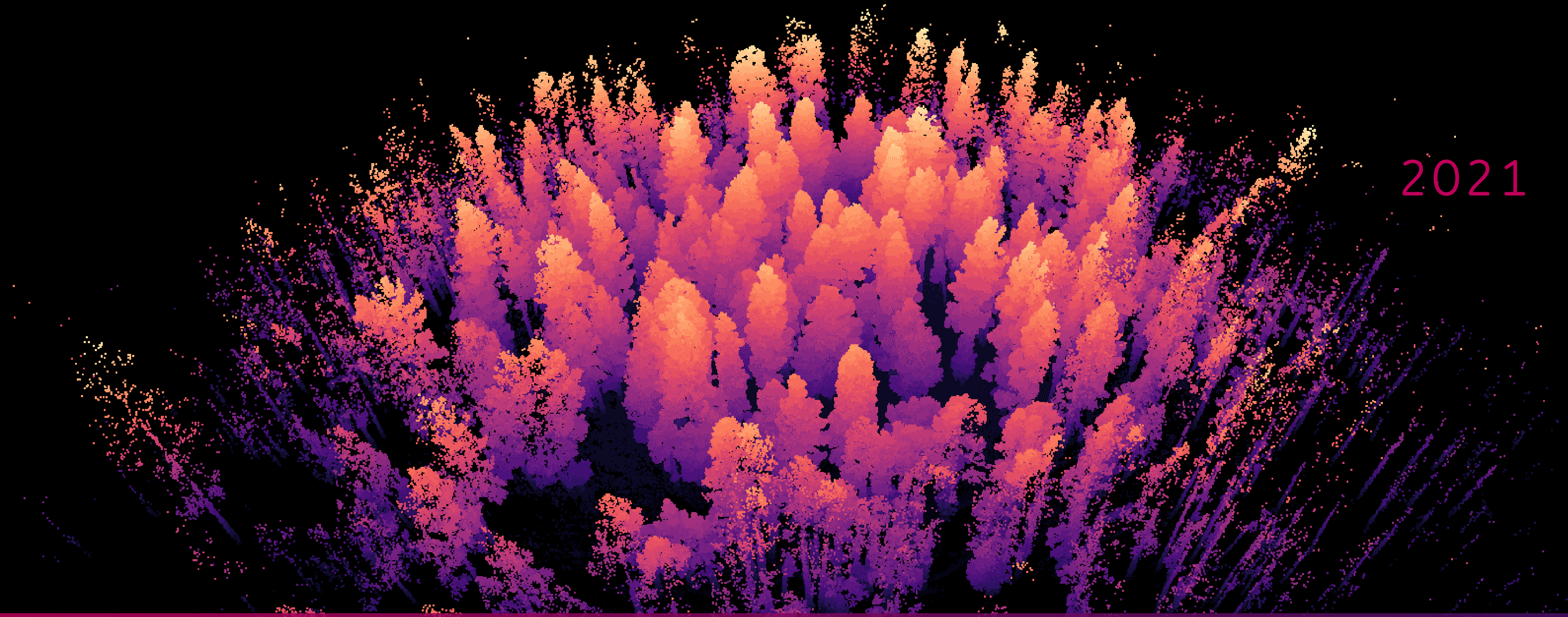

2021

Adjudicating perspectives on forest structure: How do airborne, terrestrial, and mobile lidar-derived estimates compare?

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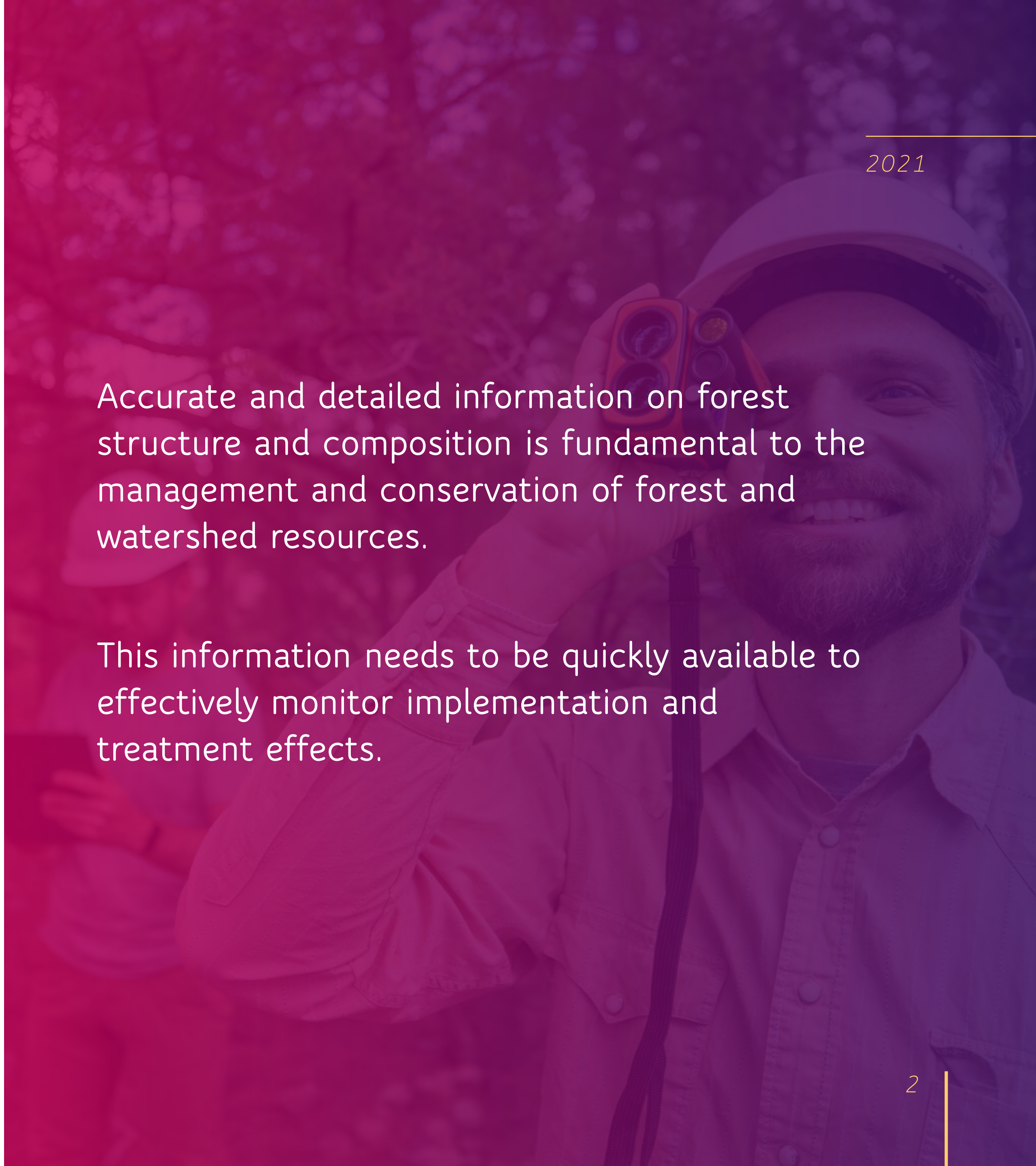
The problem

traditional field methods are resource intensive



Accurate and detailed information on forest structure and composition is fundamental to the management and conservation of forest and watershed resources.

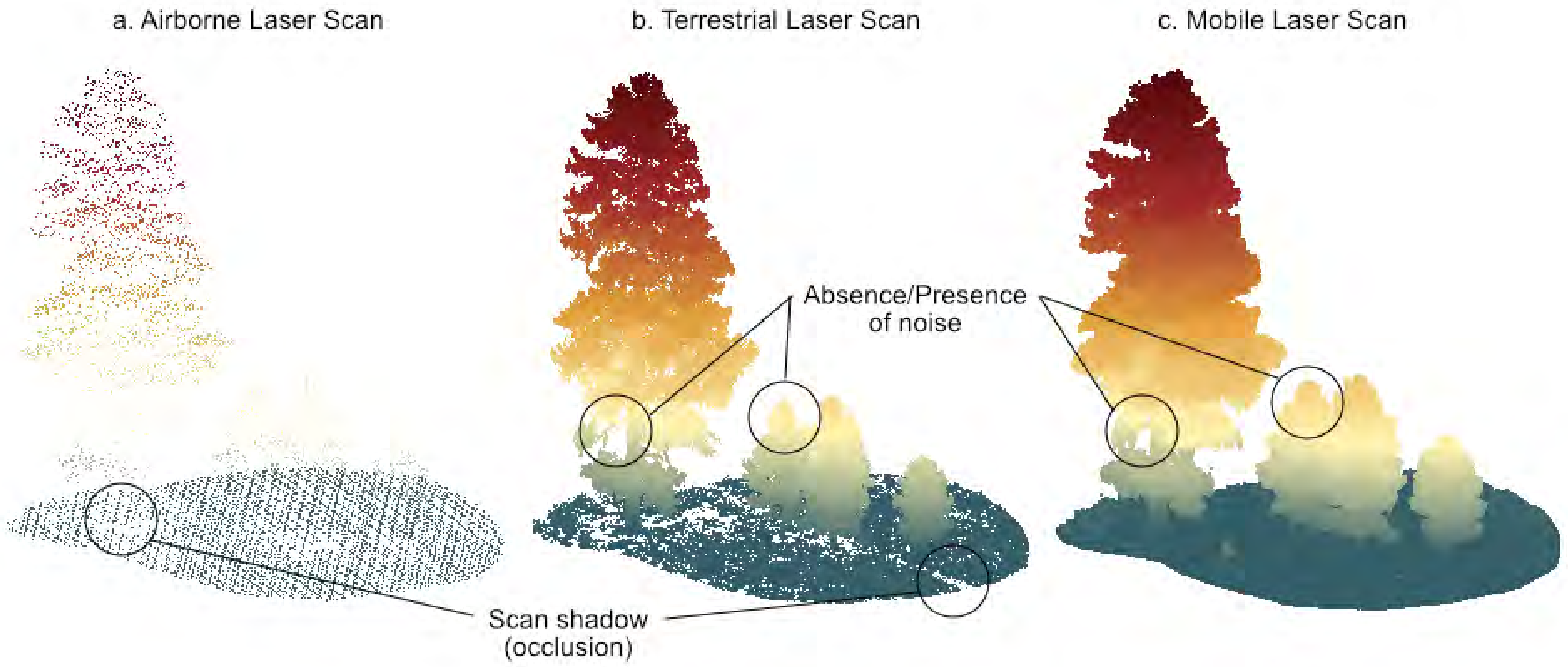
This information needs to be quickly available to effectively monitor implementation and treatment effects.

Answer: Compare lidar-derived attributes

We compared vegetation attributes at the tree-, plot- and stand-level derived from three lidar platforms: fixed-wing airborne (ALS), fixed-location terrestrial (TLS), and hand-held mobile (MLS) lidars.

Study overview

Three lidar platforms



Study site

Donager et al. 2018

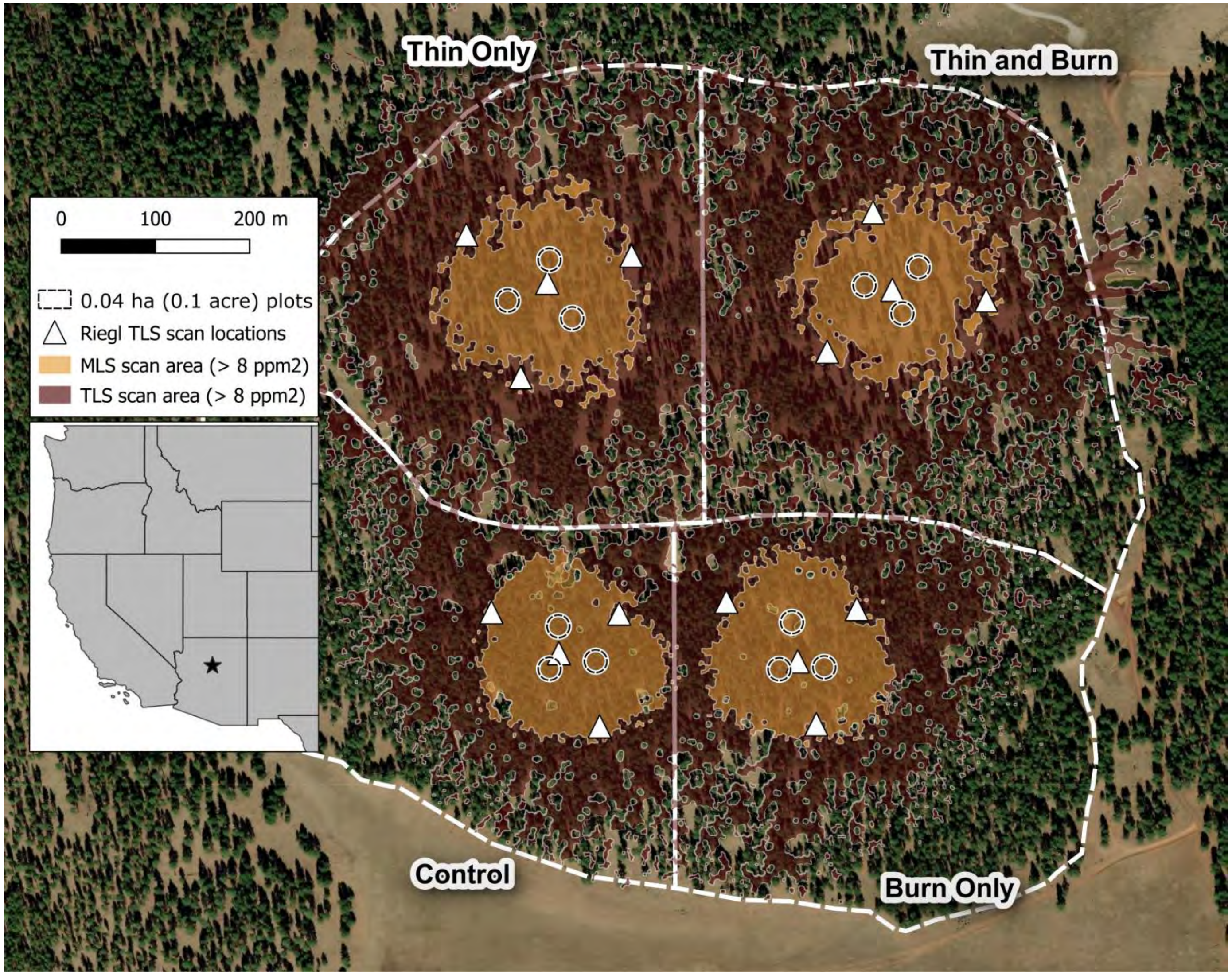
Managed by the US Forest Service and are part of the “Fire and Fire Surrogate” study network (Faiella and Bailey, 2007).

Mean elevation: 2,270m with slight variation in slope (<5%) and aspect

Mean annual precipitation: 54.6cm (predominately as rain during monsoons, July – September, remainder as snow; Hereford 2007).

Average yearly temperature: extremes 28° C to -12° C

Forest type: ponderosa pine (*P. ponderosa*)



Density Gradient

Plot	Basal Area ($m^2\ ha^{-1}$)	Density ($trees\ ha^{-1}$)	DBH (cm) Mean (SD)	Height (m) Mean (SD)	Treatment
1	7.2	25	60.9	28.5	Thin & Burn
2	17.7	74	55 (5.0)	21.6 (1.0)	Thin Only
3	4.8	99	20.7 (15.6)	7.6 (3.9)	Thin & Burn
4	15.0	99	43.2 (9.2)	21.8 (4.7)	Thin & Burn
5	4.2	124	20.1 (5.6)	9.3 (2.4)	Burn Only
6	14.9	149	35.7 (2.7)	19.9 (1.2)	Thin Only
7	38.8	322	38.1 (9.6)	16 (4.0)	Burn Only
8	32.8	371	30 (15.5)	14.4 (6.7)	Burn Only
9	6.6	644	10.4 (4.8)	15.6 (5.3)	Thin Only
10	42.4	842	22.8 (11.1)	12.4 (4.7)	Control
11	57.2	1064	23.7 (11.1)	15.5 (6.5)	Control
12	49.1	1361	19.5 (8.9)	14.8 (5.3)	Control

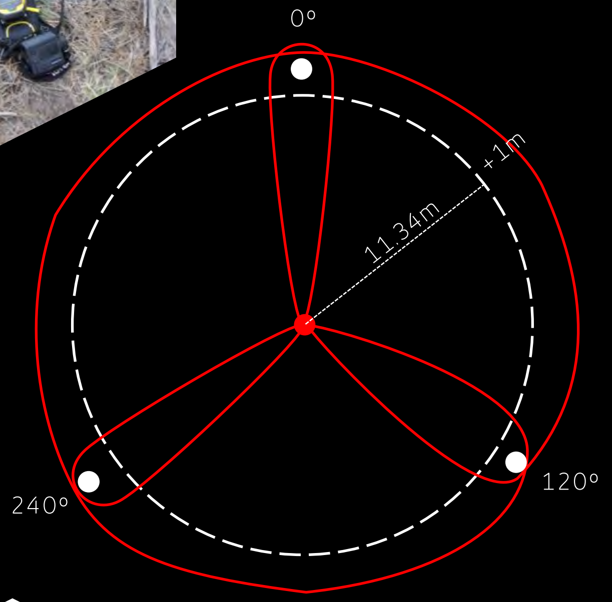
MLS scans

n=3 0.04ha circular plots per treatment

3-4 minute MLS scan (30-50M pts); structured walk

Stem-mapped TruPulse 200X & MapStar TruAngle

Scans processed in GeoSLAM Hub



GeoSLAM's slam algorithm

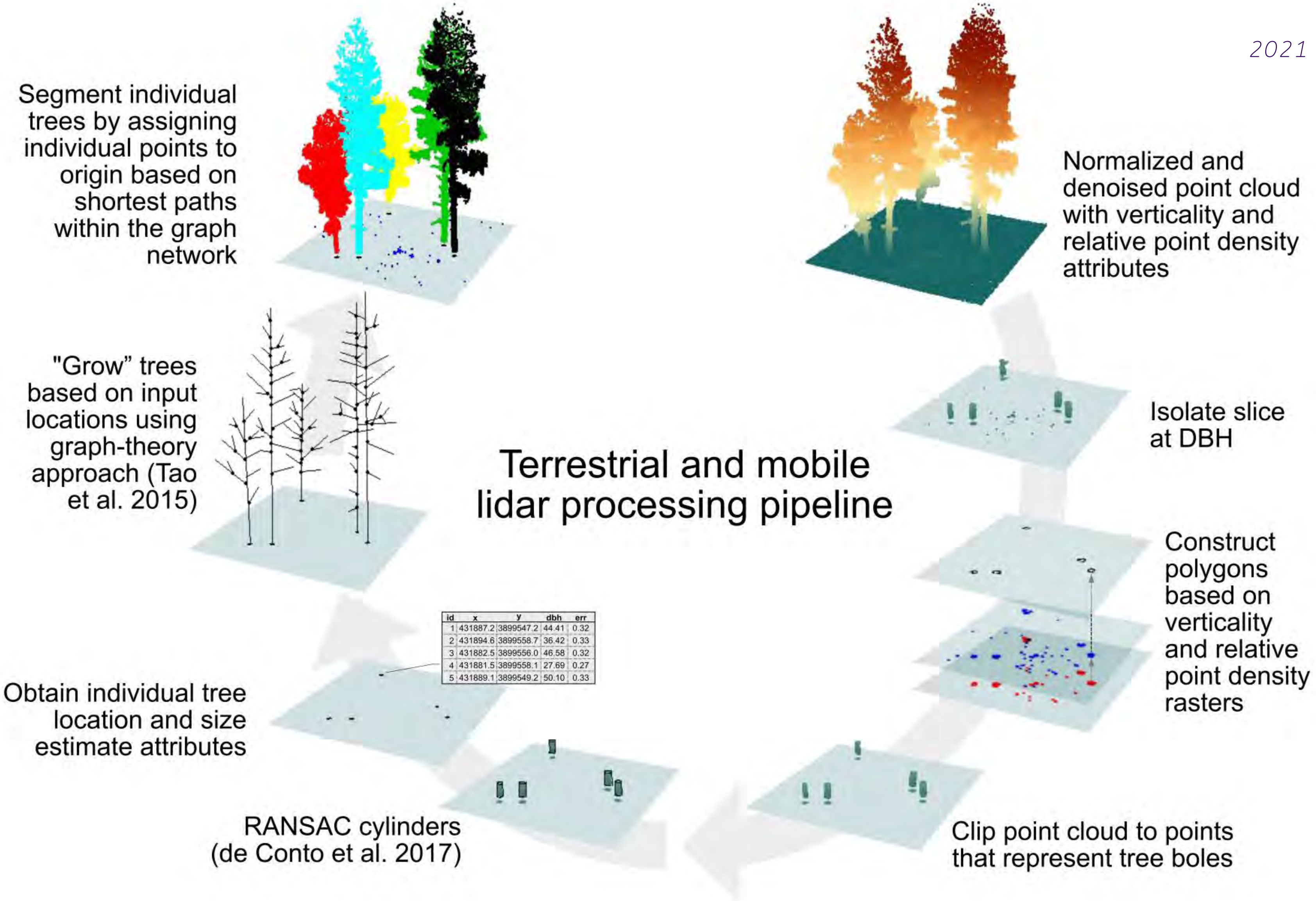
Inertial measurement unit (IMU) used to estimate an initial position

Combined with lidar data to generate a trajectory (or path).

By knowing the distance from each point on the path to the surrounding features, the device builds a three-dimensional point cloud of the space.

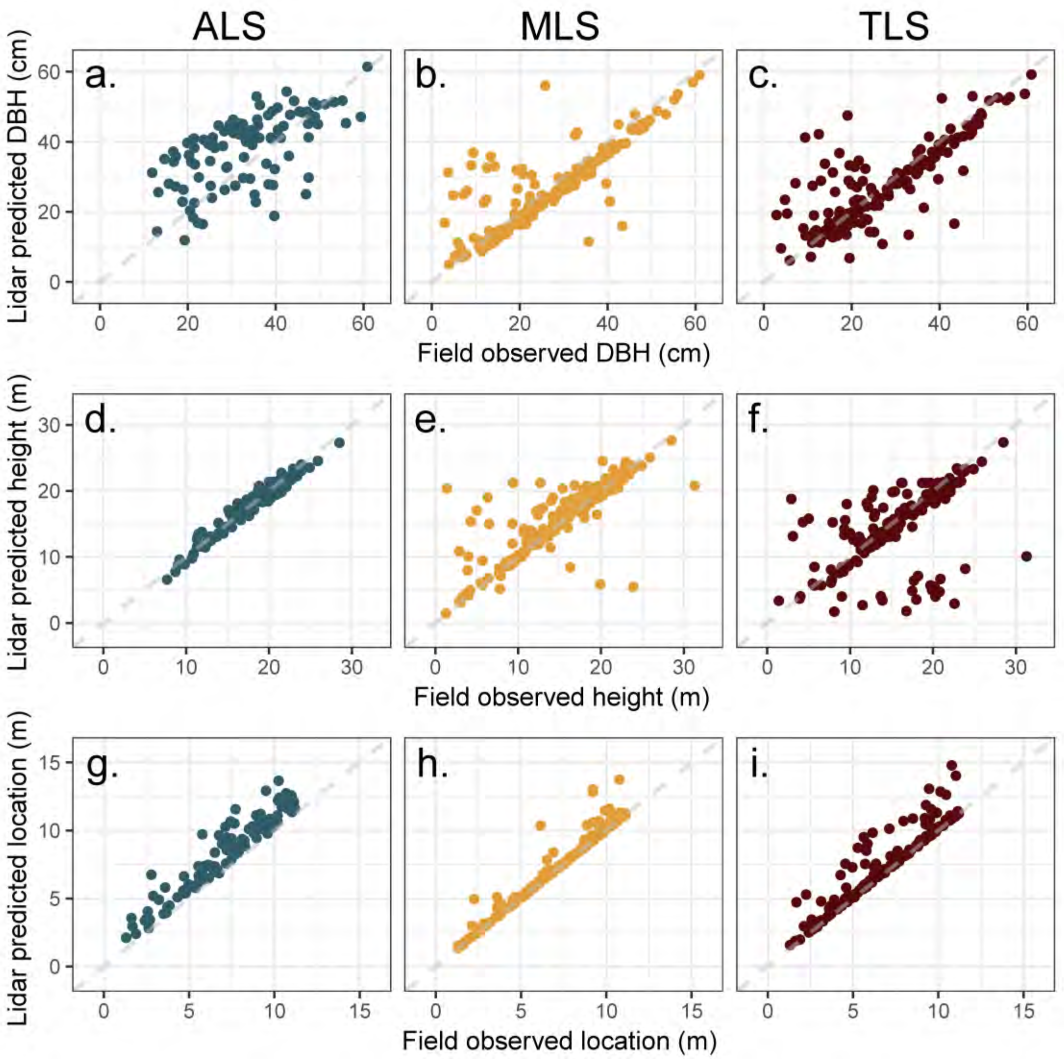
The platform then moves forward, and the entire process is repeated. Scene is exported as .laz

Pipeline


Segment individual trees by assigning individual points to origin based on shortest paths within the graph network
Normalized and denoised point cloud with verticality and relative point density attributes
"Grow" trees based on input locations using graph-theory approach (Tao et al. 2015)
Isolate slice at DBH
Terrestrial and mobile lidar processing pipeline
Construct polygons based on verticality and relative point density rasters
id x y dbh err
1 431887.2 3899547.2 44.41 0.32
2 431894.6 3899558.7 36.42 0.33
3 431882.5 3899556.0 46.58 0.32
4 431881.5 3899558.1 27.69 0.27
5 431889.1 3899549.2 50.10 0.33
Obtain individual tree location and size estimate attributes
RANSAC cylinders (de Conto et al. 2017)
Clip point cloud to points that represent tree boles

Results

Individual-tree



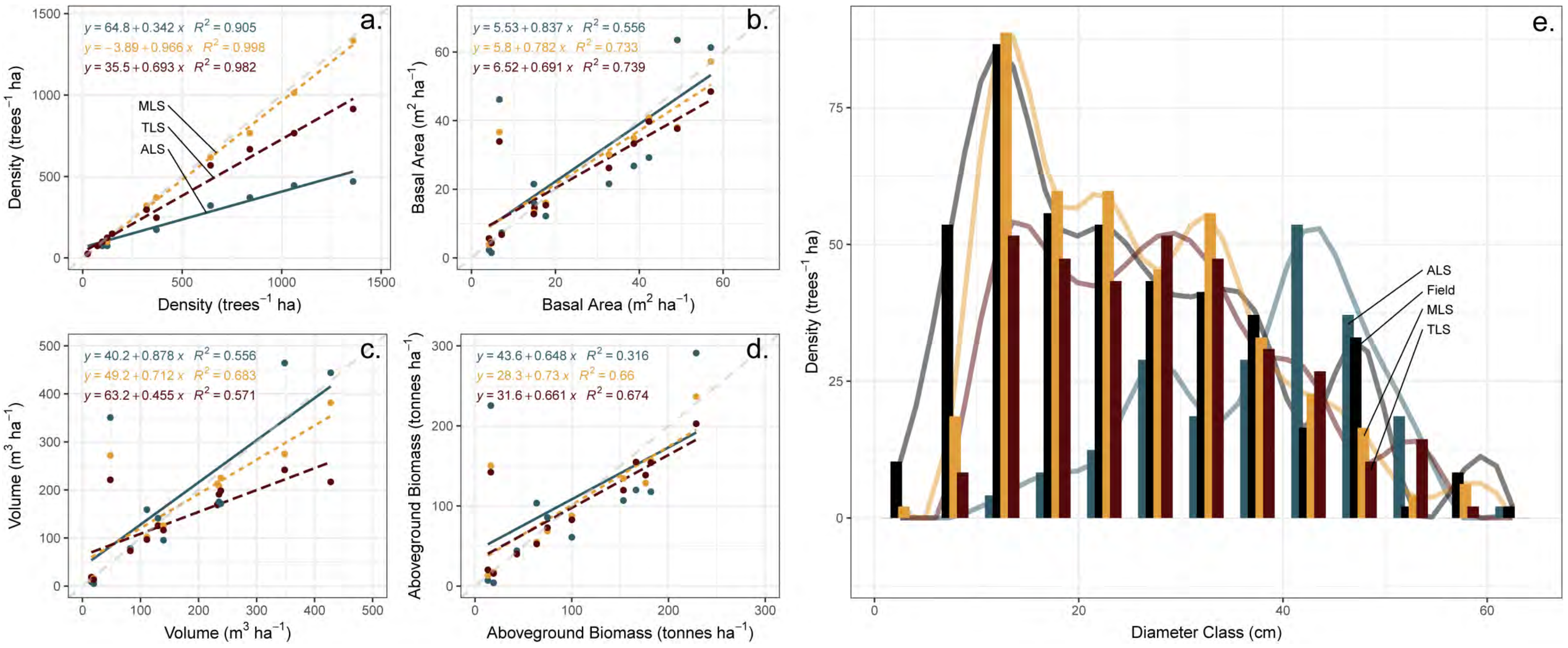
Individual tree size and location

Overpredictions of DBH by ALS were significantly larger than that of TLS and MLS; latter were not significantly different.

Both ALS and TLS tended to underpredict total tree height.

Tree locations exhibited the smallest prediction errors from MLS

Plot- and stand-level



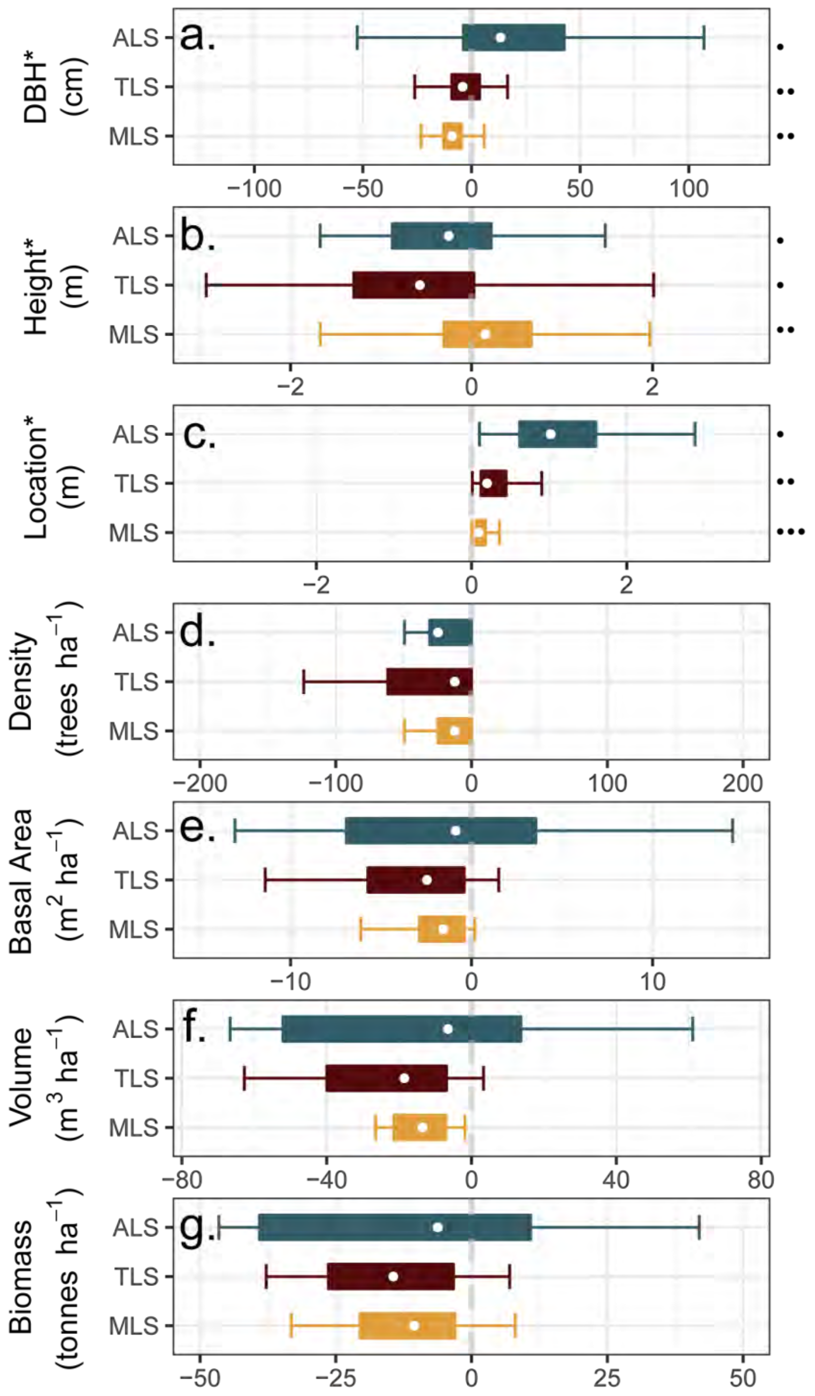
Differences

Individual-tree and plot-level

Kruskal-Wallis Rank Sum tests showed significant difference by platform between prediction errors for DBH, height and tree location.

Yet did not reveal any significant difference by platform between prediction errors for plot-level attributes of tree density, basal area, volume and aboveground biomass.

Likely a sample size issue…



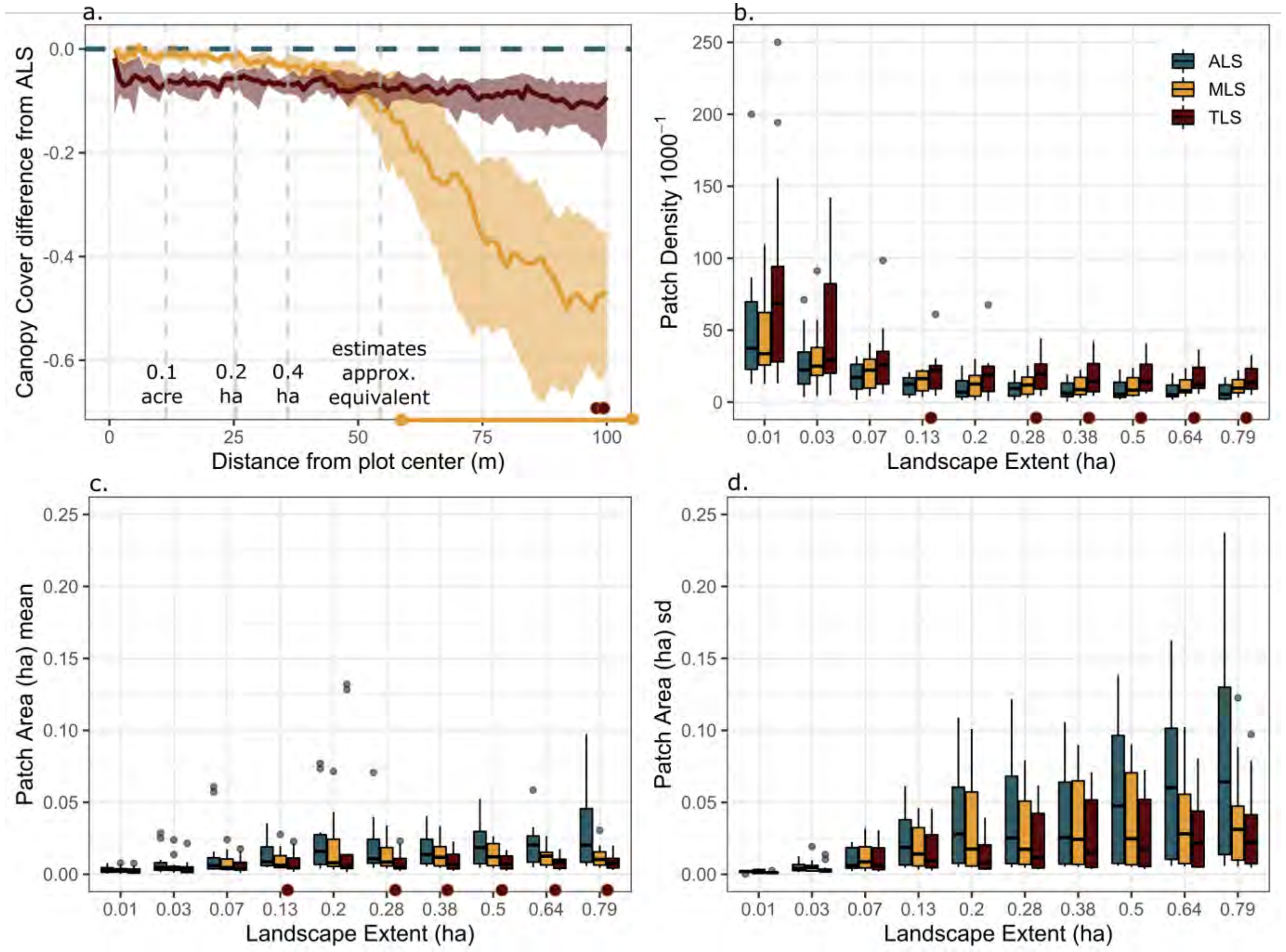
Rates and Error

	Rate			Mean Abs. Error		Percent RMSE	
Statistic	Detection	Omission	Commission	DBH (cm)	Height (m)	DBH	Height
Airborne Lidar							
Min	34.5	0	3.6	0.5	0.4	2.2	2.5
Mean (SD)	68.3 (25.2)	31.7 (25.2)	53.2 (40.8)	9.1 (7.3)	0.7 (0.3)	43.7 (30.8)	5.4 (1.9)
Max	100	65.5	133.3	28.8	1.2	124.7	8.2
Terrestrial Lidar							
Min	66.7	0	0	1.5	0.3	7.2	2.7
Mean (SD)	86.8 (13.8)	13.2 (13.8)	1.8 (4.5)	5 (3.6)	2.2 (1.2)	27.9 (19.2)	22.6 (19.9)
Max	100	33.3	15.4	15.3	5.1	77.1	52.8
Mobile Lidar							
Min	75	0	0	1.9	0.2	8.1	1.6
Mean (SD)	94.7 (8.5)	5.3 (8.5)	1.8 (6.3)	4.8 (3.9)	1.3 (1.2)	25.9 (19.9)	14 (14.2)
Max	100	25	21.8	15.6	4.4	76.1	46.9

Cover and patch

Canopy cover and patch metrics

- Differences in mean canopy cover derived from MLS data were nearly identical to that of ALS canopy cover up to 26 meters from plot center (0.21 ha).
- TLS differences in canopy cover declined very gradually across the 100 meter radial extent from plot center but were consistently underpredicted.
- Mean and SD of patch area were consistently higher for ALS as compared to MLS or TLS. Patch density displayed opposite pattern.



Conclusions

MLS is a useful tool for rapid assessment and monitoring across a range of forest conditions in a ponderosa pine forest of northern Arizona, USA.

While TLS data produced estimates similar to MLS, attributes derived from TLS often underpredicted structural values due to occlusion of tree point returns.

Additionally, ALS data provided accurate estimates of tree height for larger trees, yet it consistently underpredicted tree sizes less than 35 cm. This inaccuracy propagated to relatively large errors in area-based metrics.

Conclusions

MLS data produces accurate estimates of canopy cover and landscape metrics up to approximately 50 meters from plot center, about 30 meters greater than our walking path with the MLS scanner.

TLS tended to underpredict both canopy cover and patch metrics with a constant bias due to occlusion of portions of the canopy.

MLS data logistically simple, quickly acquirable, and accurate for small area inventories, assessments, and monitoring activities.

We suggest further work exploring the active use of MLS for forest monitoring and inventory.