Leveraging Leaf Area Density to Map Biomass and Fuels

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Improving Model Trainability and Transferability with Physics-Based and Bayesian Modeling

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About Me

- Johnathan Tenny
- 3rd Year PhD Student
- Remote Sensing and Geoinformatics Lab with Dr. Temuulen (Teki) Sankey
- Previously studied forest engineering at Oregon State University and then worked in private industry on forest management software

Lidar Approaches to Monitor Fuel Treatment Effects

Examples with TLS in Arizona

Applications for ALS

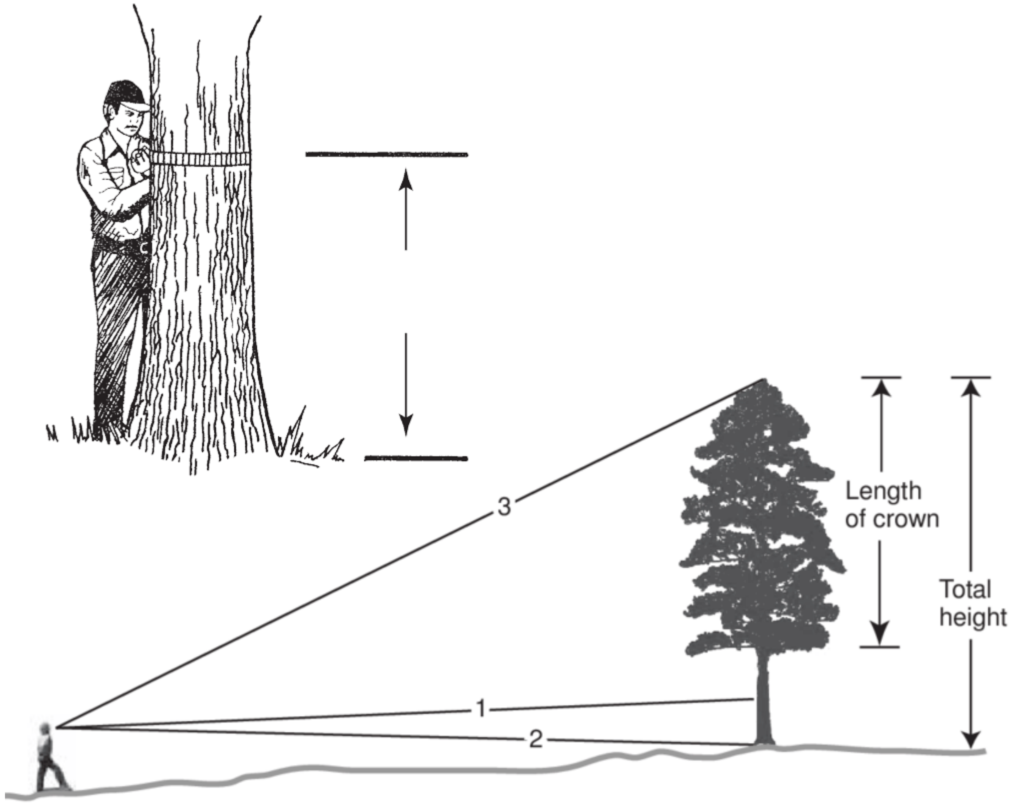
Tools you can use!

Fuel Monitoring

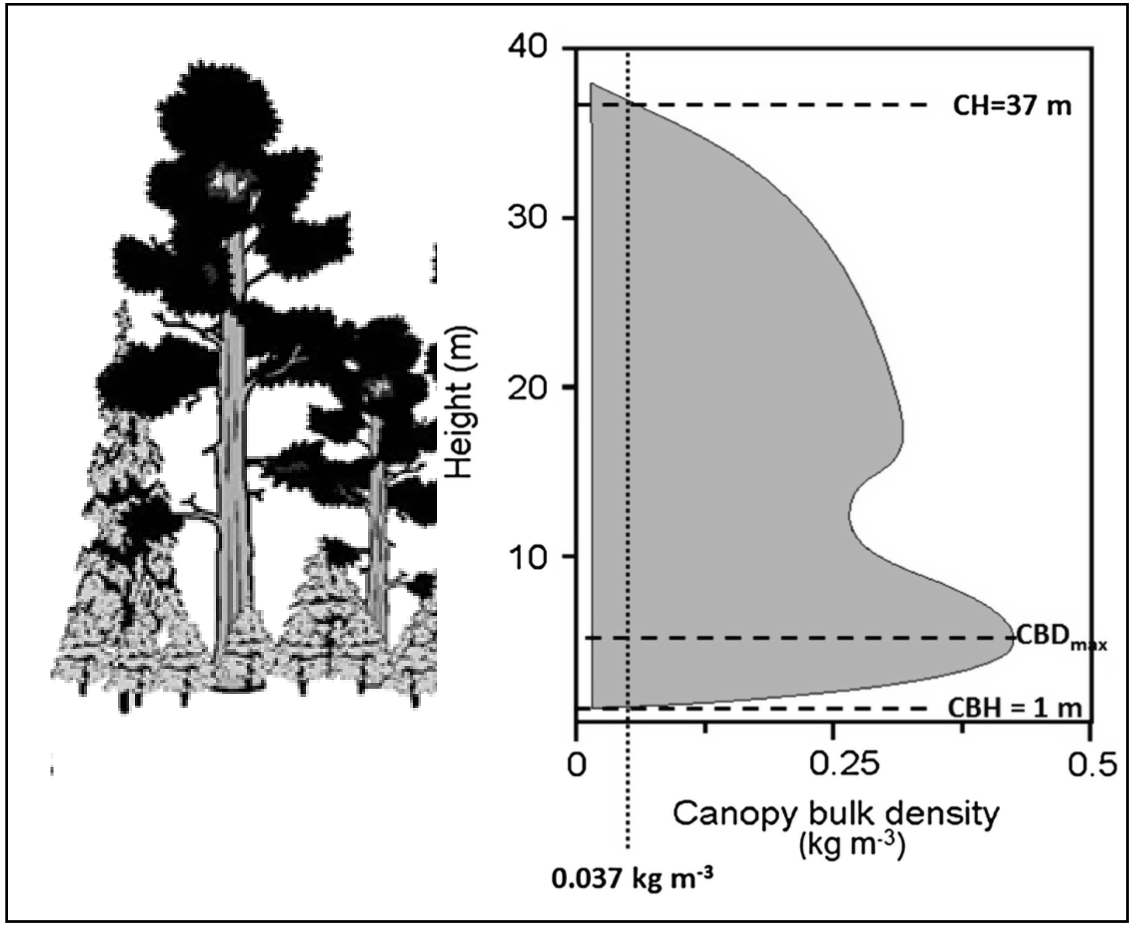
- Fuel monitoring is needed to support management decisions
- What changed? Why does it matter? Did we get the treatment effect that we wanted?
- Lidar can quickly capture vegetation structure and is very repeatable

Photo Credit: www.firesafesanmateo.org

Conventional Approach to Canopy Fuel Monitoring



$$w = EXP[1.3094 + 1.6076(\ln d)]$$



Lidar Monitoring: Area Based Approach

Index	Metrics	Scan Division	Description (simplified)
1	h_ground_cnt	Entire point cloud	Number of points classified as ground
2	h_not_ground_cnt	Entire point cloud	Number of points not classified as ground
3	h_per_ground	Entire point cloud	Percent of ground points in the scan
4	h_ng_tgi	Entire point cloud	Triangular greenness index of points classified as not ground
5	h_ng_vari	Entire point cloud	Visual atmospheric resistance index of points not classified as ground
6	h_l1_cnt	0-0.5 m height strata	Count of points in height strata
7	h_l1_per	0-0.5 m height strata	Percent of points in height strata
8	h_l1_mean	0-0.5 m height strata	Mean height of points in height strata
9	h_l1_median	0-0.5 m height strata	Median height of points in height strata
10	h_l1_std	0-0.5 m height strata	Standard deviation of points in height strata
11	h_l1_tgi	0-0.5 m height strata	Triangular greenness index of points in height strata
12	h_l1_vari	0-0.5 m height strata	Visual atmospheric resistance index of points in height strata
13	h_l1_skew	0-0.5 m height strata	Skewness of point heights in height strata
14	h_l1_kurt	0-0.5 m height strata	Kurtosis of point heights in height strata
15	h_l2_cnt	0.5-1.0 m height strata	Count of points in height strata
16	h_l2_per	0.5-1.0 m height strata	Percent of points in height strata
17	h_l2_mean	0.5-1.0 m height strata	Mean height of points in height strata
18	h_l2_median	0.5-1.0 m height strata	Median height of points in height strata
19	h_l2_std	0.5-1.0 m height strata	Standard deviation of points in height strata
20	h_l2_tgi	0.5-1.0 m height strata	Triangular greenness index of points in height strata
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23	h_l2_kurt	0.5-1.0 m height strata	Kurtosis of point heights in height strata
24	h_l3_cnt	1.0-1.5 m height strata	Count of points in height strata
25	h_l3_per	1.0-1.5 m height strata	Percent of points in height strata
...	...	...	...
236	hr100_1000_l1_kurt	0-3 m high voxelized point clouds with t	Kurtosis of point heights in height strata

- Generate **lots** of descriptors
- Use as predictors in general purpose model
  - lm with stepwise selection
  - random forest

Lidar Monitoring: Area Based Approach

Advantages:
- Flexible approach to predict almost anything

Disadvantages:
- “Black box”– hard to interpret why selected covariates were important
- Hard to train a robust model, need lots of training data
- Model might be specific to certain species composition, successional state, and disturbance history
- Unclear how the model will respond in novel conditions (e.g. post-treatment)

Question

If we want use lidar to measure canopy fuel, what techniques can improve model trainability and transferability?

Question

If we want use lidar to measure canopy fuel, how can we improve model trainability and transferability?

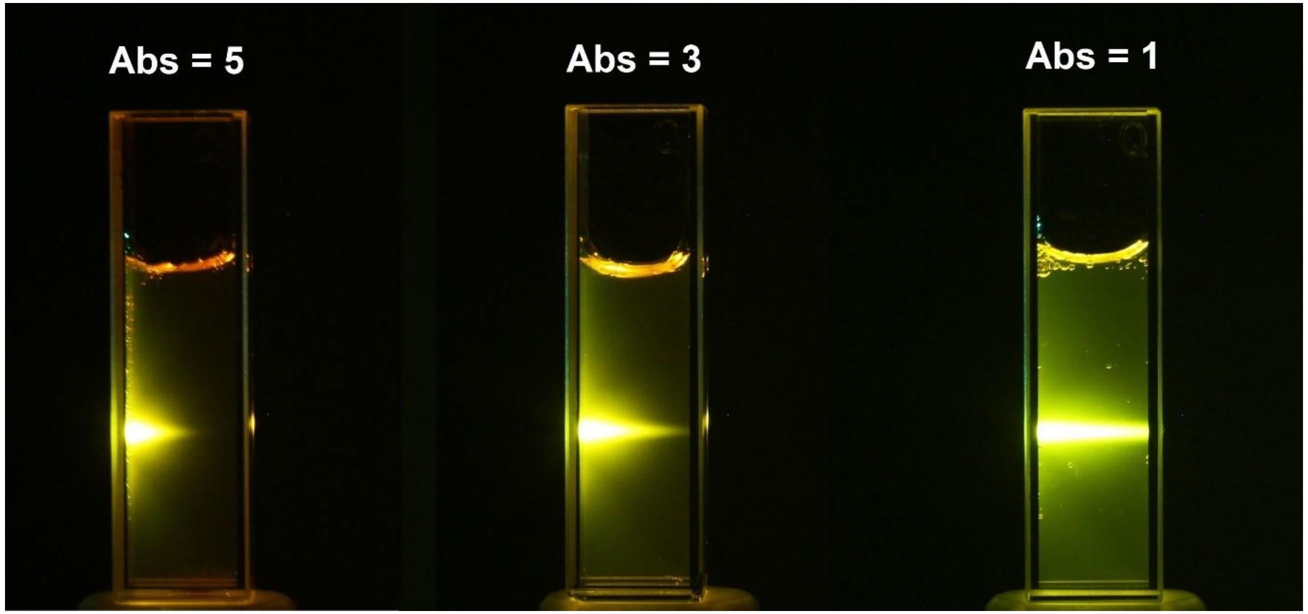
Solution

Add structure to the model (reduce model flexibility) based on prior knowledge of processes and prior study results

- Physics-based modeling
- Bayesian modeling

Analysis Methods: Physics-Based Modeling

Beer-Lambert Law: the proportion of light transmitted through a semi-transparent medium is proportional to the concentration of "stuff" in the medium



Analysis Methods: Physics-Based Modeling

Beer-Lambert Law: the proportion of light transmitted through a semi-transparent medium is proportional to the concentration of “stuff” in the medium

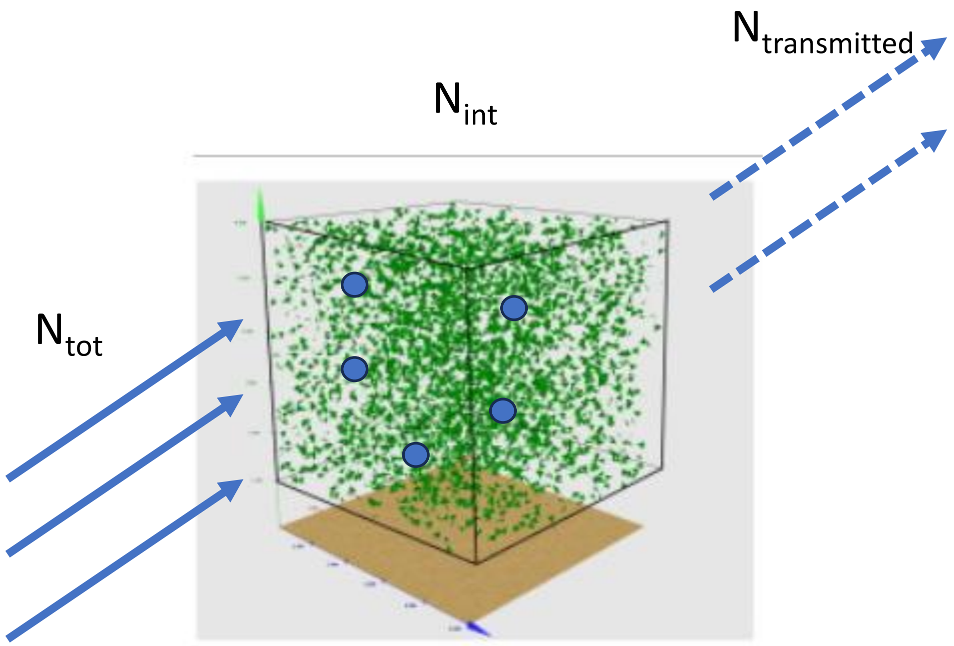
- Tree canopies are also semi-transparent
- Leaves are the “stuff” that blocks some of the light
- Can use Beer-Lambert to estimate concentration of leaves based on proportion of light transmitted through canopy

Analysis Methods: Physics-Based Modeling

Can measure light transmittance spatially with lidar

- Trace the path of <u>every</u> laser pulse (including pulses with no return)
- Estimate proportion of pulses transmitted through every voxel
- Take the natural log
- Adjust for leaf orientation, path length (voxel size), and other optional coefficients

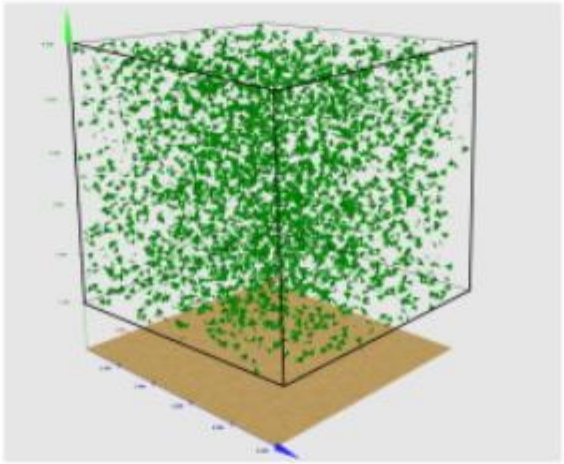
Return: leaf area density



(a) Triangles (representing leaves)

$$\rho_f = -\frac{ln(T(\Omega))}{G(\Omega).\overline{\Delta L}} = -\frac{ln\left(1-\frac{N_{int}}{N_{tot}}\right)}{G(\Omega).\overline{\Delta L}}$$

Analysis Methods: Physics-Based Modeling



(a) Triangles (representing leaves)

Leaf area density: surface area of leaves per unit volume

- Widely used metric because of relation to photosynthetic capacity (gross primary productivity)

For fire modeling, we need **leaf mass density** i.e. **canopy bulk density**

Easy: multiply leaf area density by ratio of leaf mass per unit surface area (LMA)

$$LMA = \frac{dry\ leaf\ mass}{leaf\ surface\ area}$$

Analysis Methods: Physics-Based Modeling

$$LMA = \frac{dry\ leaf\ mass}{leaf\ surface\ area} = \frac{1}{specific\ leaf\ area}$$

Leaf mass per area
- Common measurement used by tree physiologists
- *Mainly* determined by species

New Phytologist

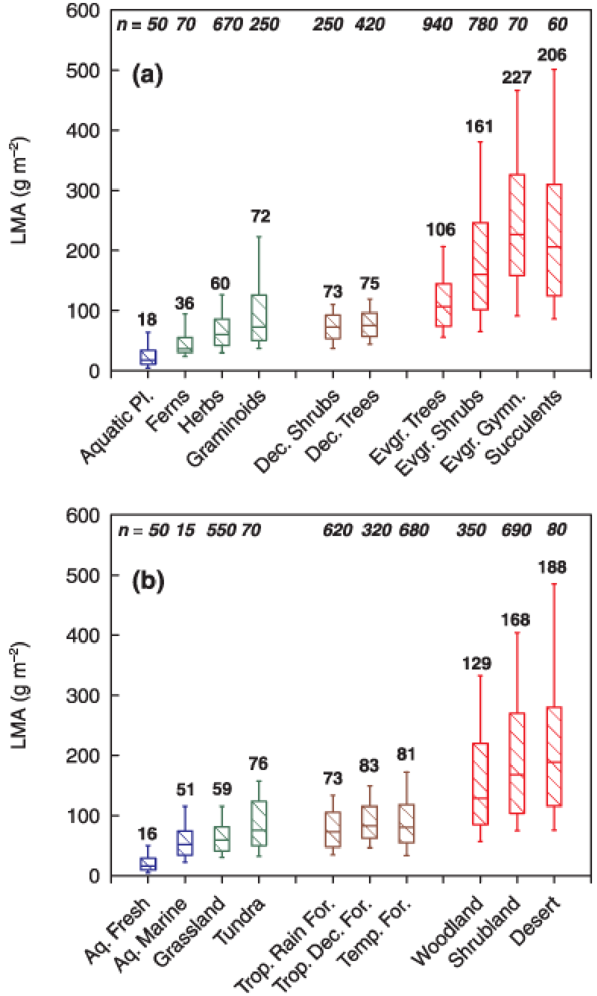
Free Access

Causes and consequences of variation in leaf mass per area (LMA): a meta-analysis

Correction(s) for this article

Hendrik Poorter, Ülo Niinemets, Lourens Poorter, Ian J. Wright, Rafael Villar

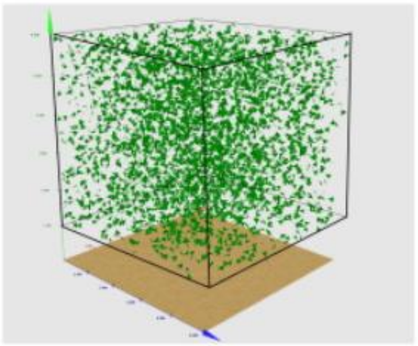
First published: 16 April 2009 | https://doi.org/10.1111/j.1469-8137.2009.02830.x | Citations: 1,981



Analysis Methods: Physics-Based Modeling

$$Canopy\ Bulk\ Density\ \left(\frac{kg}{m^3}\right) = Leaf\ Area\ Density\ \left(\frac{m^2}{m^3}\right) * Leaf\ Mass\ per\ Area \left(\frac{kg}{m^2}\right)$$

$$CBD = LAD\ * LMA$$



(a) Triangles (representing leaves)

Analysis Methods: Calibrating LMA Estimates

- Look up LMA estimates from previous studies

Prior LMA Estimates

Species	Published LMA (kg/m2)	Published LMA Source
Pinus ponderosa	0.333	Weiskittel et al (2008)
Juniperus monosperma	0.49	Grier et al (1992)
Arctostaphylos viscida	0.28	Hughes et al (1987)
Quercus emoryi	0.141	Sancho-Knapik et al (2020)
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- With Bayesian statistics, use prior LMA estimates as a starting point, then optimize LMA values to minimize the difference between conventional CBD estimates and lidar CBD estimates

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Posterior (Calibrated) LMA Estimates

Species Group	Calibrated LMA (kg/m2)
Pinus spp.	0.735
Juniperus spp.	0.190
Arctostaphylos spp.	0.647
Other trees	0.152
Other shrubs	0.178

Analysis Methods: Calibrating LMA Estimates

- Look up LMA estimates from previous studies
- May need to calibrate estimates for use in lidar analysis

- With Bayesian statistics, use prior LMA estimates as a starting point, then optimize LMA values to minimize the difference between conventional CBD estimates and lidar CBD estimates
- Prior estimates add structure to the model, improving model stability and robustness with less training data

Prior LMA Estimates

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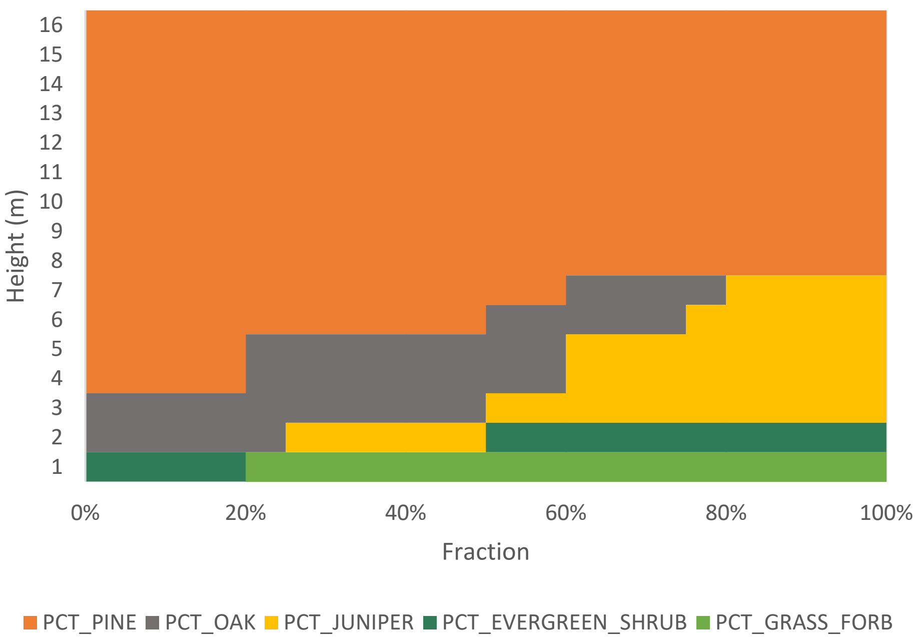
Making Predictions

Species Composition



X

Species	Leaf Mass Per Area (kg/m^2)
PINE	0.8
OAK	0.16
JUNIPER	0.11
EVERGREEN_SHRUB	0.35
GRASS_FORB	0.1

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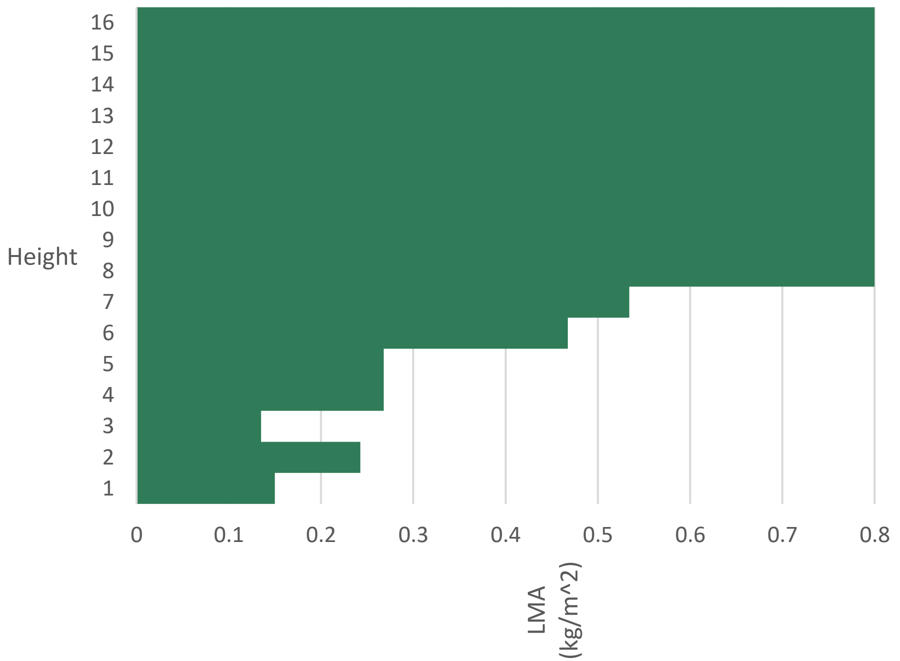
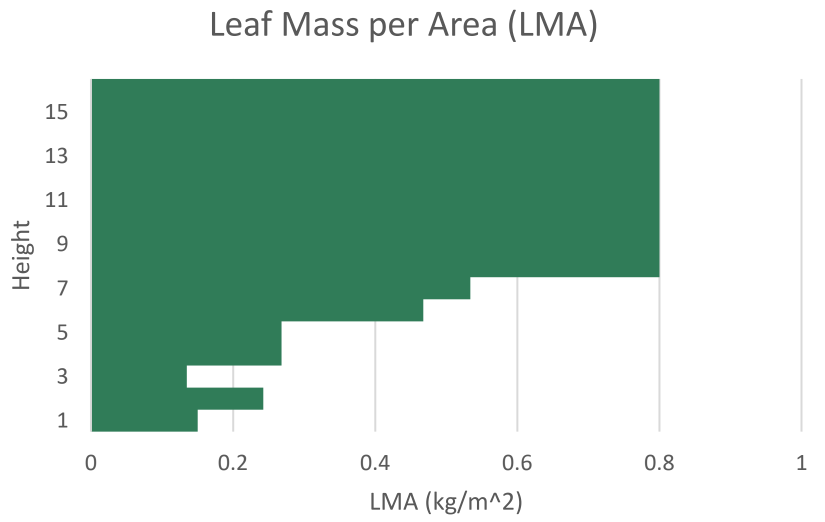
Leaf Mass Per Area (LMA)



Making Predictions



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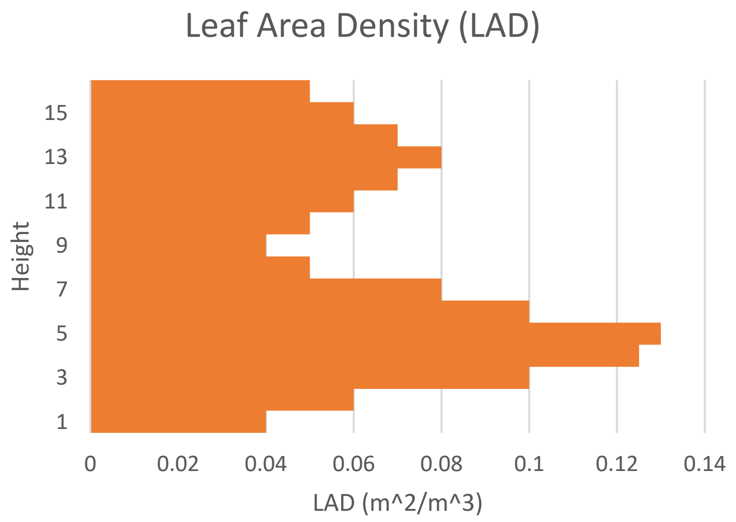

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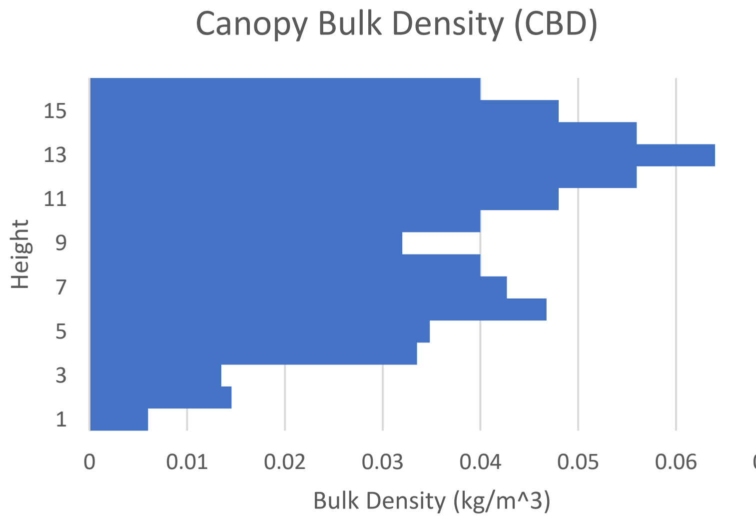
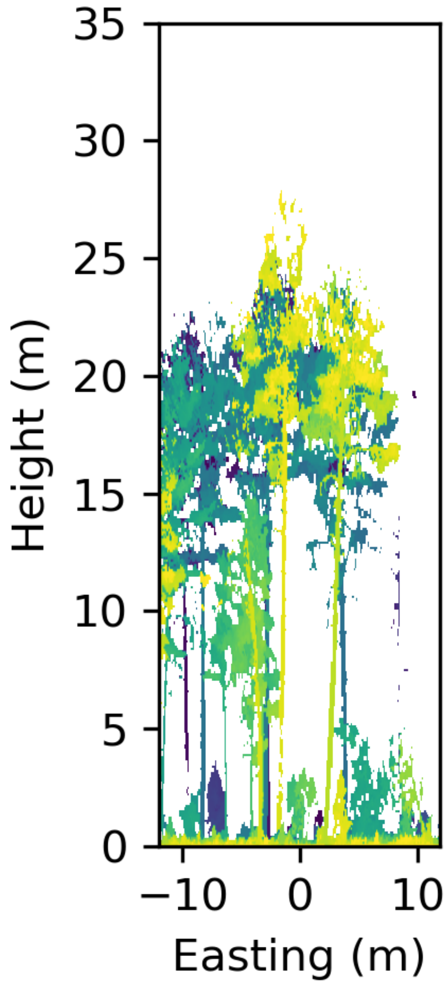


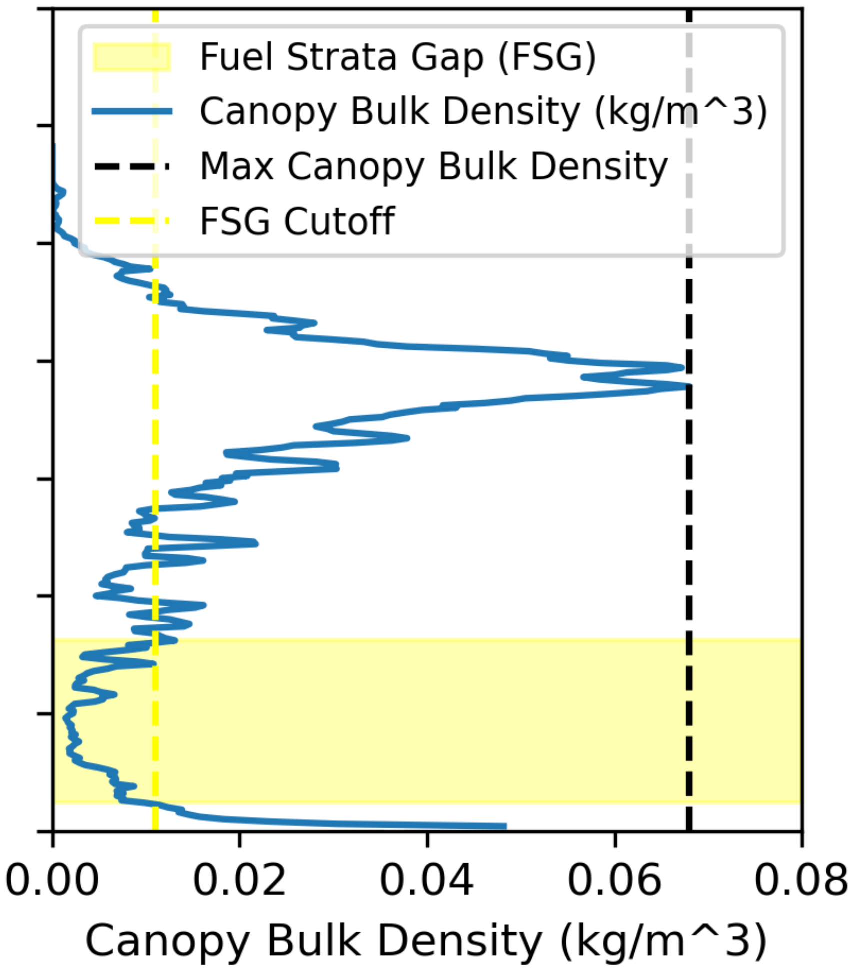
From species composition and model training process

From lidar and automated processing

Use in fire behavior modeling

Making Predictions





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Fuelbed Depth	9.1	cm
Spread Rate	0.956	km/hr
Intensity	5142.8	kW/m
Flame Length	7.9	m
Torching Index	35	km/hr
Crowning Index	53	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Lidar Approaches to Monitor Fuel Treatment Effects

Examples with TLS in Arizona

Applications for ALS

Tools you can use!

Why TLS for treatment monitoring?

We want comparable data before and after treatment

Why TLS for treatment monitoring?

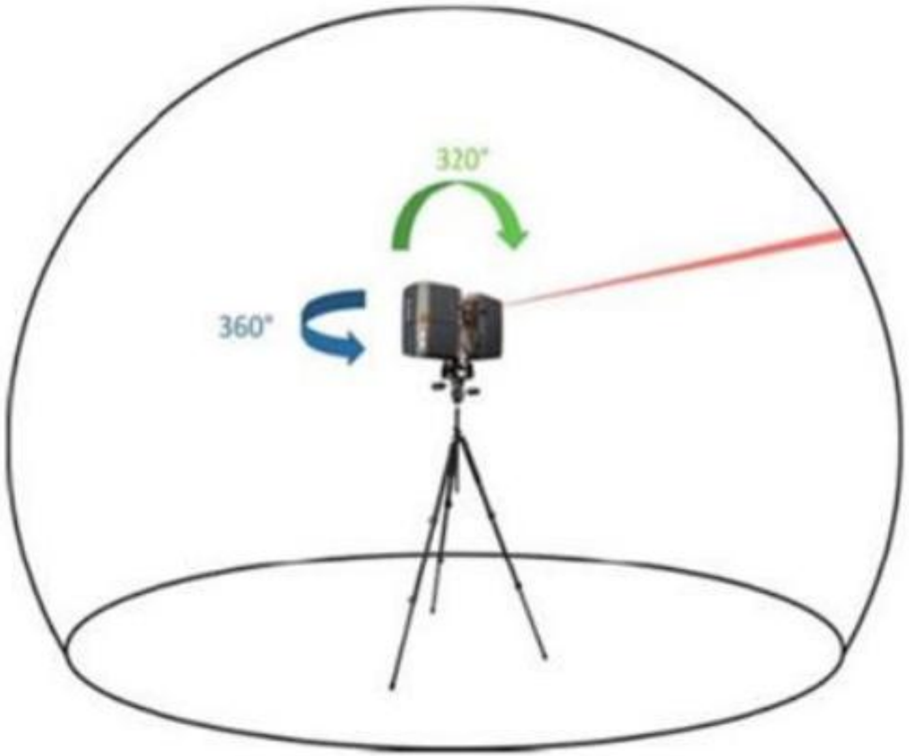
Many common tools aren't practical for fuel treatment evaluations

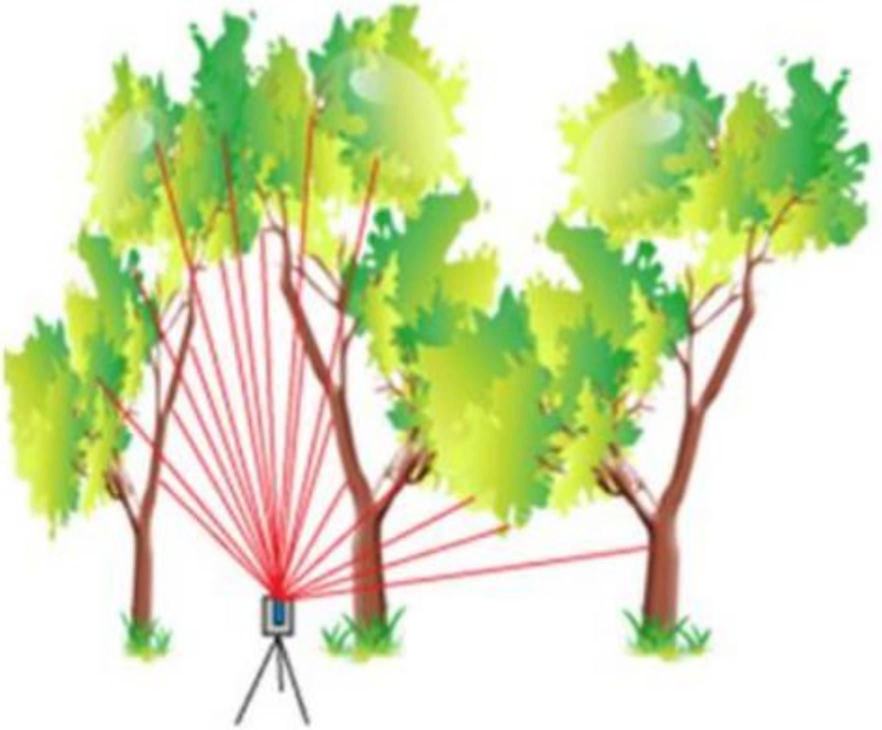
Satellite imagery (e.g. Landsat) can't see below top of canopy, limited in ability to describe structure

Aerial lidar is expensive to fly before and after individual treatments

Drones are limited by complex regulations, weather/lighting conditions, take-off/landing locations, advanced training requirements, post-processing complexity, equipment cost, and financial risk of crashing

Why TLS for treatment monitoring?





Dassot, M., Constant, T., & Fournier, M. (2011). The use of terrestrial LiDAR technology in forest science: application fields, benefits and challenges. Annals of Forest Science, 68(5), 959–974. doi:10.1007/s13595-011-0102-2

Why TLS for treatment monitoring?

Pros

- Detailed measurements of 3D structure
- Highly portable
- Fast, easy data collection in the field
- Processing can be highly automated
- Results are visual and fun to show off
- Sampling techniques are similar to traditional plot-based monitoring/timber cruising

Cons

- Sampling techniques are similar to traditional plot-based monitoring/timber cruising

Lecia BLK 360 G1

Resolution: Up to 60,000 pts/sq m @ 10m

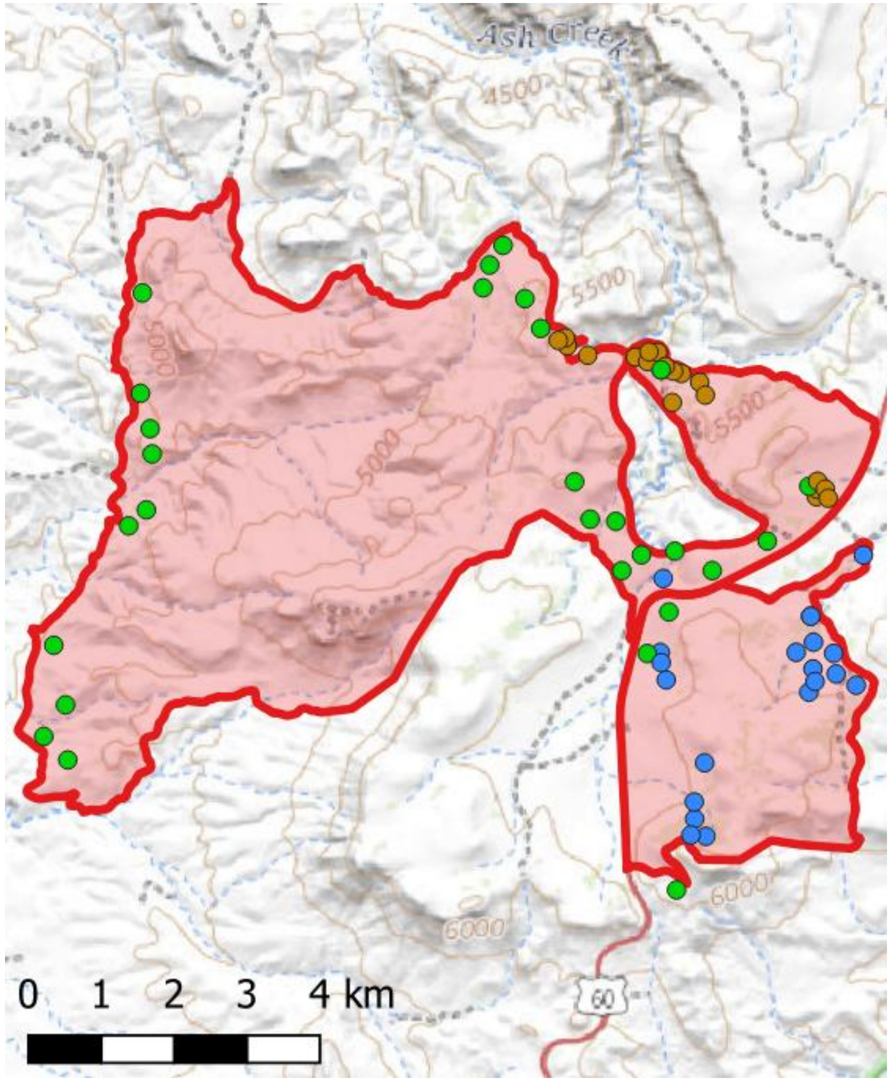
SCANNING

Distance measurement system	High speed time of flight enhanced by Waveform Digitizing (WFD) technology
Laser class	1 (in accordance with IEC 60825-1:2014)
Wavelength	830 nm
Field of view	360° (horizontal) / 300° (vertical)
Range*	min. 0.6 - up to 60 m
Point measurement rate	up to 360'000 pts / sec
Ranging accuracy*	4mm @ 10m / 7mm @ 20m
Measurement modes	3 user selectable resolution settings

IMAGING

Camera System	15 Mpixel 3-camera system, 150Mpx full dome capture, HDR, LED flash Calibrated spherical image, 360° x 300°
Thermal Camera	FLIR technology based longwave infrared camera Thermal panoramic image, 360° x 70°

Study Area



14,000 acre management area in Central Arizona.

High risk, high treatment priority, prescribed burns planned.

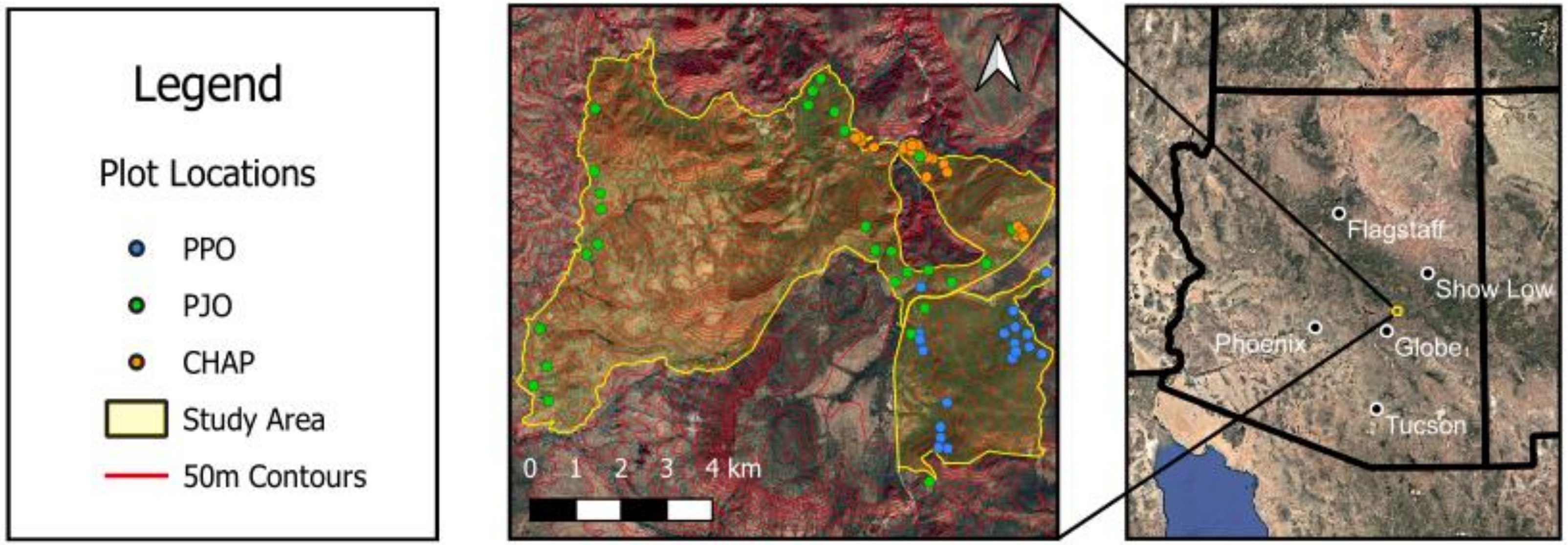
Collected 68 plots covering ponderosa pine forest, pinyon-juniper woodland, and chapparal.

Study Area

14,000 acre management area in Central Arizona.

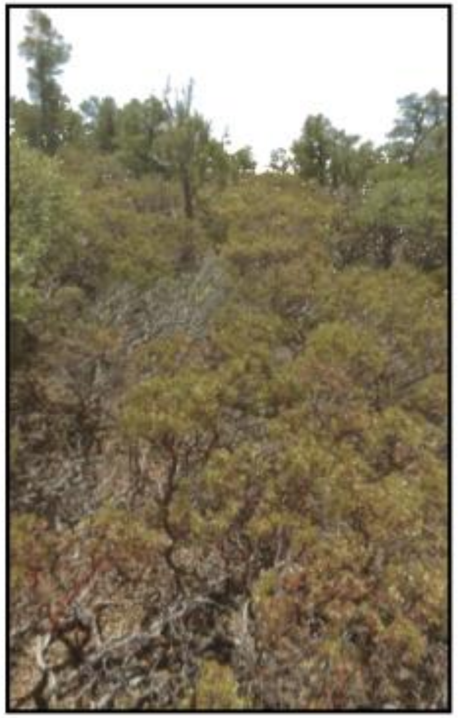
Intense elevational gradients and microclimates

Collected 68 plots covering diverse vegetation structure



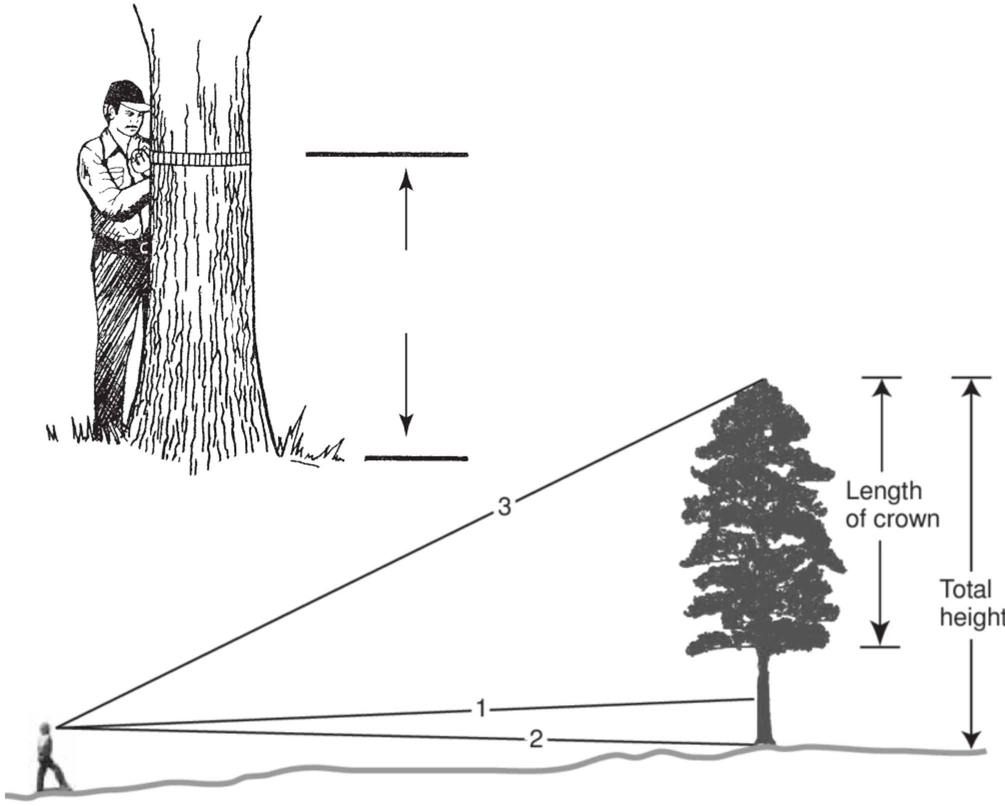
Ponderosa pine-oak (PPO)

Pinyon-juniper-oak (PJO)



Chaparral (CHAP)

Field Methods



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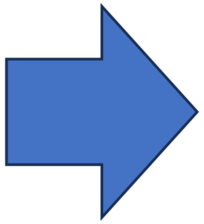

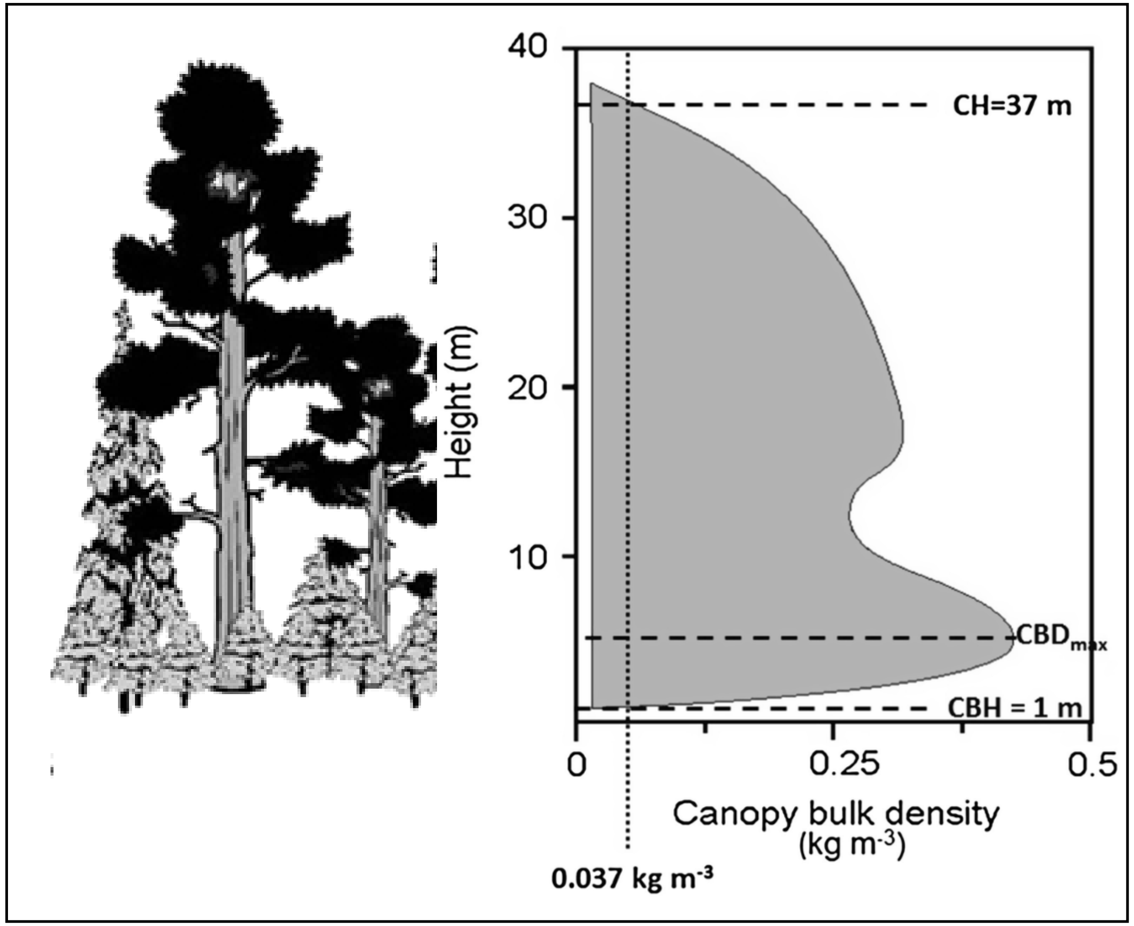

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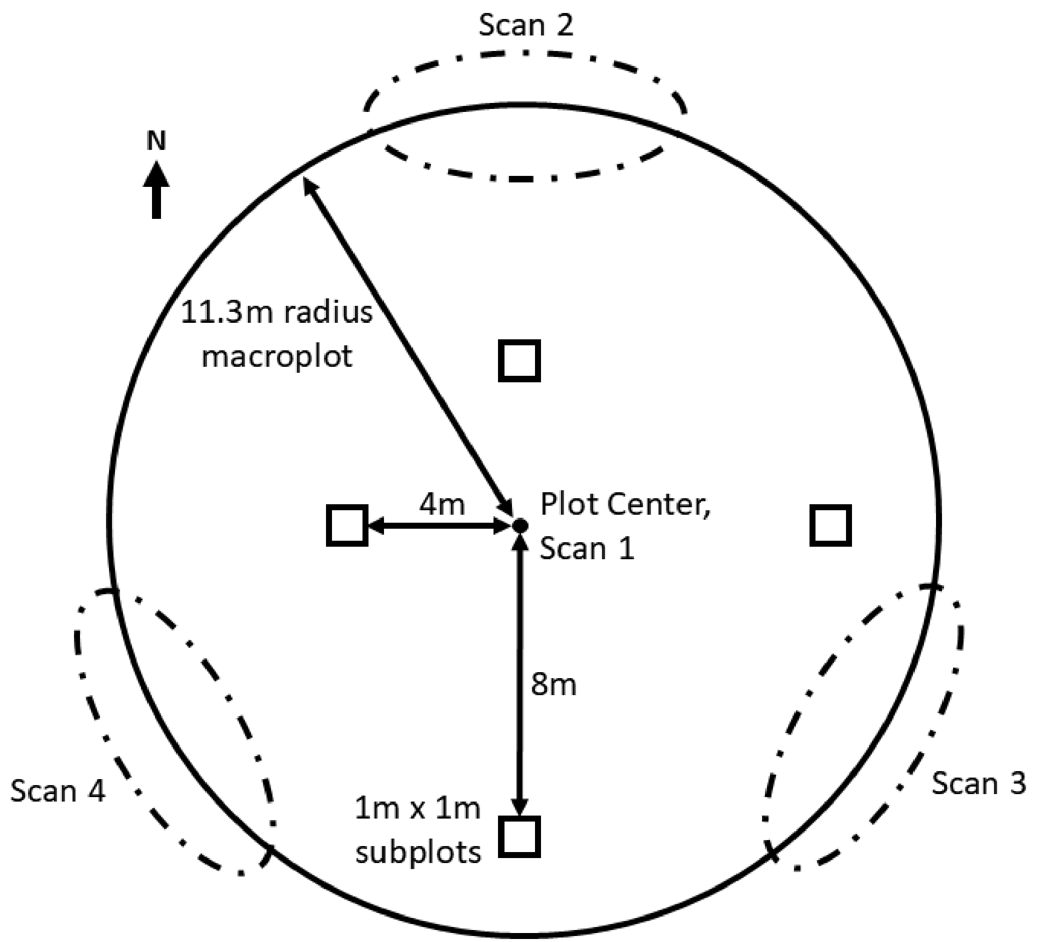
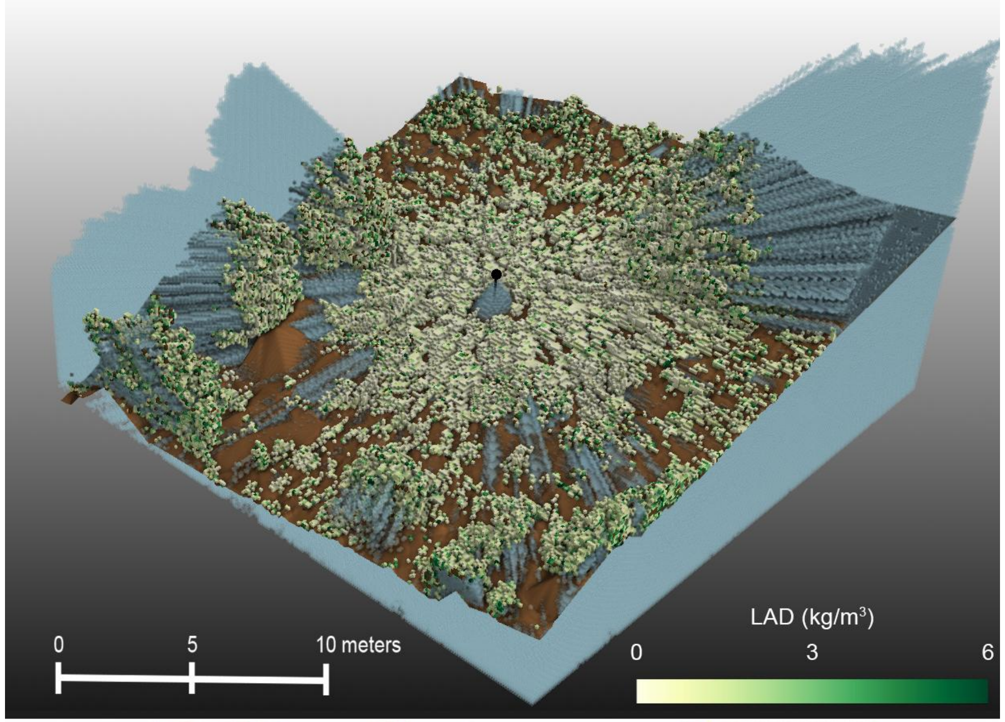
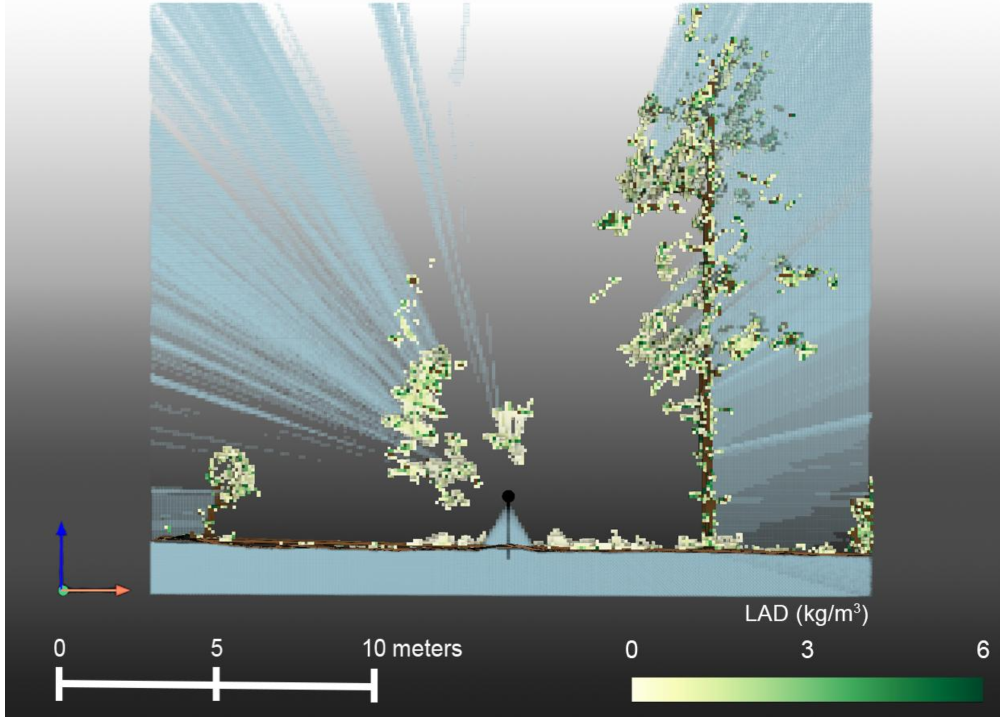


- Central lidar scan + three perimeter scans
- Measurements on all trees and shrubs >1m tall in a ~1/10th acre plot:
  - Species
  - Diameter and/or stem count
  - Height
  - Height to lowest canopy
- Surface fuel measurements at four quadrats:
- SB40 surface fuel class

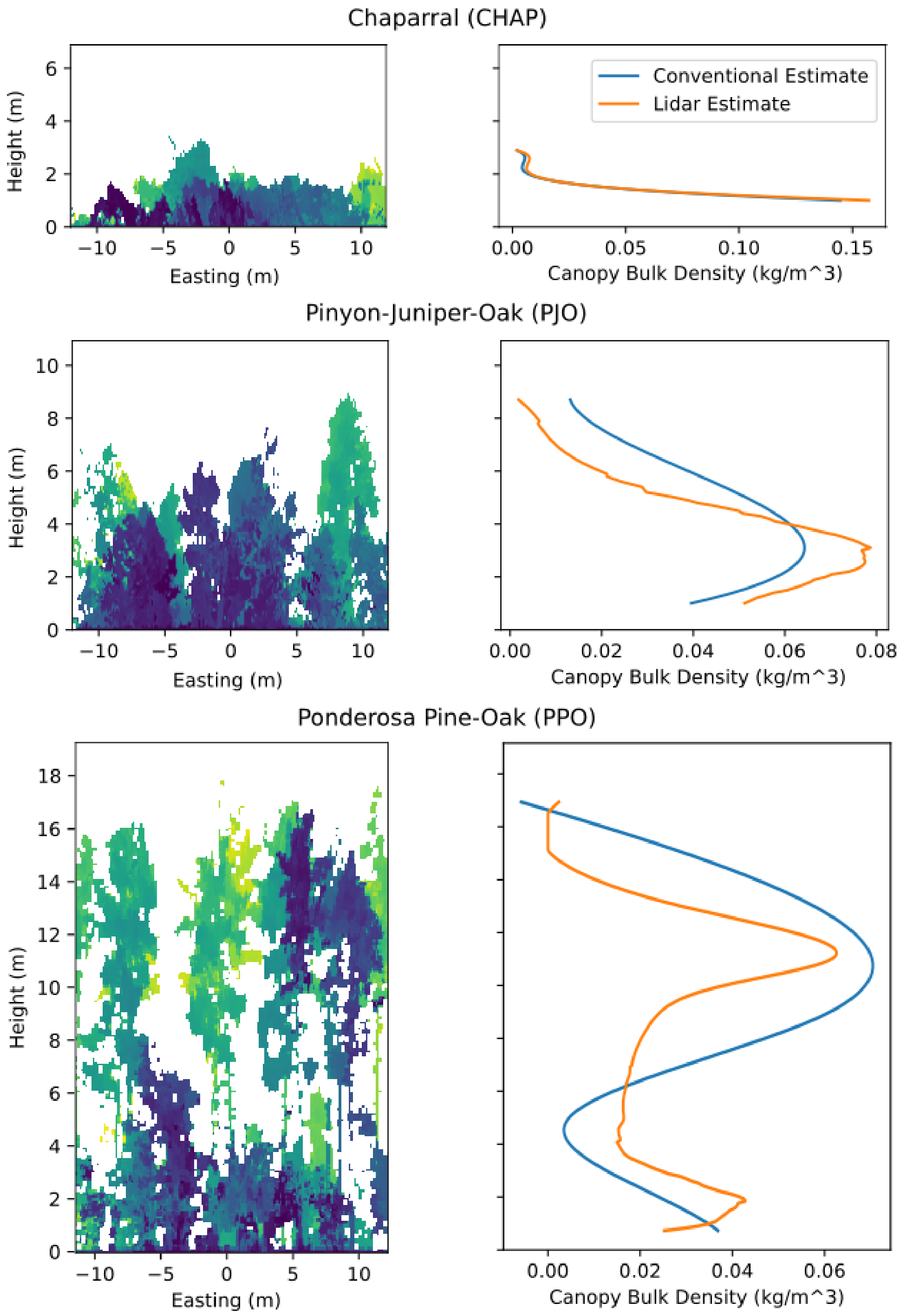
LAD Modeling

- Estimate LAD in 10cm voxels
- Classify voxels as occluded if >80 percent of pulses intercepted before reaching voxel
- Classify voxels as non-foliage if transmittance through voxel is near zero (e.g. tree trunks and rocks)
- Bin LAD by height-above-ground and aggregate with mean, ignoring occluded and non-foliage voxels
- Estimate proportion of leaf mass contributed by different species, multiply by estimate of leaf mass per area for each species

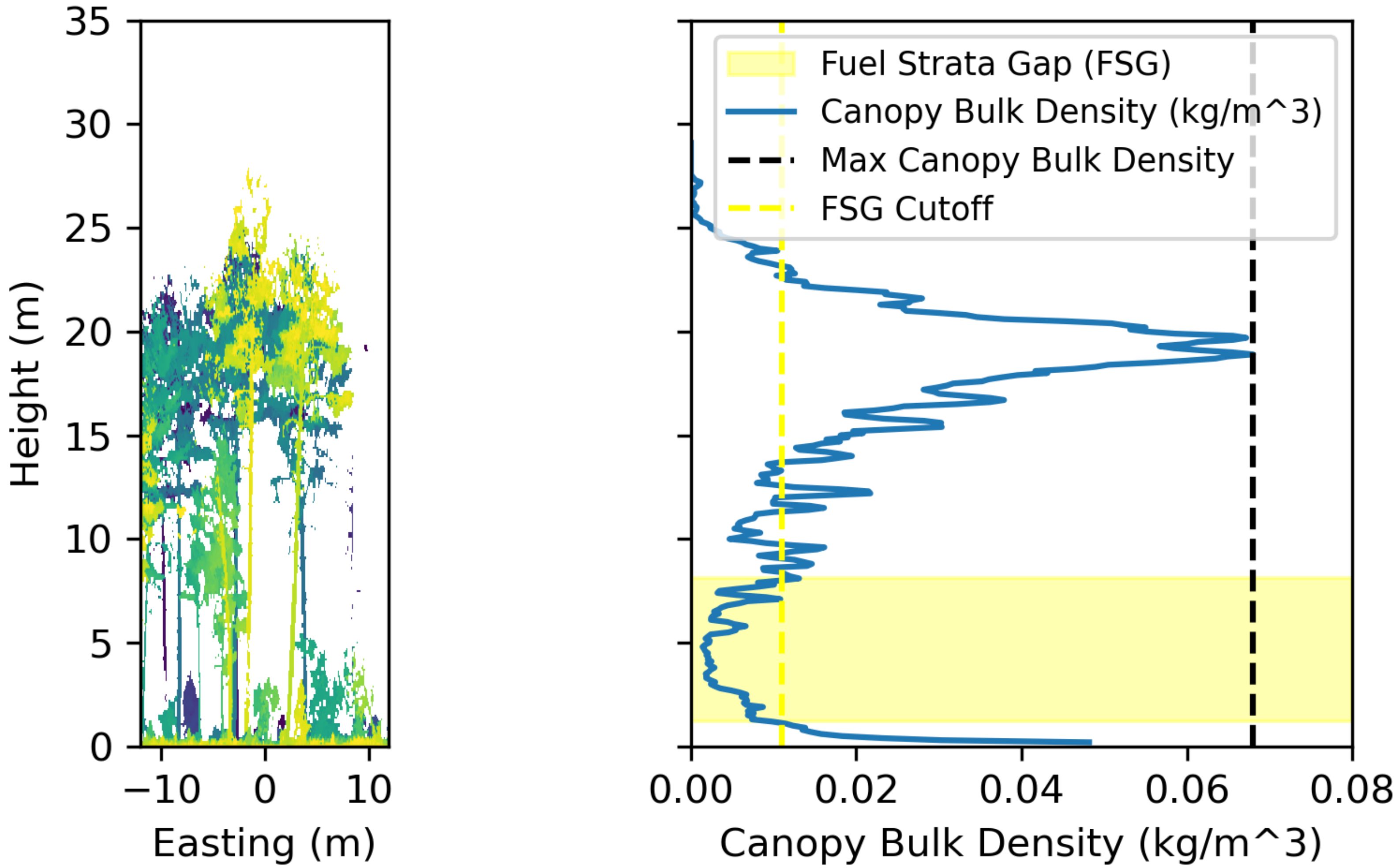




Example CBD Profiles



Estimating CFL and CBD_max



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Max CBD	0.068	kg/m^3
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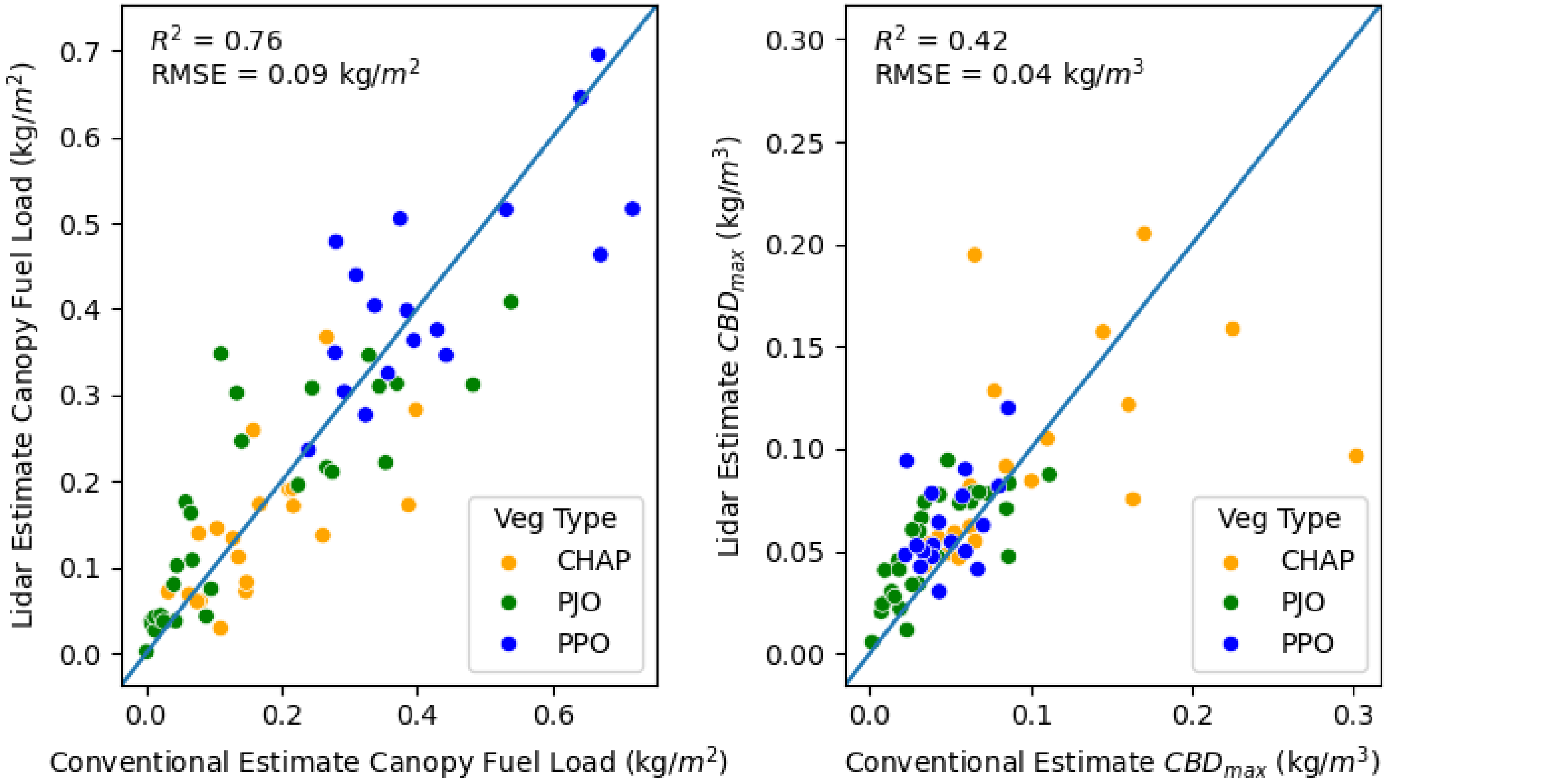
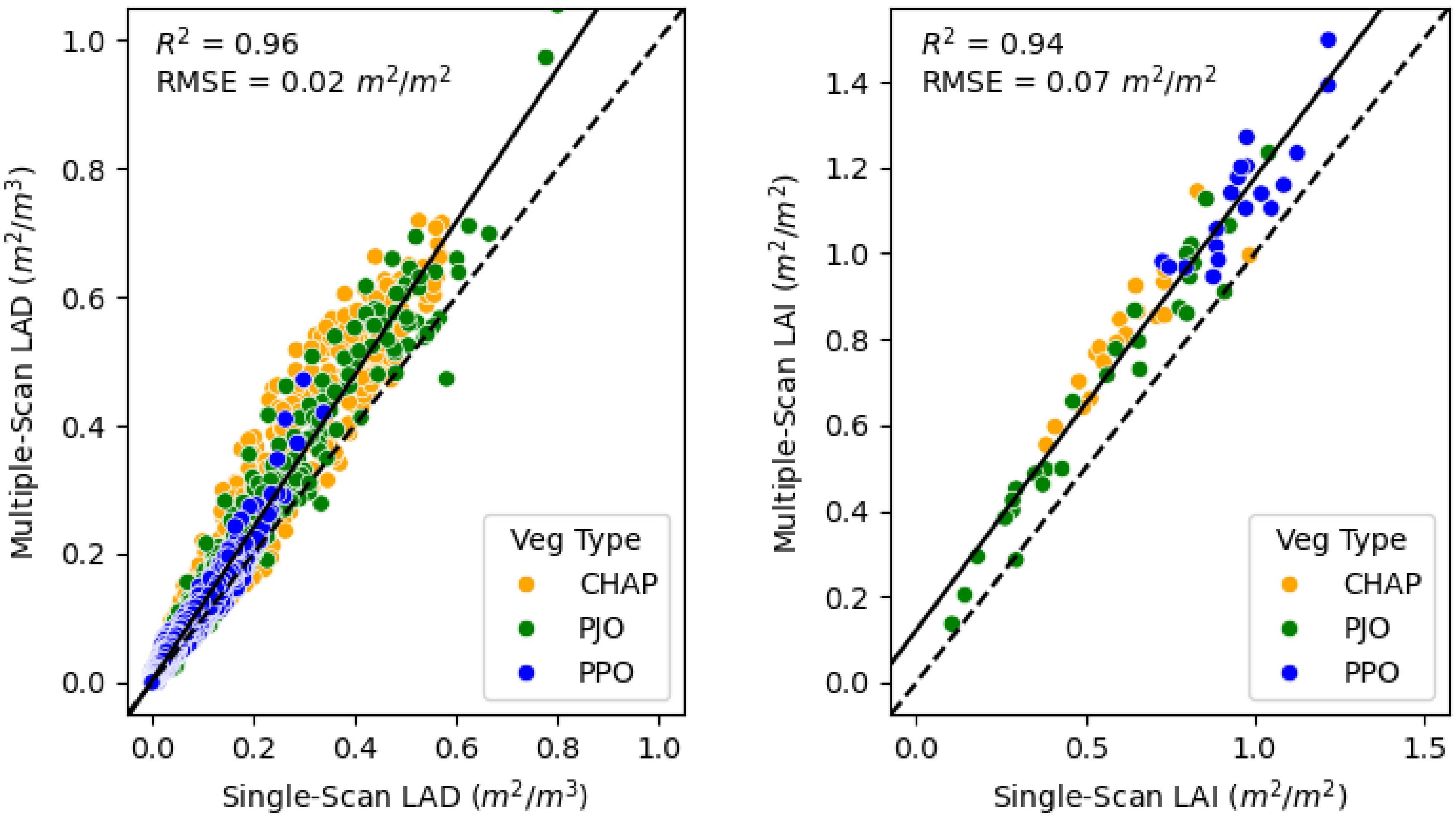
Spread Rate	0.956	km/hr
Intensity	5142.8	kW/m
Flame Length	7.9	m
Torching Index	35	km/hr
Crowning Index	53	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Estimating CFL and CBD_max



Single-Scan vs Multiple-Scan



Sources of Bias

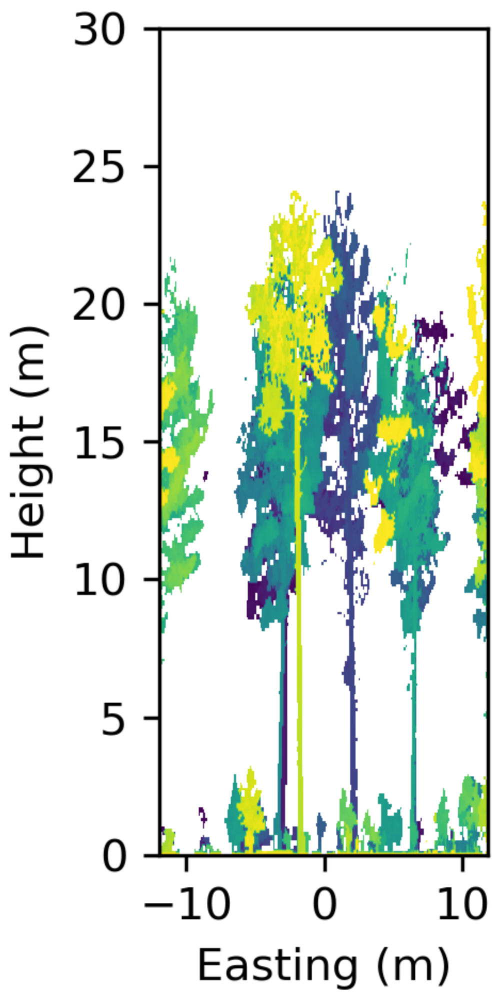
- Species composition: calibrated leaf mass per area varies widely between species
- Height above ground (and probably distance from sensor): negative bias in CBD prediction as scan density decreases
- Occlusion: if you don’t consider occlusion, negative bias. If you treat occluded areas as NA, positive bias.

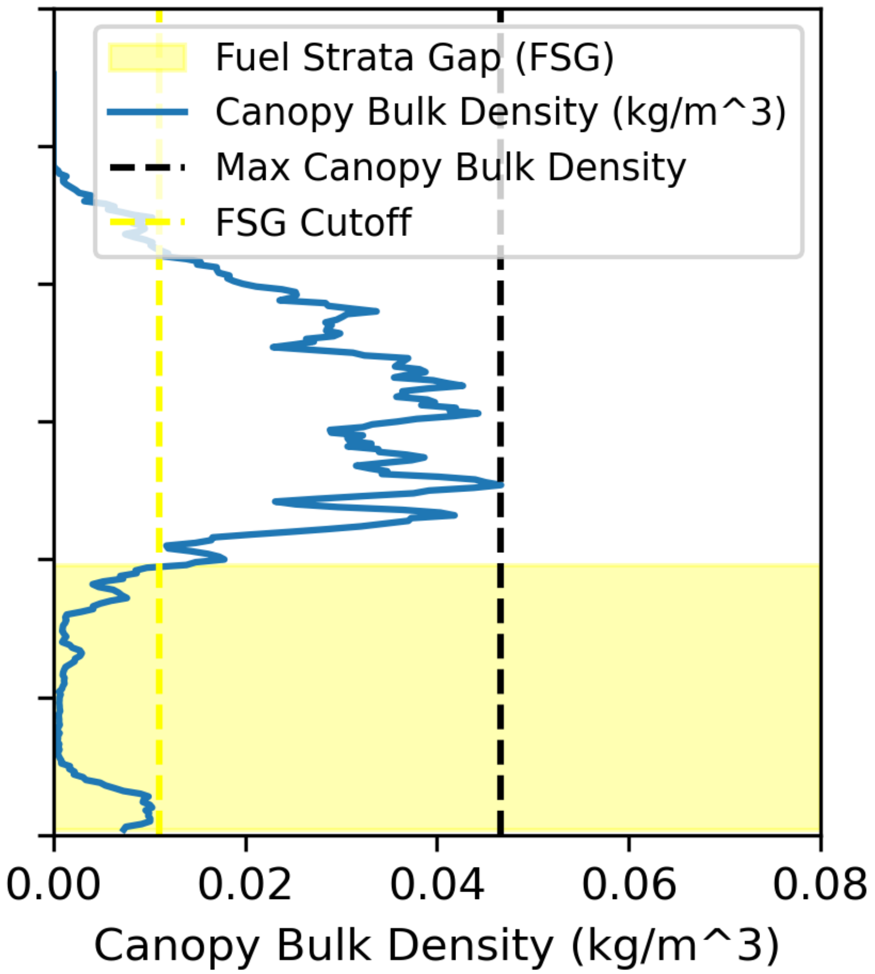
Application to Pre- and Post-Treatment Data

- End of Tonto NF study (so far)
- Next: preliminary results from across the SW

Application to Pre- and Post-Treatment Data

Application to Pre- and Post-Treatment Data

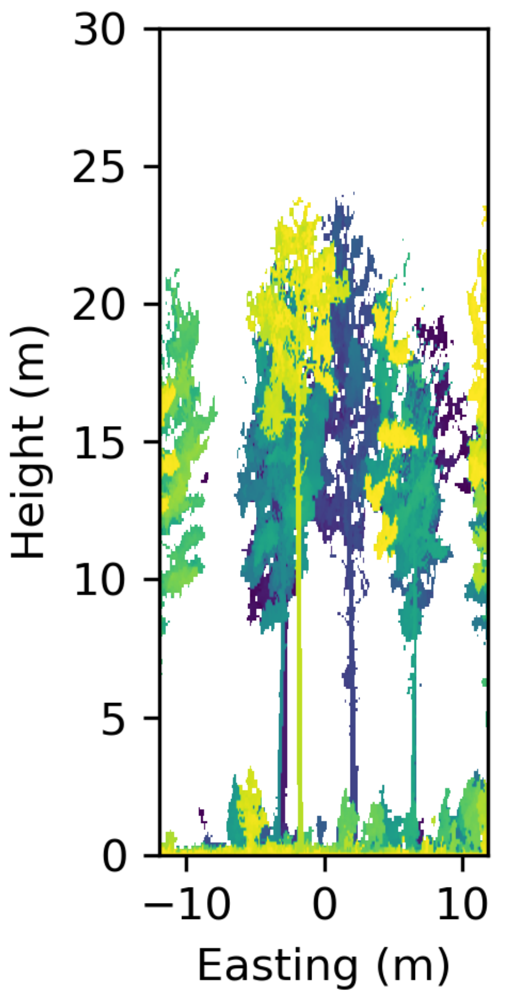


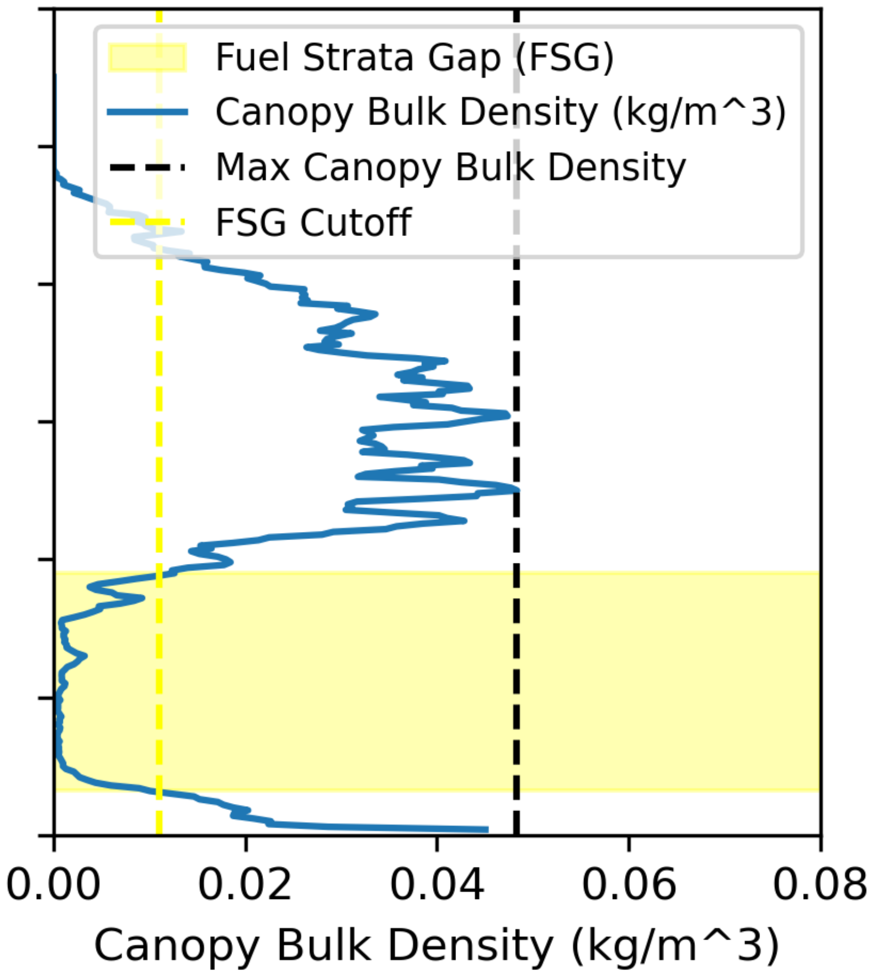


Name	Value	Units
Max CBD	0.0467	kg/m^3
Fuel Strata Gap	9.6	m
Surface Fuel Load	0.6	kg/m^2
Fuelbed Depth	4.6	cm
Spread Rate	0.215	km/hr
Intensity	460.9	kW/m
Flame Length	1.3	m
Torching Index	999	km/hr
Crowning Index	69	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Application to Pre- and Post-Treatment Data

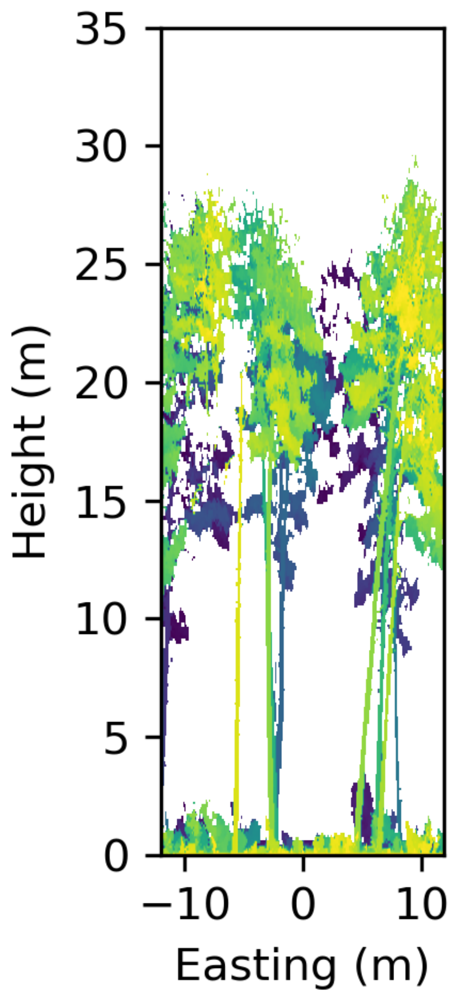


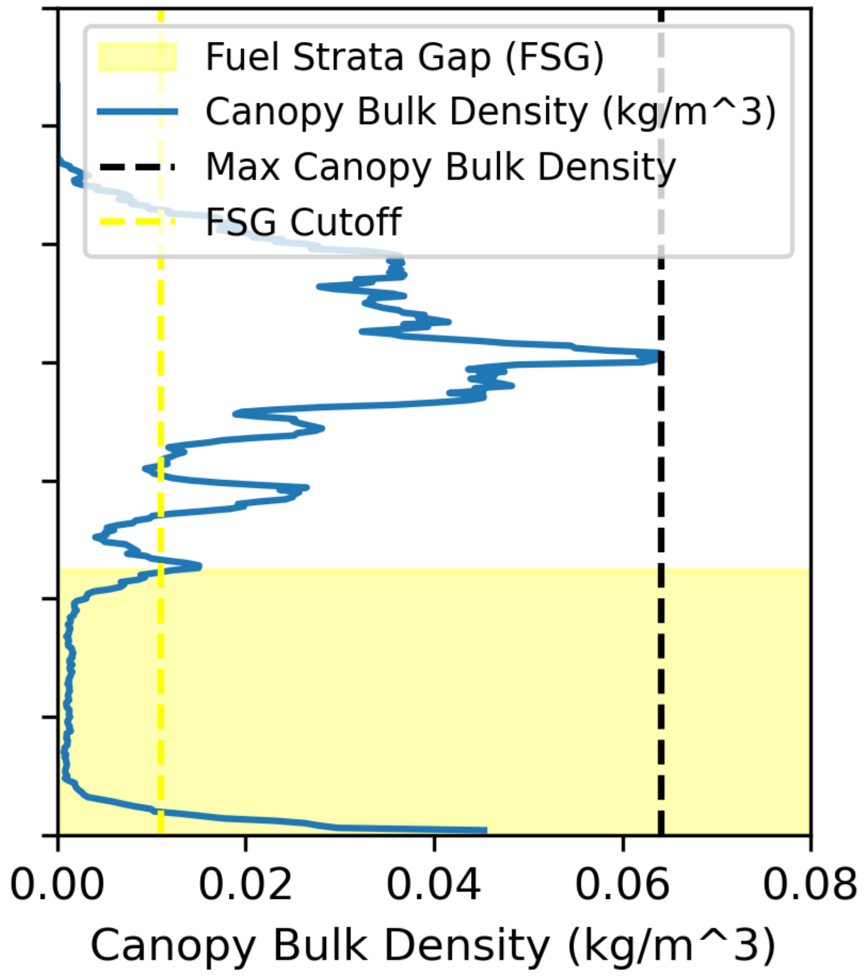


Name	Value	Units
Max CBD	0.0483	kg/m^3
Fuel Strata Gap	7.9	m
Surface Fuel Load	1.86	kg/m^2
Fuelbed Depth	9.1	cm
Spread Rate	0.609	km/hr
Intensity	3698.9	kW/m
Flame Length	3.4	m
Torching Index	41	km/hr
Crowning Index	67	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Application to Pre- and Post-Treatment Data

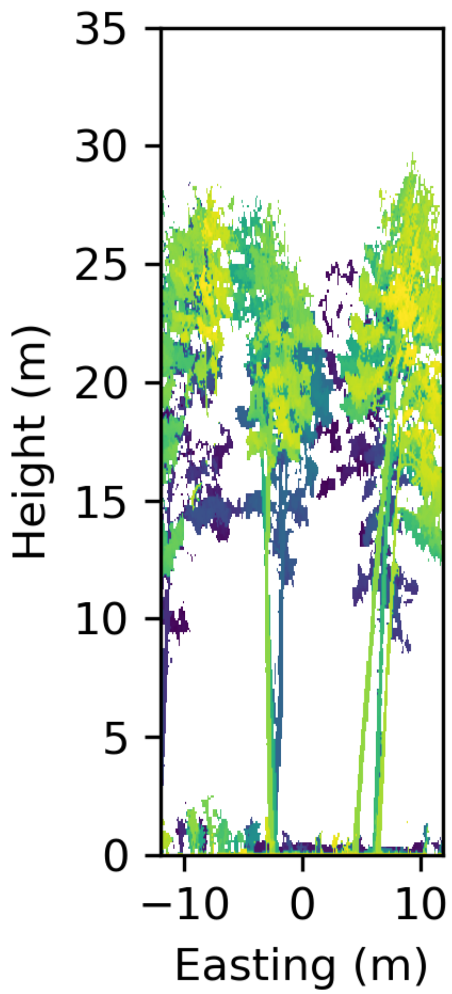


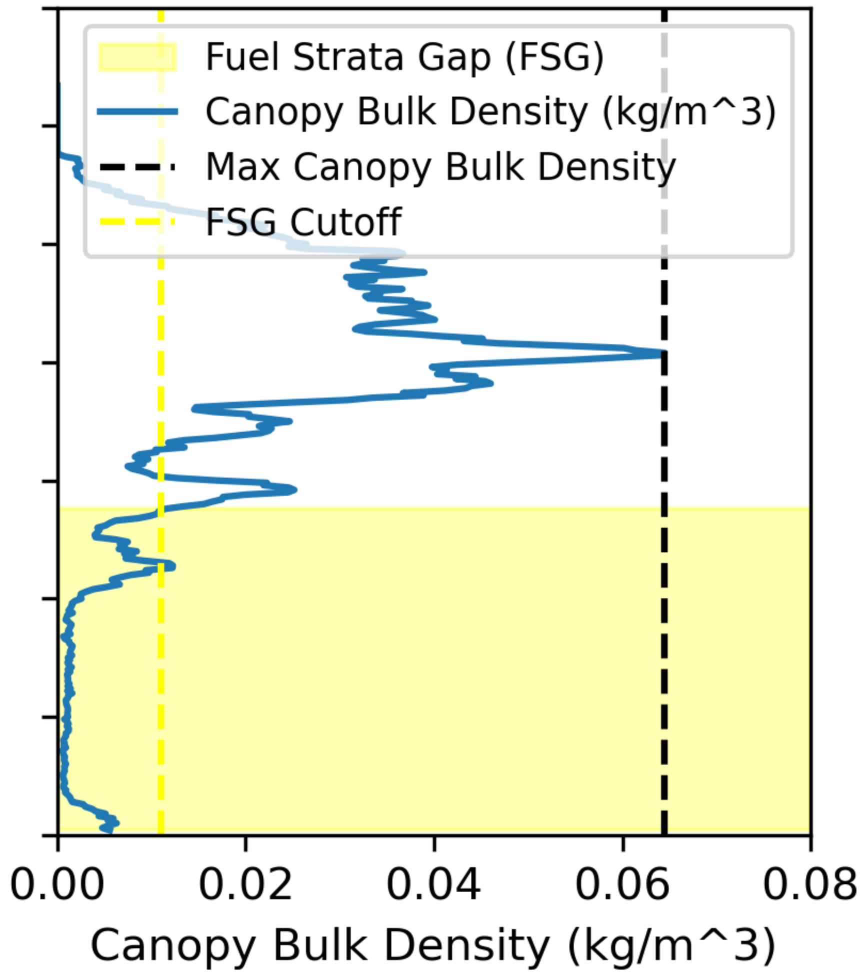


Name	Value	Units
Max CBD	0.0642	kg/m^3
Fuel Strata Gap	11.2	m
Surface Fuel Load	1.86	kg/m^2
Fuelbed Depth	9.1	cm
Spread Rate	0.609	km/hr
Intensity	3698.9	kW/m
Flame Length	3.4	m
Torching Index	60	km/hr
Crowning Index	55	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Application to Pre- and Post-Treatment Data

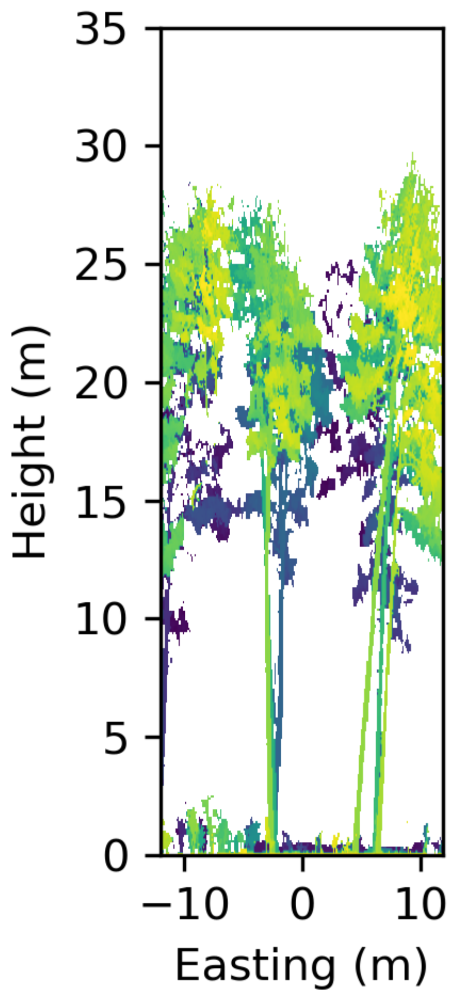


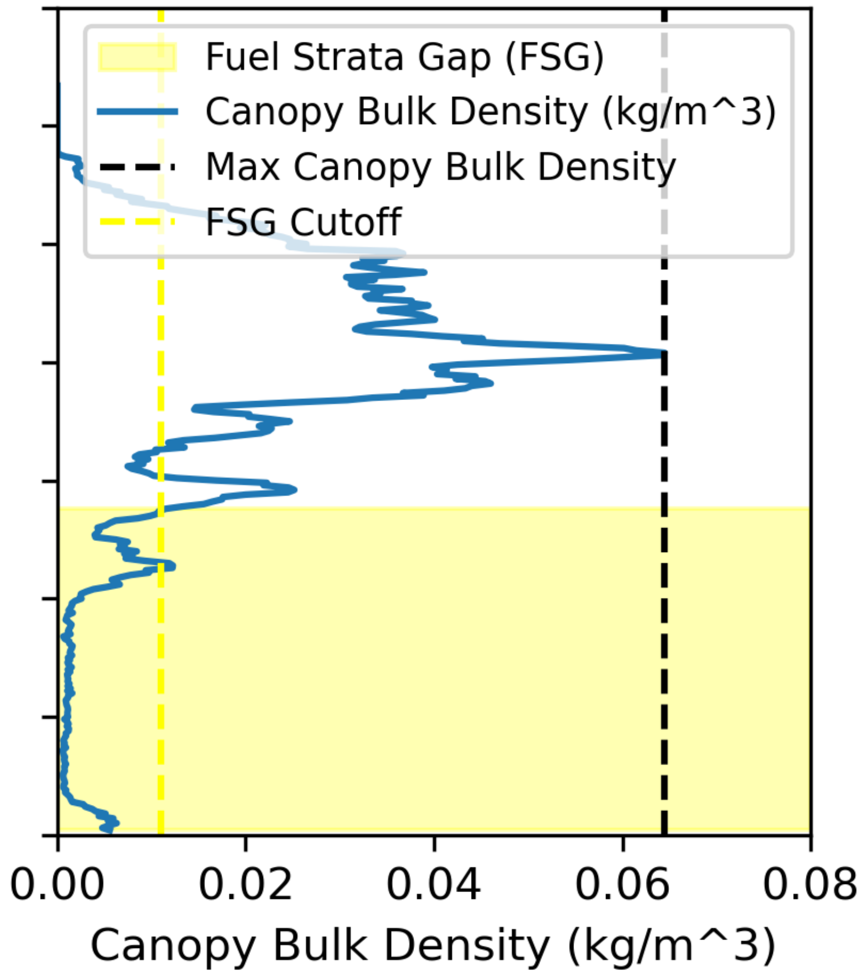


Name	Value	Units
Max CBD	0.0645	kg/m^3
Fuel Strata Gap	13.6	m
Surface Fuel Load	0.6	kg/m^2
Fuelbed Depth	4.6	cm
Spread Rate	0.215	km/hr
Intensity	460.9	kW/m
Flame Length	1.3	m
Torching Index	999	km/hr
Crowning Index	55	km/hr

Potential fire behavior based on 40km/hr wind; 'very low' moisture

Application to Pre- and Post-Treatment Data





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Lidar Approaches to Monitor Fuel Treatment Effects

Examples with TLS in Arizona

Applications for ALS

Tools you can use!

Applications for ALS

Can we apply these methods to ALS?

Methods:

- LAD profile
- Lookup leaf-mass-per-area and calibrate Bayesian-style
- Model fire behavior with a canopy bulk density profile

Yep, these methods are compatible with ALS!

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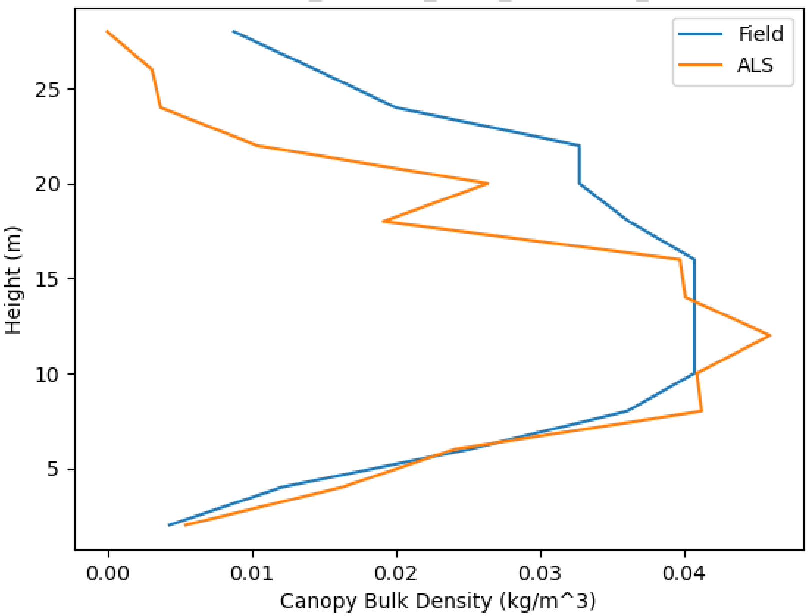
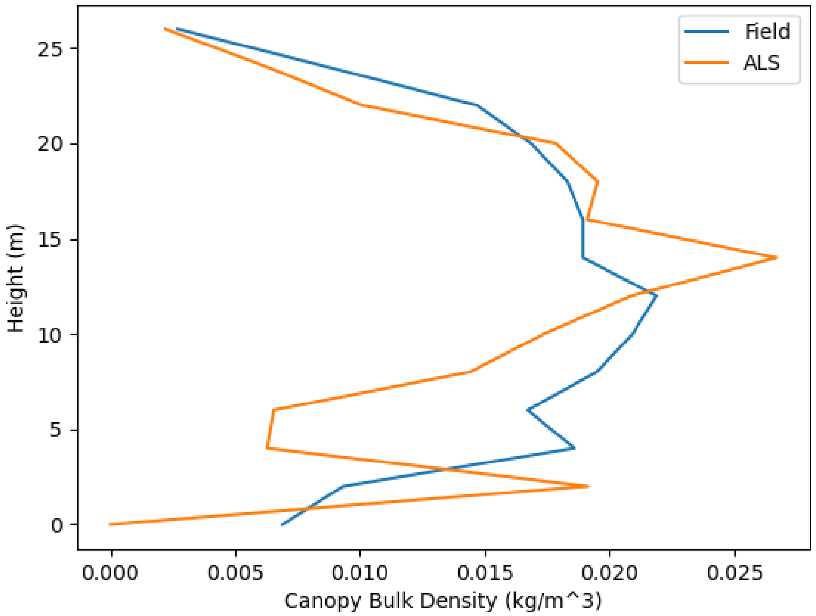
Preliminary Results Estimating CBD with ALS

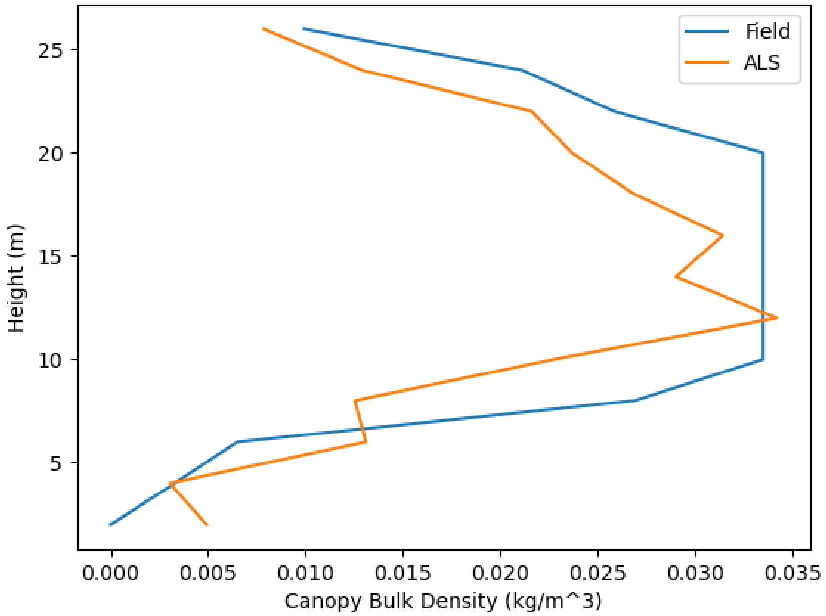
Example Plot 1



Example Plot 2

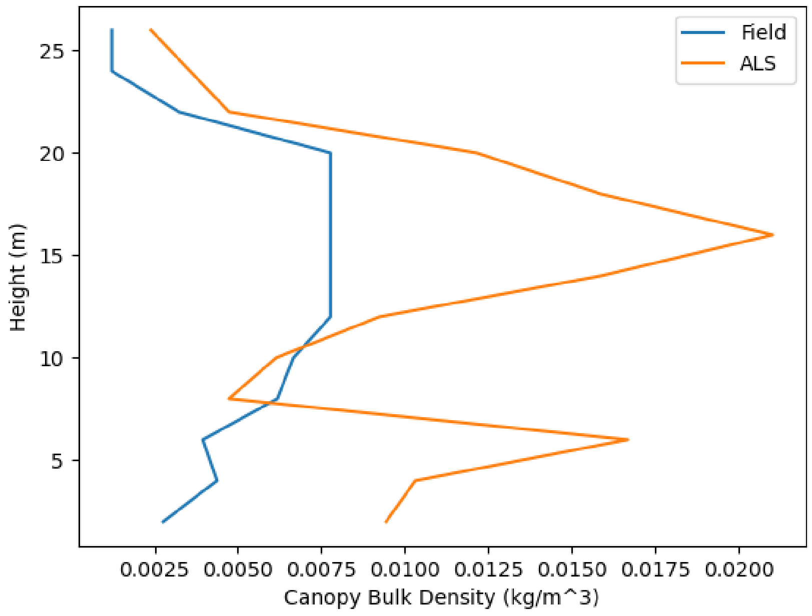


Example Plot 3

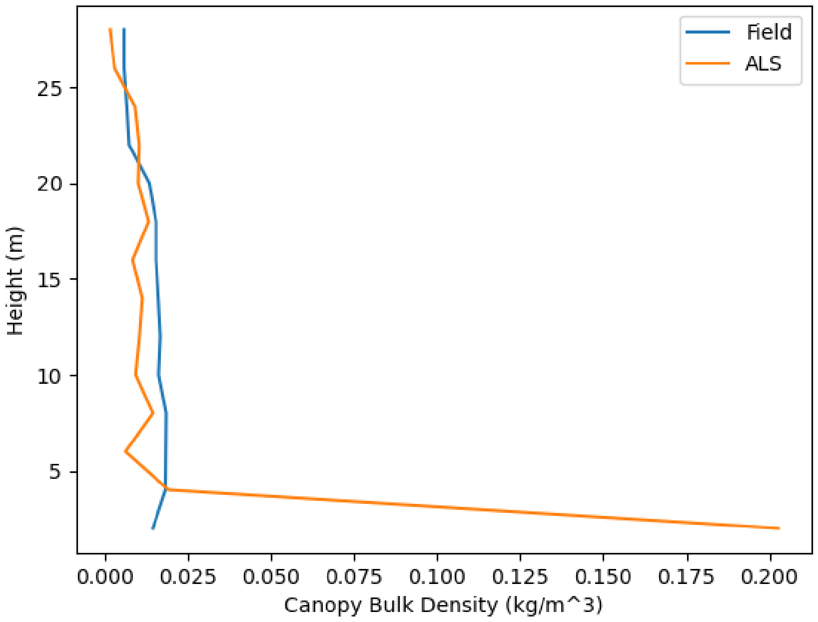


Preliminary Results Estimating CBD with ALS

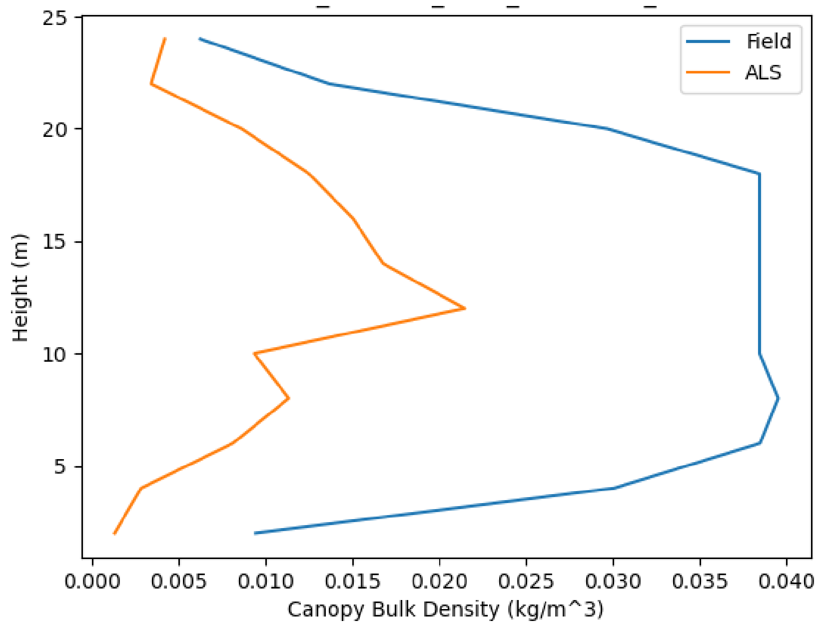
Example Plot 1



Example Plot 2



Example Plot 3



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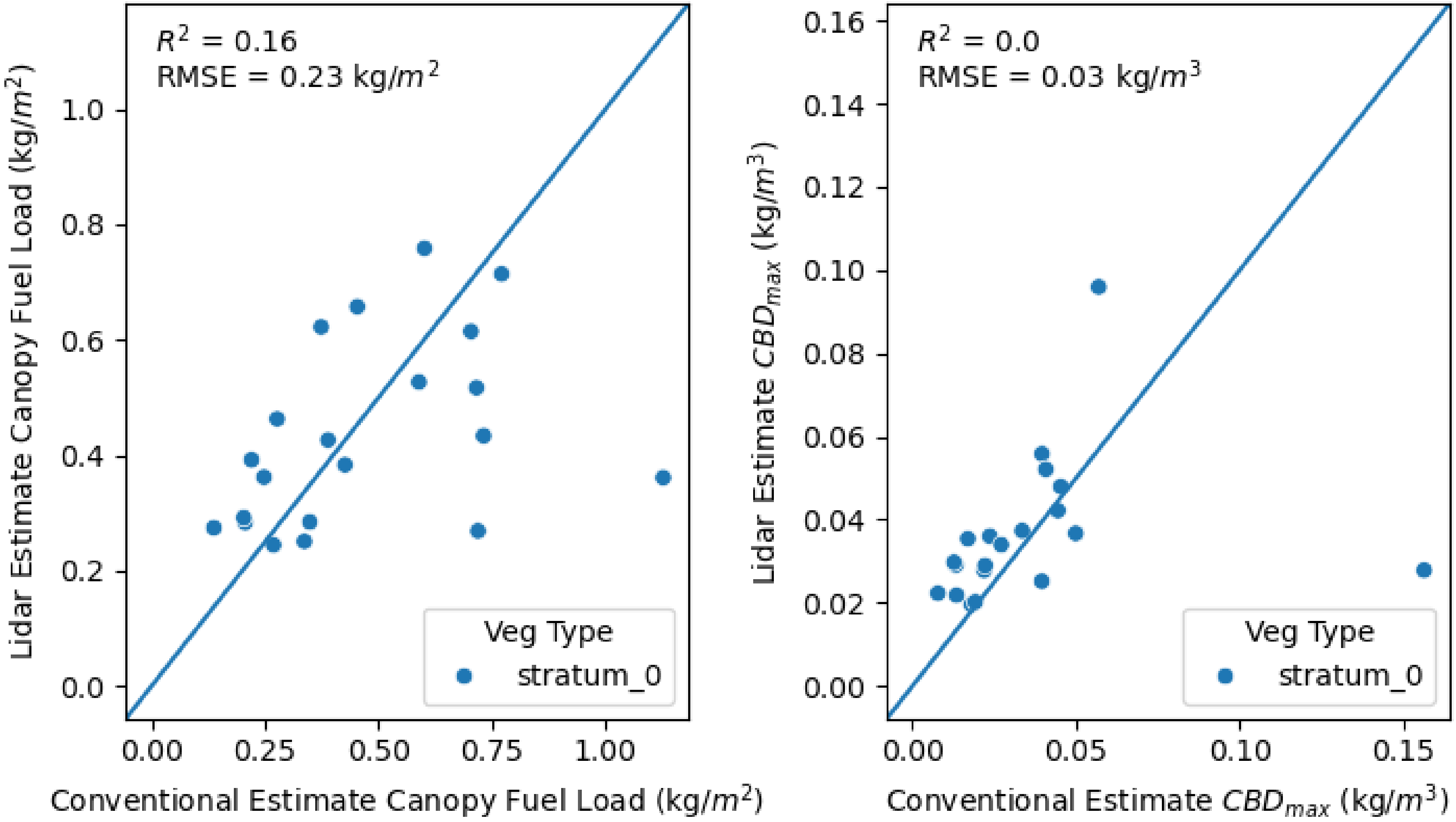

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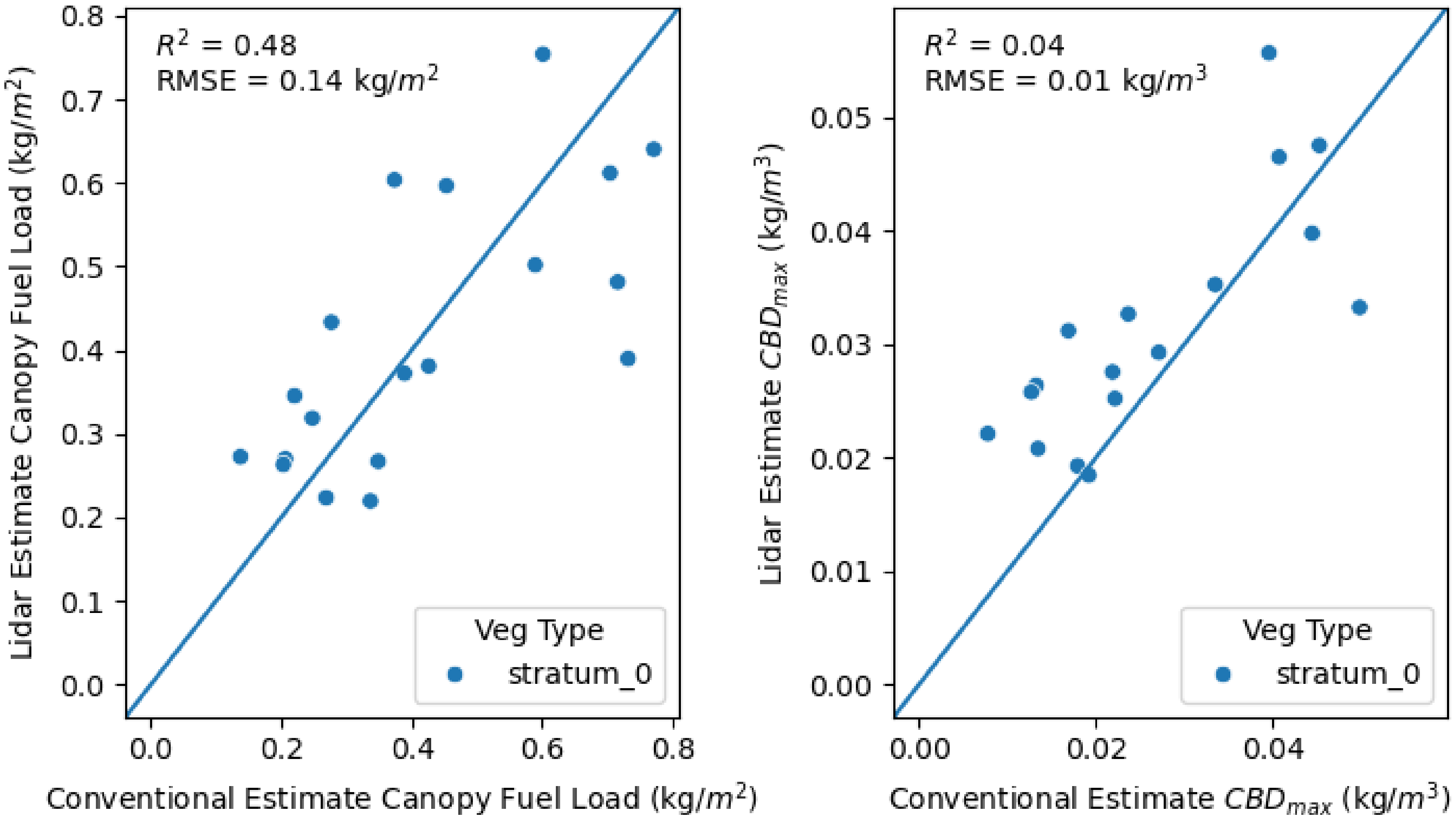
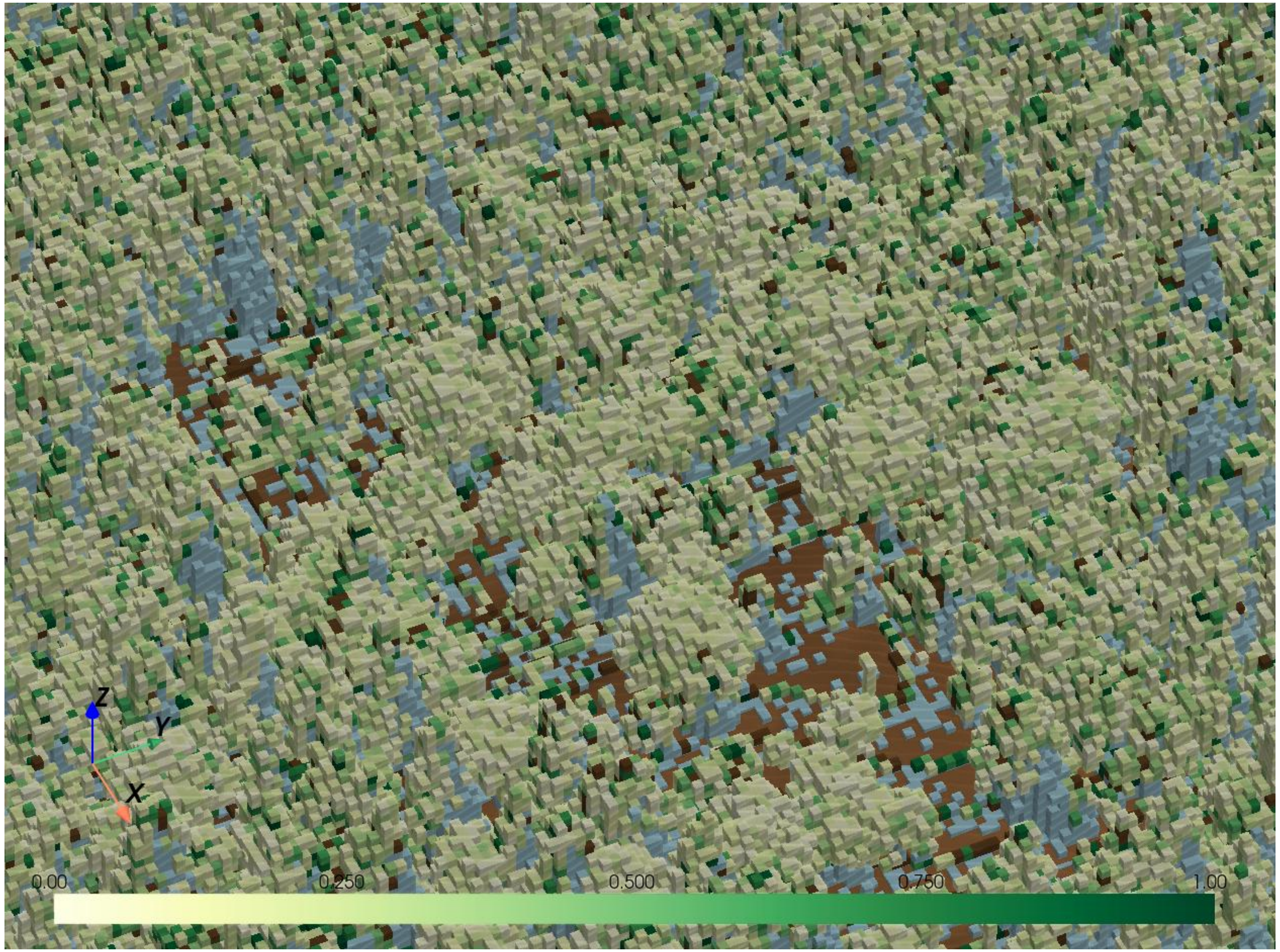
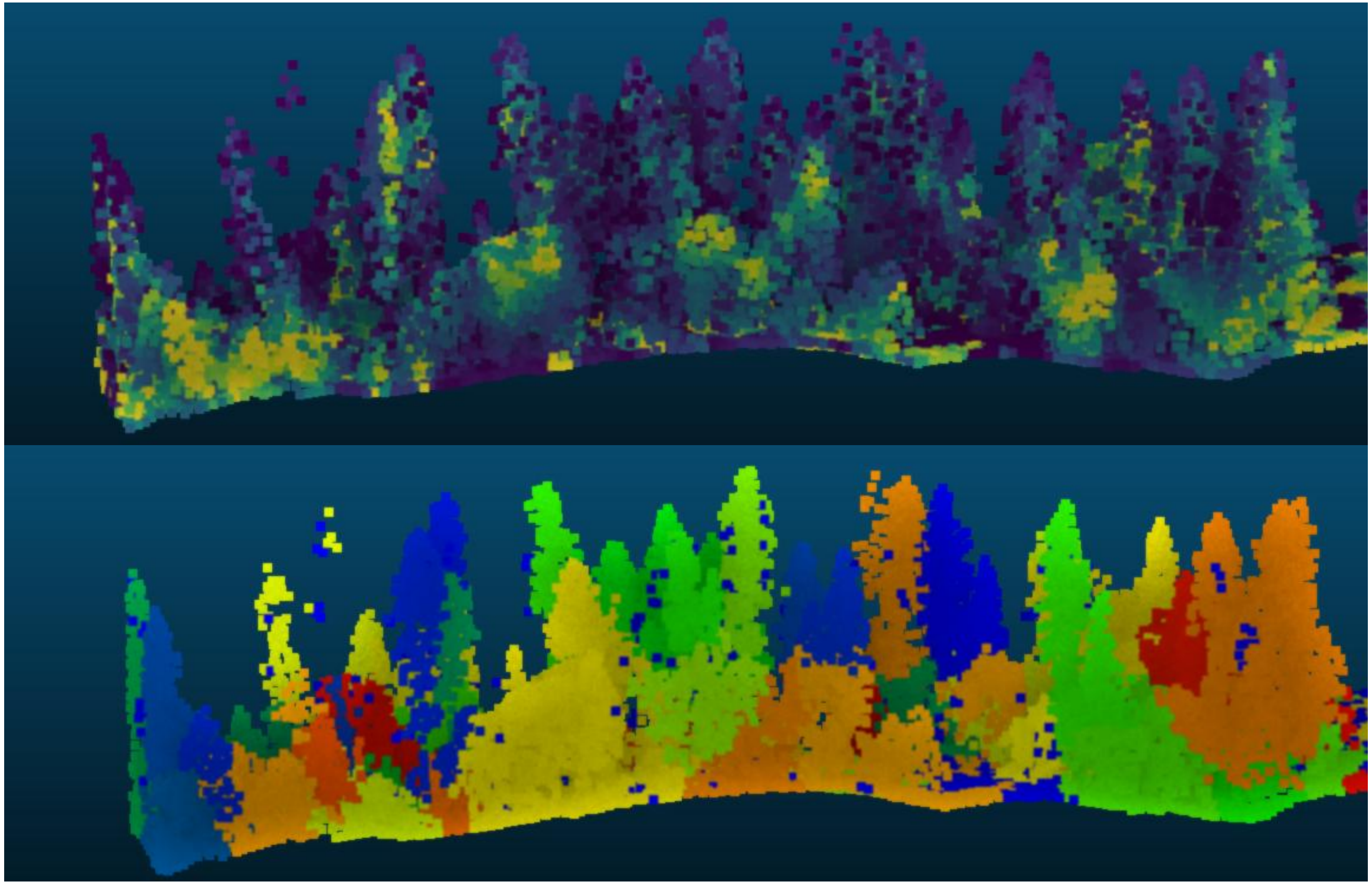


Profiles are boring, what about 3D?



What about individual tree methods??



Lidar Approaches to Monitor Fuel Treatment Effects

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Publication (in review)

Canopy and surface fuels measurement using terrestrial lidar single-scan approach in the Mogollon highlands of Arizona

Journal:	*International Journal of Wildland Fire*
Manuscript ID	WF24221.R1
Manuscript Type:	Research Paper
Date Submitted by the Author:	22-Mar-2025
Complete List of Authors:	Tenny, Johnathan; Northern Arizona University, School of Informatics, Computing, and Cyber Systems Sankey, Temuulen; Northern Arizona University, School of Informatics, Computing, and Cyber Systems Munson, Seth; USGS, Southwest Biological Science Center Sánchez Meador, Andrew; Northern Arizona University, School of Forestry; Ecological Restoration Institute Goetz, Scott; Northern Arizona University, School of Informatics, Computing, and Cyber Systems
Keyword:	TLS, plant area density, biomass, leaf mass per area, vertical profile

Software

j-tenny / **voxelmon**

- Software will be made openly available on Github following acceptance of publication
- Flexible tools for estimating LAD, fitting models, making predictions
- Programmed in Python with code compiled and parallelized using Numba
- Processing single-scan TLS data takes ~30-40 seconds per plot on desktop computer (CPU: AMD Ryzen 7 5800X)

Software

j-tenny / **pyrothermel**

(Available now) Python bindings for the Rothermel-based models that power Behave and FlamMap

j-tenny / **NFDRS4py**

(Available now) Python bindings for National Fire Danger Rating System w/ physics-based fuel moisture modeling

Software

j-tenny / **open-fire-toolkit**

(Release TBD) Spatio-temporal tools for fire behavior/fire risk modeling with remote sensing inputs and custom pipelines

Software

Computree + LVOX: Estimate LAD within a GUI application

Intellimon: Cloud hosting and processing for TLS data

Points2pano: Python code for visualizing pre- and post-treatment TLS data

Silvxlabs/NSVB: Python implementation of the new FIA equations for foliage biomass estimation

Data

TRY Database, BIEN Database: sources of global plant traits including leaf-mass-per-area

Conclusion

Leaf area density estimates combined with leaf-mass-per-area data and Bayesian statistics can result in robust, easy-to-train foliage biomass models suitable for ecological gradients.

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Single-scan TLS can provide rapid, repeatable canopy bulk density profiles for use in risk analysis and treatment effect monitoring.

Conclusion

Leaf area density estimates combined with leaf-mass-per-area data and Bayesian statistics can result in robust, easy-to-train foliage biomass models suitable for ecological gradients.

Single-scan TLS can provide rapid, repeatable canopy bulk density profiles for use in risk analysis and treatment effect monitoring.

Leaf area density estimates provide potential opportunities to improve understory tree segmentation and 3D fuel maps

Acknowledgements

Special thanks to my advisor, Teki Sankey as well as my committee: Seth Munsen, Andrew Sánchez Meador, and Scott Goetz

And our field techs from USGS SW Biological Science Center: Anthony Chesney, Kevin Coronado, Sarah Costanzo, Pari Cribbins, and Alex Croydon

Questions, discussion and feedback

Contact: jt893@nau.edu
LinkedIn: Johnathan Tenny

What about surface fuels?

Surface Fuels

- Two kinds of surface fuels:
  - standing surface fuels: live (or recently dead) fuels that grow near surface
  - downed surface fuels: fuels that fall from the canopy

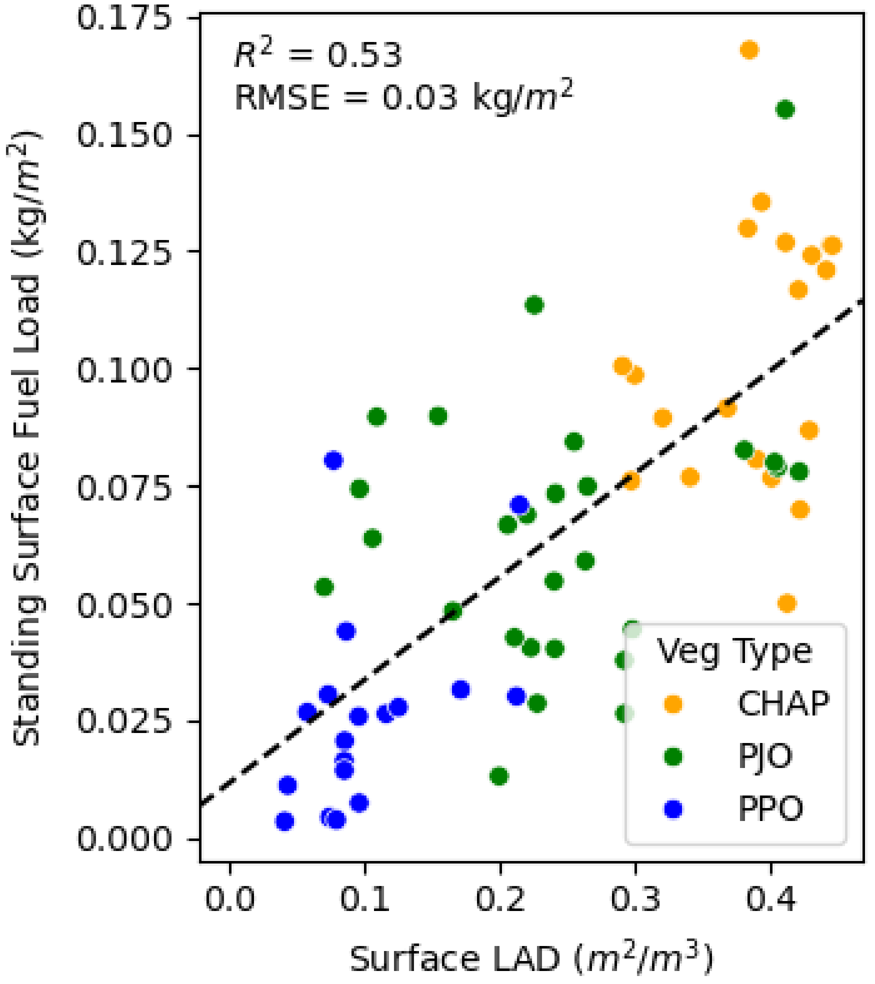
Surface Fuels

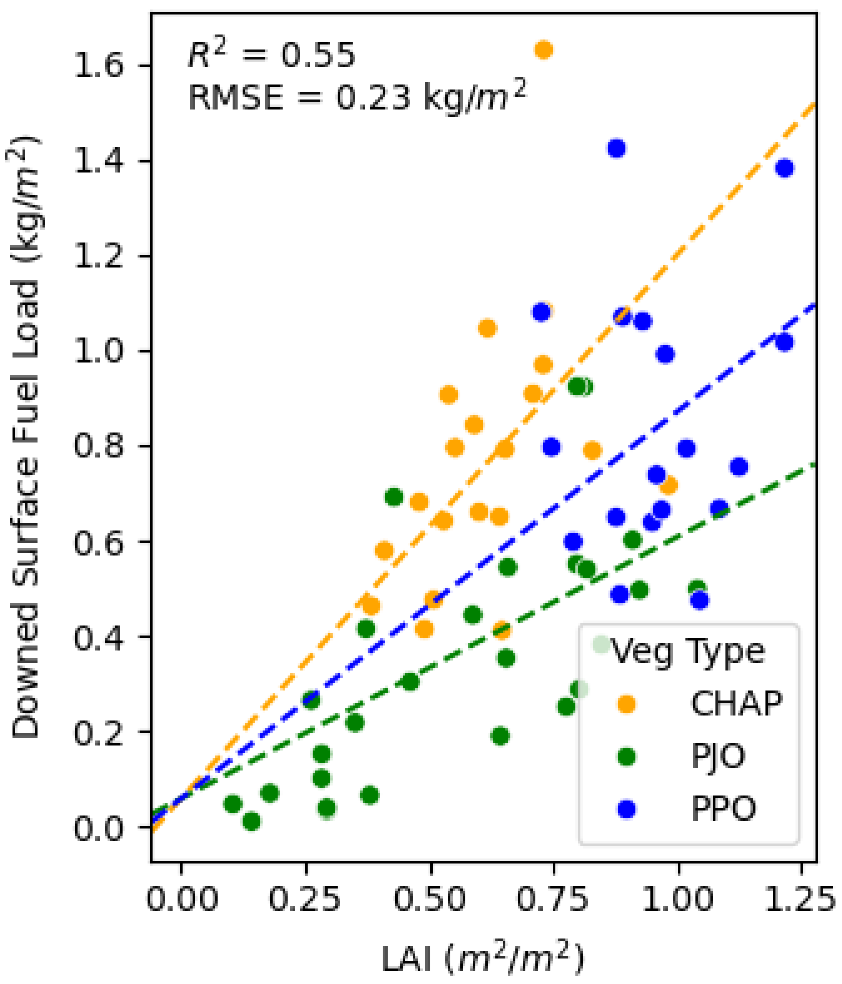
- Two kinds of surface fuels:
  - standing surface fuels -> can estimate leaf area density and leaf mass per area
  - downed surface fuels

Surface Fuels

- Two kinds of surface fuels:
  - standing surface fuels -> can estimate leaf area density and leaf mass per area
  - downed surface fuels -> consider relationship to canopy, environment, and disturbance history

Surface Fuels





Exploring Data From Wild Bill Prescribed Burn

Why measure canopy instead of stems?

Stems (basal area)

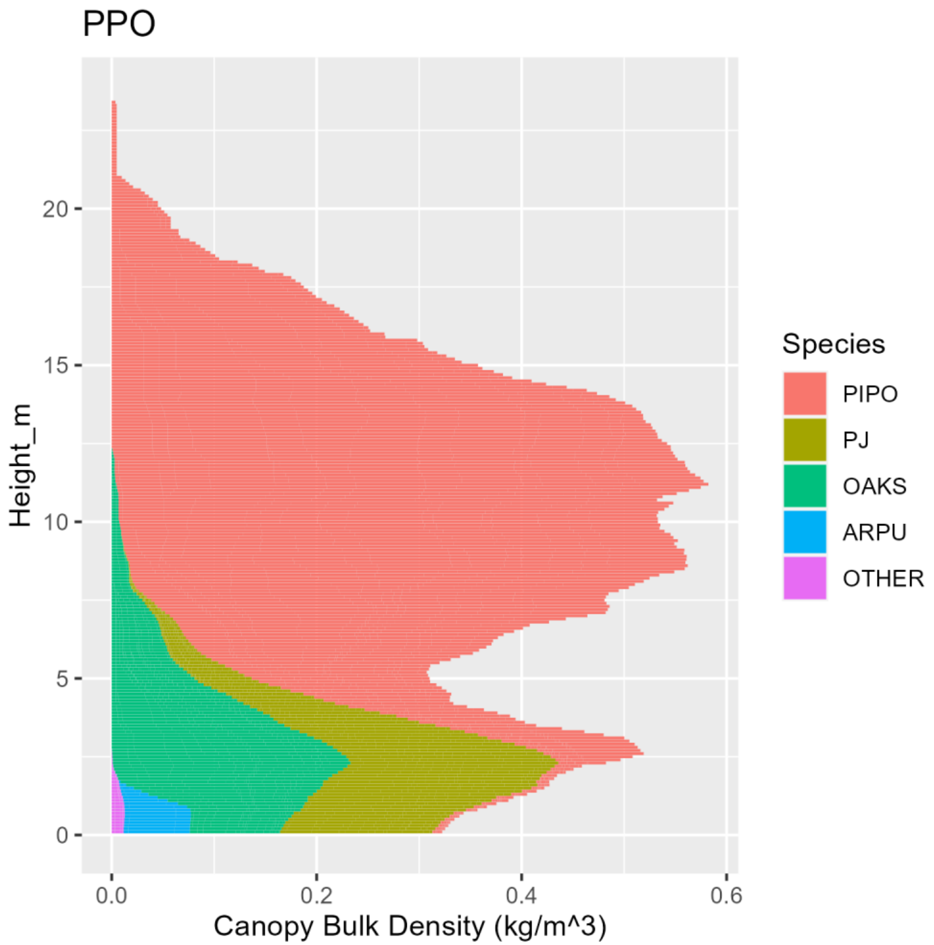
- Determines lumber value of trees
- Important for estimating total biomass
- Correlated with canopy biomass and leaf area
- Easy to measure by hand
- Hard to measure with remote sensing

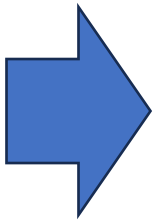
Canopies (bulk density, leaf area)

- Canopy is primary carrier of canopy fire
- Woody debris/litter falls from canopies
- Canopies modify wind fields
- Canopies provide shade and precipitation interception
  - Modifies surface fuel moisture
  - Modifies understory composition and density
  - Modifies snow accumulation and persistence
- Canopy area drives evapotranspiration and plant water use
- Hard to measure by hand
- Easy to measure with remote sensing

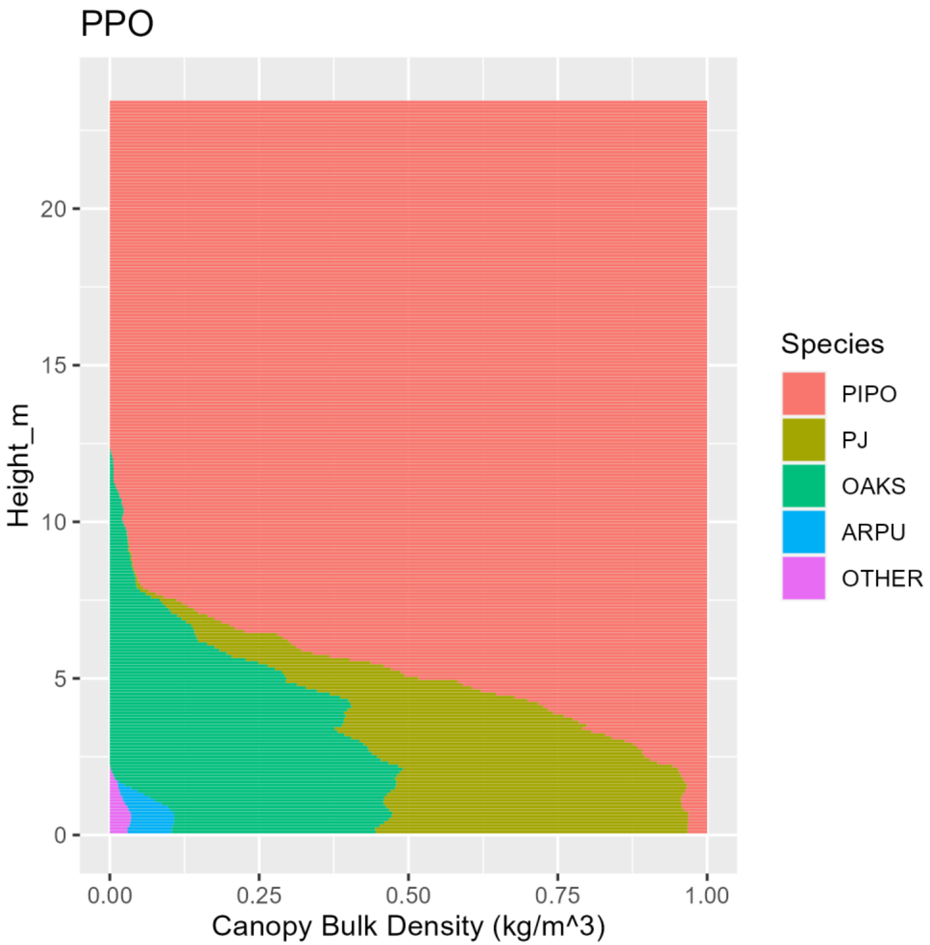
Traditional Estimates of Canopy Fuels

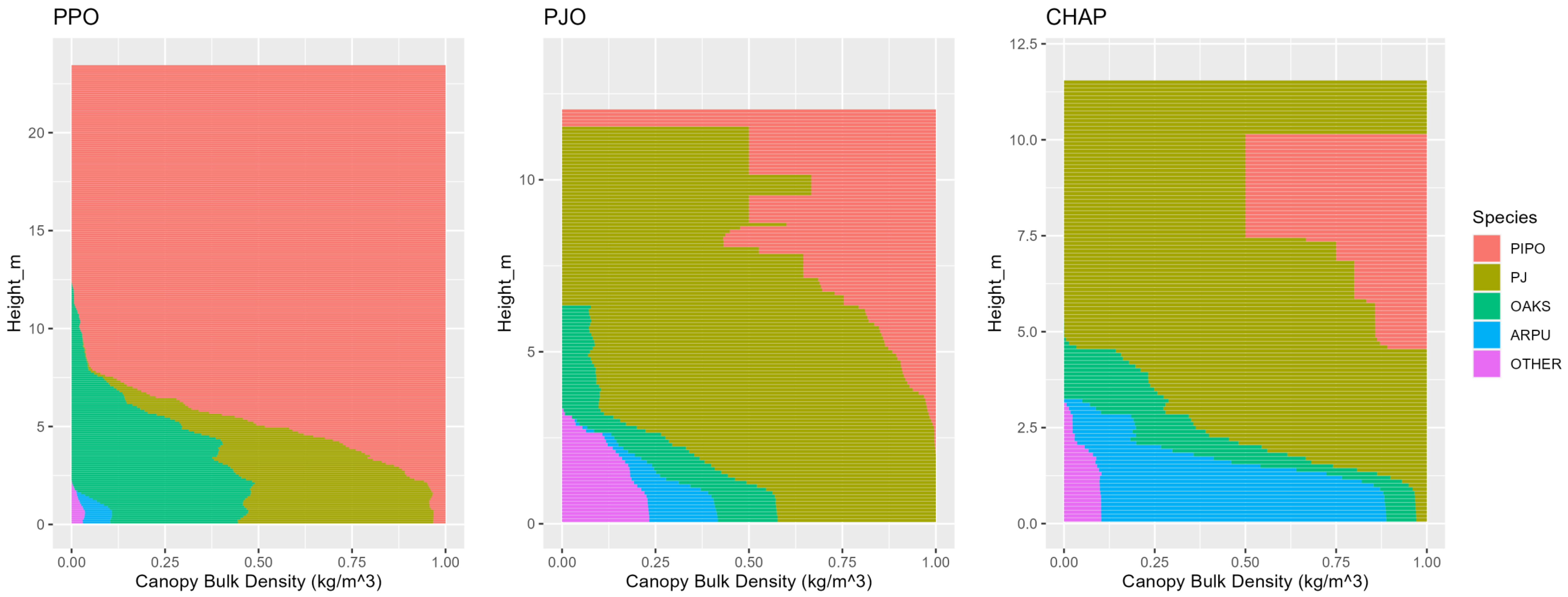
Class Aggregate Canopy Bulk Density Profile





Class Vertical Species Distribution





PPO
PJO
CHAP
Height_m
Canopy Bulk Density (kg/m^3)
0.00
0.25
0.50
0.75
1.00
0
5
10
15
20
0.0
2.5
5.0
7.5
10.0
12.5
Species
PIPO
PJ
OAKS
ARPU
OTHER

Equation 1

$$CBD = LAD * LMA_{avg}$$

Equation 2

$$LMA_{avg} = \sum_{i=1}^{n_{sp}} LMA_{sp_i} * p_{sp_i}$$

Equation 3

$$CBD = LMA_{sp_1} * p_{sp_1} * LAD + LMA_{sp_2} * p_{sp_2} * LAD \ldots + LMA_{sp_n} * p_{sp_n} * LAD$$

CBD = canopy bulk density at given height (kg/m^3)

LAD = leaf area density at given height (m^2/m^3)

LMA_{avg} = weighted average of leaf mass per area at given height (kg/m^2)

p_{sp_i} = proportion of CBD contributed by species group i at given height

LMA_{sp_i} = leaf mass per area for species group i (kg/m^2)

n_{sp} = number of species groups in model