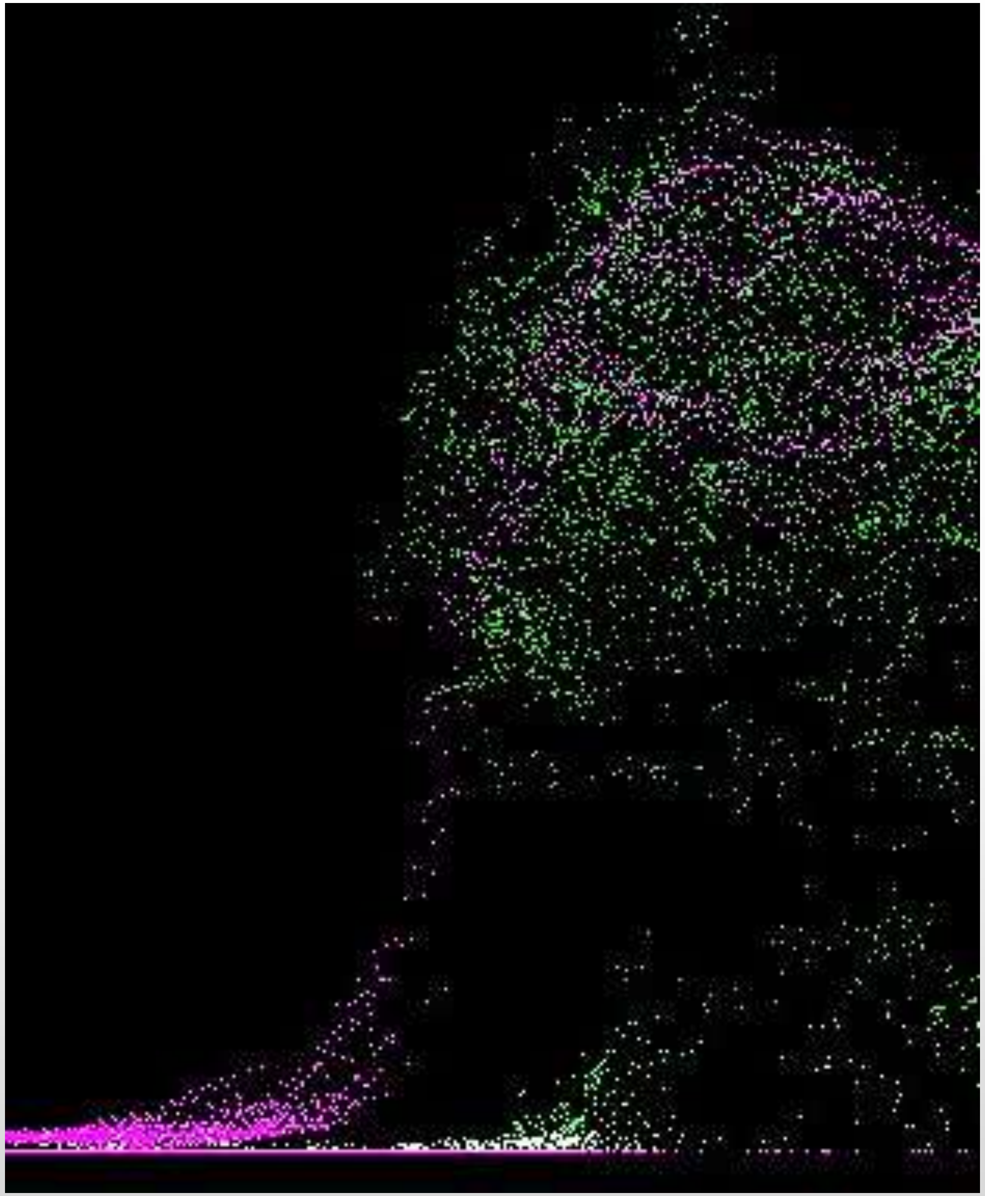
How we value historic data

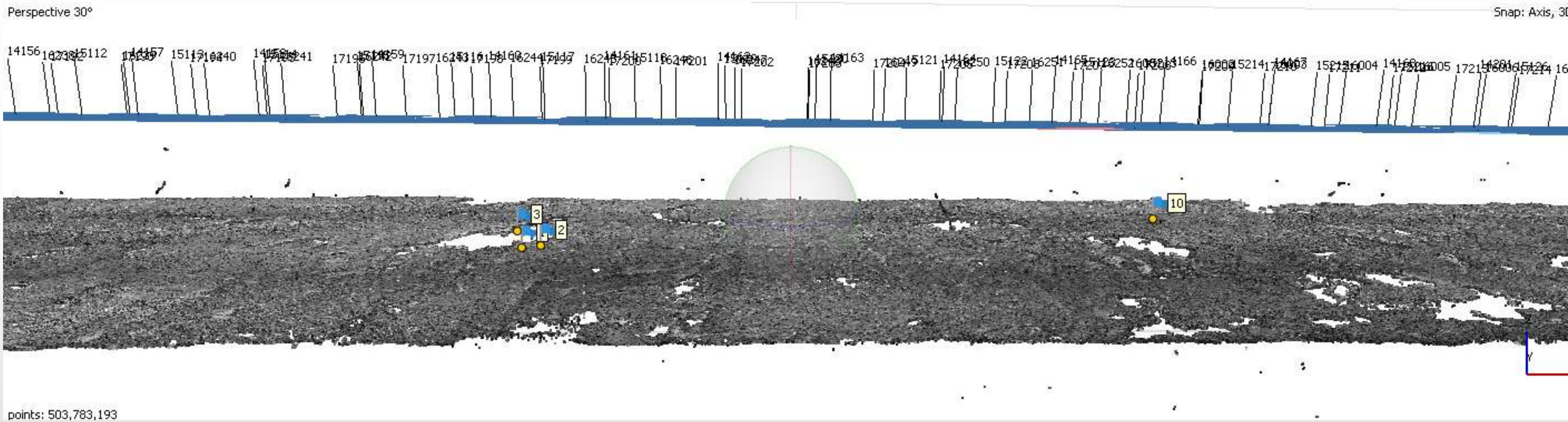
While not all data is in this condition, we have not taken advantage of the wealth of historic information we have in this province

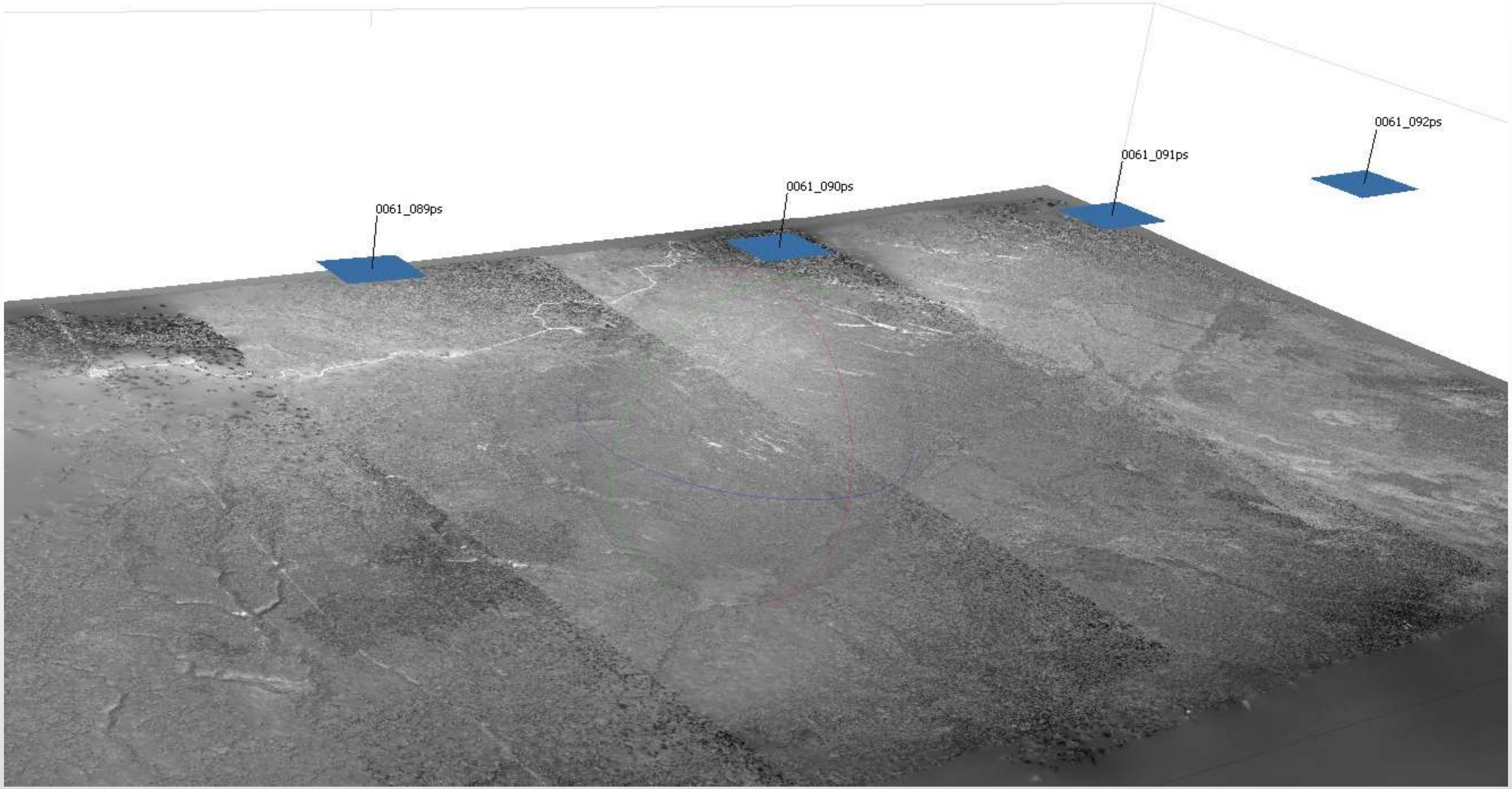
We set out to mine this archive and see what is possible

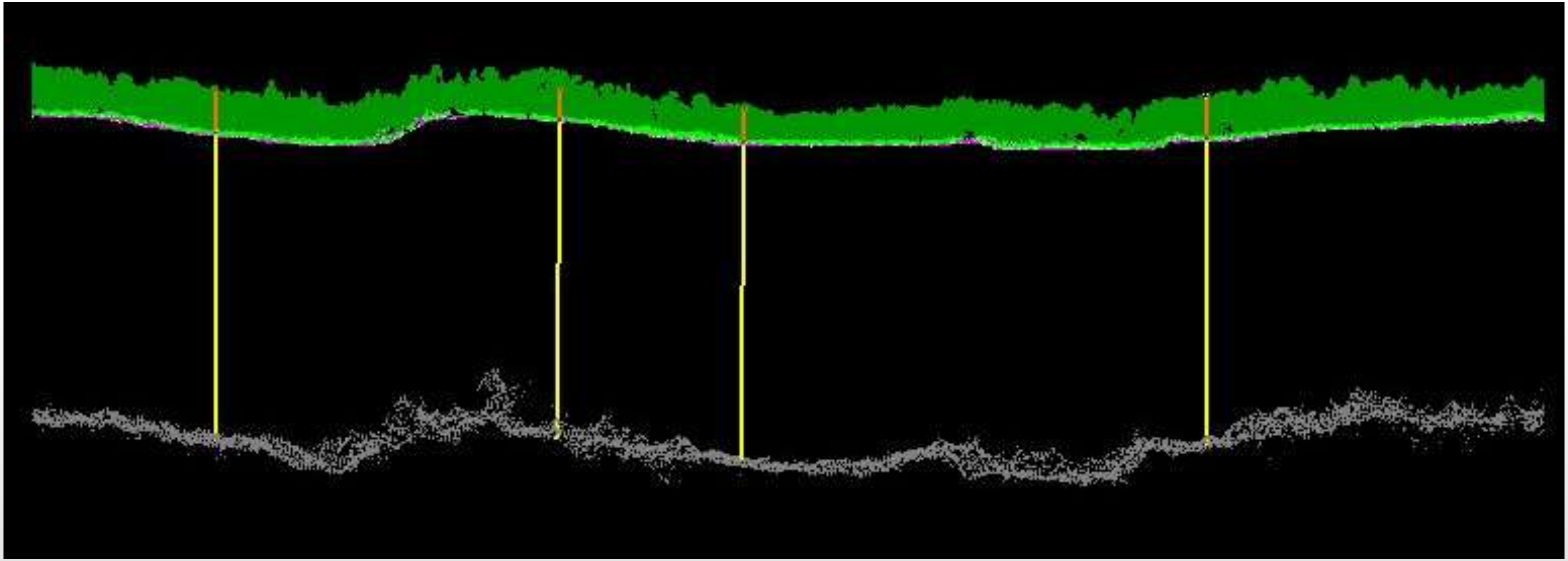
Concurrent SGM and LiDAR – Dog Mat 2018



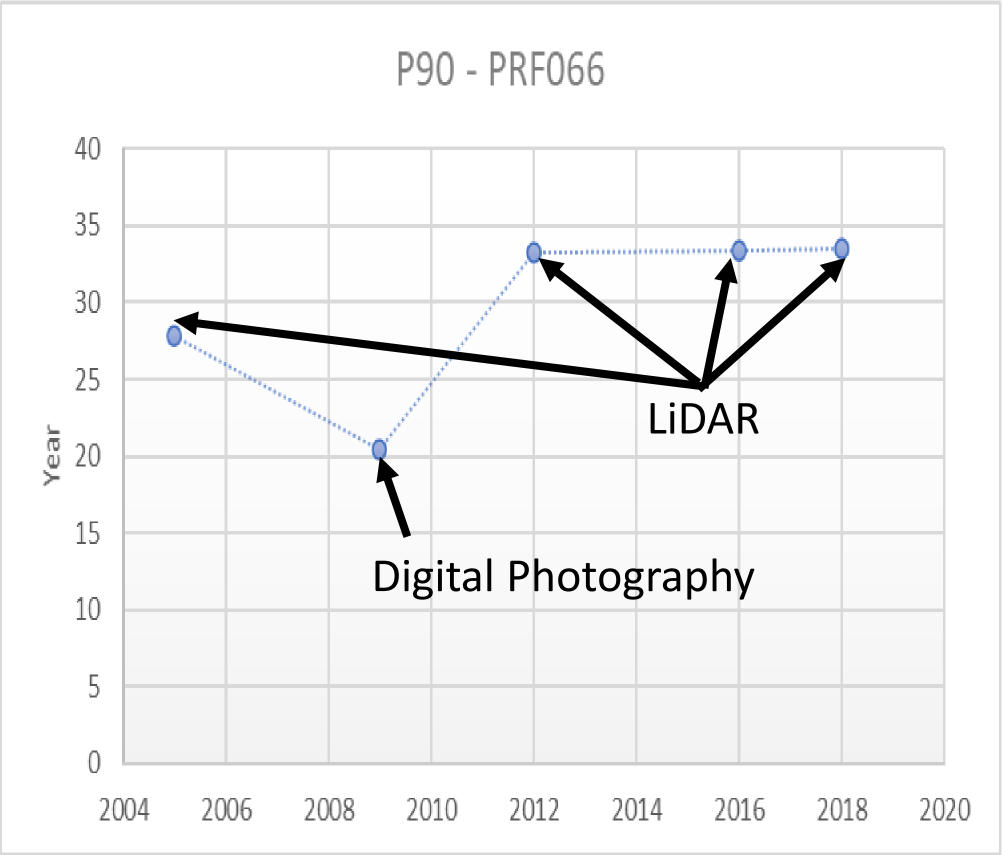


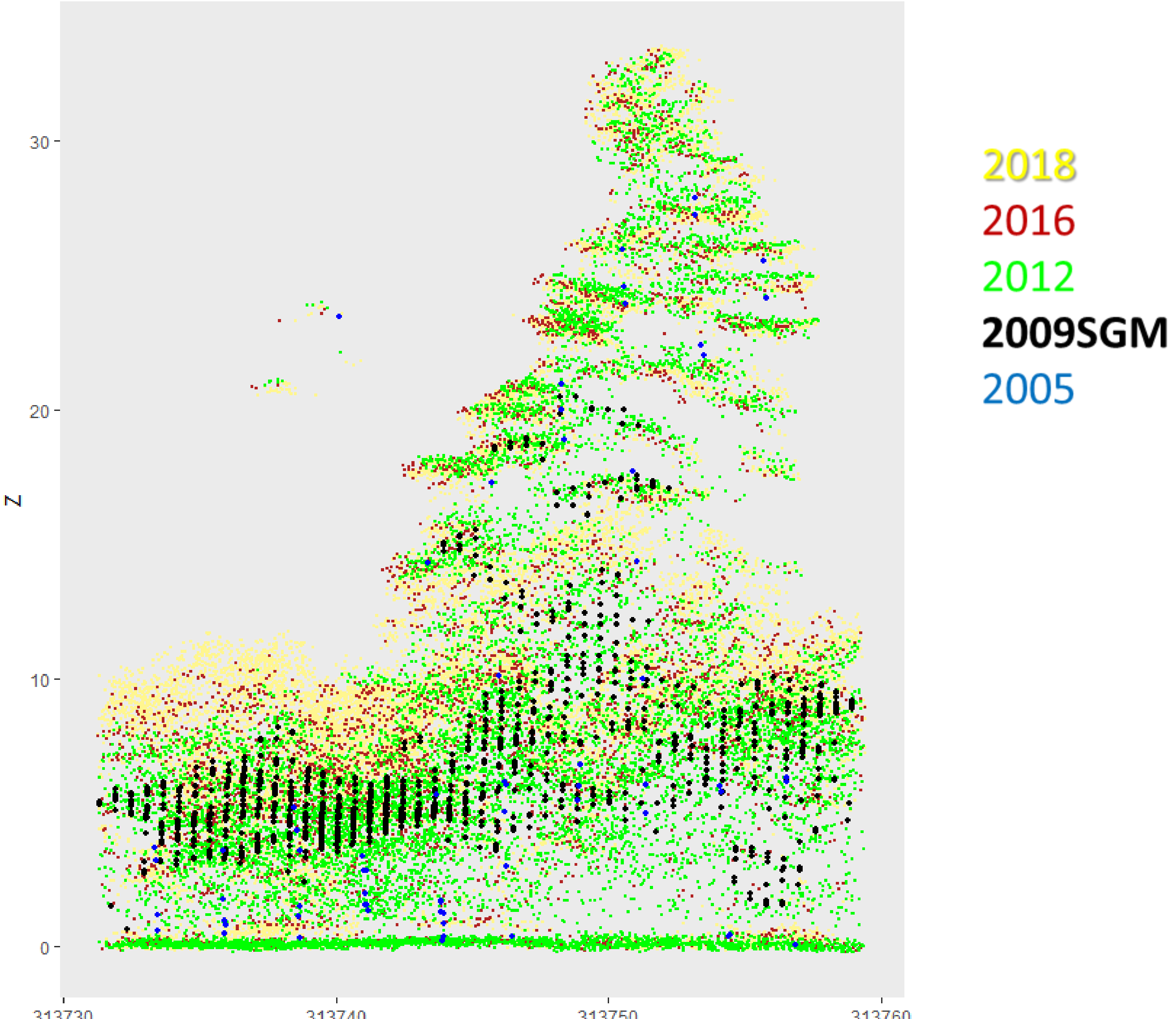

Perspective 30°
points: 503,783,193
3
2
10


0061_089ps
0061_090ps
0061_091ps
0061_092ps

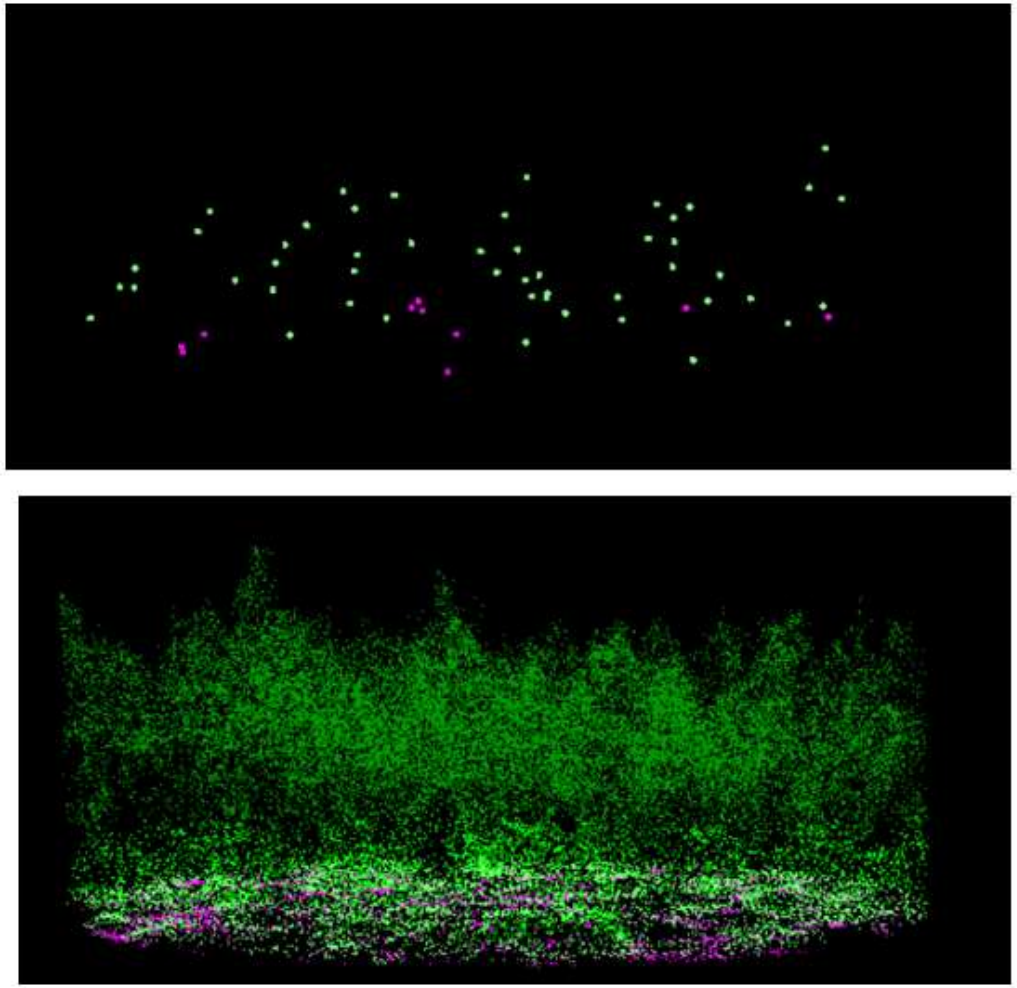


Finding 1 – Digital photography didn't work where there was not enough overlap - Inconsistent





Finding 2 – LiDAR is getting much better



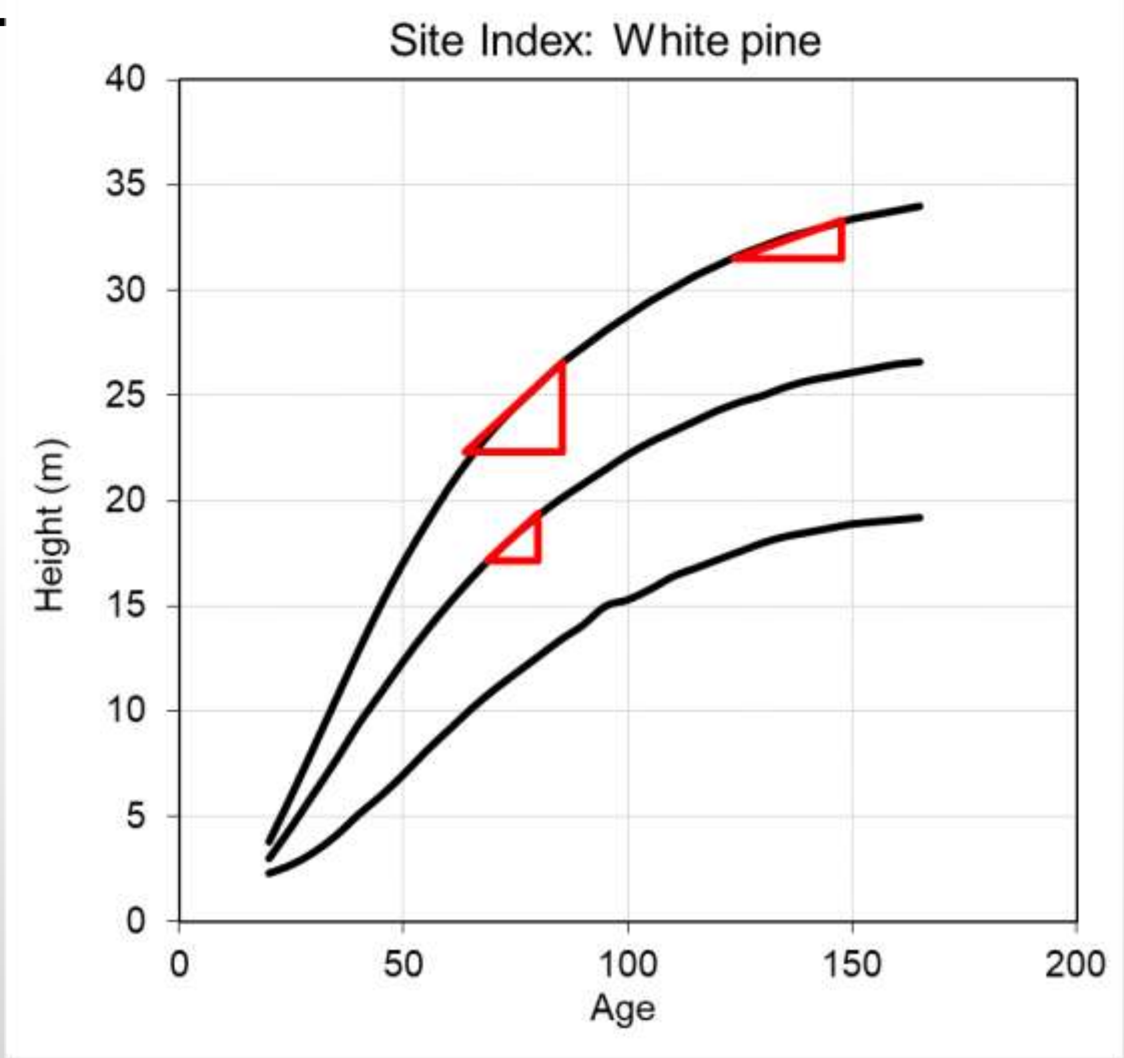
2005

2018

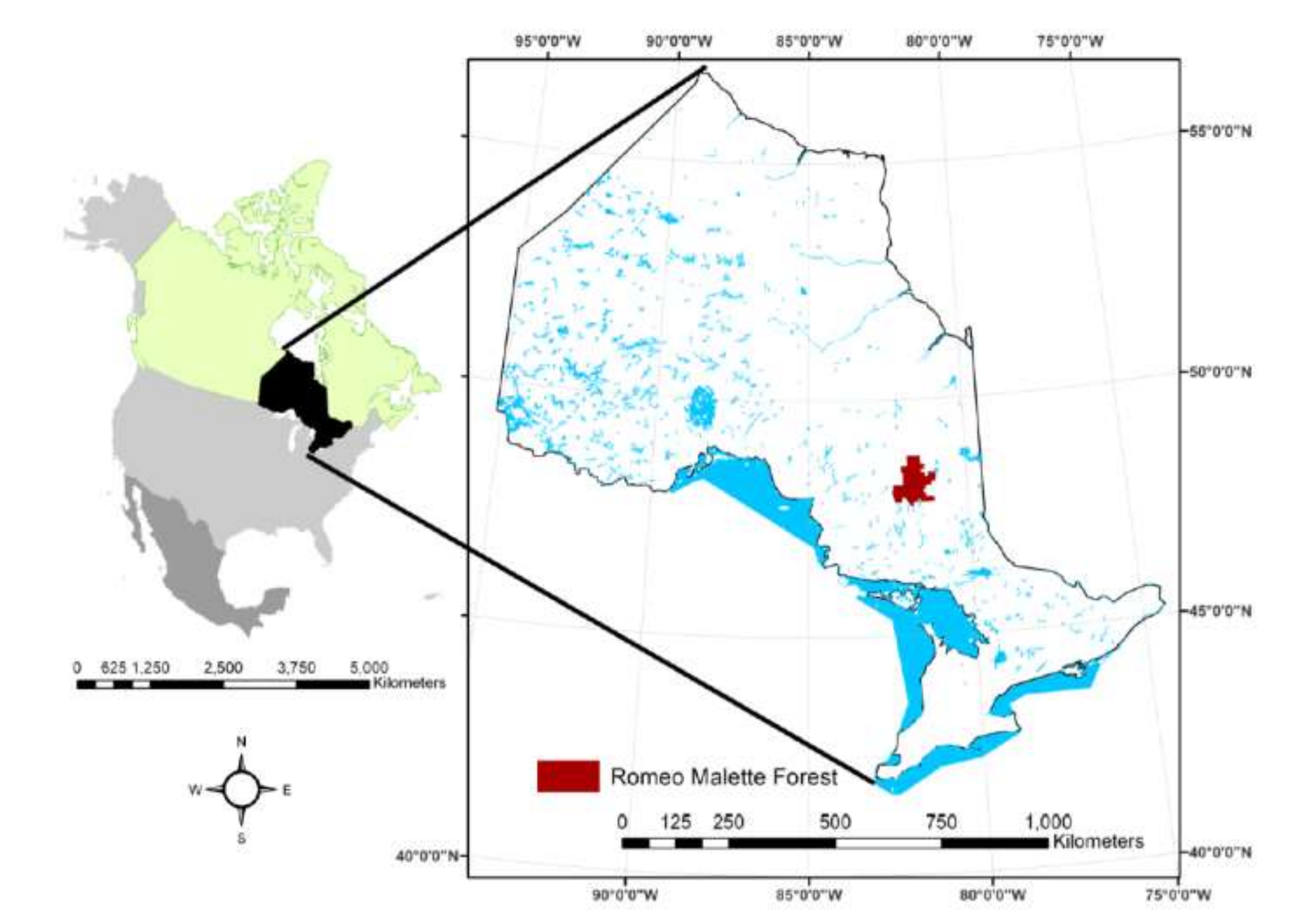
Project overview

If we have two estimates of height (from LiDAR) can we estimate SI?

- Area-based
- Compare to field estimates of SI
- Compare forest types



LiDAR – Prediction and Mapping of Site Productivity



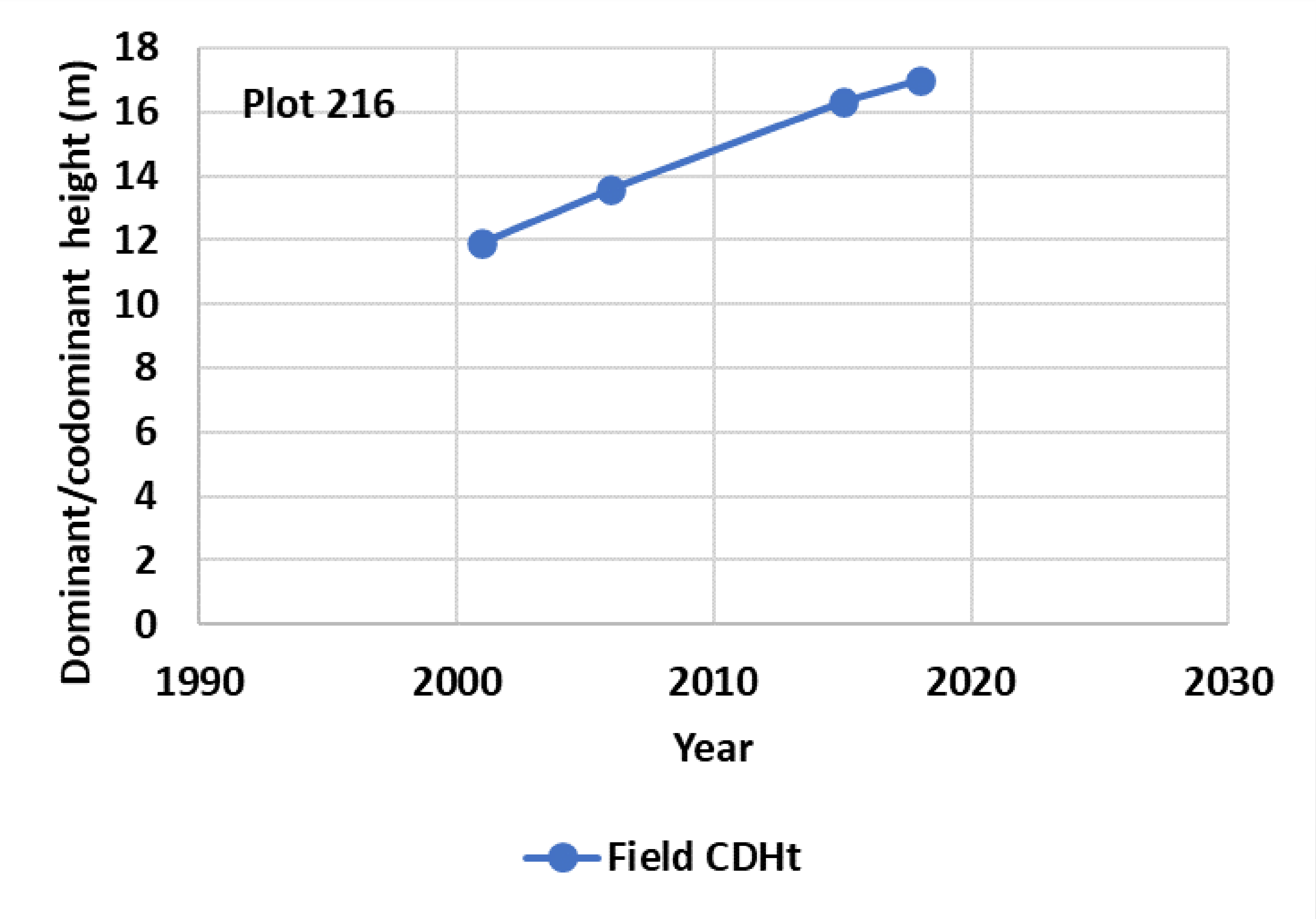
- Presenting results from the Romeo Malette Forest

Field Data

- Jack pine & black spruce, relatively pure
- Multiple ground measurements
- Sub metre GPS
- Range of ages
- Range of productivities
- Planted & natural

	Species	
Origin	Jack pine	Black spruce
Natural	4	13
Planted	7	3

Jack pine

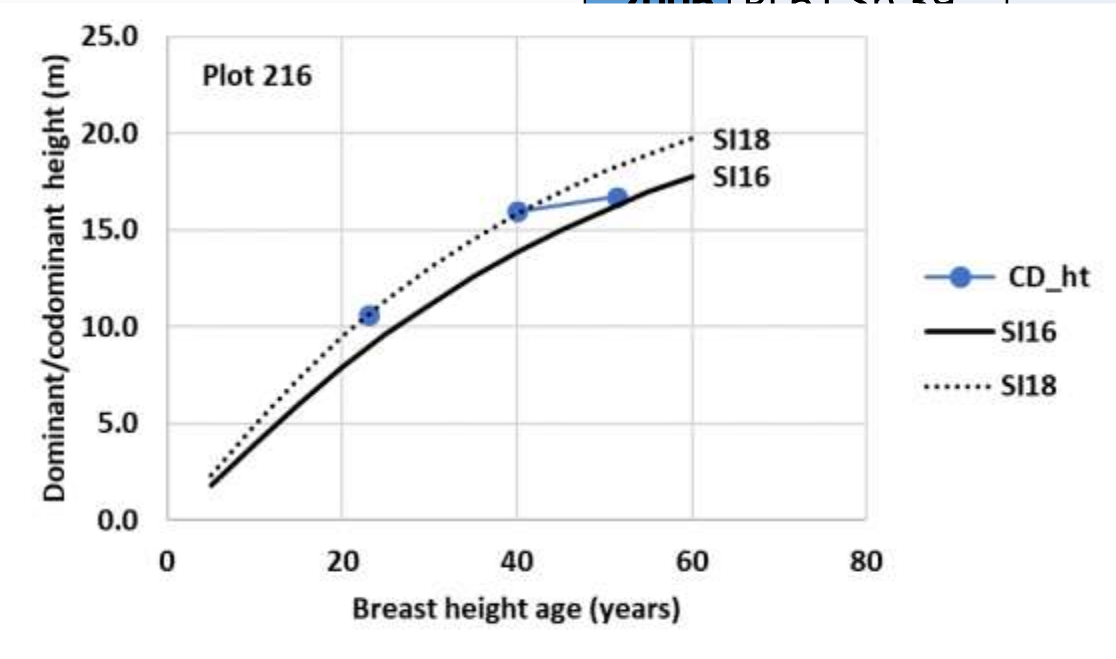


Plot 216
Dominant/codominant height (m)
18
16
14
12
10
8
6
4
2
0
1990
2000
2010
2020
2030
Year
Field CDHt

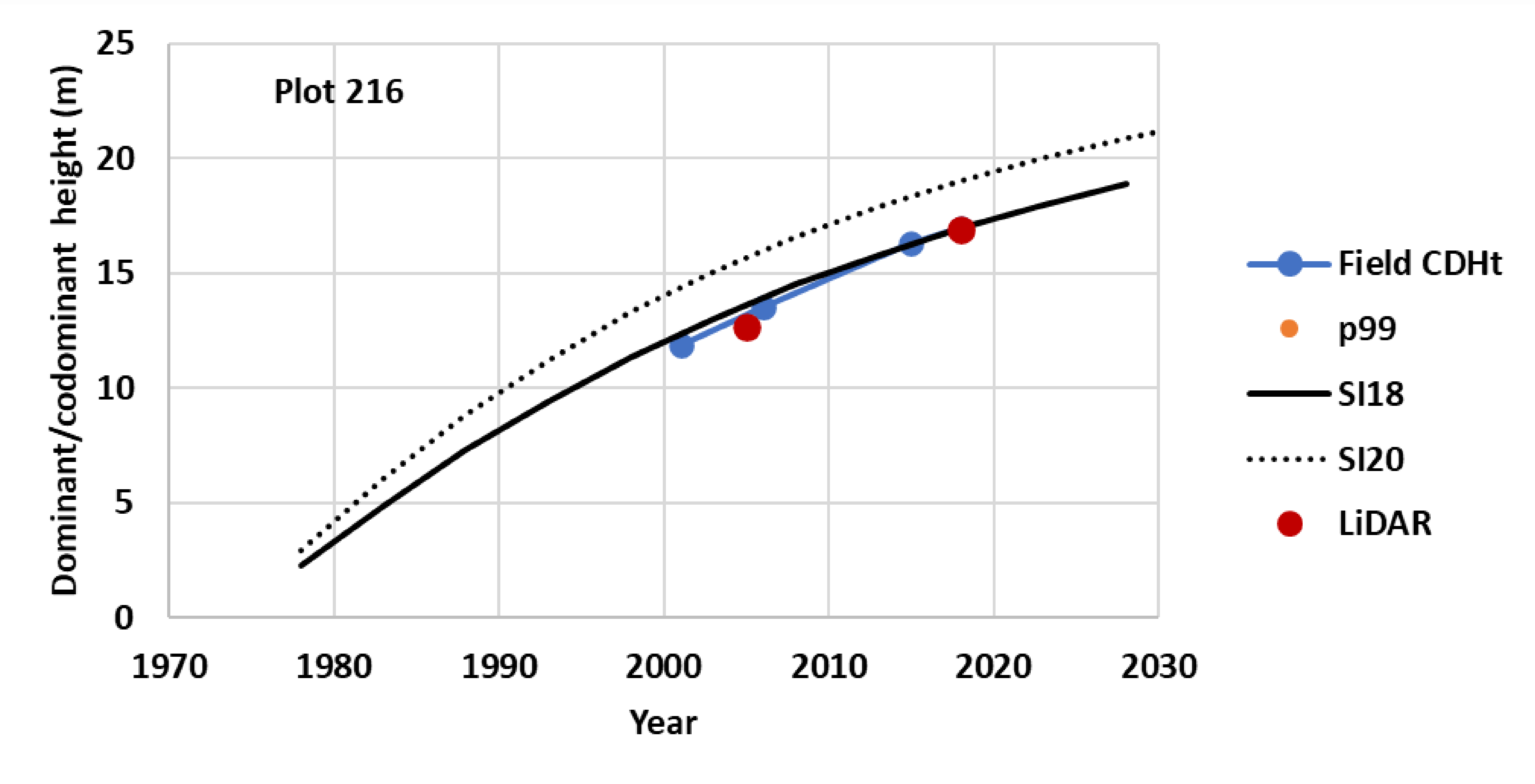
Finding 3 – Reference SI is complicated

- Plot 216, a Pj plantation, established 1971

Year	Species composition	bh age Measured (A)	Year bh age = 0	CHt (m)	bh age Calculated (B)	SI (m) using (B)	SI (m) using (A)
2001	Pj 61 Sb 39	23	1978	10.6	27.8	16.1	18.0
2006	Pj 61 Sb 39			12.8	32.8	16.9	
		40	1975	16.0	41.8	17.7	18.1
		51.5	1966.5	16.7	44.8	17.8	16.4
			1973.2			17.1	17.5



Jack pine



Plot 216
Dominant/codominant height (m)
25
20
15
10
5
0
1970
1980
1990
2000
2010
2020
2030
Year
Field CDHt
p99
SI18
SI20
LiDAR

Site index

SI = f(age, height)

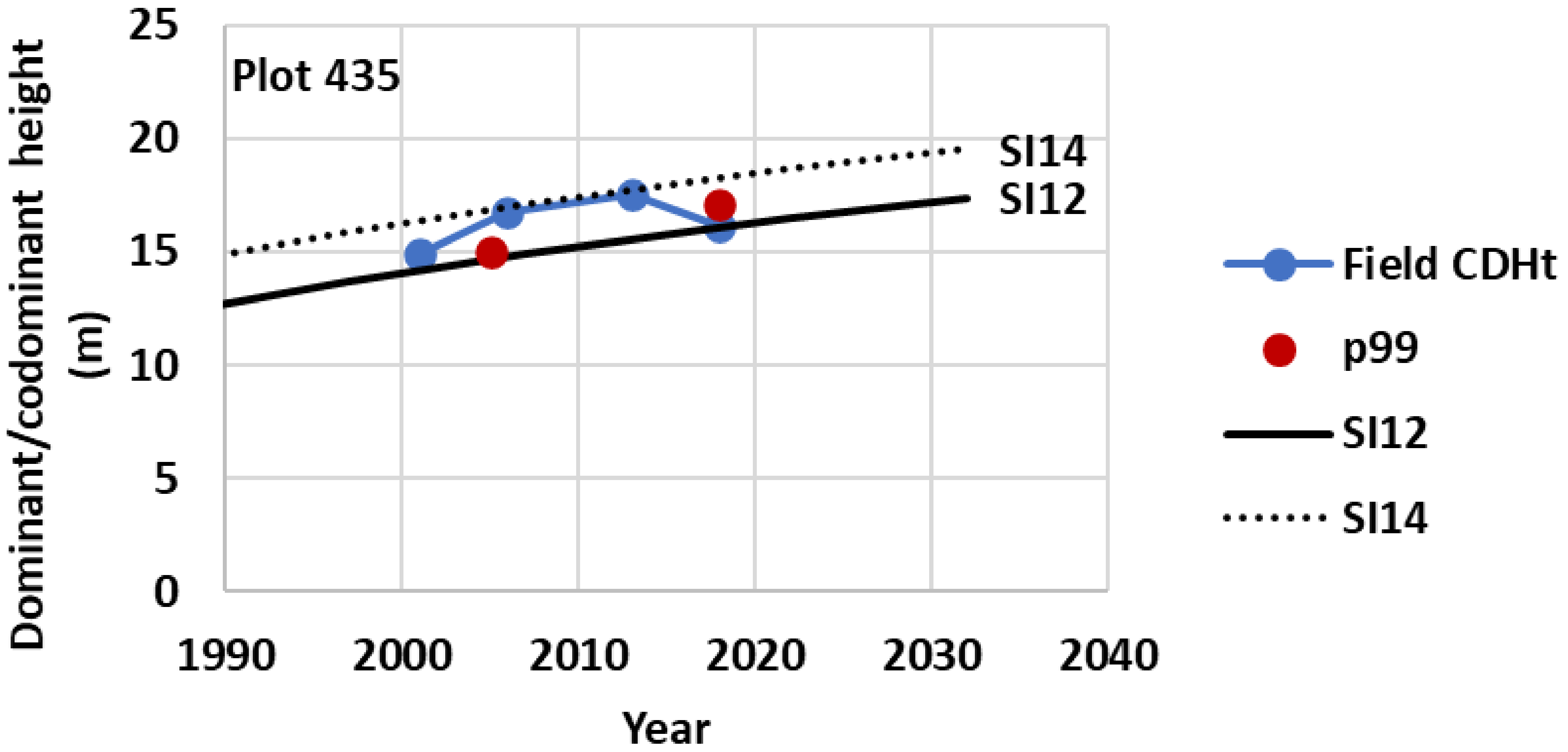
- Require "height" at two times (t1 and t2)
- Assume age2 – age1 = t2 – t1
- Assume SI is constant over time

Can estimate SI without age

SI = f(height1, height2, t1, t2)

- ```
  age_p99_calc = (2018 - 2005)/(((1 - a0/p99_2005)/(1 - a0/p99_2018))**(1/a1)-1);
  ```
- ```
  SI_p99_calc = a0/(1 - (1 - a0/p99_2005)*(age_p99_calc/50)**a1);
  ```

Black spruce



SI basics

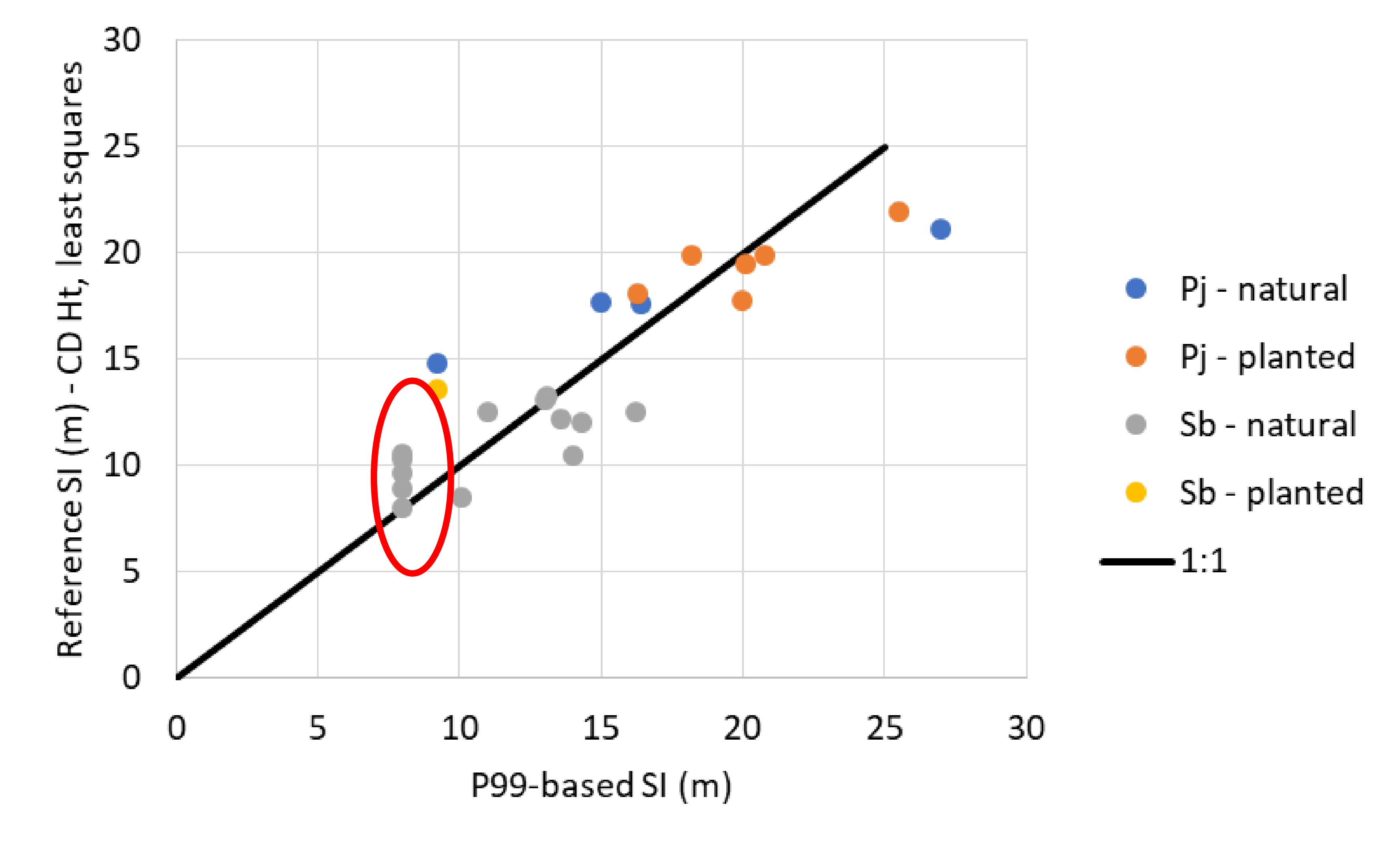
Most SI curves in Ontario, and all the curves developed by Mahadev Sharma are increasing functions of age.

- Can't predict SI if height decreases over time
  - 3 out of 27 plots (11%) had a decrease in p99
  - 8 out of 27 plots had an increase of < 5% in p99 from 2005 – 2013 (all had age_bh > 80)
  - 22 out of 106 field measurement intervals (21%) had a decrease in CD height
- Height growth slows with age and becomes less than the measurement precision

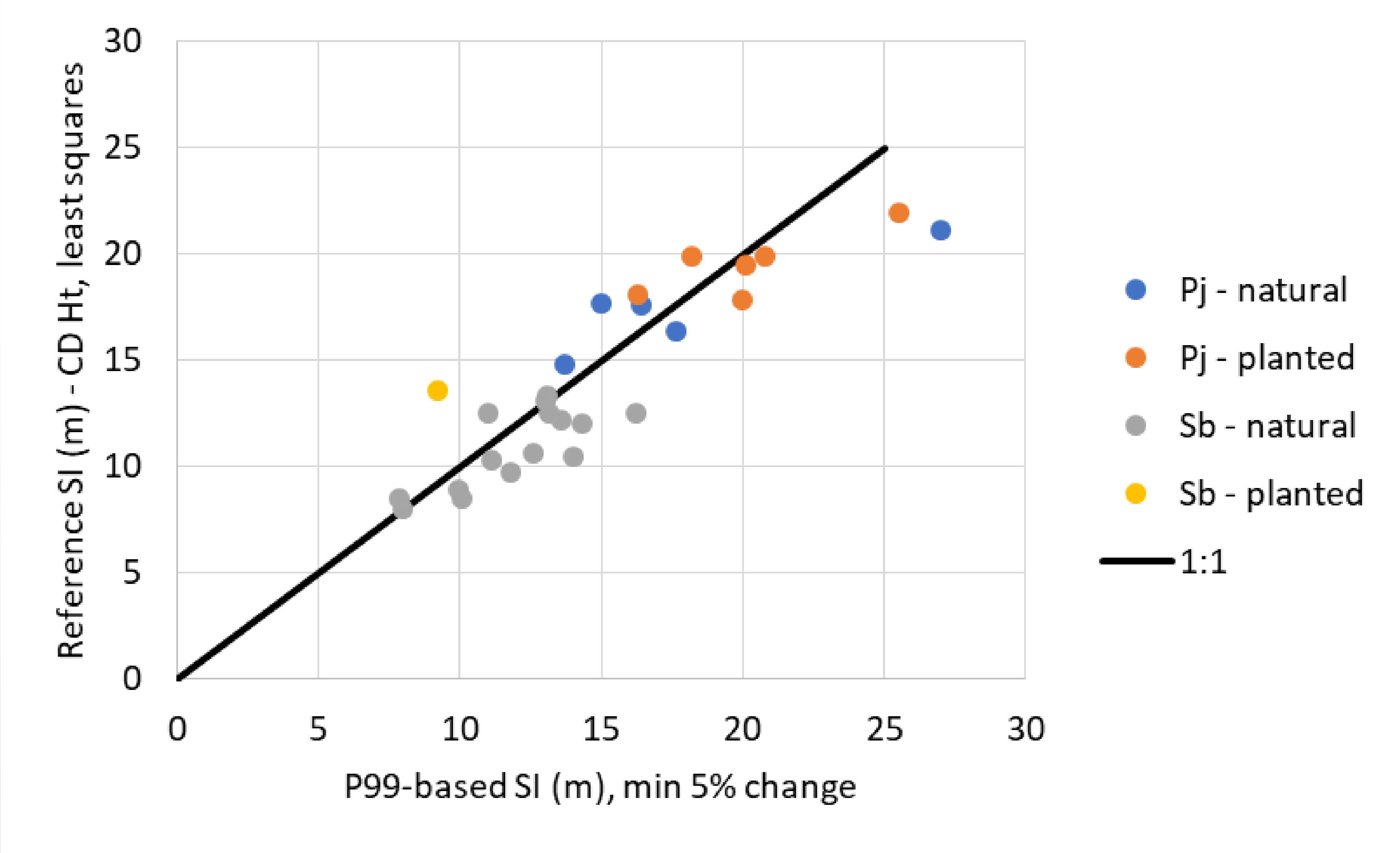
For older stands, age is a problem and height change is a problem

- Can we assume age is some "old" age and that height isn't changing?

LiDAR SI

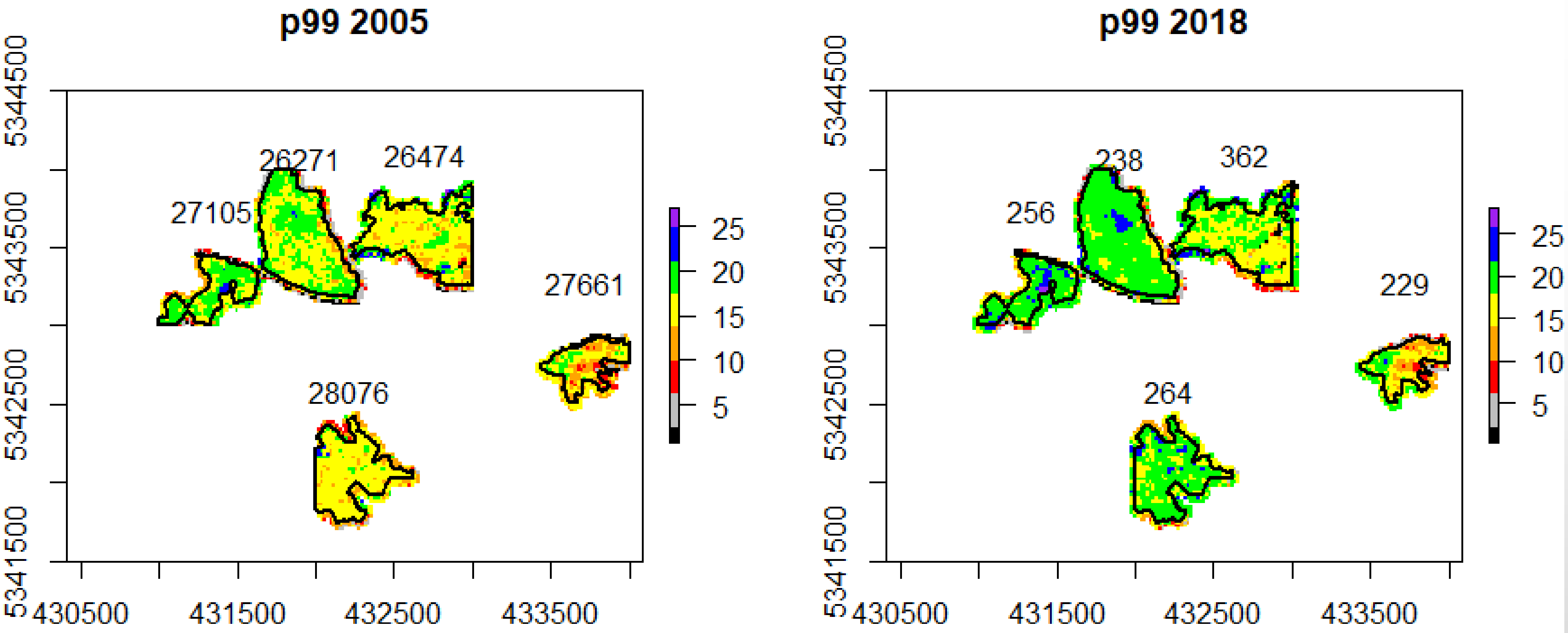

30
25
20
15
10
5
0
0
5
10
15
20
25
30
Reference SI (m) - CD Ht, least squares
P99-based SI (m)
Pj - natural
Pj - planted
Sb - natural
Sb - planted
1:1

LiDAR SI



Reference SI (m) - CD Ht, least squares
P99-based SI (m), min 5% change
0
5
10
15
20
25
30
Pj - natural
Pj - planted
Sb - natural
Sb - planted
1:1

Polygons



256 – fire origin Pj from 1957 + PCT in 1971

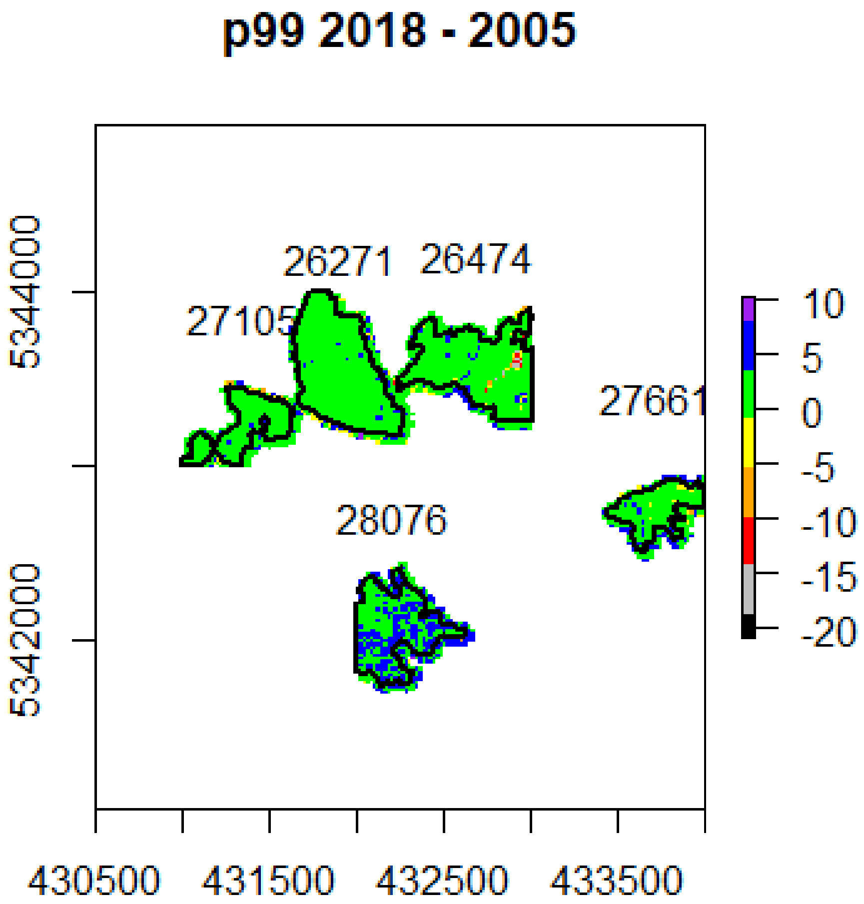
238 – same as 256 but no PCT

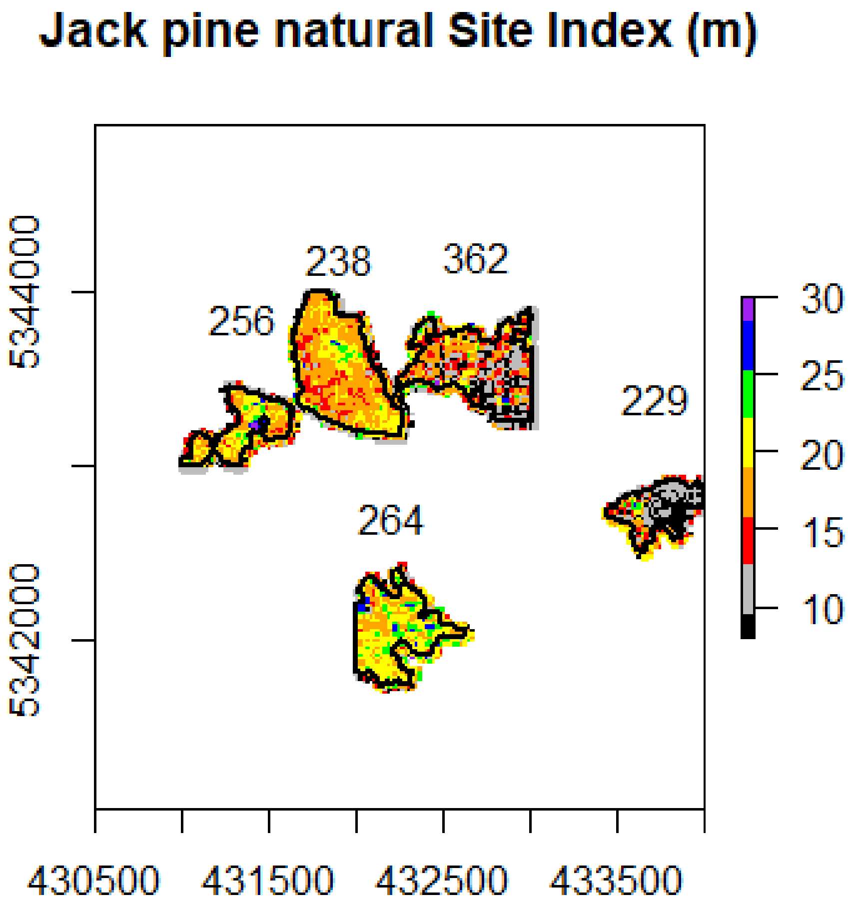
362 – fire origin SP1 from about 1900

229 – fire origin SB1 from about 1900

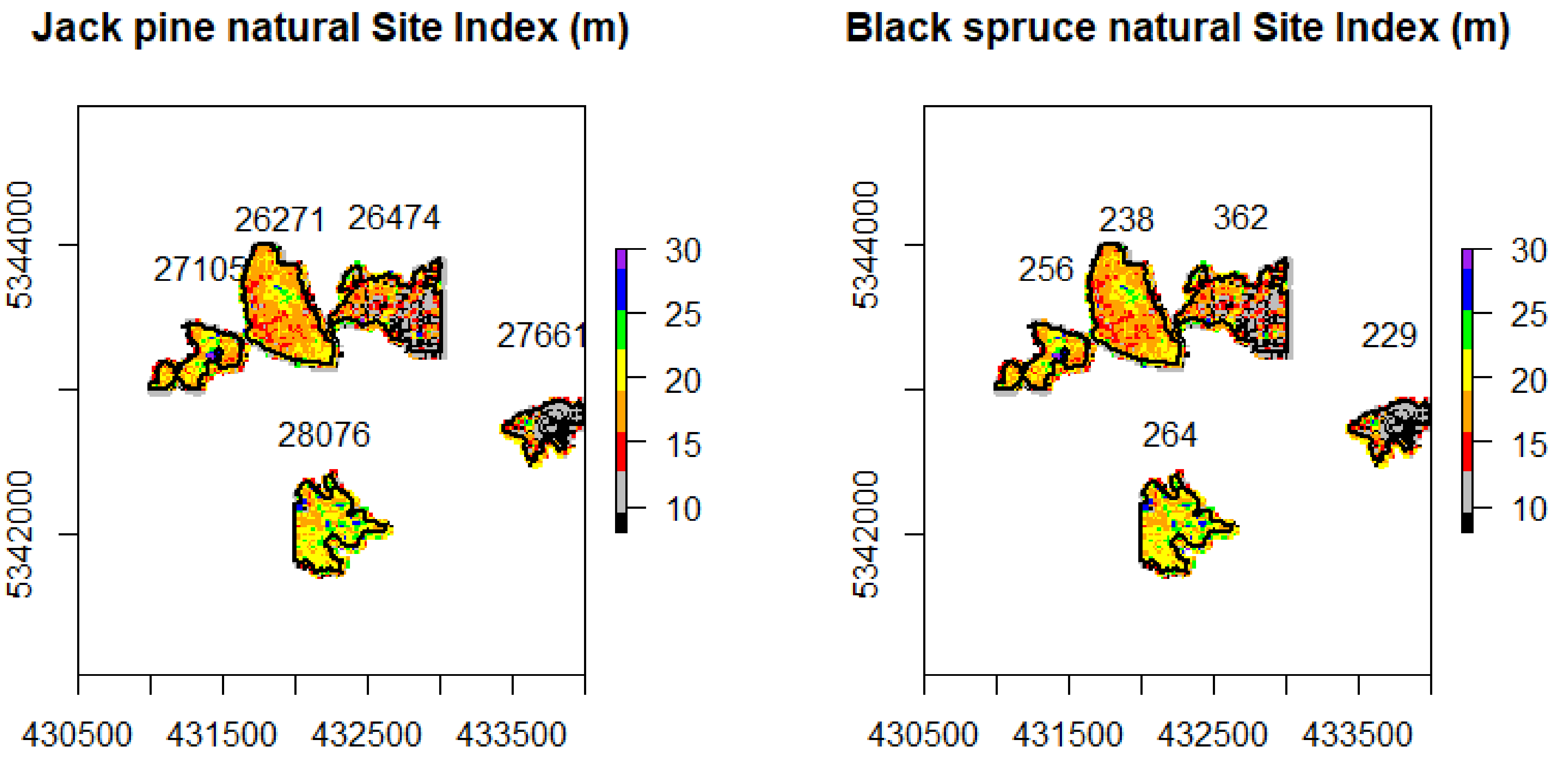
264 – Pj, mix of planted and natural from 1976

Pj SI

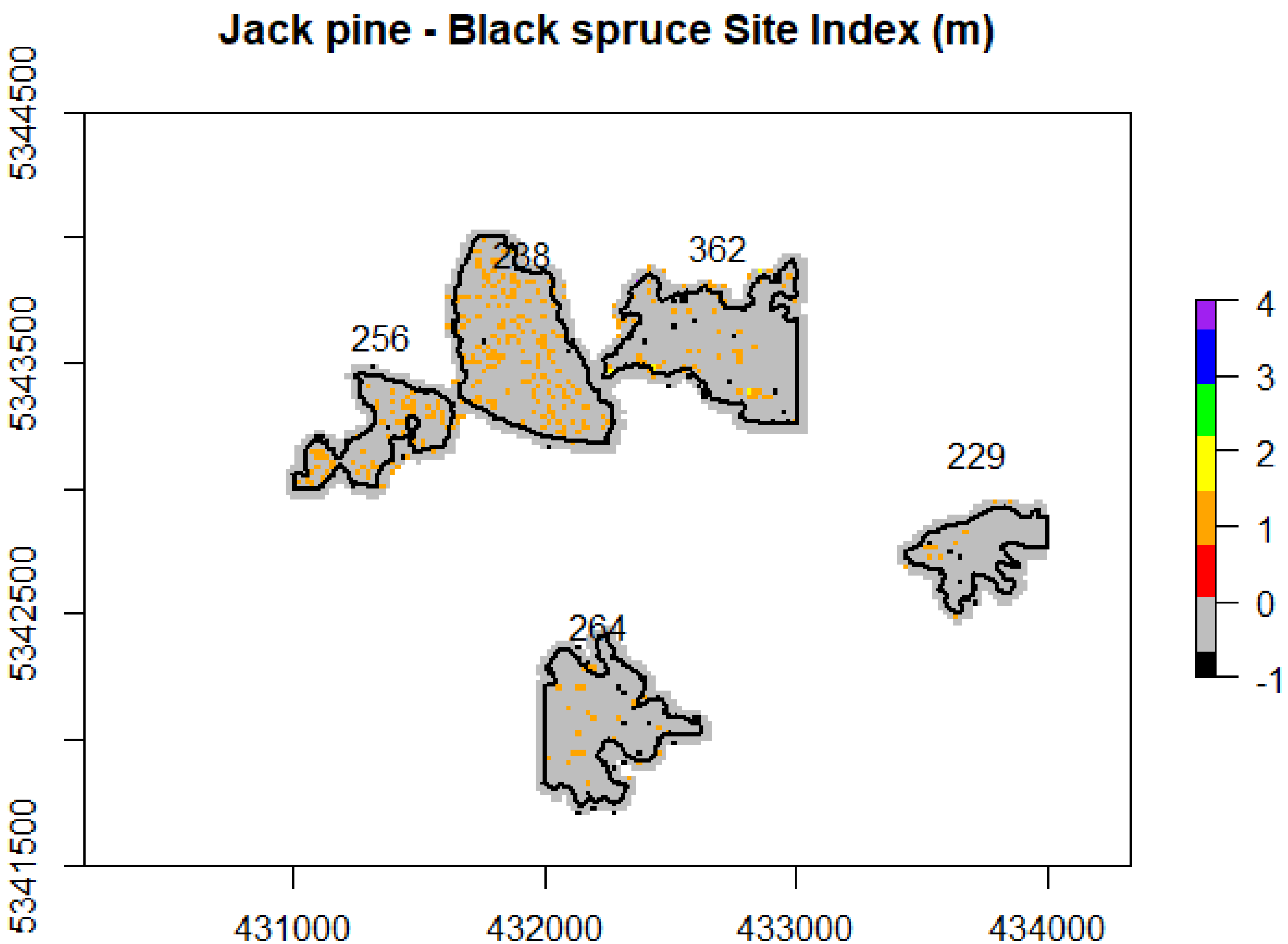

p99 2018 - 2005
26271
26474
27105
27661
28076
5344000
5342000
430500
431500
432500
433500
10
5
0
-5
-10
-15
-20

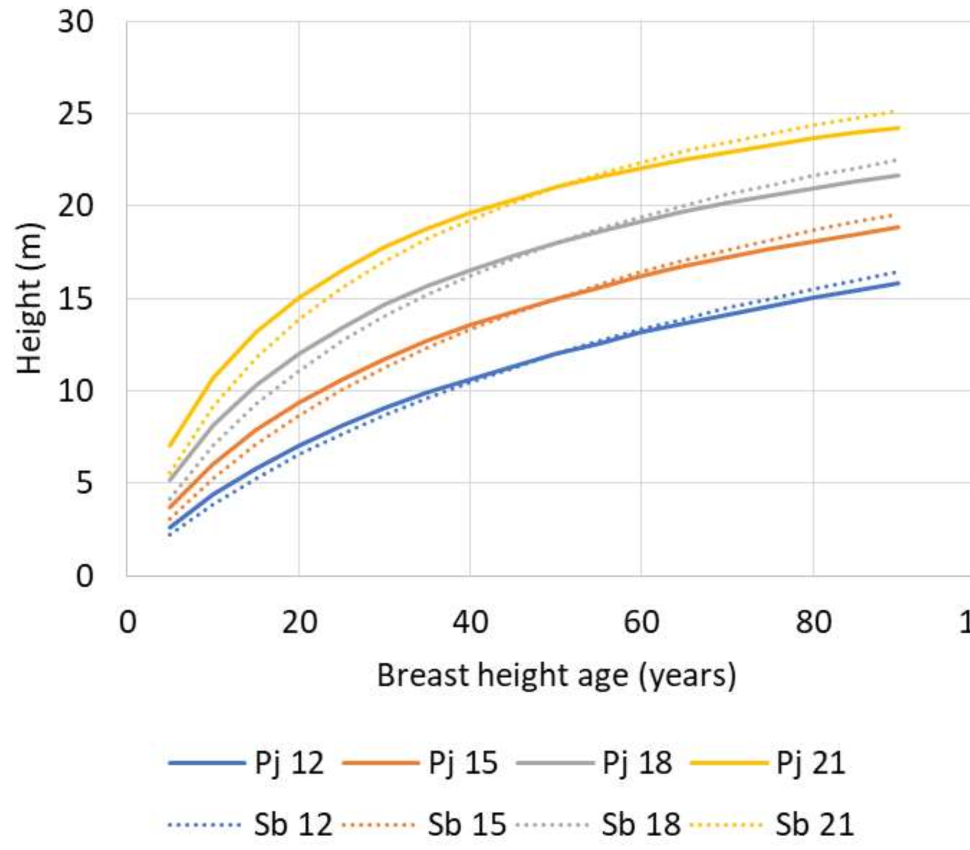

Jack pine natural Site Index (m)
238
362
256
229
264
5344000
5342000
430500
431500
432500
433500
30
25
20
15
10

Pj & Sb SI


Jack pine natural Site Index (m)
Black spruce natural Site Index (m)
26271
26474
27105
27661
28076
238
362
256
229
264
5344000
5342000
430500
431500
432500
433500
30
25
20
15
10

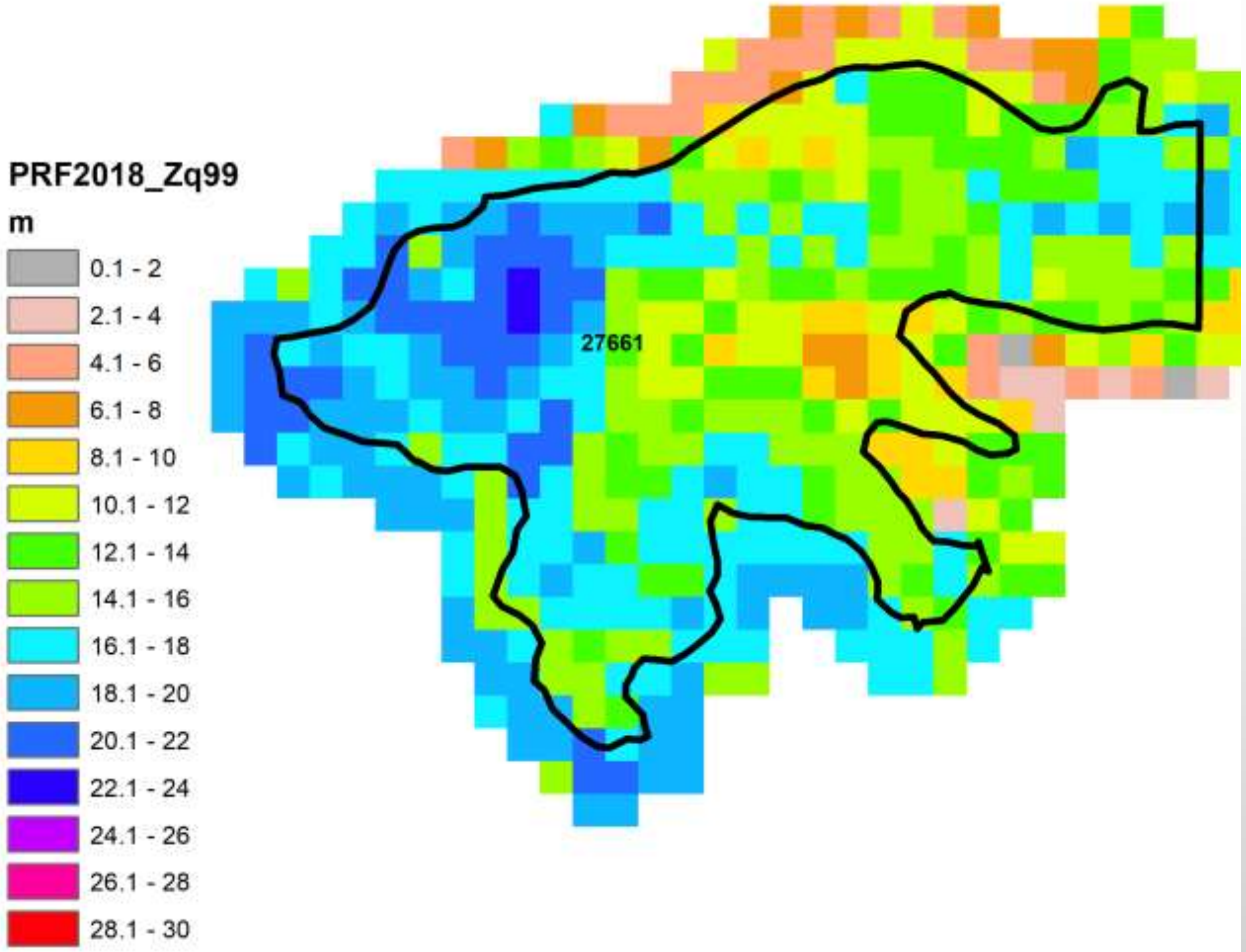
Difference between Pj and Sb Site index



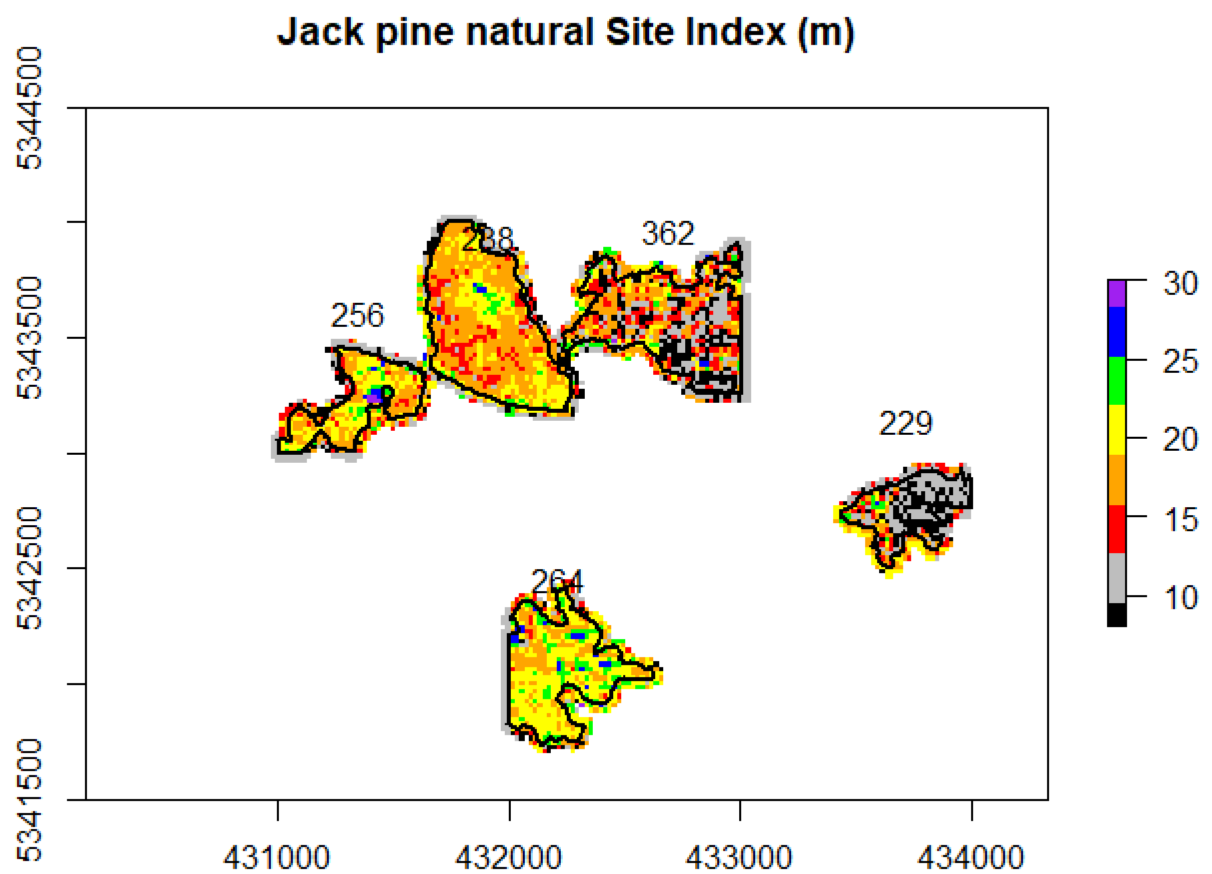


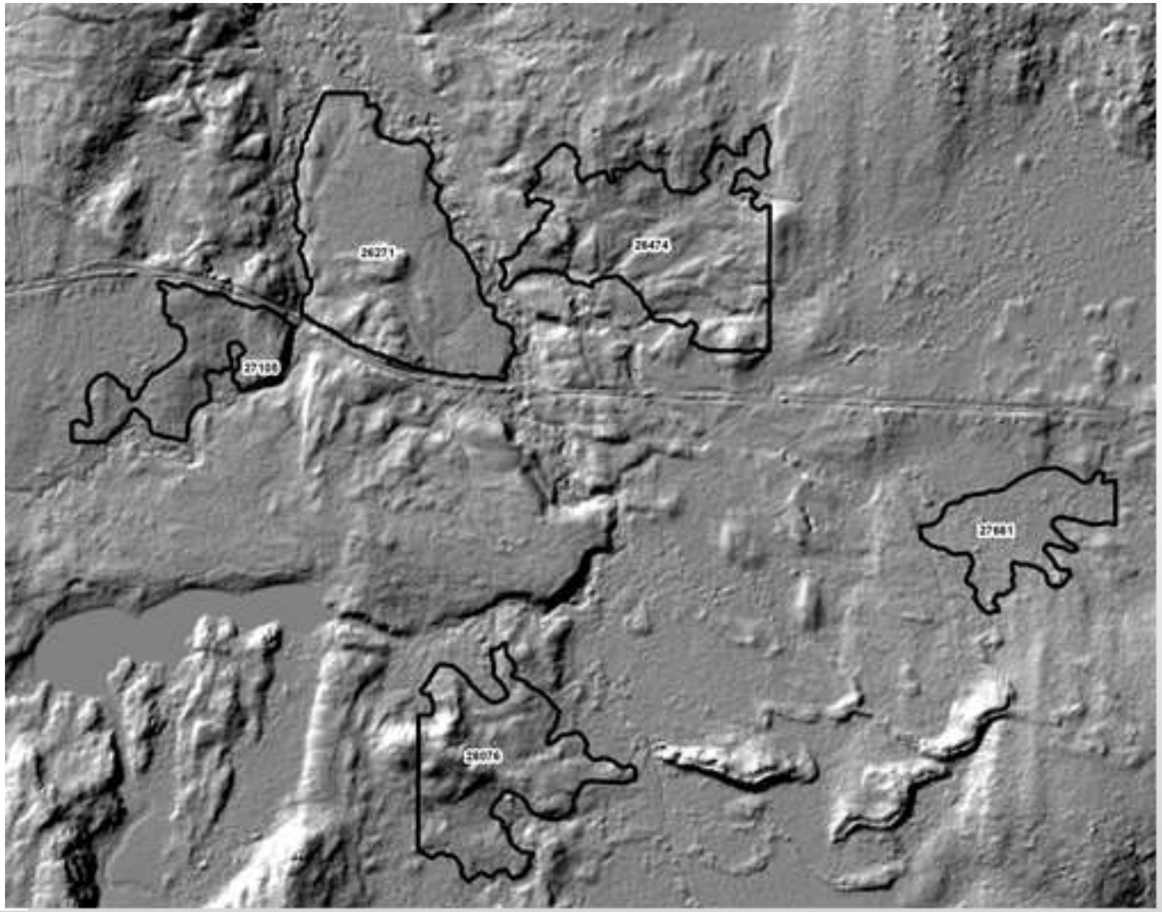
Influence of species mixtures

CE 40LA 30SB 20BF 10

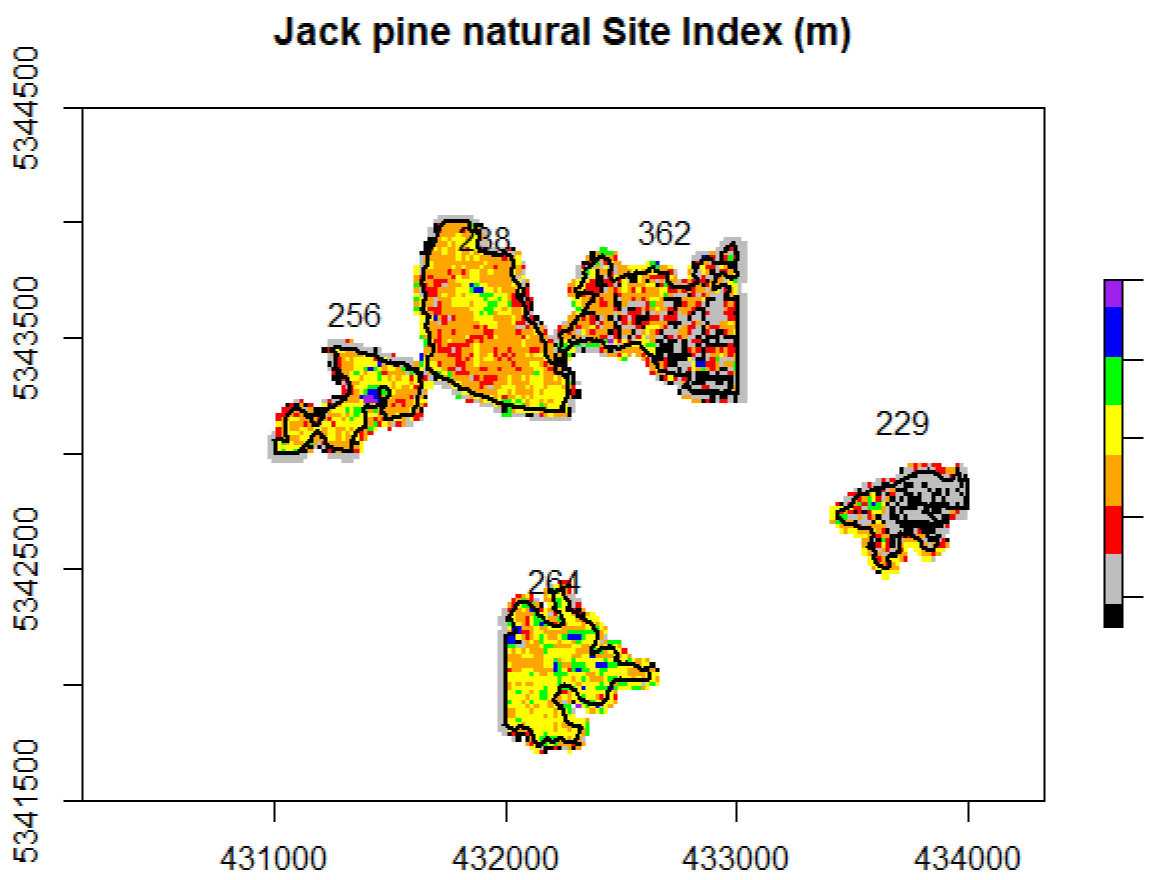


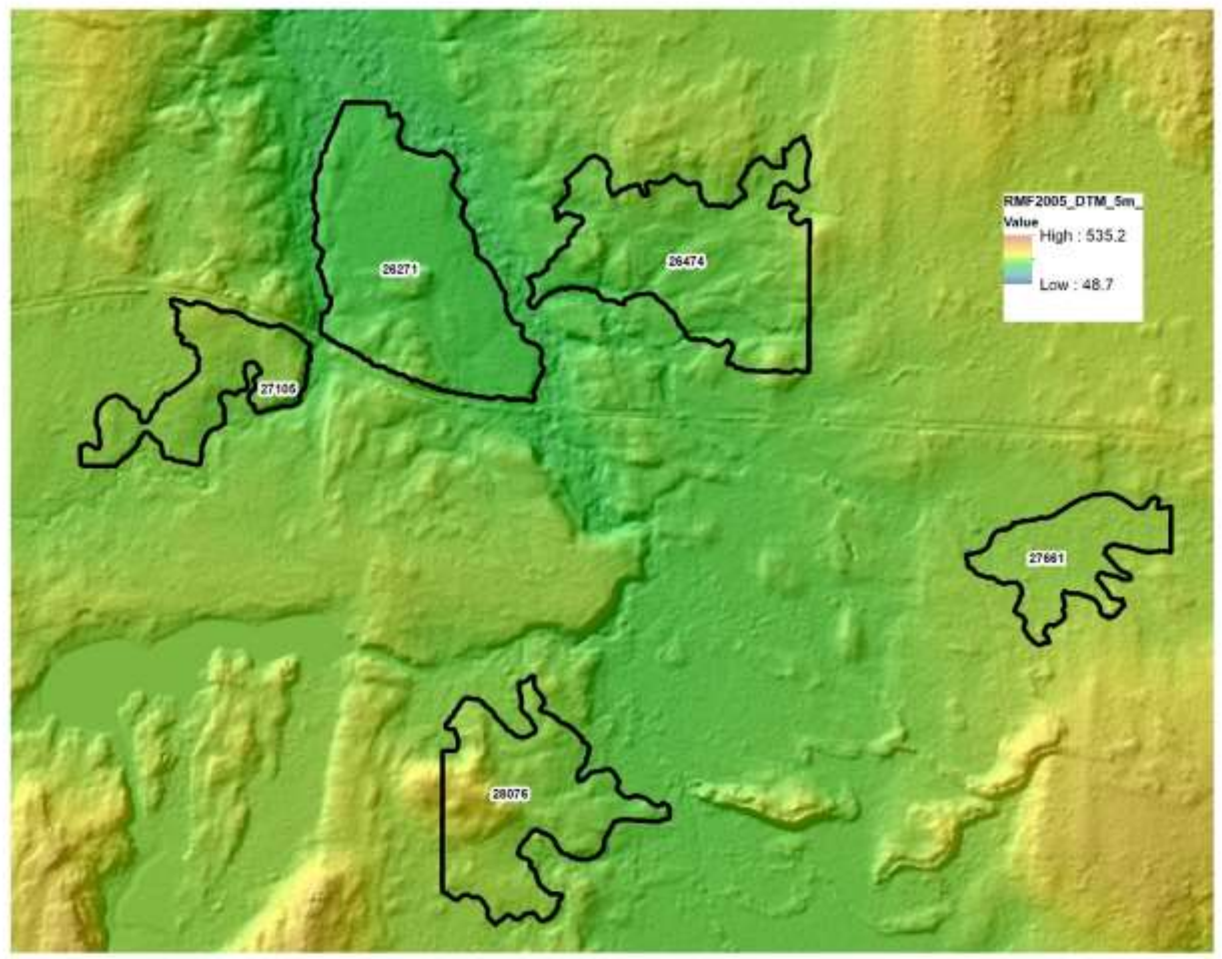
SI vs. DTM


Jack pine natural Site Index (m)
256
288
362
229
264
30
25
20
15
10
5344500
5343500
5342500
5341500
431000
432000
433000
434000



SI vs. elevation





Summary

Results

- Good results for jack pine, black spruce, white pine, red pine and poplar.
- Does not require age
- Does not require calibration data

Limitations

- Weak SI curves for some species
- SI concept of limited use for shade tolerant species.
- Still require leading species
- Validation data has unknown errors

Next steps

- Link to DTM derivatives?
- Application for inventory projection?

LiDAR – Prediction and Mapping of Site Productivity

Penner, M.; Woods, M.;
Bilyk, A. Assessing Site Productivity
via Remote Sensing—Age-Independent
Site Index Estimation in Even-Aged
Forests. Forests **2023**, 14, 1541.
https://doi.org/10.3390/f14081541

forests MDPI

Article

Assessing Site Productivity via Remote Sensing—Age-Independent Site Index Estimation in Even-Aged Forests

Margaret Penner [1,*], Murray Woods [2,†] and Alex Bilyk [3]

1 Forest Analysis Ltd., Huntsville, ON P1H 2J6, Canada
2 Ontario Ministry of Natural Resources and Forestry, McKellar, ON P0G 1C0, Canada; woods.murray@gmail.com
3 Overstory Consultants, Thunder Bay, ON P7G 0W3, Canada; abilyk@overstoryconsultants.com
* Correspondence: mpenner@forestanalysis.ca
† Retired.

Abstract: Forest productivity is a key driver of forest growth and yield and a critical information need for forest management and planning. Traditionally, this information has come from field plots, but these are expensive to measure and have limited coverage. Remote sensing, on the other hand, can provide forest inventory attributes on landscape scales and with a relatively low cost. A common predictor of forest productivity is site index (SI), traditionally estimated from age and height. In plantations, age can often be treated as a known quantity, but in natural-origin forests (of which Canada has vast swaths), age is often unknown and must be estimated, requiring expensive field work and resulting in a high level of error which, in turn, introduces error into SI estimates. The objective of this study is to generate estimates of SI from two successive LiDAR captures. The 99th percentiles (p99) of LiDAR returns from two successive captures 13 years apart were used along with species-specific SI curves to estimate SI. The results were compared to field-based estimates of SI for two major boreal species, jack pine and black spruce in managed and unmanaged conditions. Overall, the difference between the LiDAR-based SI and the field estimate was 2% with a relative mean squared error of 18%. For the few situations in which the height change was small or negative (less than 0.5%/year), SI was estimated from the average p99 and an assumed age of 100. The advantage of this method is that it does not require field sampling or estimates of age. Using two successive LiDAR captures, wall to wall estimates of SI can be generated at the grid cell level (e.g., 20 × 20 m), a level of detail generally not found in inventories. Overall, our results demonstrate the excellent potential for estimating SI from LiDAR alone, without age, to provide detailed productivity information for forest management and inventory that has been lacking in most large-scale inventories until now.

Keywords: LiDAR; forest inventory; height growth; ALS; successive inventories

check for updates

Citation: Penner, M.; Woods, M.; Bilyk, A. Assessing Site Productivity via Remote Sensing—Age-Independent Site Index Estimation in Even-Aged Forests. *Forests* **2023**, *14*, 1541. https://doi.org/10.3390/f14081541

Thank you!

Ministry of Natural Resources and Forestry

Comments? Questions?

Contact Information: Margaret Penner - mpenner@forestanalysis.ca
Murray Woods – woods.murray@gmail.com
Alex Bilyk -abilyk@overstoryconsultants.com