Assessing airborne laser scanning for forestry applications

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Who am I? Why am I here?

Senior researcher – focus on:

- airborne LiDAR
- terrestrial LiDAR
- and other sensors

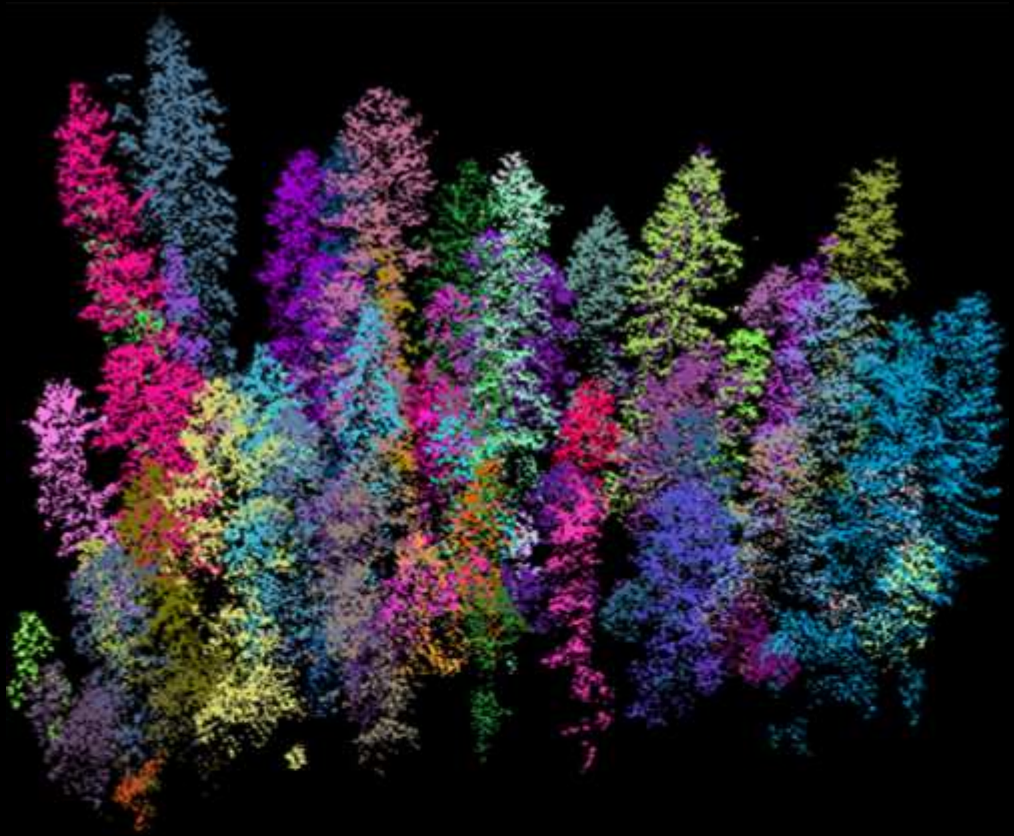
Main responsibilities:

- Research new methods to estimate forest characteristics;
- Explore the utility of new and existing sensor platforms;
- Develop tools for the support of forest managers;

Overview

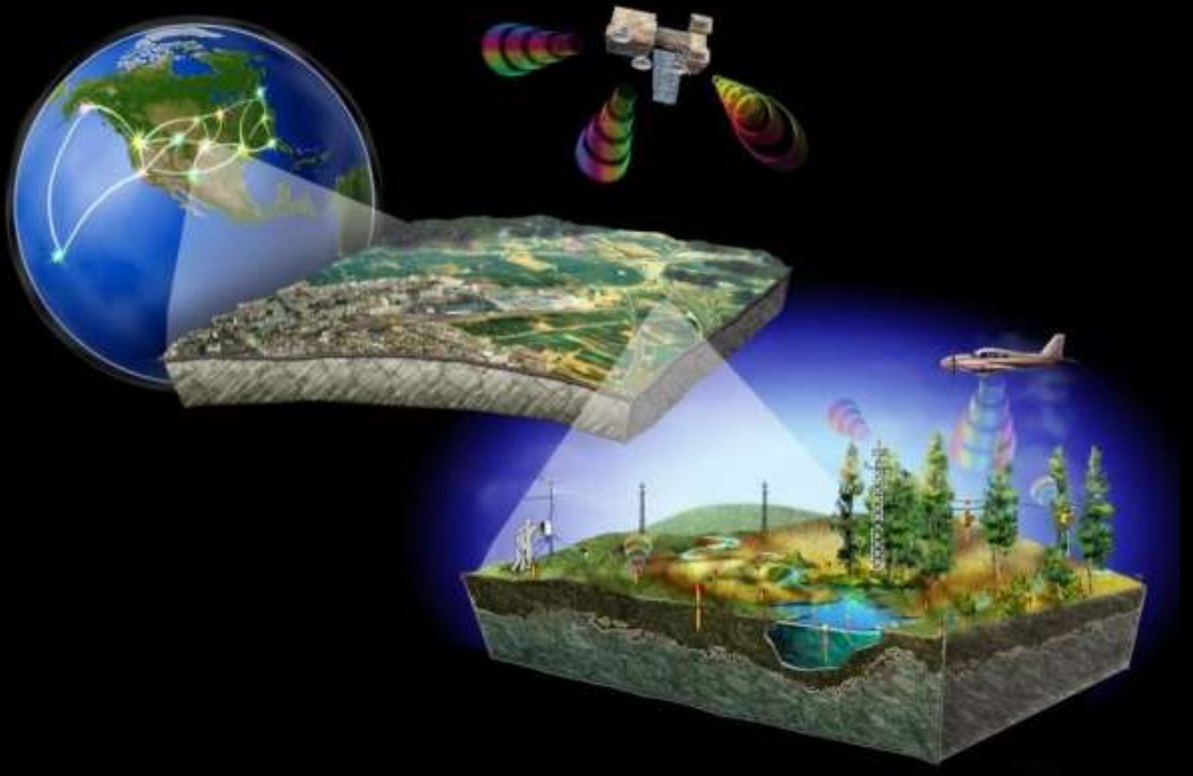
Airborne LiDAR & tools:

- Area based analyses:
  - Height and crown length;
  - Leaf area index;
  - Estimating basal area and mean DBH;
  - Mapping understory layers;
- Individual tree delineation;



What is remote sensing?

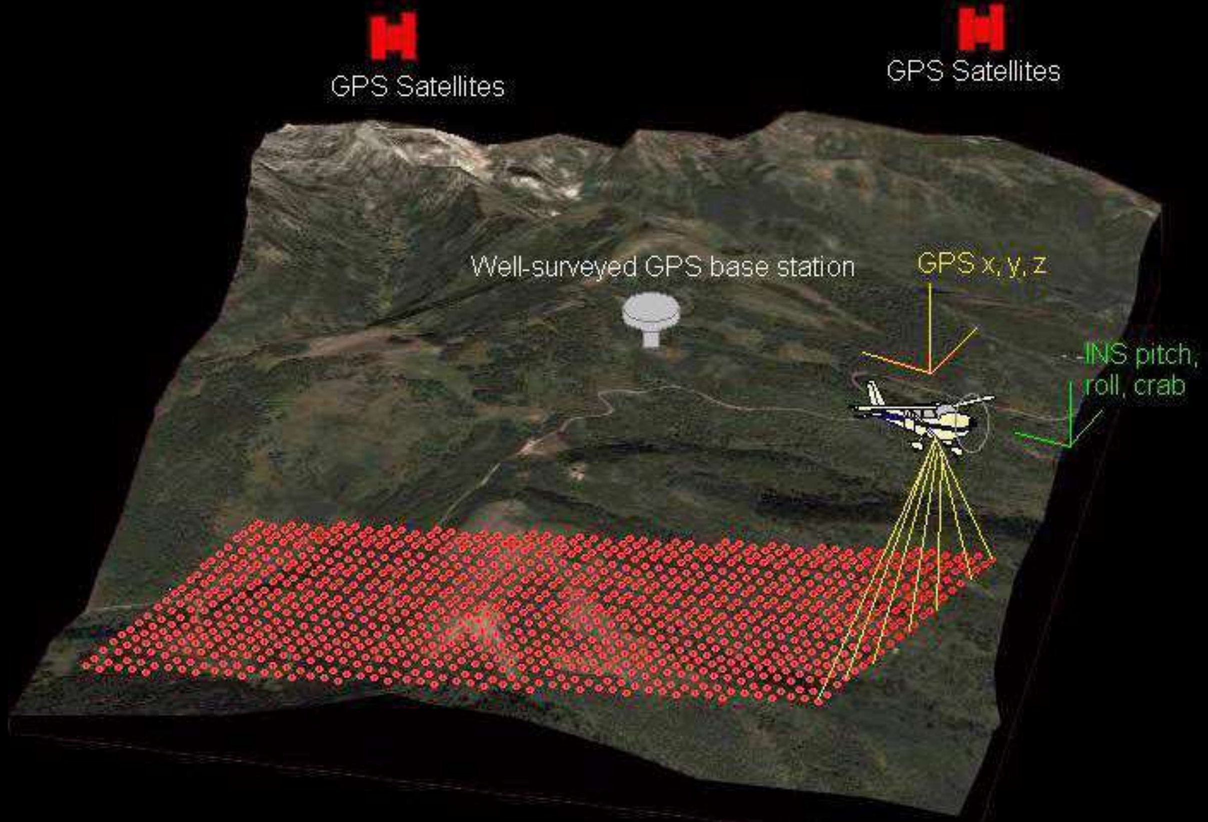
Remote Sensing is a method of obtaining information about the properties of an object at a distance, no physical contact.



Brief Background on airborne laser scanning (ALS), a.k.a. LIDAR.

What is ALS?

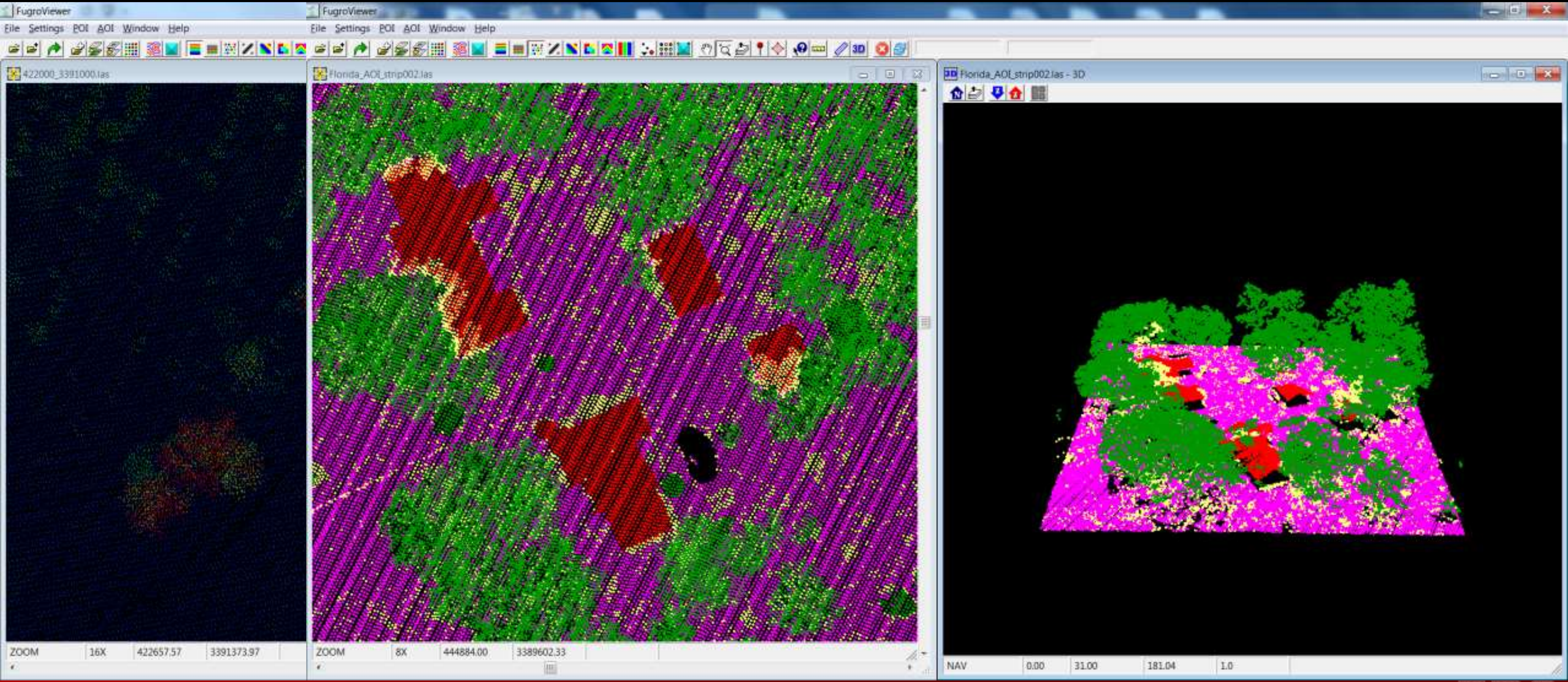
3D location determined using a combination of the speed of light, scan angle, GPS and IMU within the plane



What the data actually looks like:

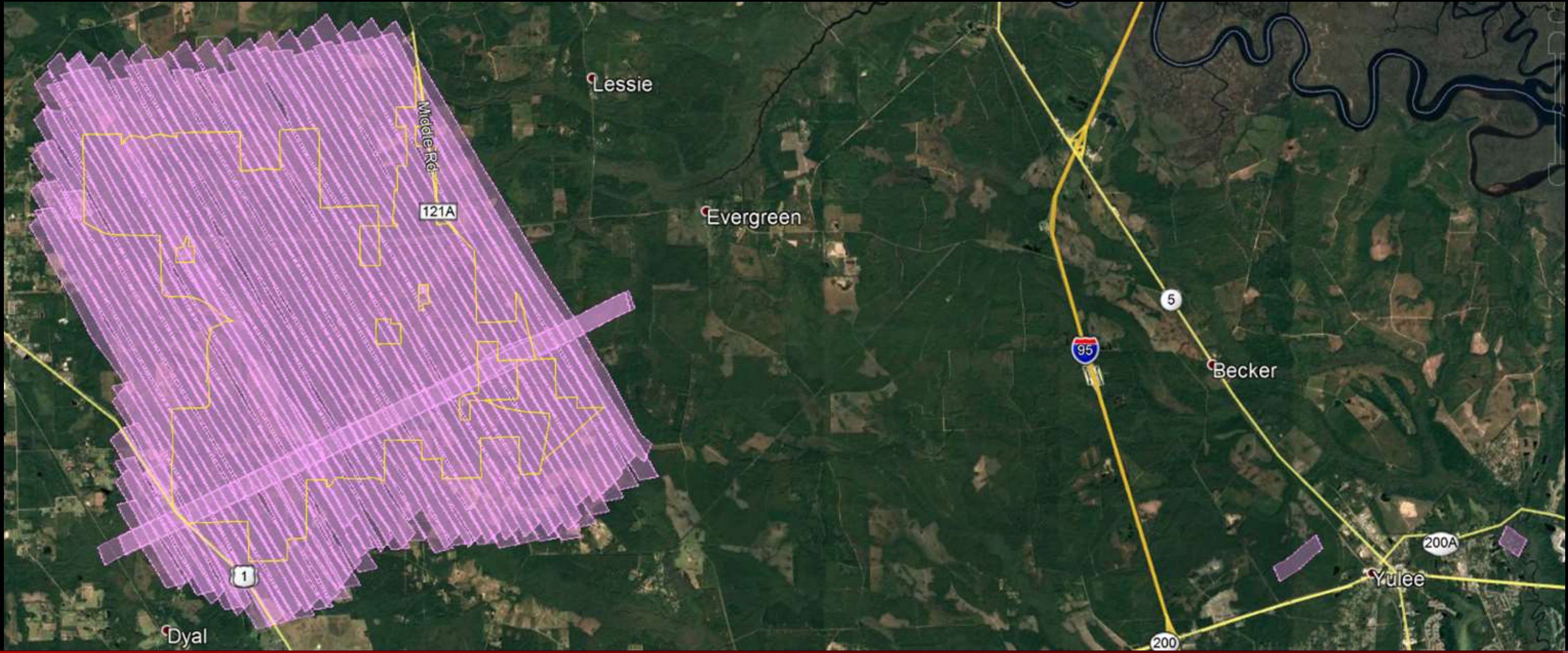
X	Y	Z	Int.	Rtn. No.	No. rtn. in pulse	Class	Scan angle	GPS_time
725470.26	4162710.94	10.65	5397	2	3	1	-21	396786.742
725470.29	4162710.96	9.50	771	2	4	1	-21	396786.742
725470.32	4162710.96	8.38	385	2	3	1	-21	396786.742
725470.14	4162710.98	16.35	5782	1	1	1	-21	396786.742
725470.22	4162711.18	15.76	11950	1	1	1	-21	396786.742
725470.35	4162711.50	15.57	10794	1	1	1	-21	396786.742
725470.26	4162711.12	13.40	5011	1	1	1	-21	396786.742
725470.53	4162711.93	14.54	5011	1	1	1	-21	396786.742
725470.37	4162711.32	11.70	6553	1	3	1	-21	396786.742
725470.53	4162711.78	11.80	3855	1	4	1	-21	396786.742
725470.68	4162712.16	11.74	5782	1	3	1	-21	396786.742
725469.64	4162711.04	13.21	1927	1	3	1	-21	396786.749

Sample ALS data



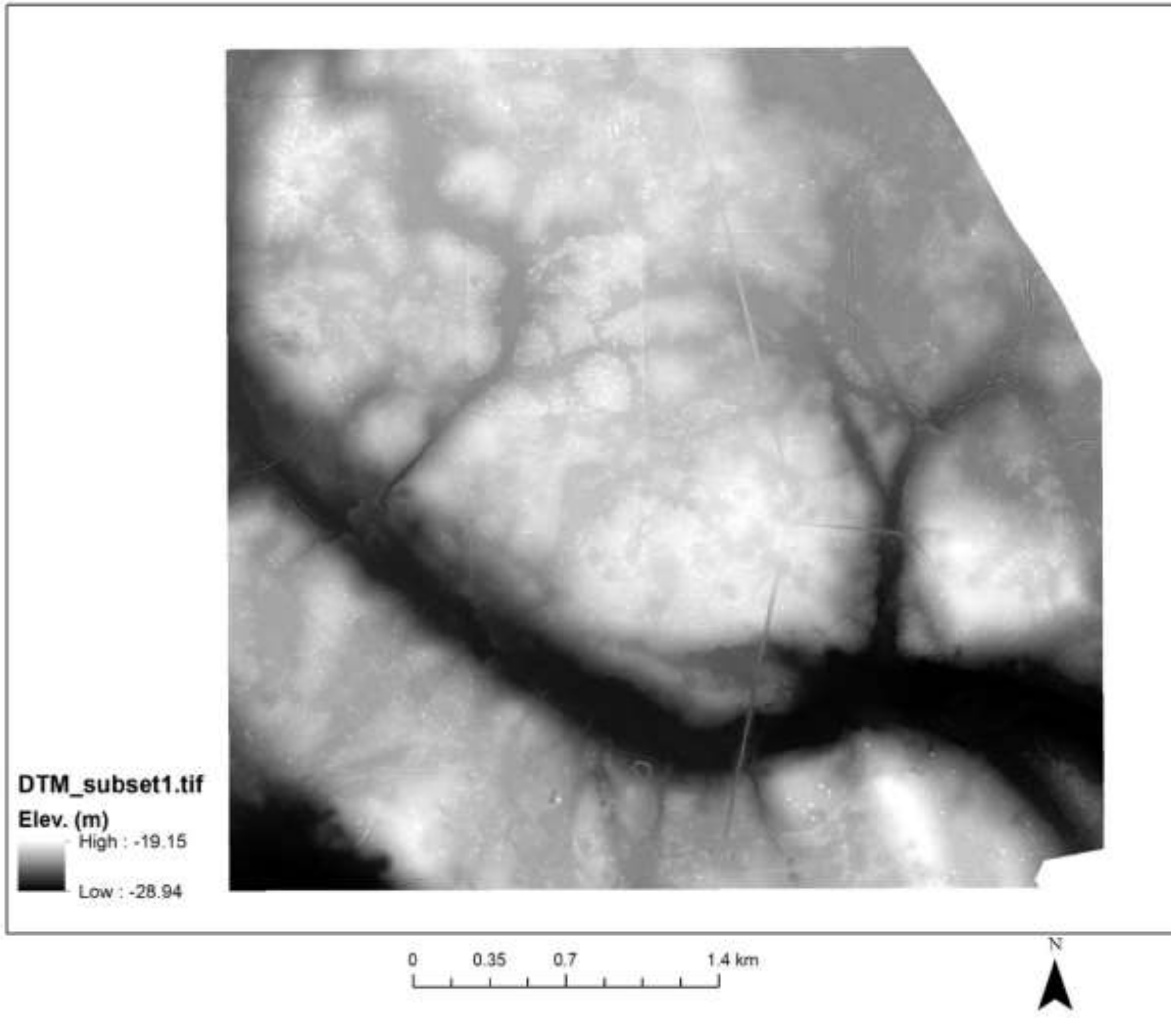
Sample flight overview

- ~111km^2 area;

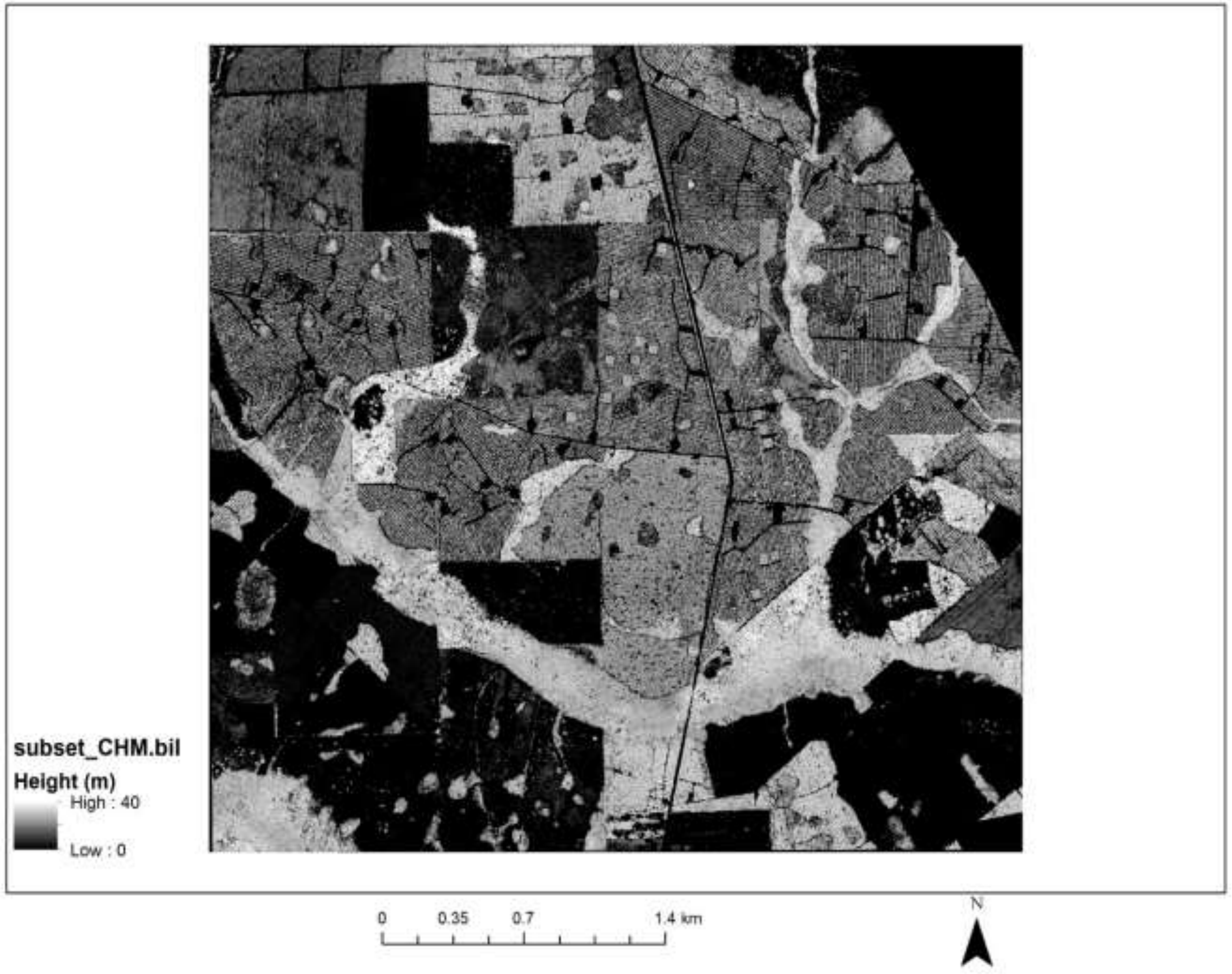


Applications for airborne laser scanning (ALS)

Basic height products



The underlying terrain



Vegetation height

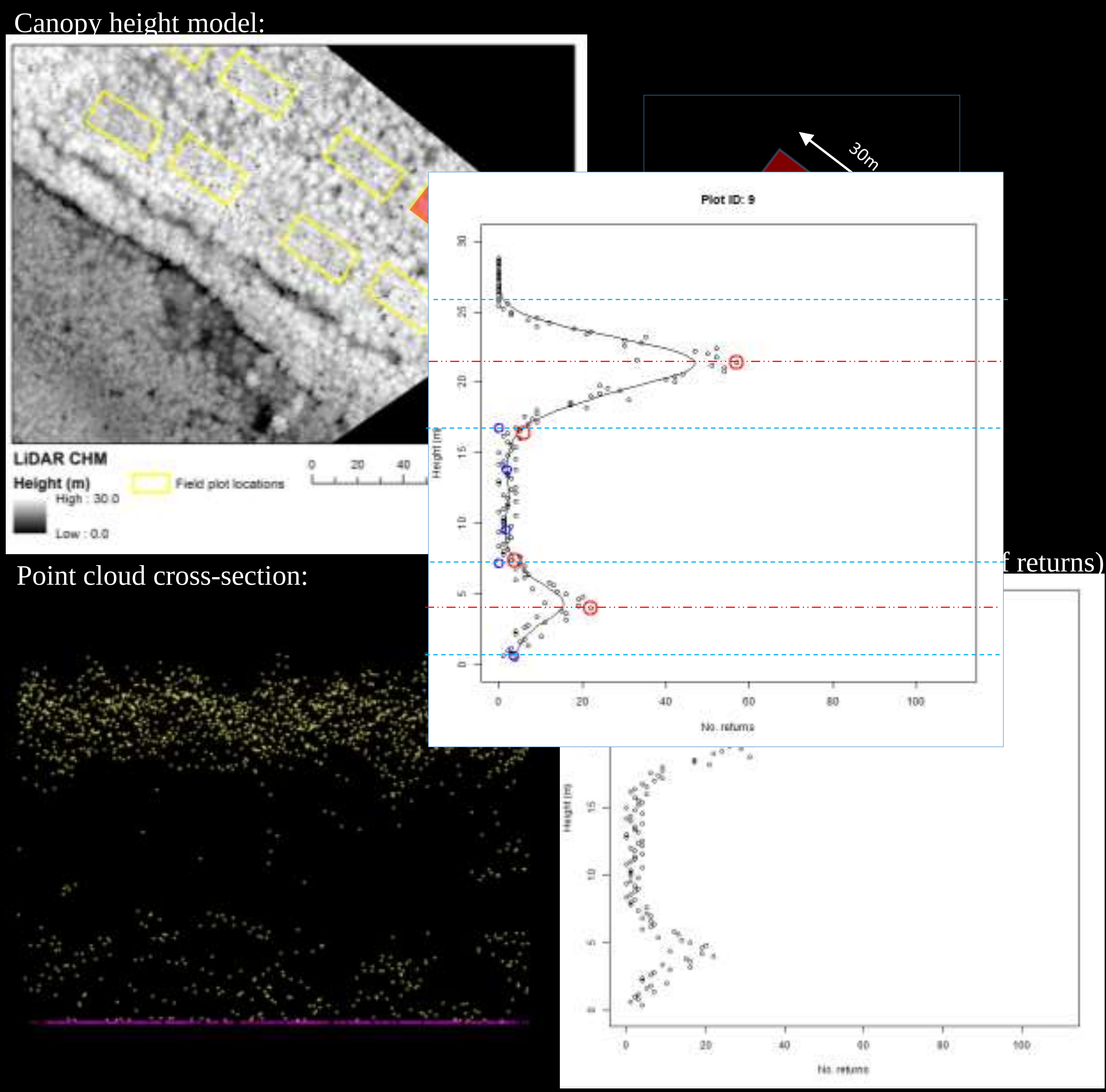
Outline

LiDAR tools for the estimation of:

- Canopy top height;
- Height to the live crown;
- Total LAI;
- Canopy only LAI;
- Understory only LAI;
- Generating custom model estimates;
- Mapping the understory;
- Delineating individual tree crowns;

An example of detecting vertical layers

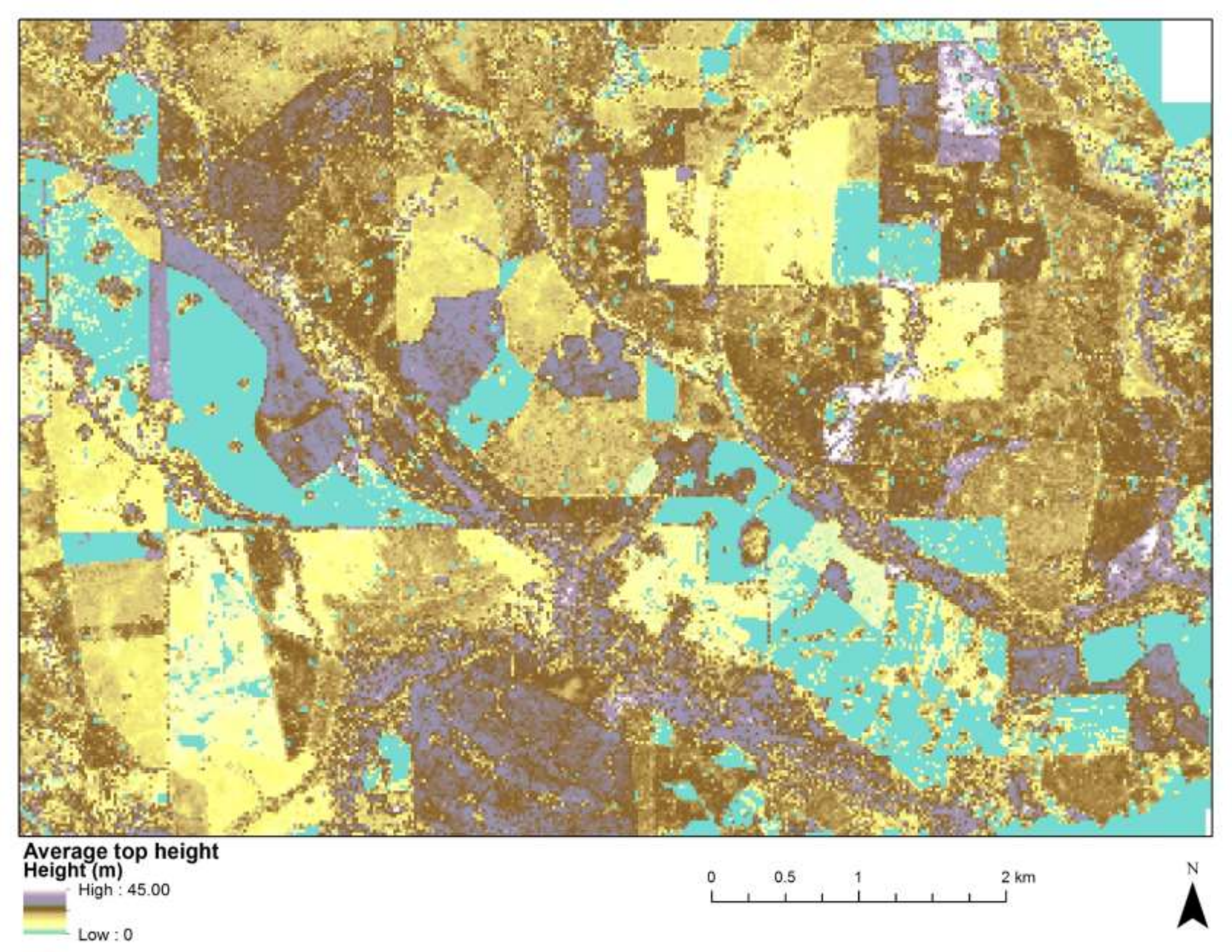
- At the field plot scale (e.g. 15m x 30m);
- A focus on analyzing vertical profiles (binned returns)
  - vertically stacked ‘virtual’ boxes containing the sum of returns within;
- One bin here is: 15 x 30 x 0.2m.



Average canopy top height

-Analyses performed

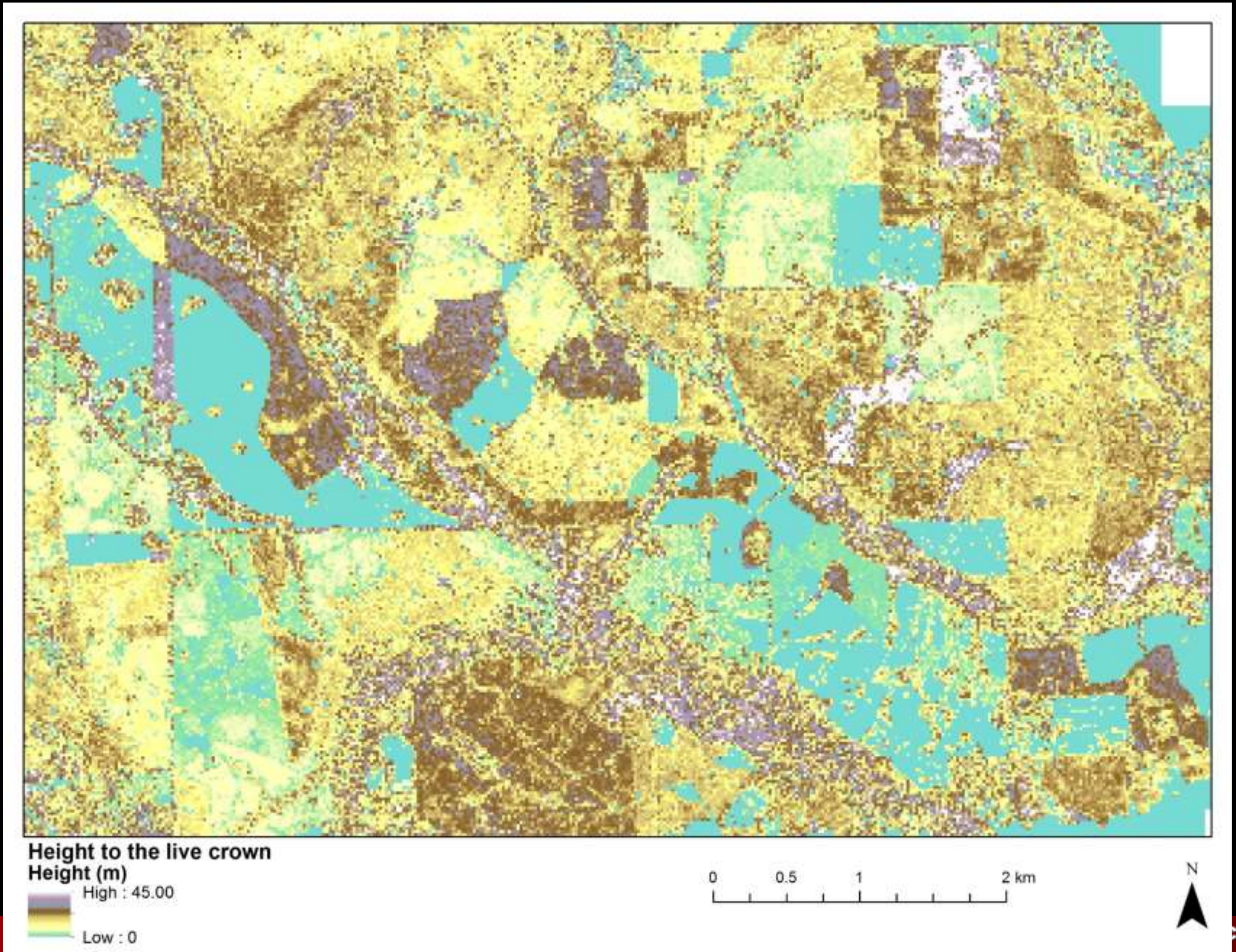
20x20m
Florida (FL01) Area of interest



Average Height to the Live Crown

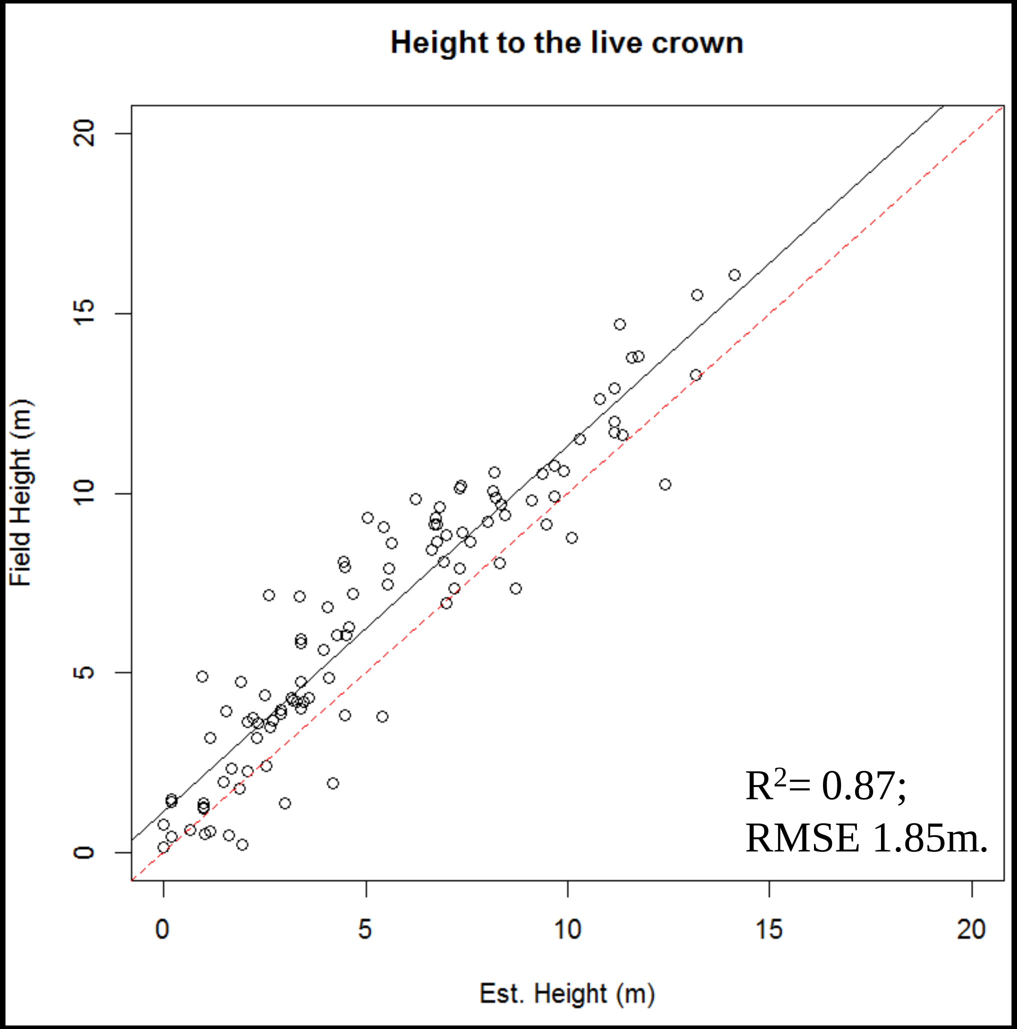
-Analyses performed

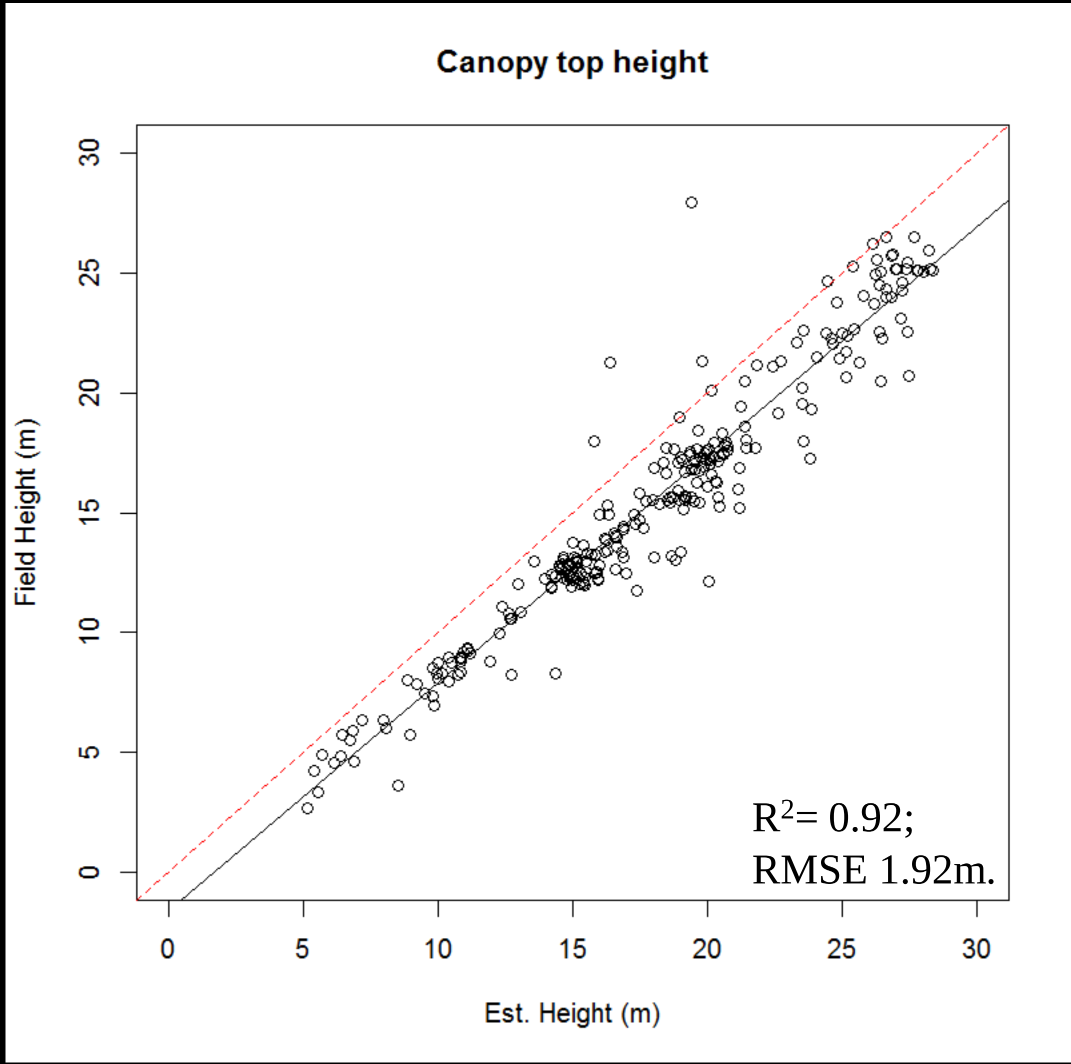
20x20m
Florida (FL01) Area of interest



Estimating canopy heights

-“Big flight” plot level inventory metric estimation (field metrics from x6 sites) FL, GA and TX.





Some brief background on leaf area index

Leaf Area Index (LAI) background

Poor Growth in
Low Leaf
Area Stands

Good Growth in
High Leaf
Area Stands

Why is leaf area is important?

Leaf Area Index (LAI)

- Is a ratio of one-sided green leaf area per unit ground surface area;

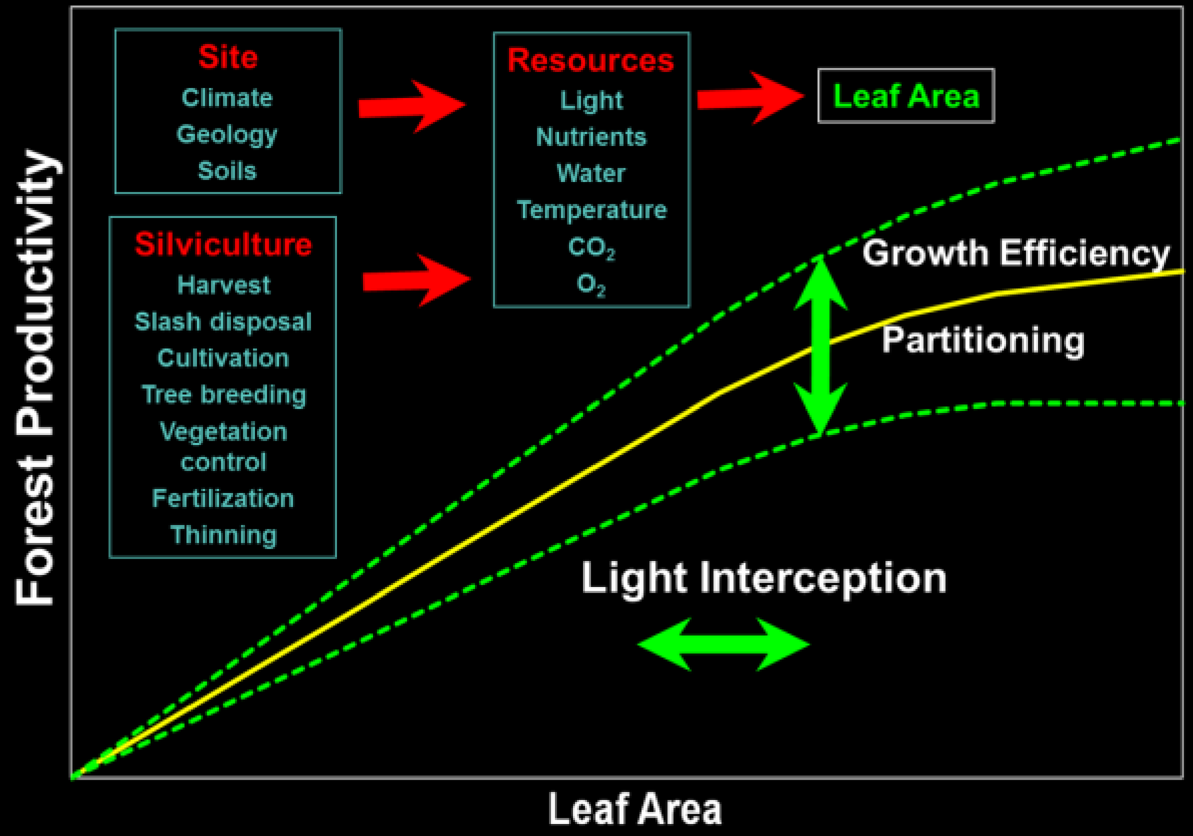
$$LAI = {}^{Leaf\ area(m^2)}/_{Ground\ area\ (m^2)}$$

- LAI ranges from 0 (bare ground) to over 10 (dense vegetation).

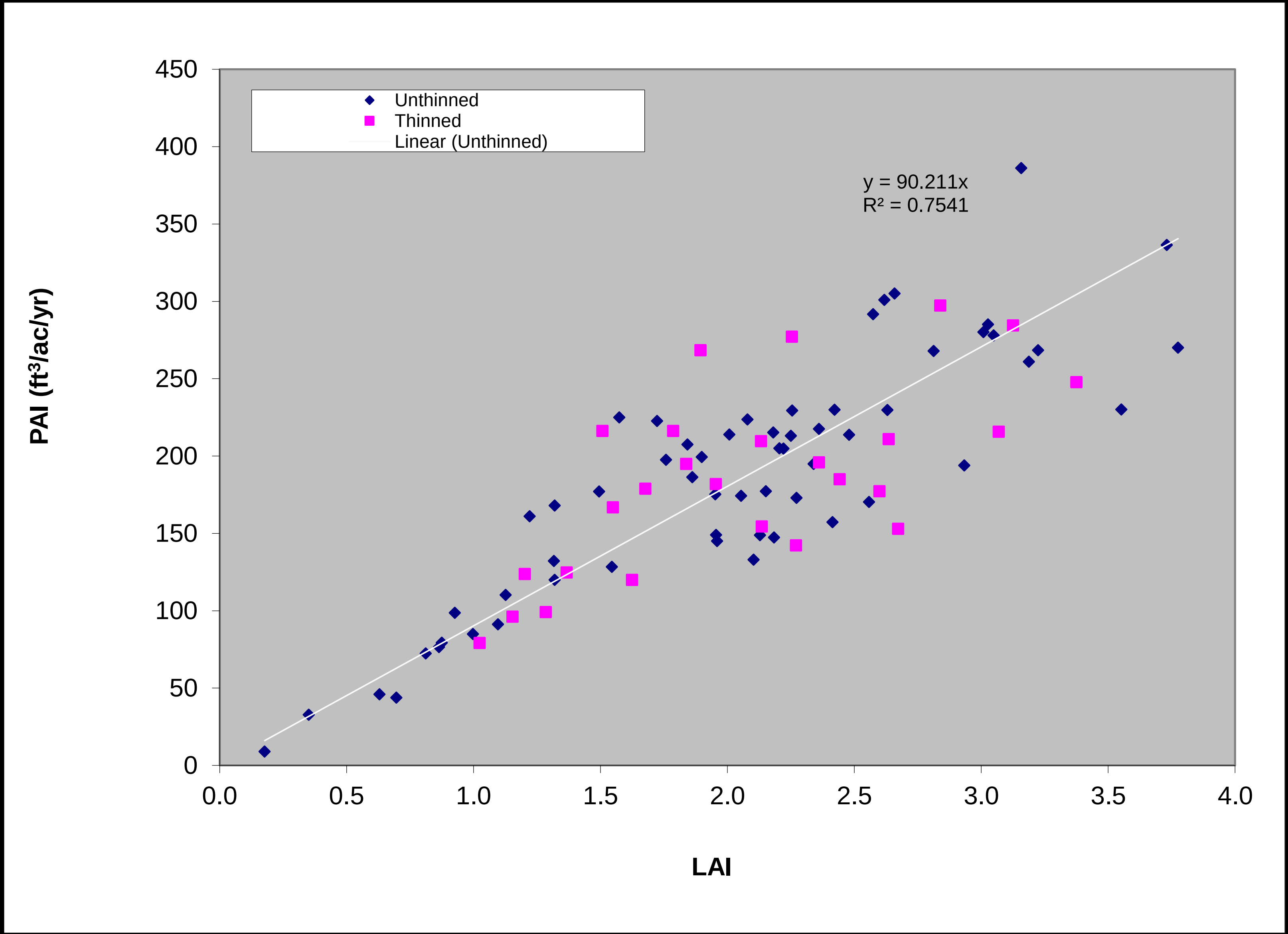
Used in predicting:

- photosynthetic primary production
- evapotranspiration
- productivity

"Leaves grow trees"



Leaf Area vs. Periodic Annual Increment in Loblolly pine



Periodic Annual Increment (PAI)

Estimating LAI from LiDAR data

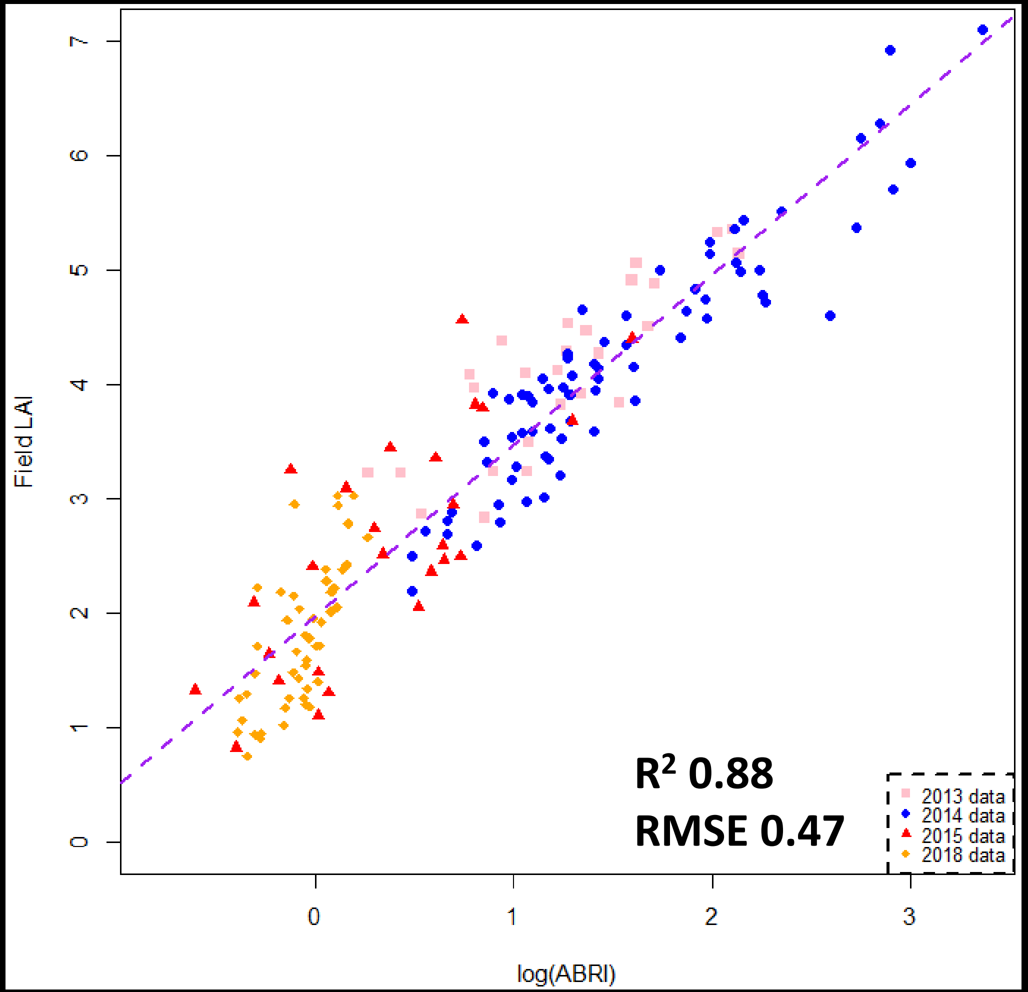
-(Loblolly pine - USA)

- Calibrated using field LAI 2200 measurements;
- Data from:
  - four acquisitions (2013, 2014, 2015, 2018);
  - different LiDAR systems;
  - Summer and winter dates;
  - *VA, NC, GA and FL;*

Above (T) and Below (T) Ratio Index (ABRI):

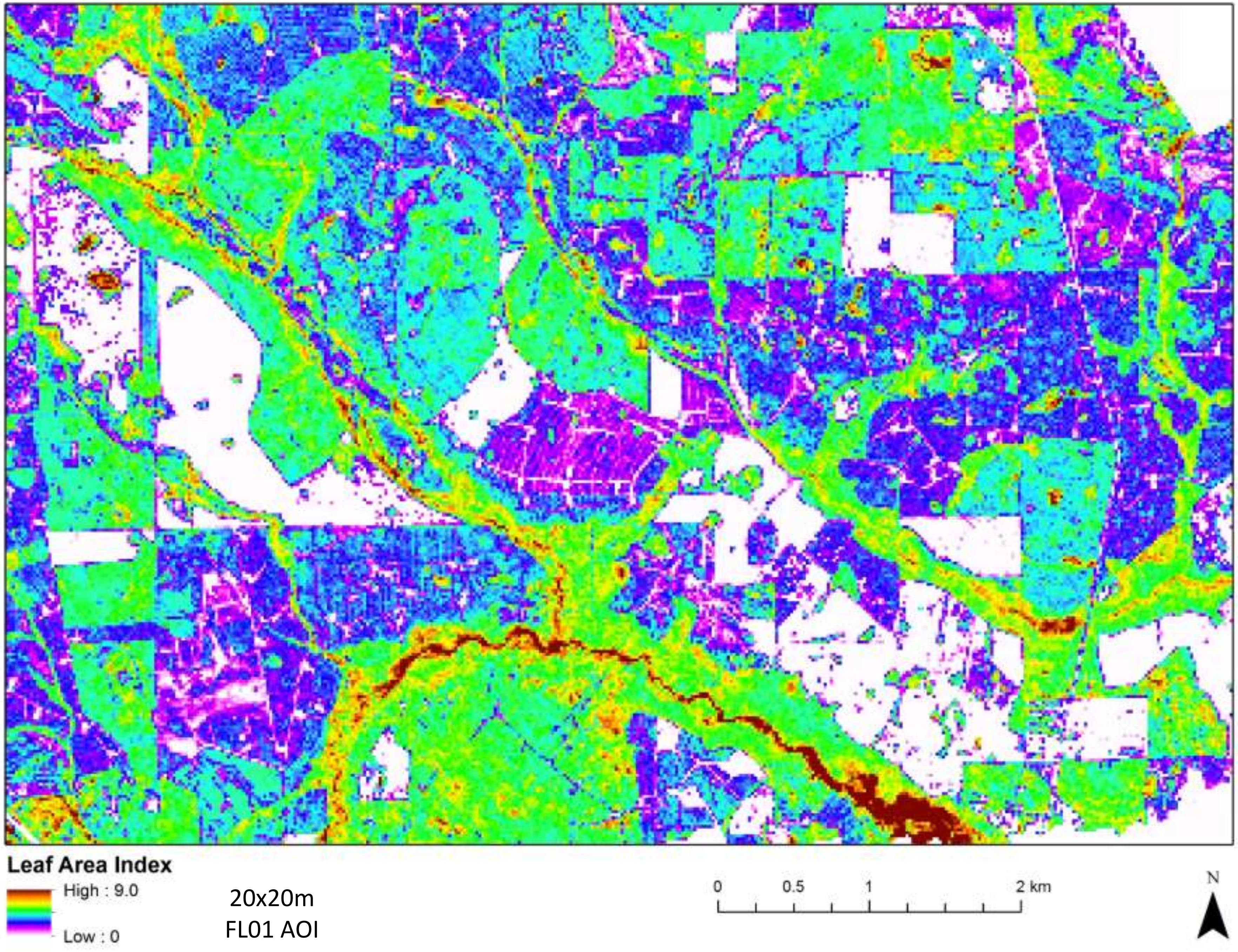
$$ABRI = \frac{\sum R_{>T}}{\sum R_{<T}} \longrightarrow LAI_e = \beta_0 + \beta_1 \times ABRI$$

- Where T is the height threshold (e.g. 1.0m above ground), R is the weighted number of returns (1/NRP).



Leaf Area Index

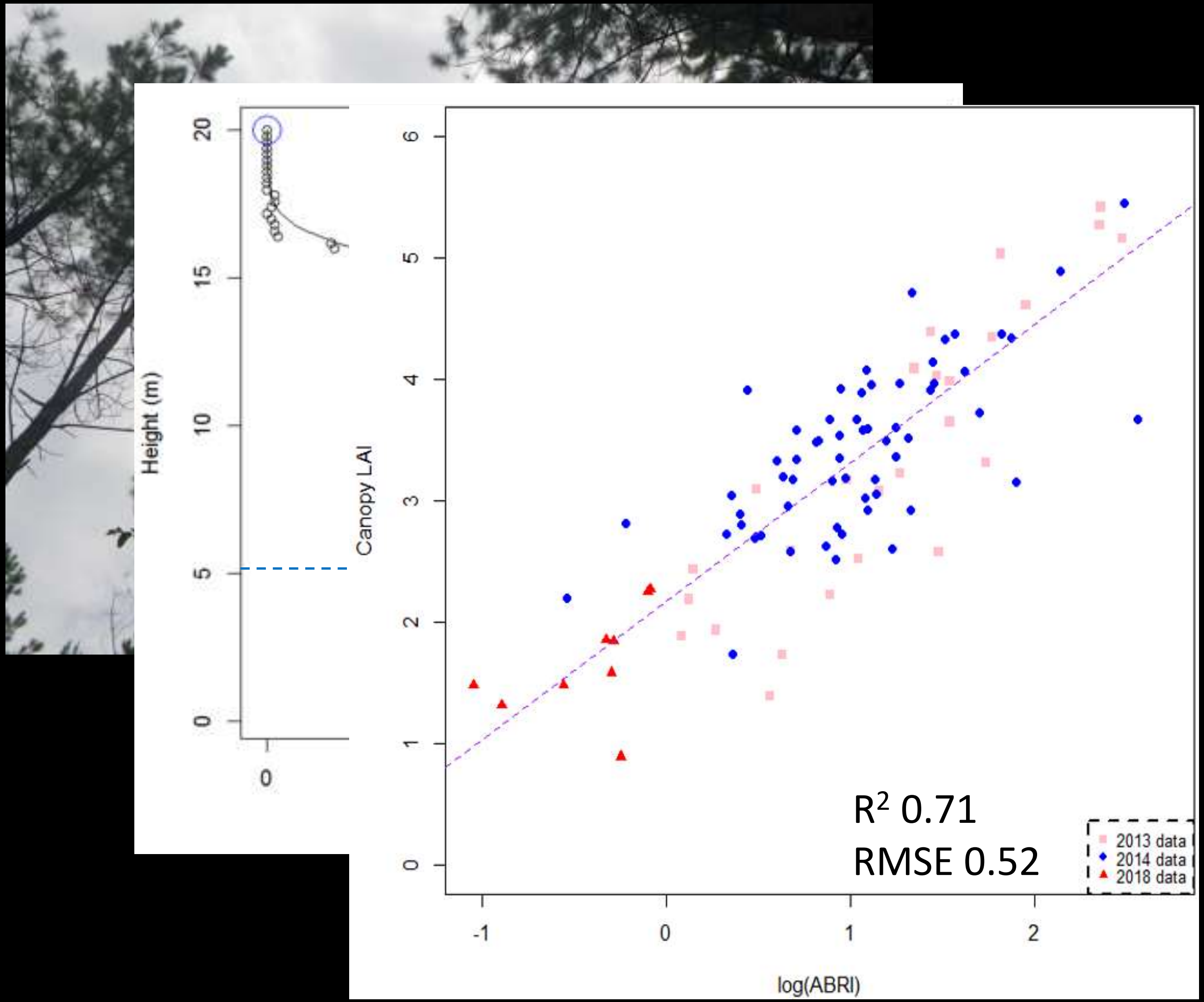
20x20m
Florida (FL01) Area of interest



LAI of the dominant canopy only

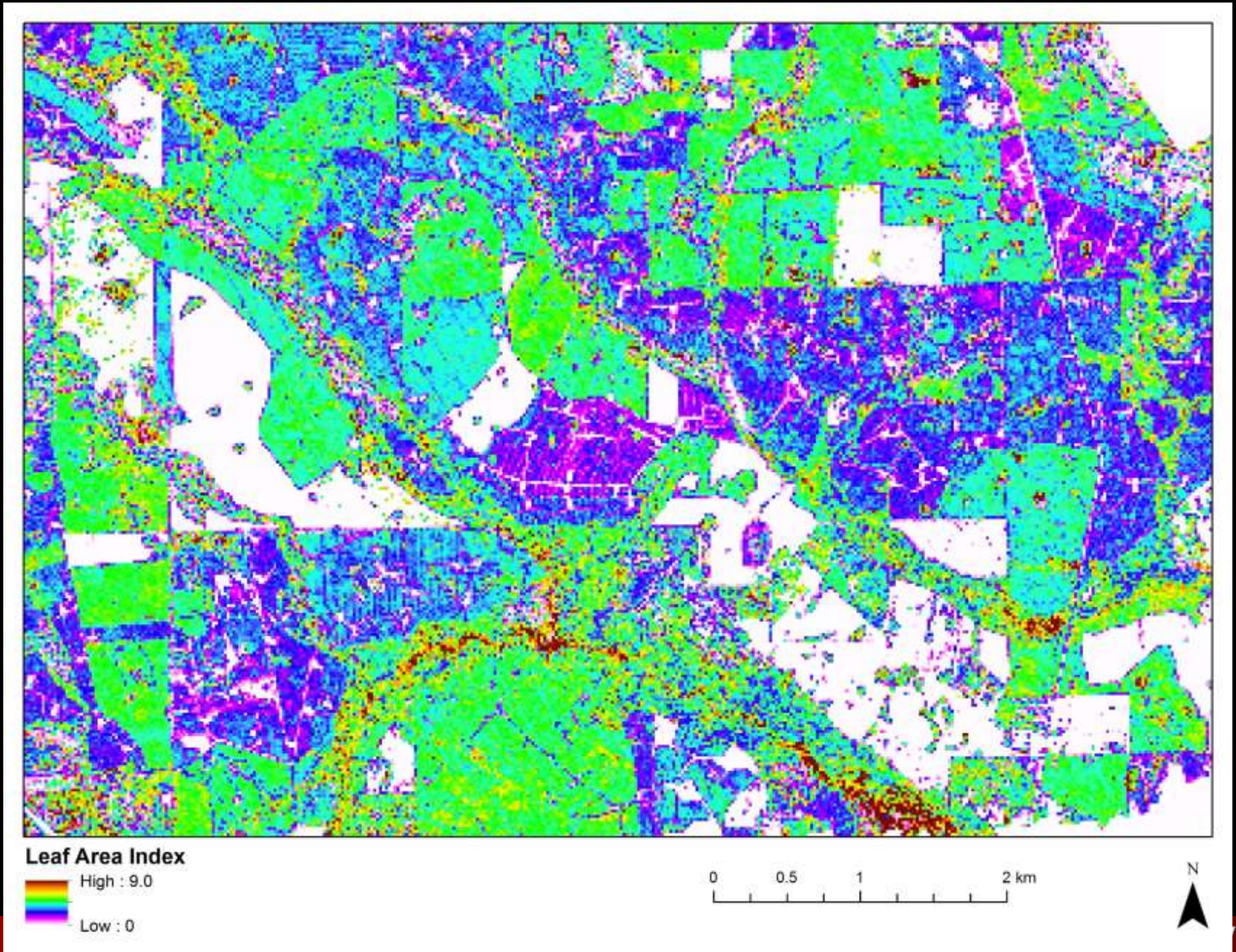
Process:

1. Detect dominant canopy base height
2. Apply LAI model using new height threshold



Canopy only Leaf Area Index

20x20m
Florida (FL01) Area of interest



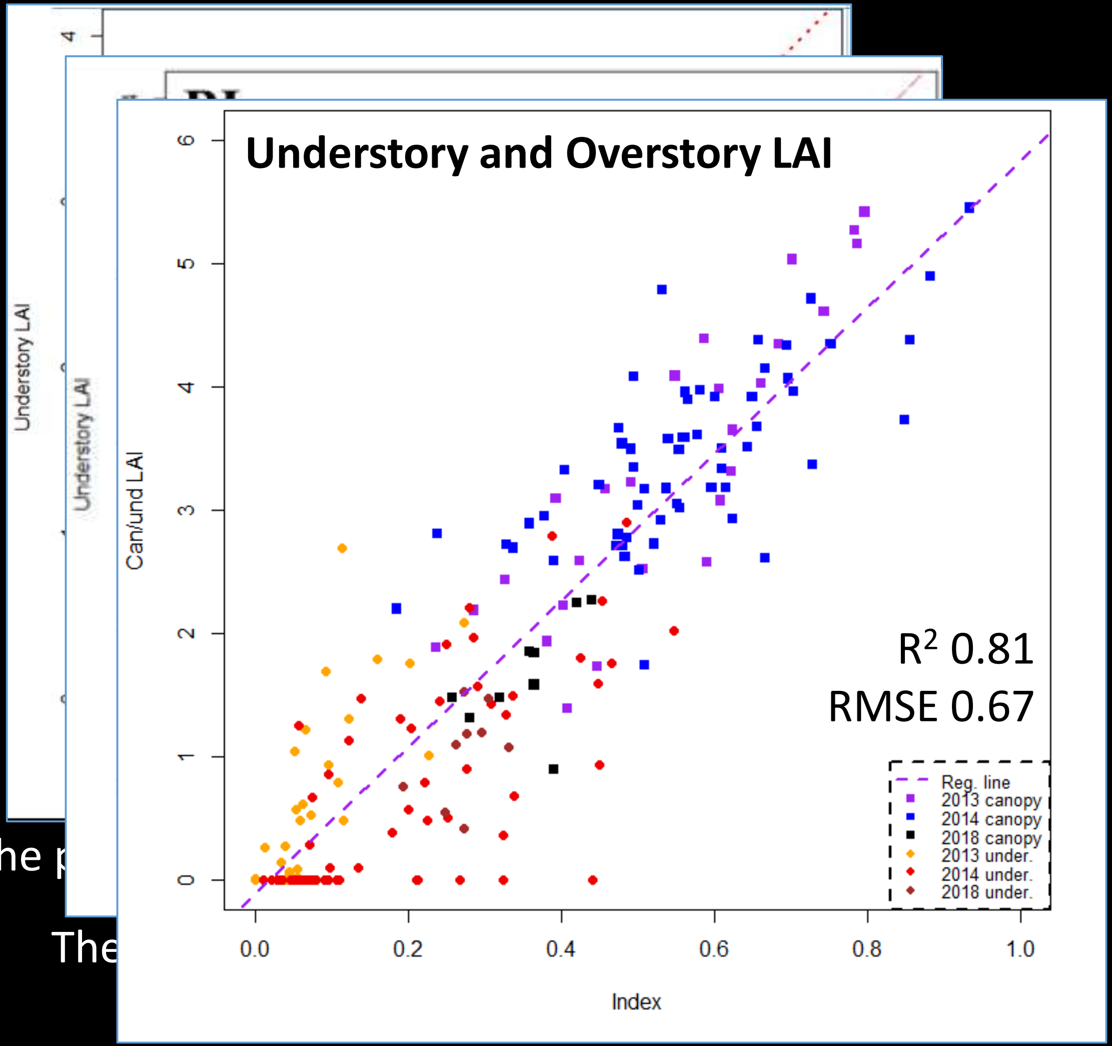
Understory contribution to total LAI

[New research]

- Required a different equation;
- Uses LiDAR return intensity (≈reflected energy);
- Accounting for light extinction at lower levels:

$$BL_{under} = \left(\frac{\left(\frac{\sum I_{UnderFirst} + \sum I_{UnderSingle}}{\sum I_{Total}}\right) + \sqrt{\frac{\sum I_{UnderIntermediate} + \sum I_{UnderLast}}{\sum I_{Total}}}}{\left(\frac{\sum I_{First} + \sum I_{Single}}{\sum I_{Total}}\right) + \sqrt{\frac{\sum I_{Intermediate} + \sum I_{Last}}{\sum I_{Total}}}} \right)$$

- Understory energy ≈ intensity from 0.5m to the HTLC;



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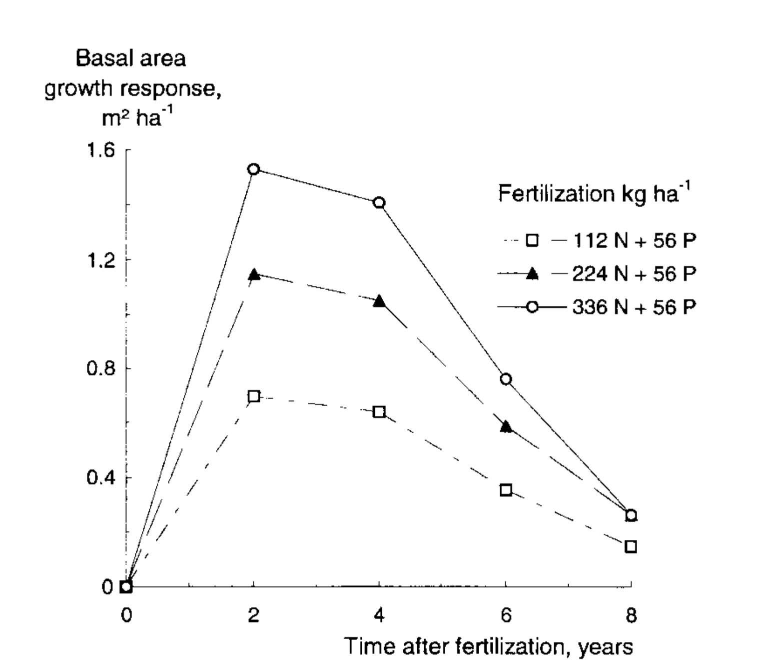
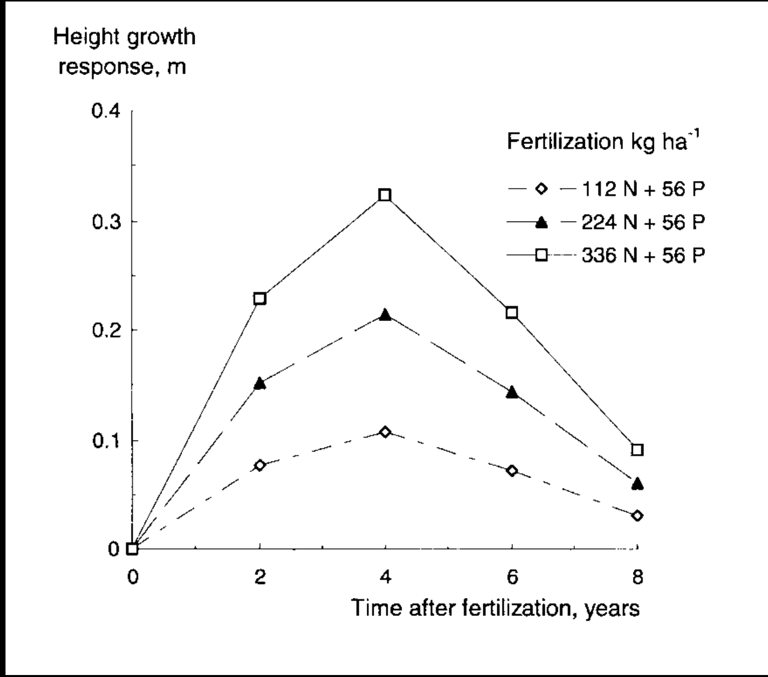
BL equation applied to under- and over-story

Estimating annual increment from LAI





Response to Nitrogen Fertilization is short lived

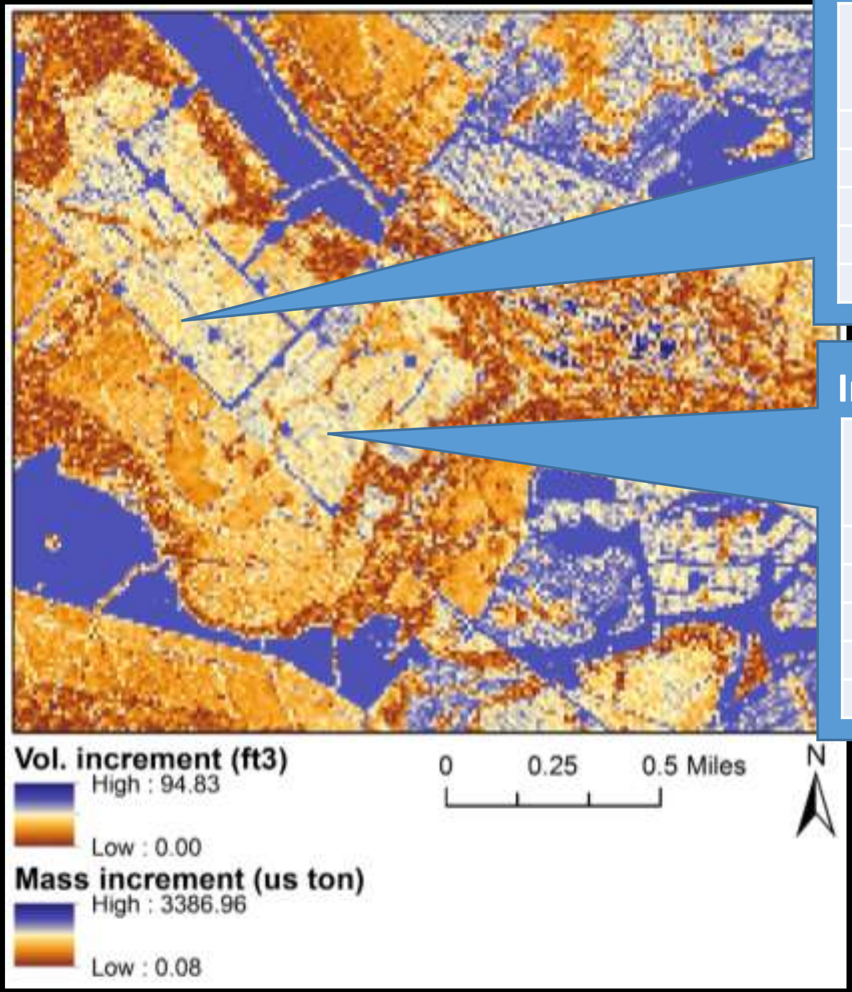
Generation of increment maps over 10 years

Area contains a mix of loblolly pine and broadleaved vegetation in SC, USA

Input: estimates of LAI from the canopy only..

Outputs: volume and mass per acre per year.

Mean density of Loblolly pine assumption: 1 cubic ft = 0.028 US ton.



Initial LAI: 1.68

Year	Cumulative Inc. (ft^3 per acre)	Cumulative Inc. (us ton per acre)
2	246.28	6.90
4	574.64	16.09
6	820.92	22.99
8	903.01	25.28
10	903.01	25.28

Initial LAI: 2.74

Year	Cumulative Inc. (ft^3 per acre)	Cumulative Inc. (us ton per acre)
2	102.84	2.88
4	239.96	6.72
6	342.80	9.60
8	377.08	10.56
10	377.08	10.56

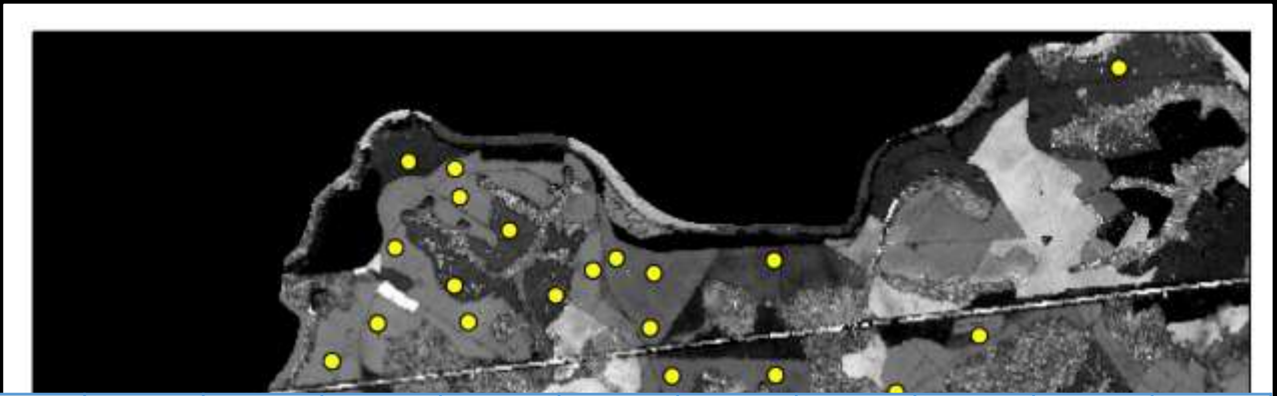
Spatial resolution of 15x15m

Modelling estimates of quadratic mean diameter and basal area in Brazil

Mapping custom models (part 1)

-An example

- 141 covariates can be calculated summarizing the distribution of:
  - return heights or;
  - Intensity;



LiDAR covariates

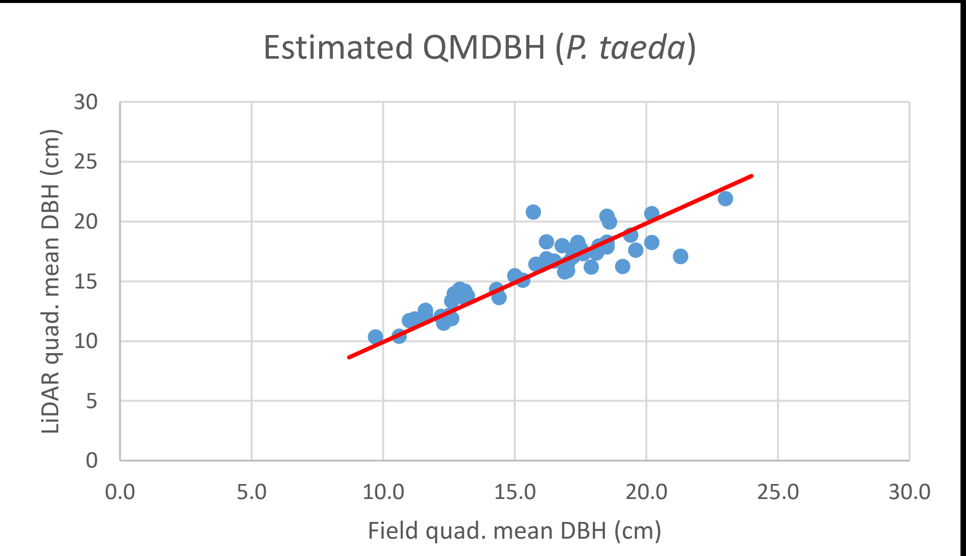
FID	mean_ht_all	var_ht_all	CV_ht_all	skew_ht_all	kur_ht_all	max_ht_all	min_ht_all	med_ht_all	stdev_ht_all	MAD_ht_all	range_ht_all
0	4.7	23.3	103.3	0.3	-1.6	14.5	0.0	3.7	4.8	4.6	14.5
1	5.4	33.1	106.6	0.2	-1.7	15.7	0.0	0.2	5.8	5.6	15.7
2	1.7	3.8	116.3	0.9	-0.2	8.7	0.0	0.5	2.0	1.7	8.7
3	1.2	3.1	144.5	1.5	1.7	8.2	0.0	0.0	1.8	1.4	8.2
4	1.5	4.2	134.2	1.2	0.3	8.2	0.0	0.0	2.0	1.7	8.2
5	1.4	3.9	142.8	1.3	0.9	8.5	0.0	0.0	2.0	1.7	8.5
7	2.3	3.9	87.8	0.4	-1.0	7.7	0.0	1.9	2.0	1.7	7.7
6	1.6	4.3	128.5	1.2	0.4	8.5	0.0	0.3	2.1	1.8	8.5
8	3.3	6.3	75.7	0.1	-1.1	9.5	0.0	3.6	2.5	2.2	9.5
9	4.9	22.0	95.0	0.1	-1.7	14.4	0.0	6.4	4.7	4.5	14.4
10	2.7	12.0	127.5	1.0	-0.5	12.5	0.0	1.1	3.5	3.0	12.5
11	4.4	26.7	116.6	0.4	-1.6	14.9	0.0	0.0	5.2	5.0	14.9
12	6.2	8.3	46.2	-1.0	0.2	13.0	0.0	6.9	2.9	2.2	13.0
13	5.4	8.9	55.7	-0.8	-0.6	11.7	0.0	6.2	3.0	2.4	11.7
14	12.8	65.3	63.3	-0.9	-1.1	21.8	0.0	17.0	8.1	7.2	21.8
15	12.9	66.2	63.2	-0.8	-1.2	22.3	0.0	17.3	8.1	7.3	22.3
16	5.8	9.5	53.3	-0.7	-0.5	13.1	0.0	6.6	3.1	2.5	13.1

Example location near Telêmaco Borba, Brazil;

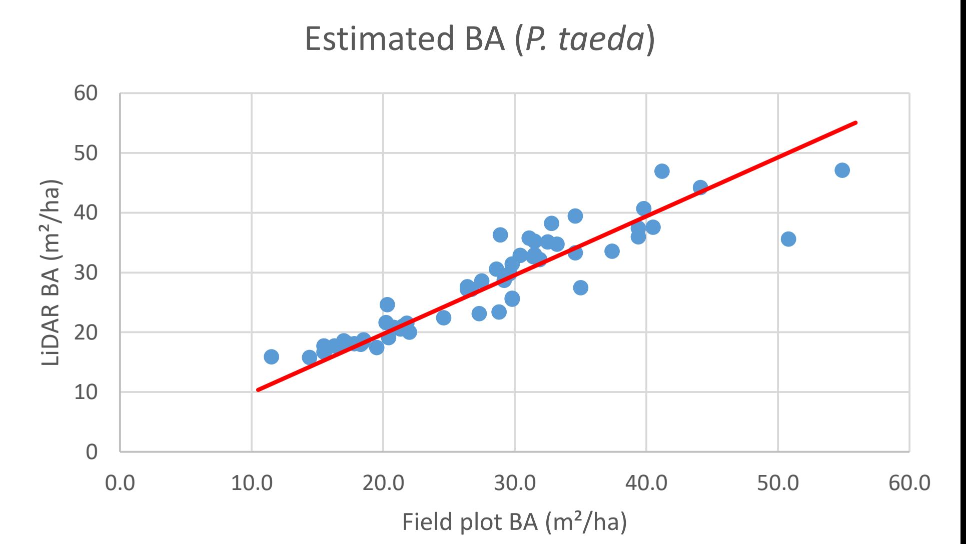
Correlations with LiDAR derived covariates

-Quadratic mean DBH and Basal Area

Group 1 – "P. taeda"

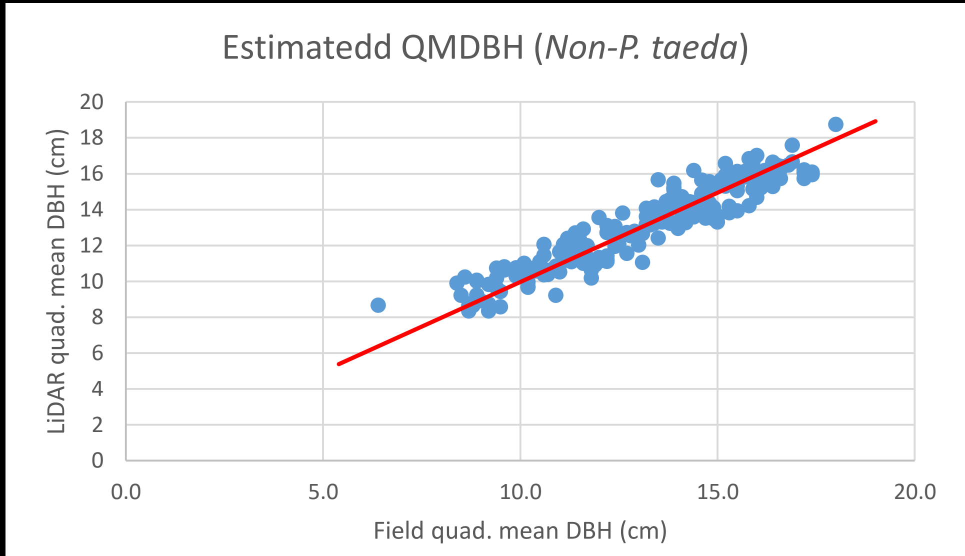


R^2= .889
RMSE= 1.406
Inputs:
- *Vp35*
- *FR_D_06*

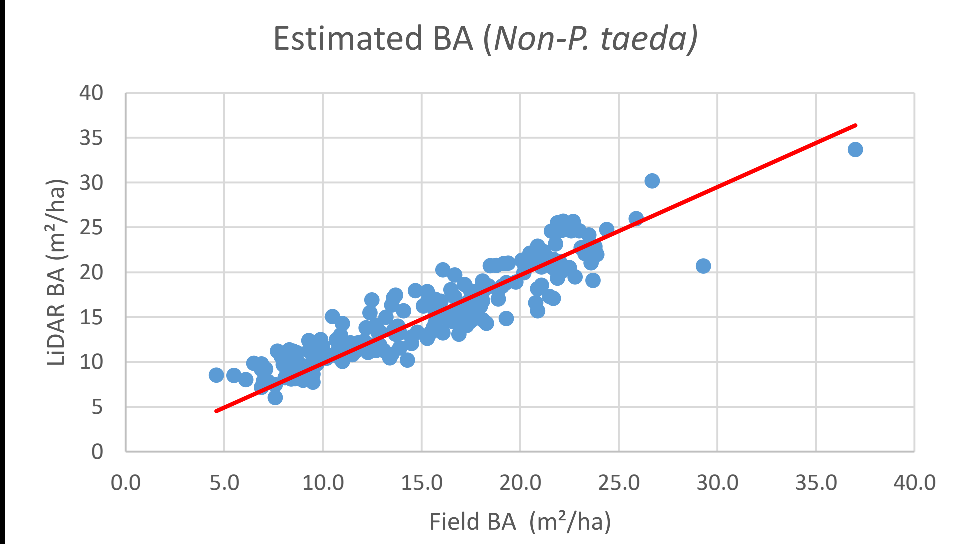


R^2= .855
RMSE= 3.627
Inputs:
- *Vp5*
- *var_ht_veg*

Group 2 – "Non-P. taeda"



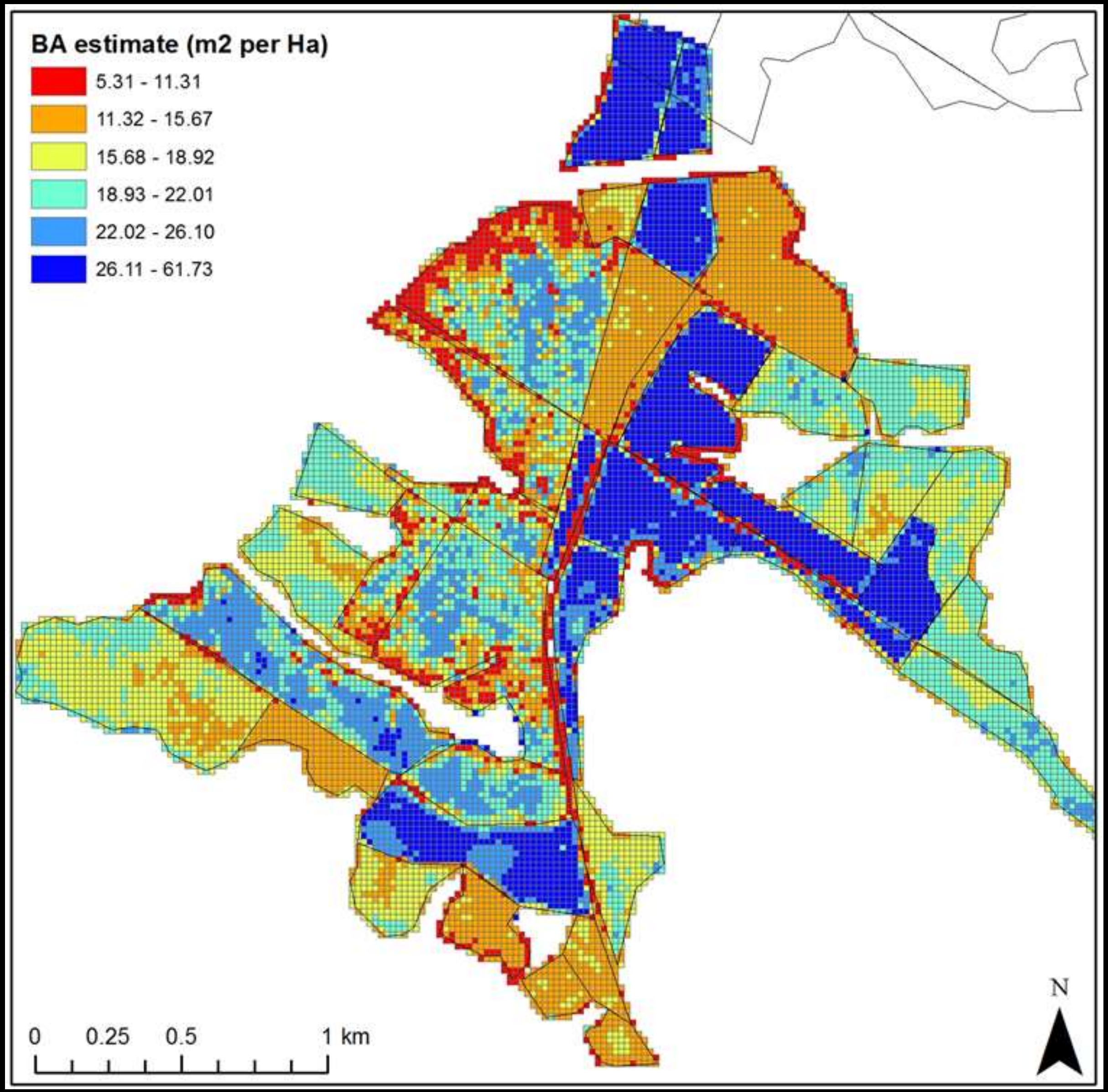
R^2= .803
RMSE= 0.819
Inputs:
- *Vp85*
- *p40*
- *FR_D_10*



R^2= .847
RMSE= 2.098
Inputs:
- *mean_ht_all*
- *FR_D_08*
- *p45*

Custom model creation

- Plot level LiDAR summary metrics can be extracted and statistically analyzed (e.g. by regression);
- Once a model has been created, a map of the estimate can be produced;
- Different models can be applied for different land cover classes, e.g. Loblolly pine and Eucalyptus;
- These relationships are often site specific.



Klabin data, Telêmaco Borba, *Brazil*

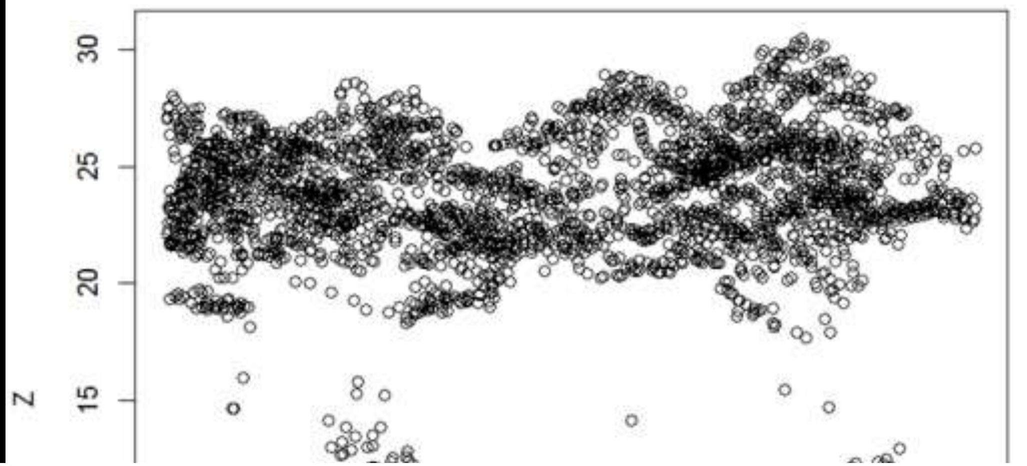
Mapping understory

- Purpose: to provide a means of finding competing vegetation in managed pine plantations.
- Applications in:
  - Competition control;
  - Locating potential fire risk;

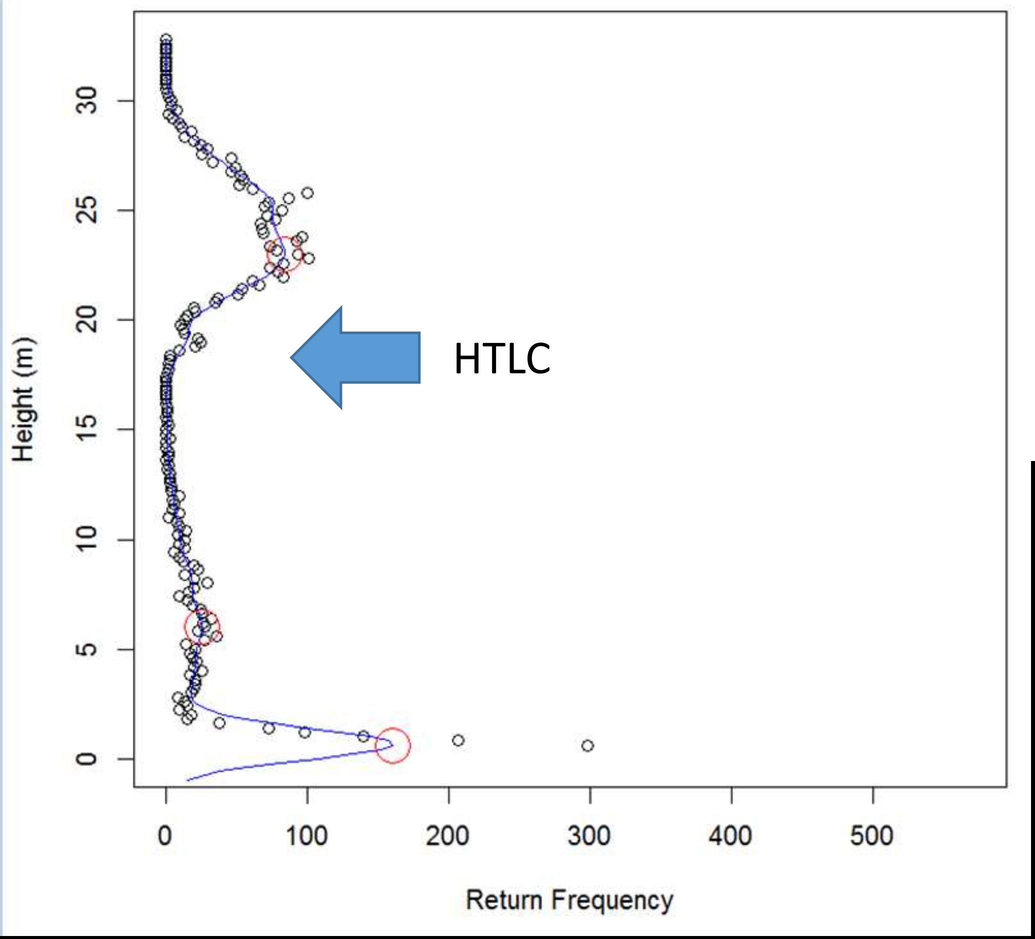
Understory detection

- Goal: filter out noise and classify those returns belonging to understory layers.
- First, classify the upper canopy, and remove it;
- DBSCAN clustering used to find and remove isolated points in 3D space, e.g. from tree stems;
- Example: 20x20m plot.

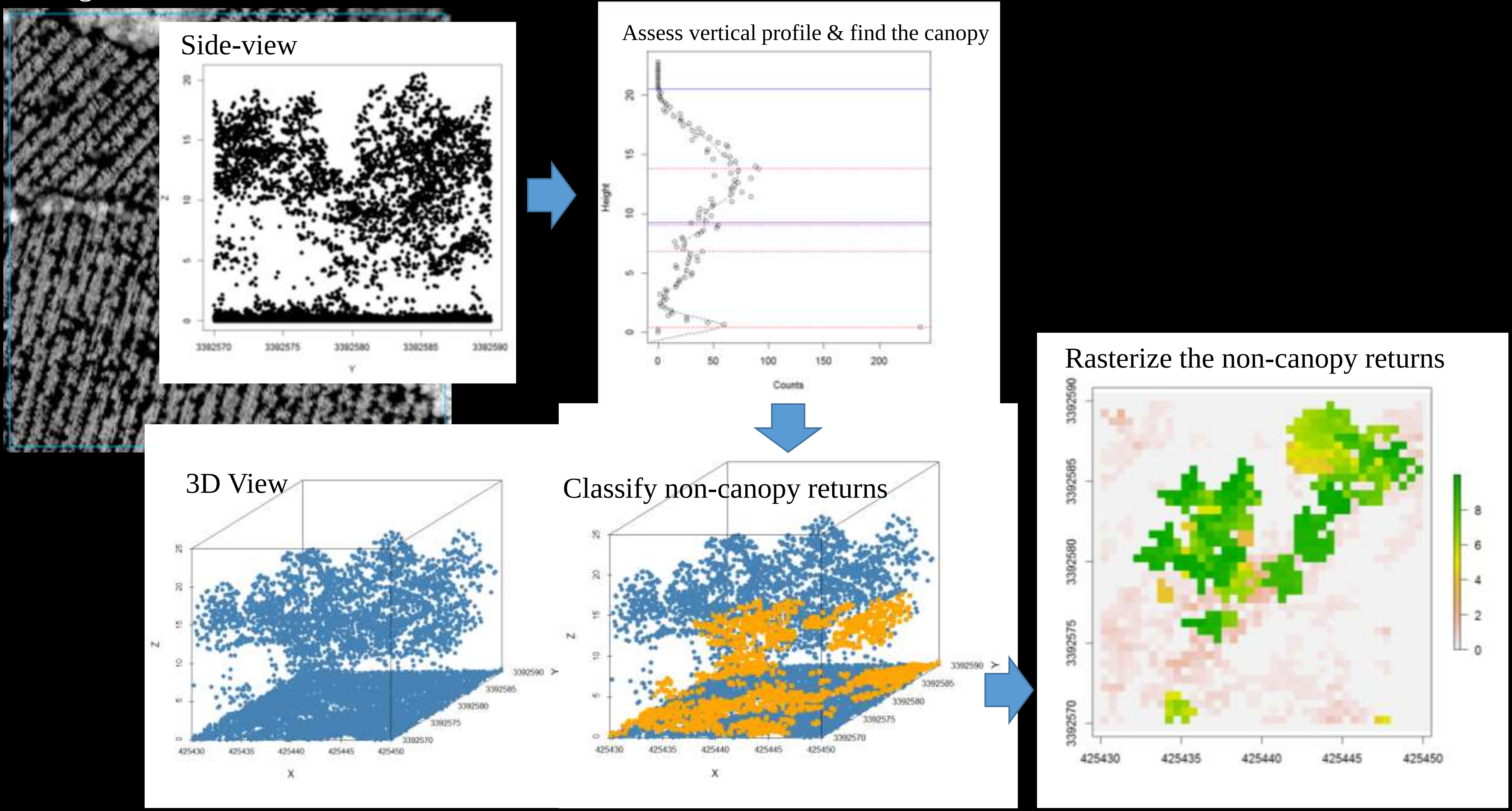
1



2

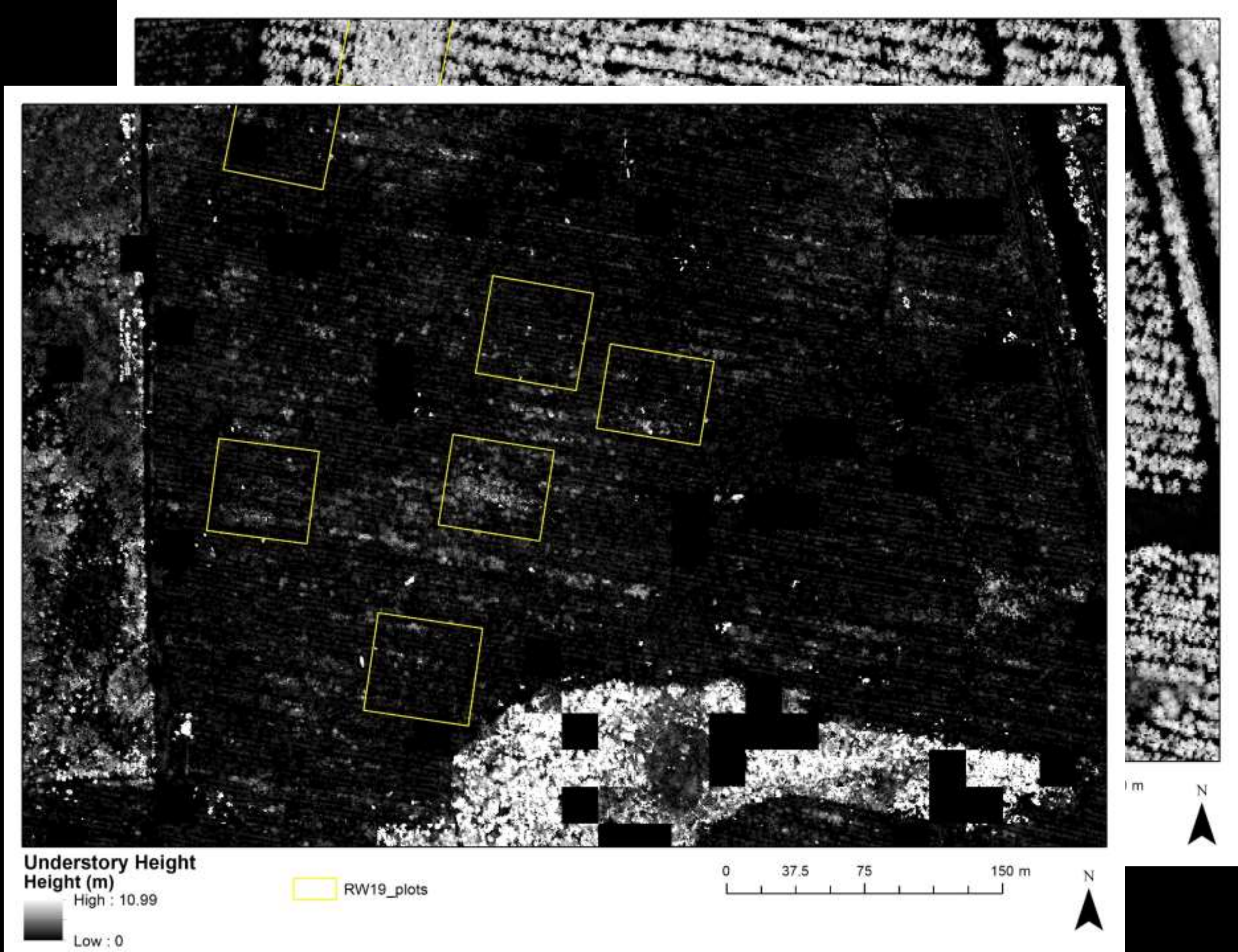


For a given 20x20m area



Mapping understory

-Analyses Work-in-progress

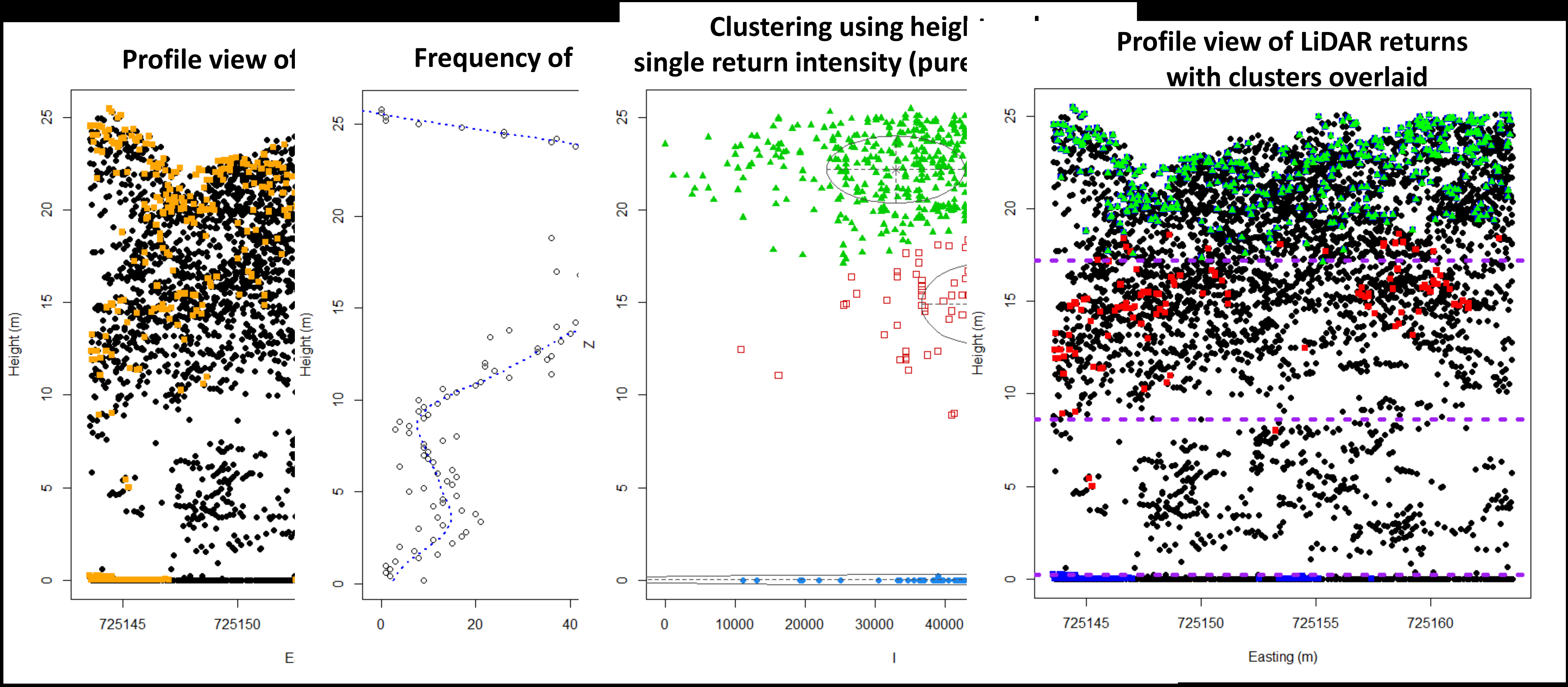


Classifying overlapping layers

- Currently in development;
- Purpose: to enhance the existing understory mapping method for more complex forests;
  - Particularly where the competing vegetation can intersect with the main canopy;

Classifying overlapping layers [work in progress]

-broadleaved mid-story

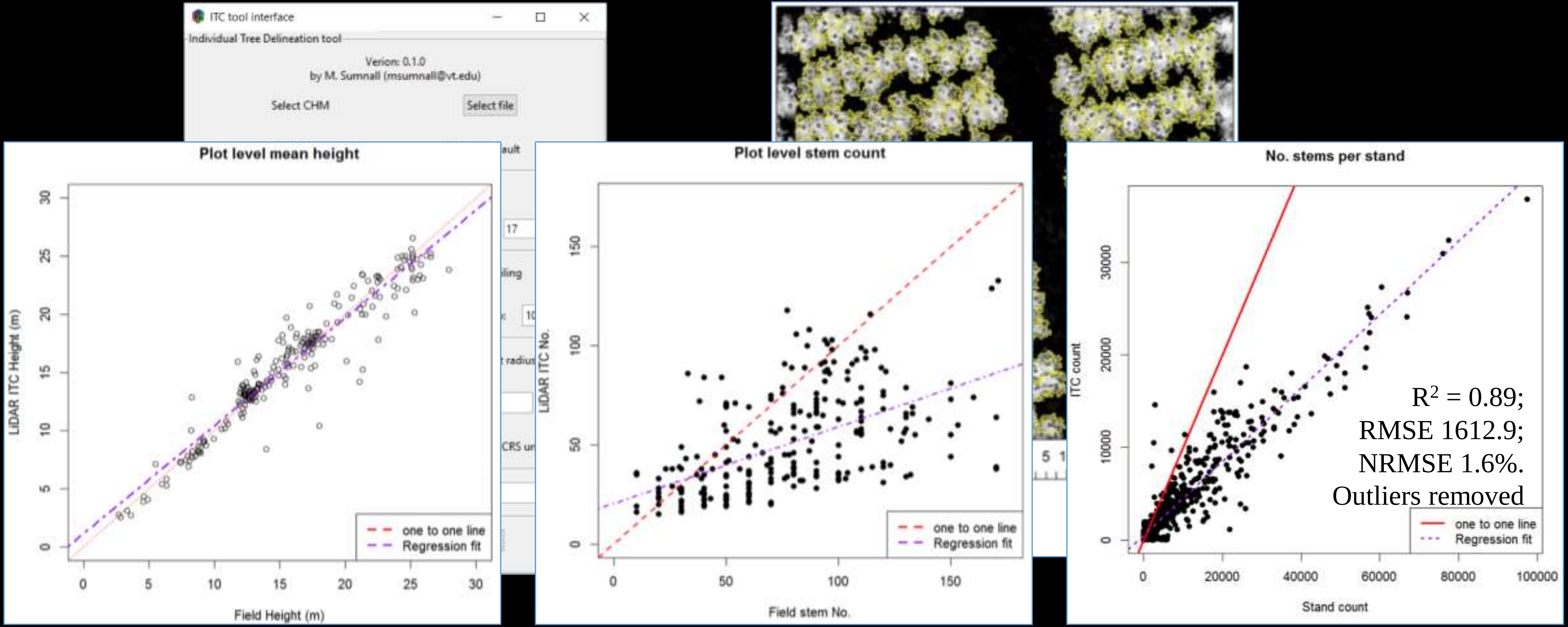


Individual tree crown (ITC) delineation

- Purpose: estimate the number or, height, and spatial location of individual trees automatically;
- Applications in:
  - Assessment of population;
  - ITC volume and estimates of ITC LAI (not validated, but aligns with plot level validation) – can allow the assessment of vigor at small scales.
- Requirements:
  - A raster canopy height model;

Individual tree crown delineation

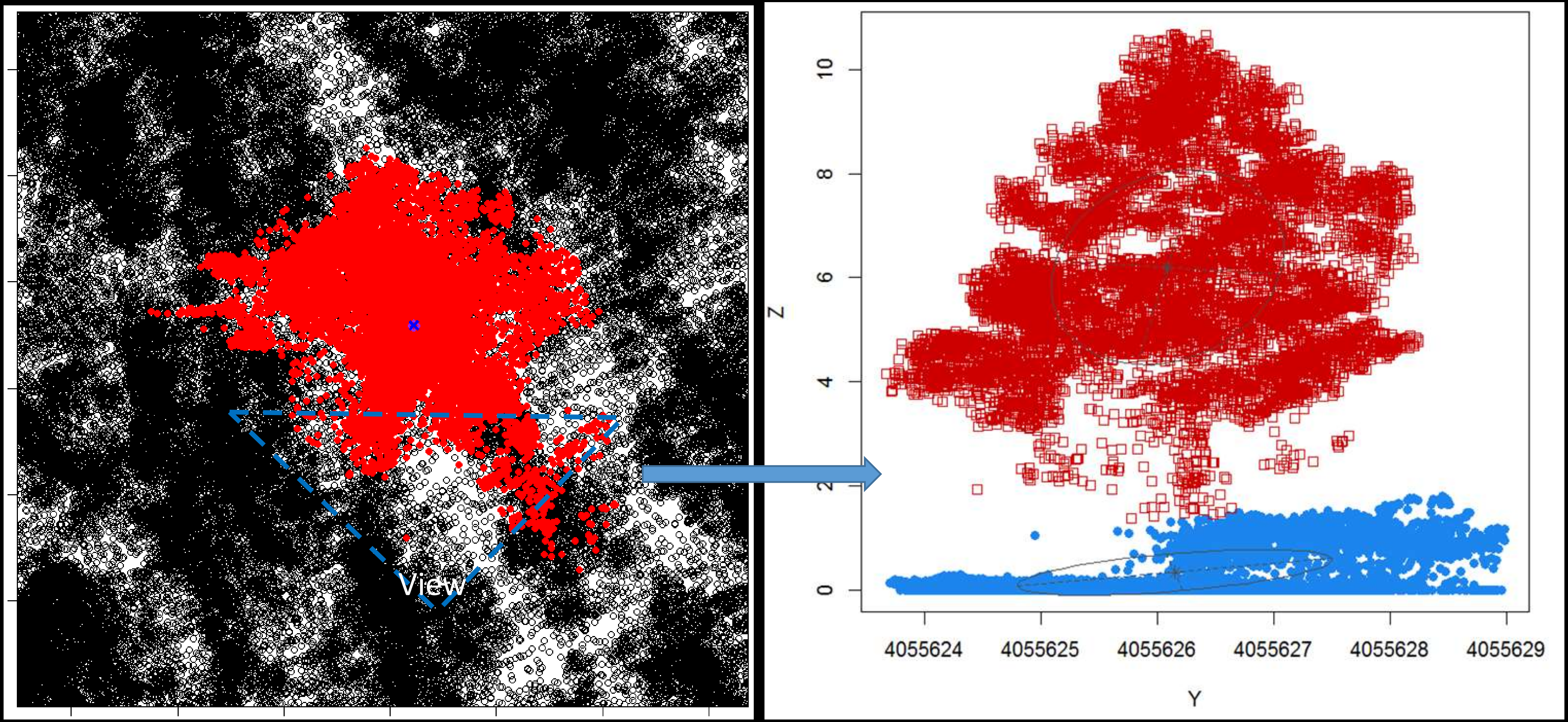
- There is a new (re-designed) individual tree delineation method;
- Validation from all available sites from 2018 and 2015.



Classifying trees within the point cloud
-making a better method

Top down

Side view

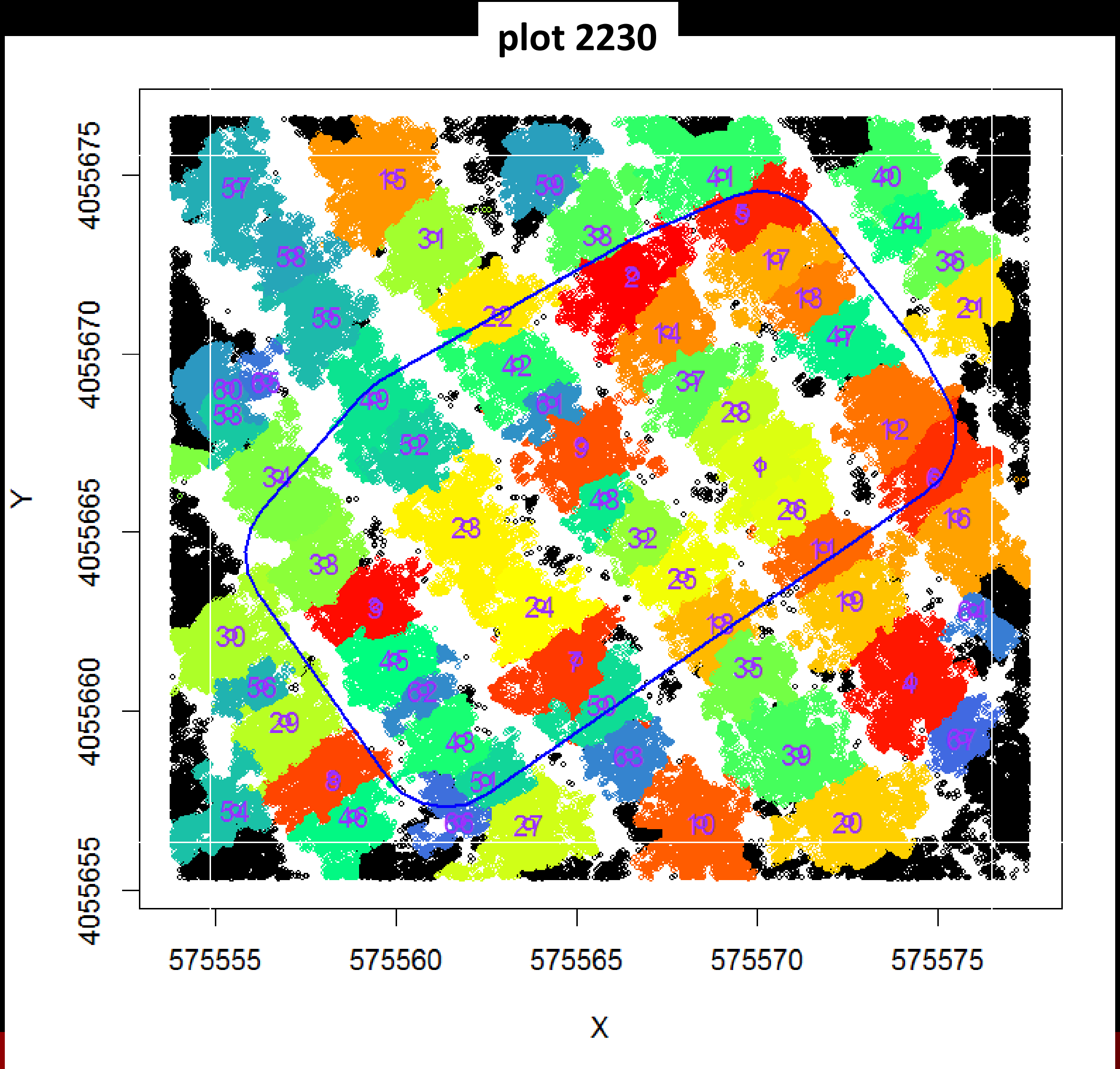


Classifying trees within the point cloud
-making a better method

Points grouped into crown objects.

Arbitrary colors assigned.

100% correct classification of plot tree locations.



Summary

- Tested & transferable methods;
- Estimate features below the stand-scale:
  - Plot-size;
  - Individual tree;
- Metrics for forest inventory can be estimated e.g. basal area;
- Applications in predicting future quantities;
- And monitoring competition;
- Methods are being updated all the time;

Questions?