



AI-enabled forest ecology: progress and challenges

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ML4EO 2026, Exeter



UNIVERSITY OF
CAMBRIDGE

Imagine a tree



Pinus nigra ssp. salzmannii
Cambridge University Botanical Gardens

Imagine a tree like a forest ecologist

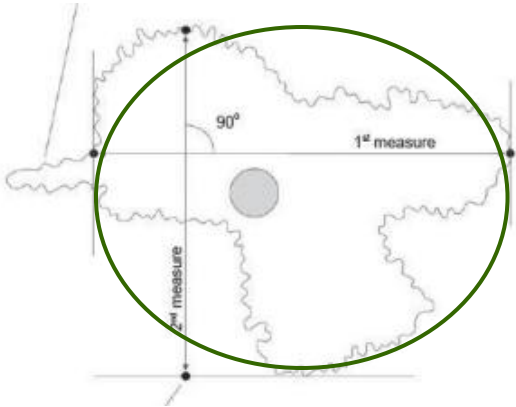
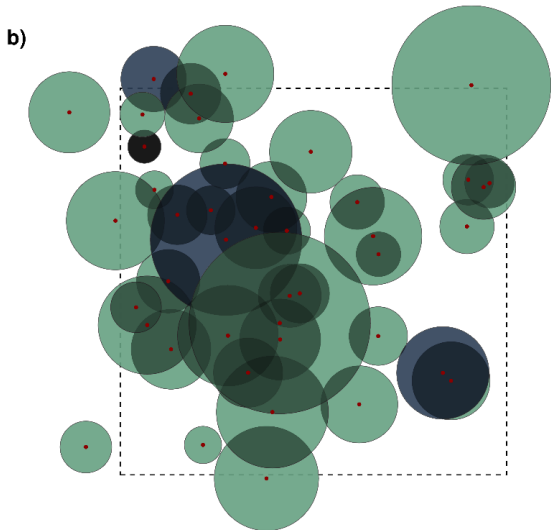


Figure 1.4—Crown diameter measurement.

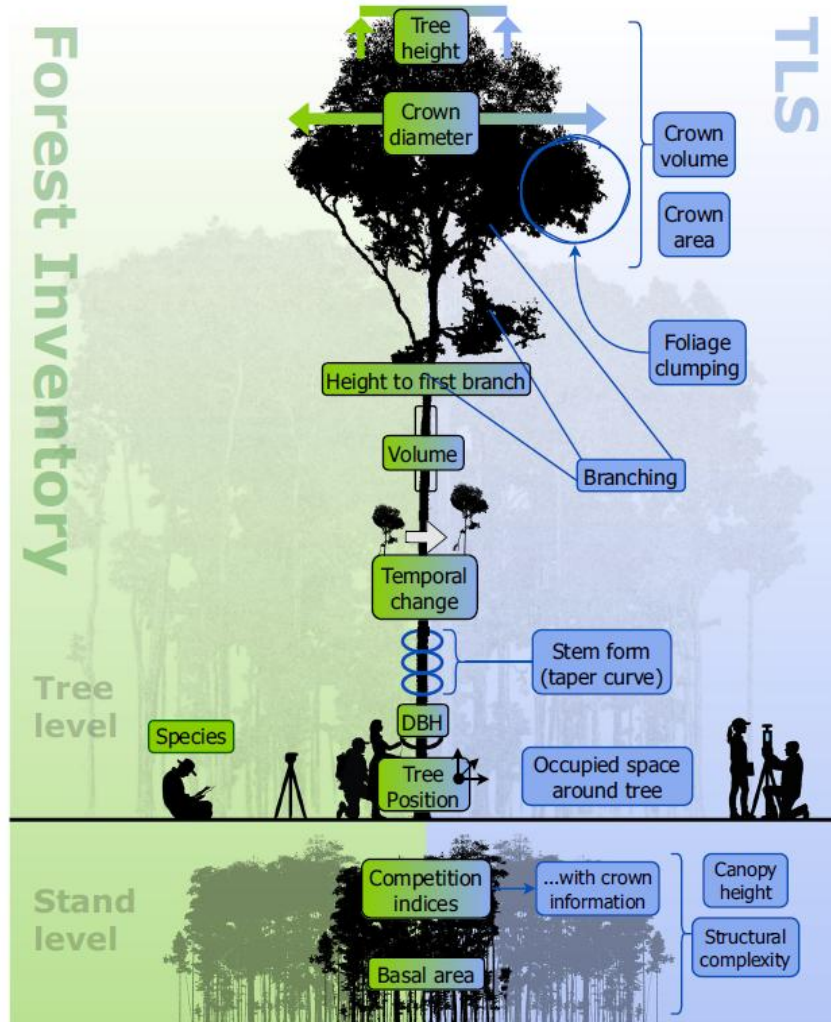


Pinus nigra ssp. salzmannii
Cambridge University Botanical Gardens

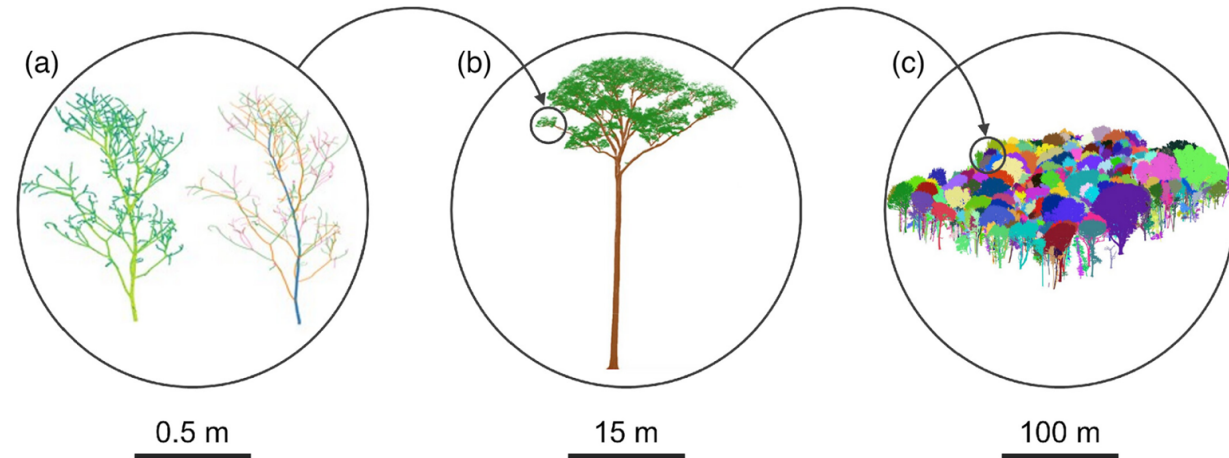
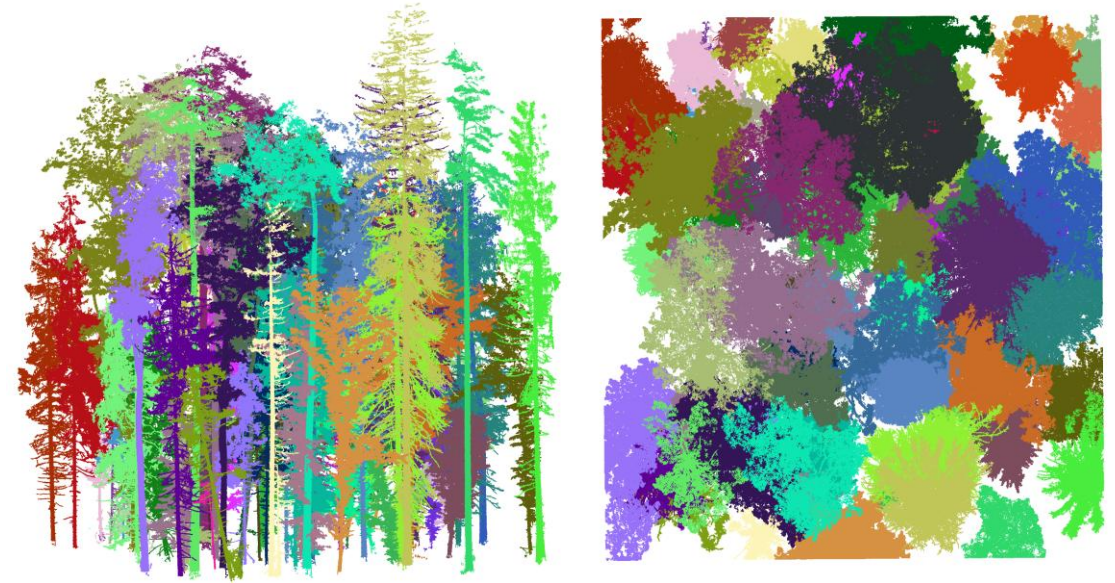
Proxy for:
Age
Carbon/biomass
Leaf area
Crown shape

As a basis to
quantify:
Demography
Stand structure
Competitive
interactions
Population
dynamics

High resolution remote sensing offers rich direct measures (2D and 3D)

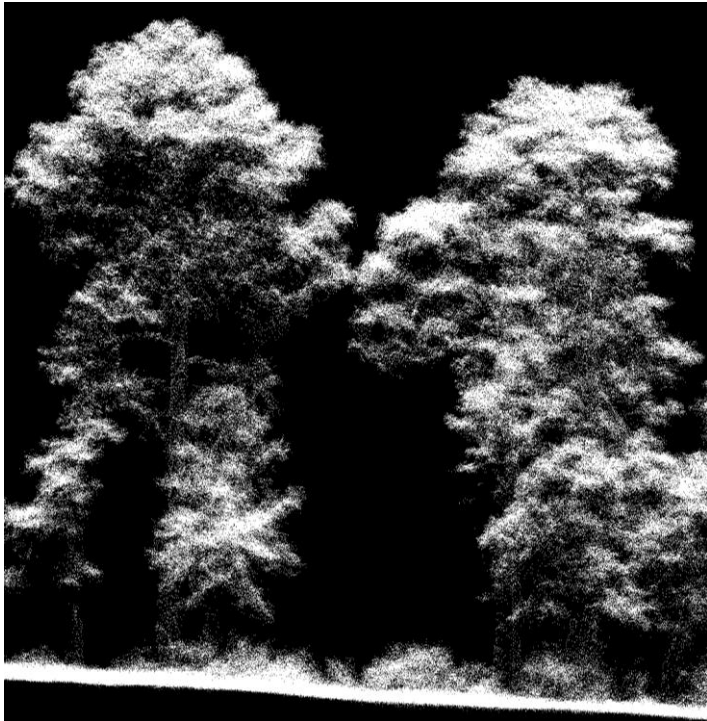


Integration of remote sensing and traditional methods (Maeda et al. 2026)



Lines et al. 2022

Processing raw data at scale to extract ecologically interesting properties is challenging

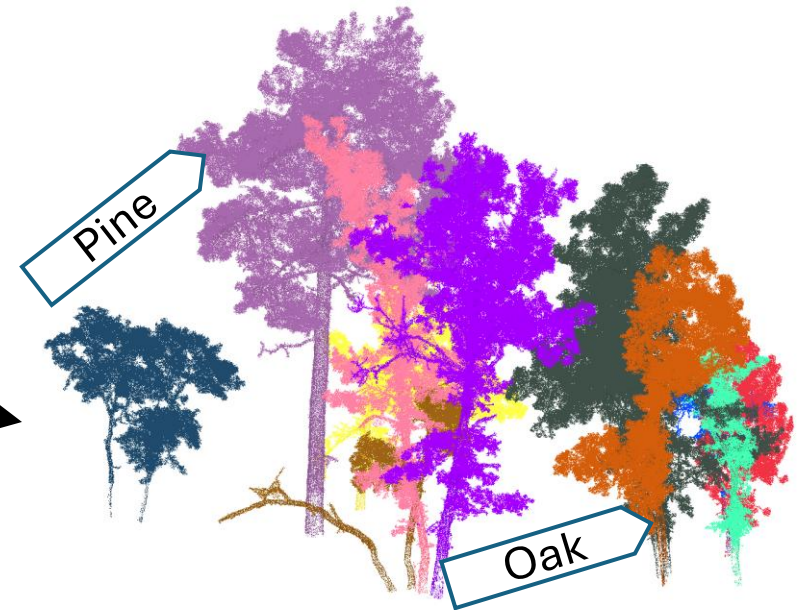
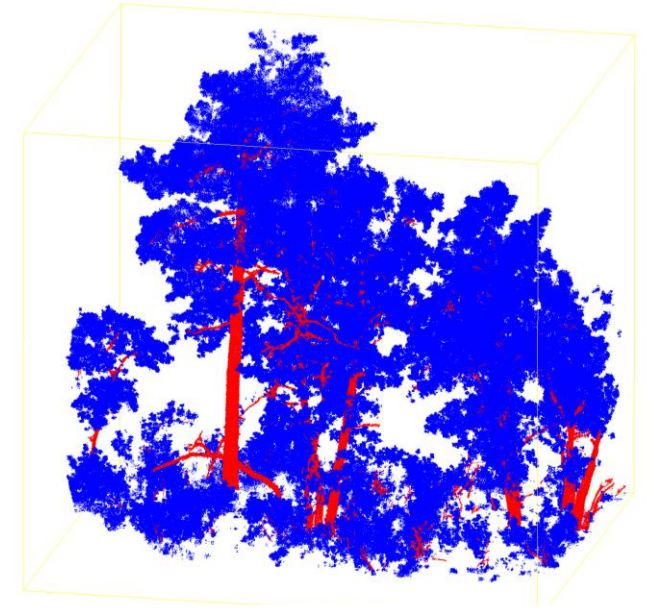


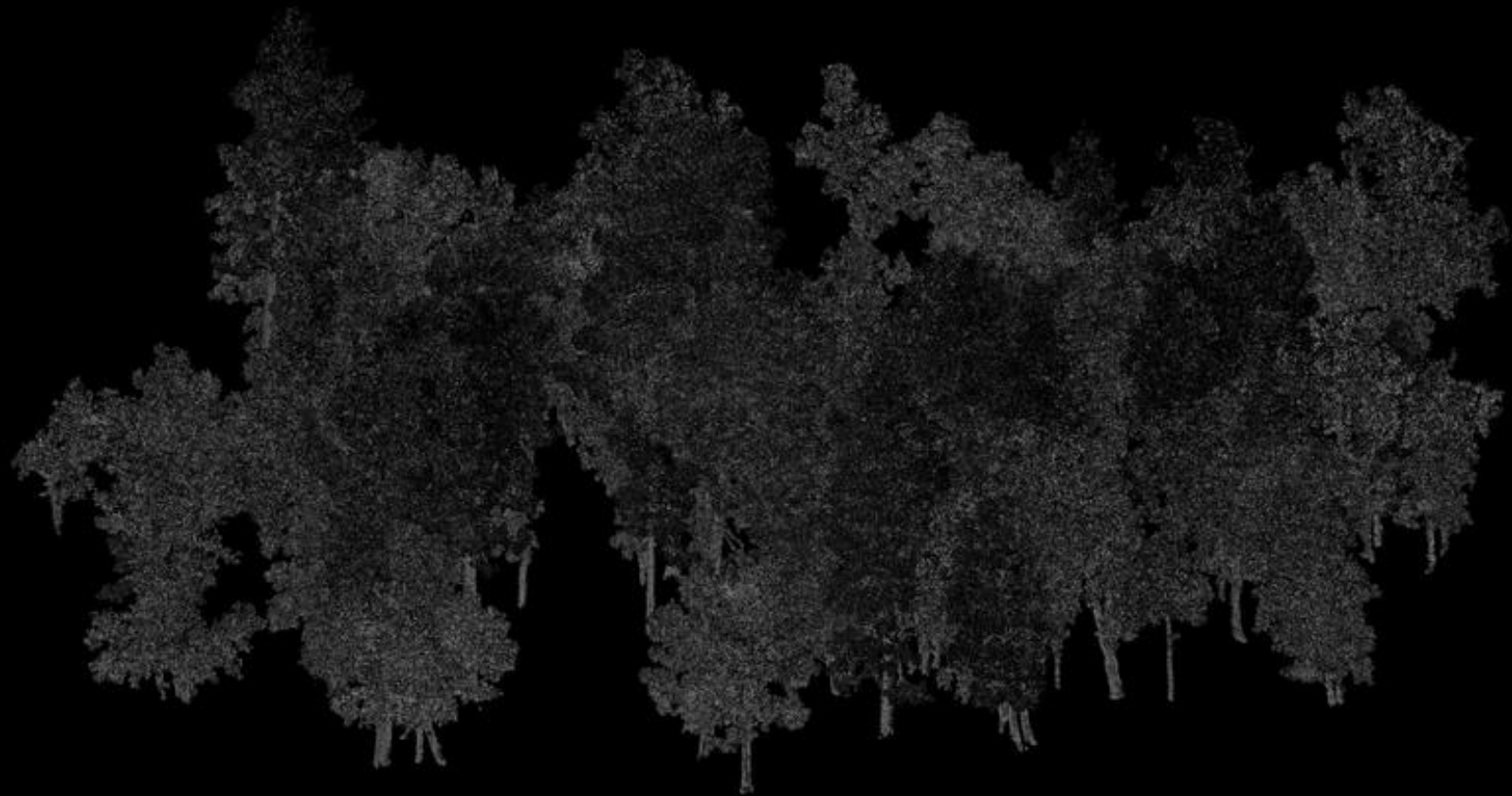
What is there?
How many trees are there?
Which species are they?
What is the quality of this habitat?
What size are the trees?
Is there regeneration?
How much X is there (biomass, nutrient, leaf area)?
What functions is this forest providing?
How resilient is this forest?
How **accurate** is this information?
Is it accurate **enough**?



Deep learning as a solution for processing

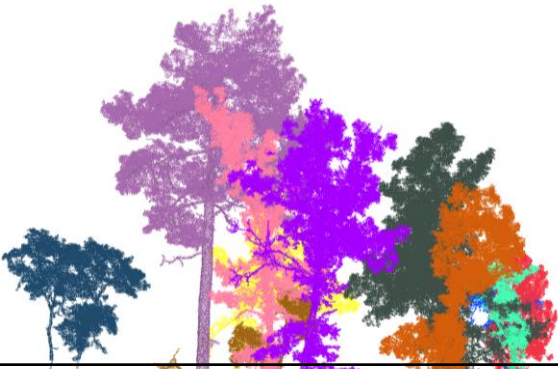
- Semantic segmentation (leaves/wood/other)
- Instance segmentation (individuals)
- Species ID
- *Microhabitats, deadwood, lower vegetation...*





Have we made progress?

>15 studies on deep learning for 3D instance segmentation on TLS/MLS since 2021....



Approach			
PointNet			
YOLOv3 based			
PointNet++ based			
PointNet++			
PointGroup			
YOLOv5			
PointGroup			
Hybrid			
Hybrid			
RandLA-Net			
BFE-Net			
sparse UNet backbone			

time

The most recent major intercomparison study finds a **graph-based (non-DL) method** is current SOTA (Cherlet et al. 2026, *ISPRS JPRS*)



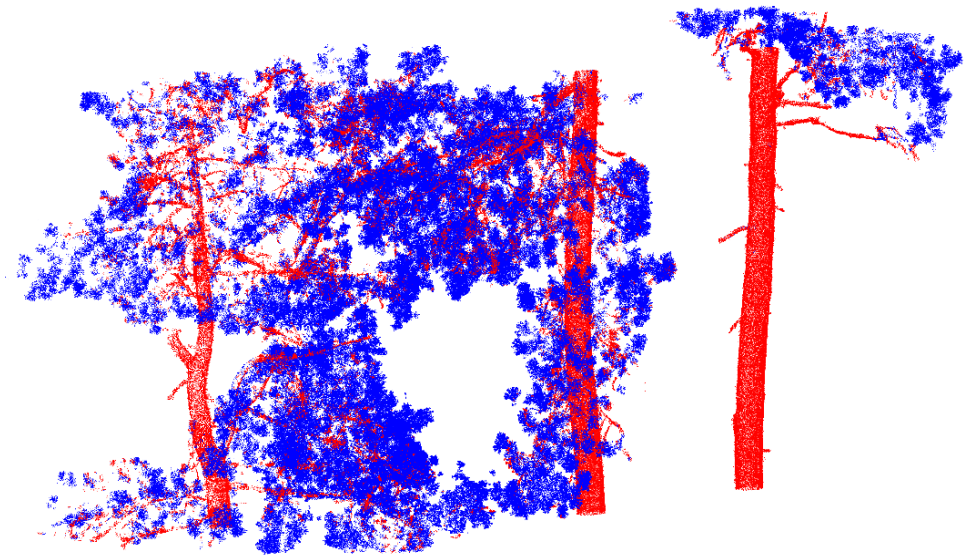
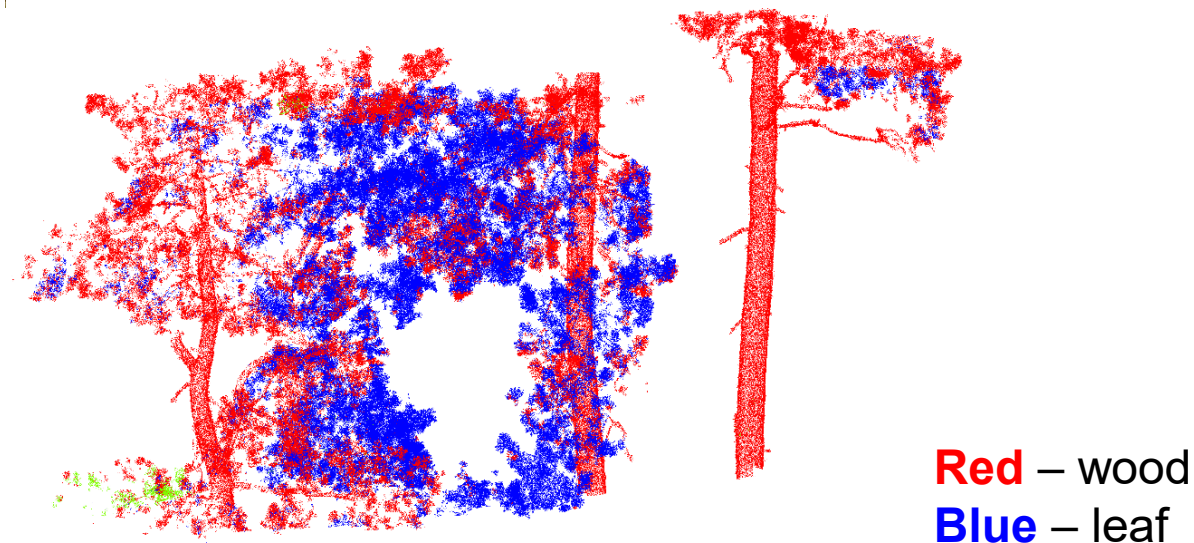
Over-emphasis on standard model development means 'successful' tools are not useful



Original model
trained in
monoculture
ecosystem,
multi-sensor



Retrained on
mixed natural
forest, single
sensor



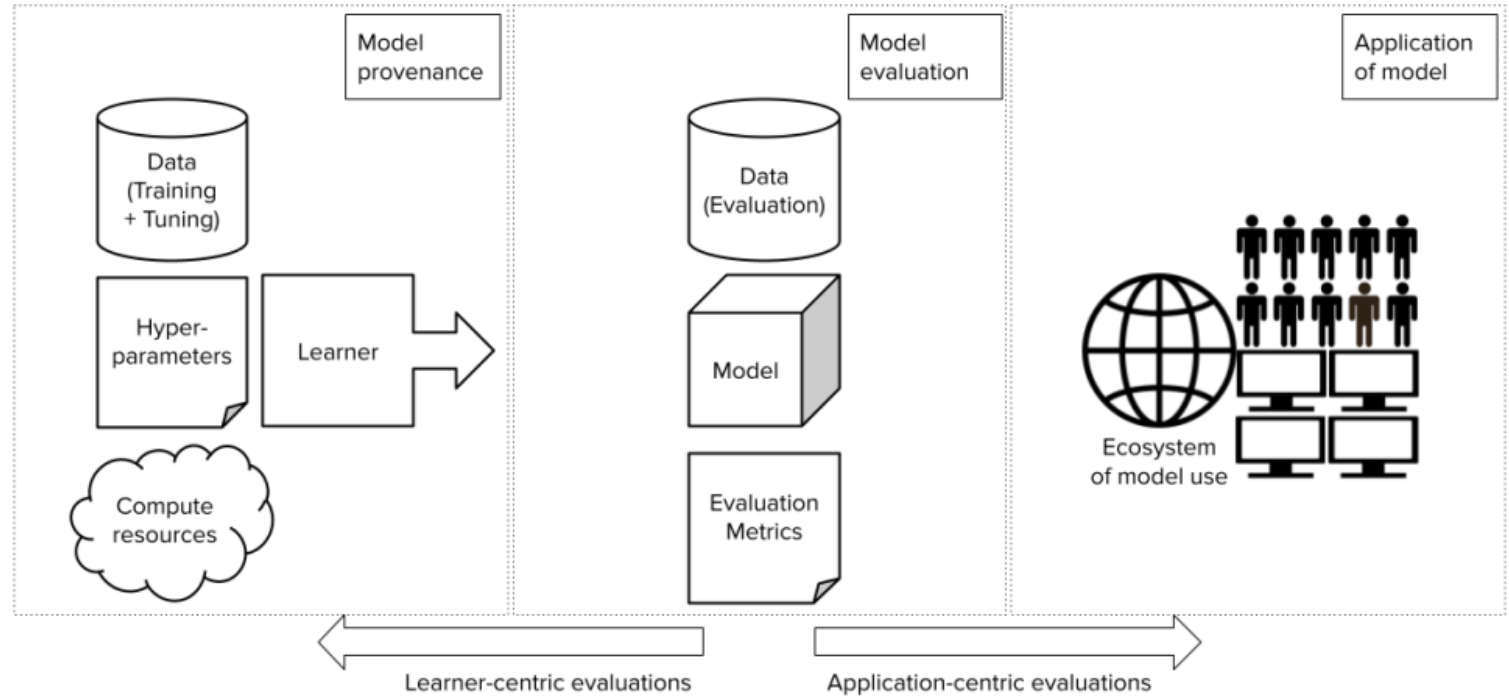
A focus on technical development

Agreed benchmarks

Model development

Model evaluation

Task evaluation



Hutchinson et al 2022

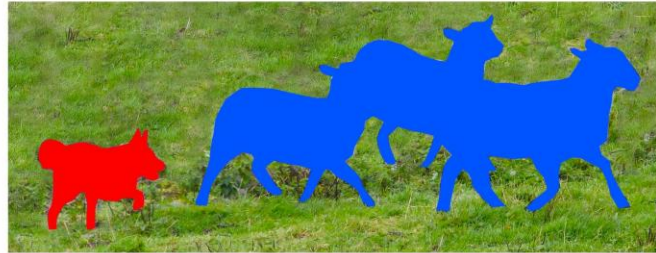
Benchmarking, evaluation, and truth



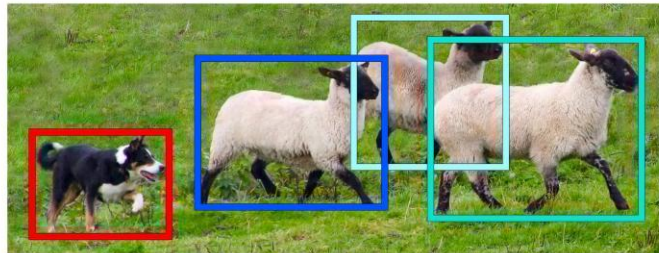
The history of machine learning is built on successes in *automating doable tasks*



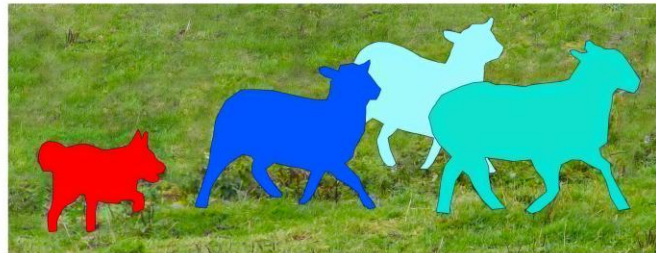
Image Recognition



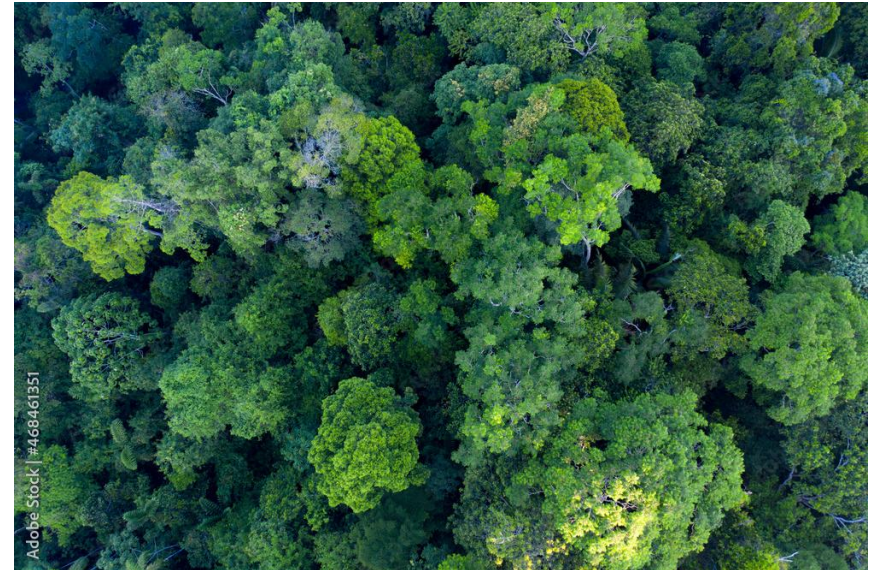
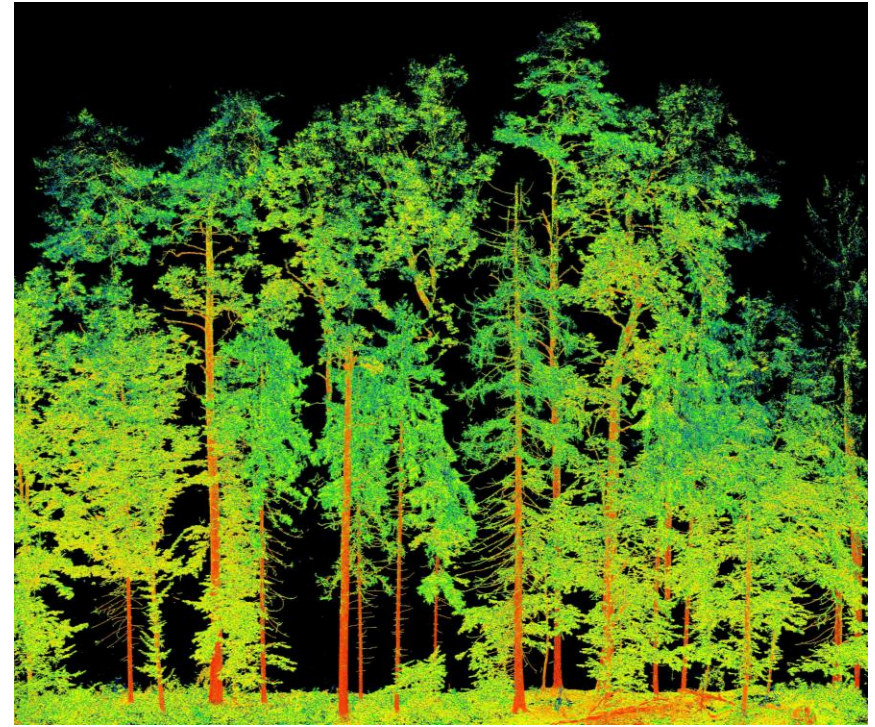
Semantic Segmentation



Object Detection



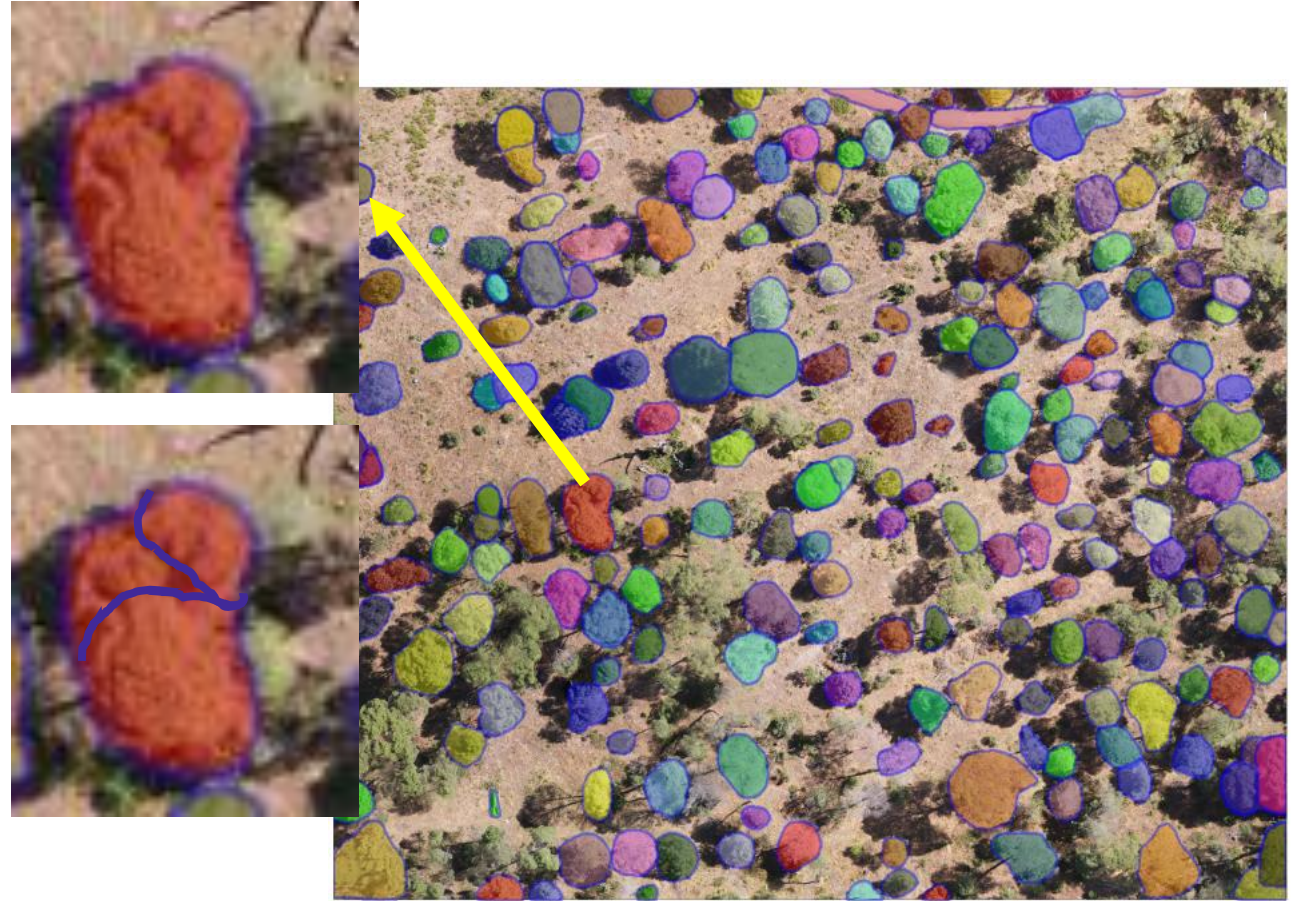
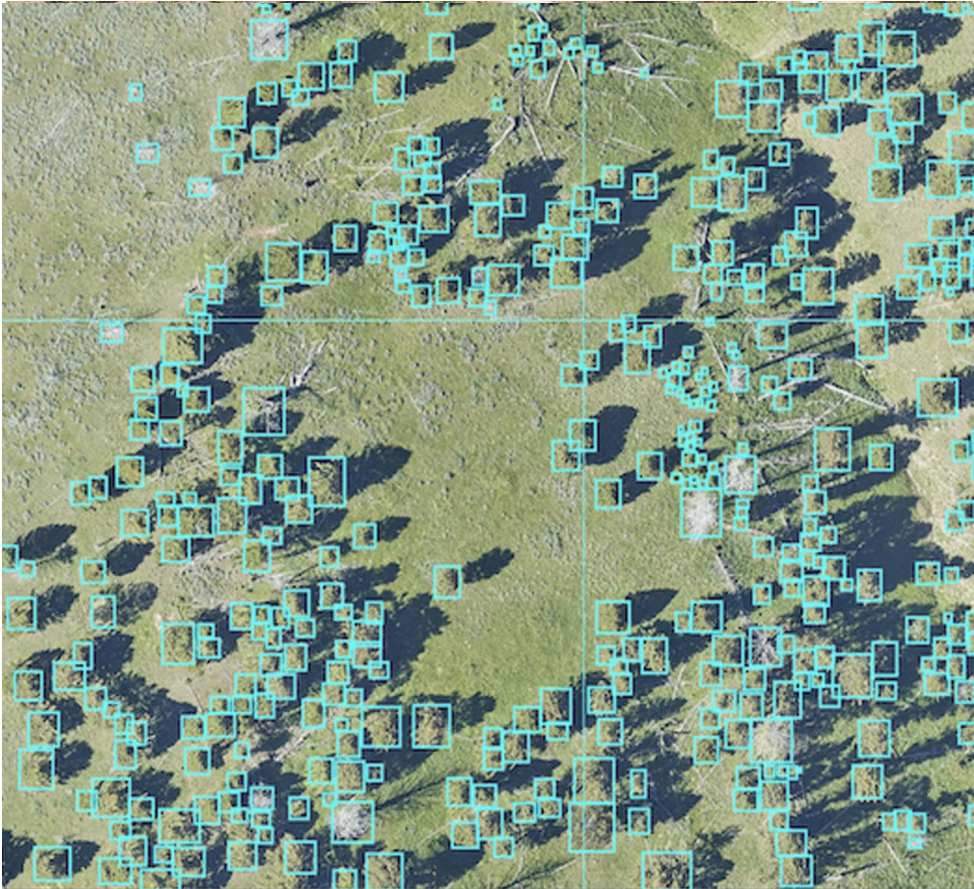
Instance Segmentation



Did we skip a step?

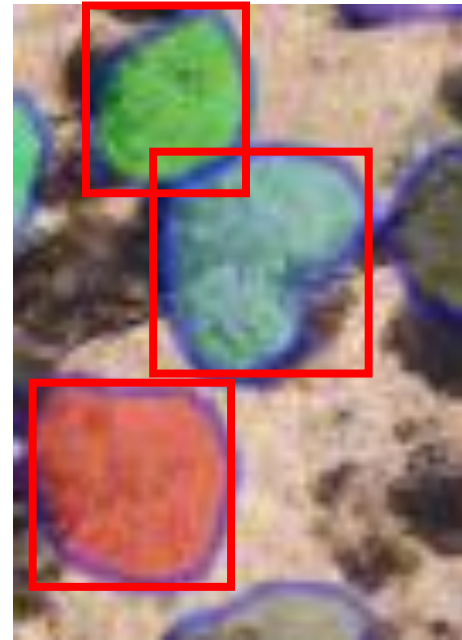
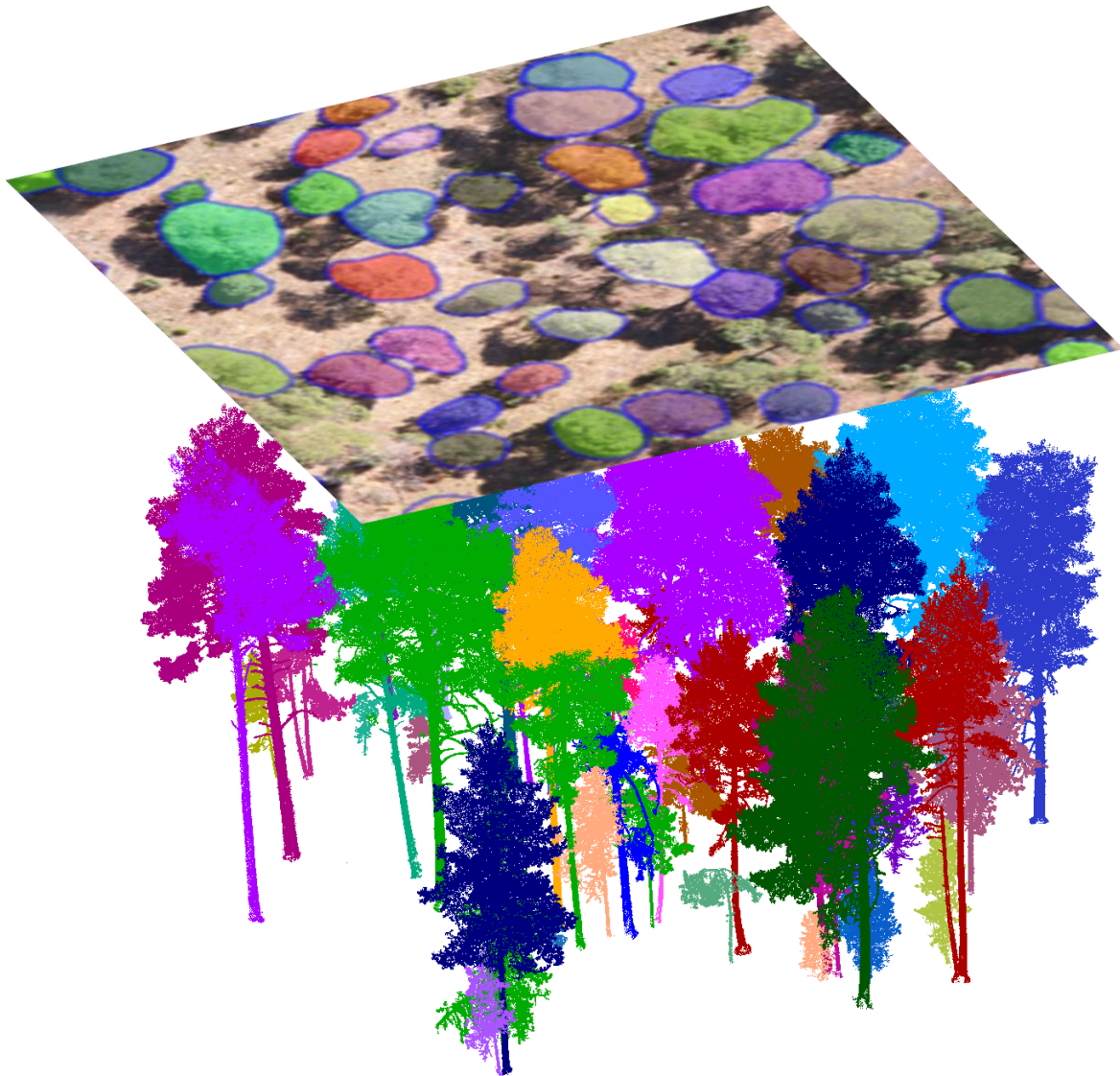
The (ground) truth matters: individual tree segmentation in imagery

Crown segmentation tools *look good*



Ground truthing is **crucial** for believable and robust monitoring.

3D data offer the opportunity for high quality ground truth validation



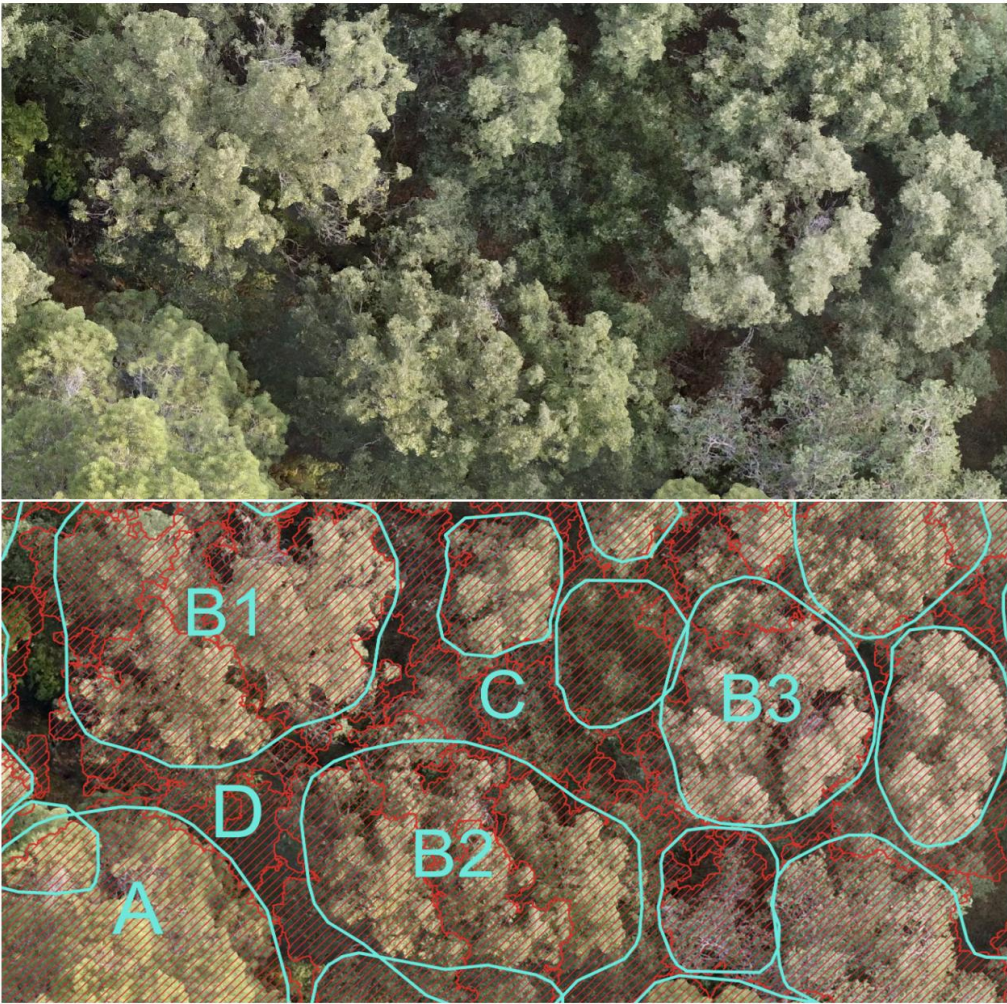
Most 2D image tree segmentation methods are trained on manual delineation.

Co-located data from ground 3D data and aerial imagery allowed us to evaluate deep learning models.

We cut the 2D UAV imagery with our 3D individual trees to create high quality test data.

Compared two DL models' performance on TLS and manual labels, using bounding boxes and IoU 0.5, 0.75.

Manual label ‘truth’ vs TLS ‘truth’ shows 2D aerial crown delineation more challenging than previously thought

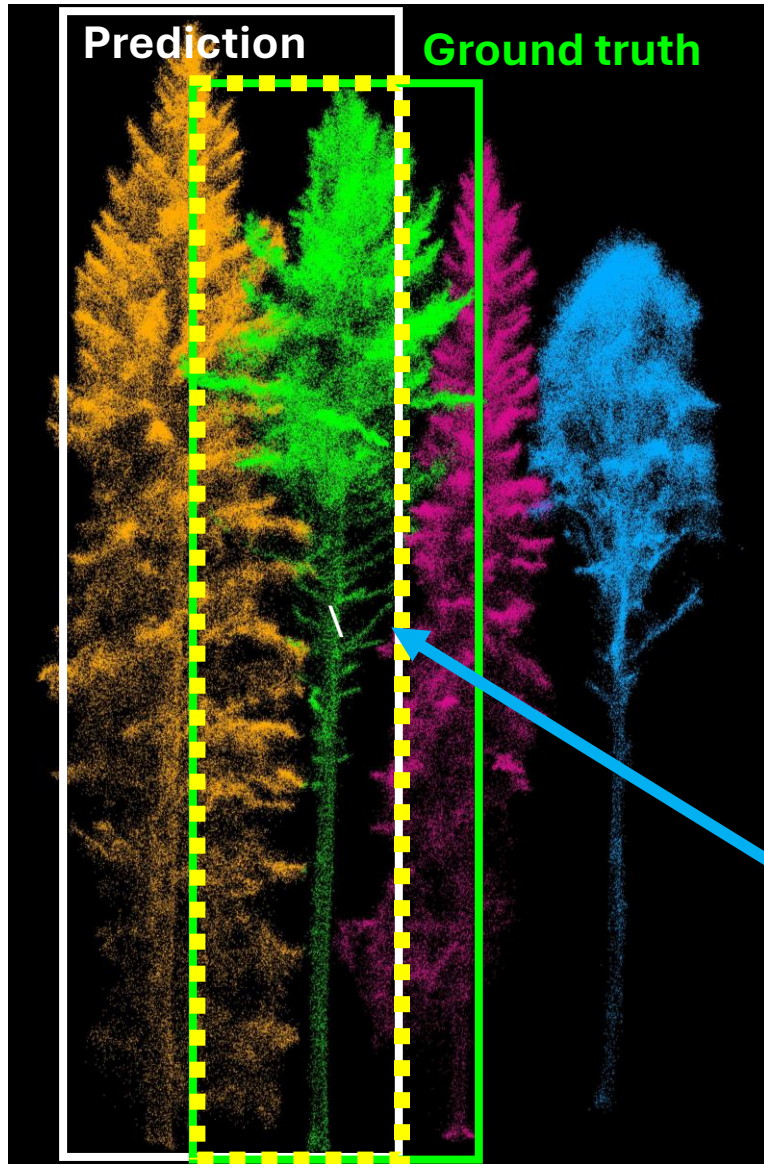


			AP ₅₀		AP ₇₅		F1	
			All	Can	All	Can	All	Can
Manual drawn labels	Almorox	DF						
	(Manual)	DT						
TLS labels, manually checked	Alto Tajo	DF						
	(TLS)	DT						
	Joensuu	DF						
	(TLS)	DT						

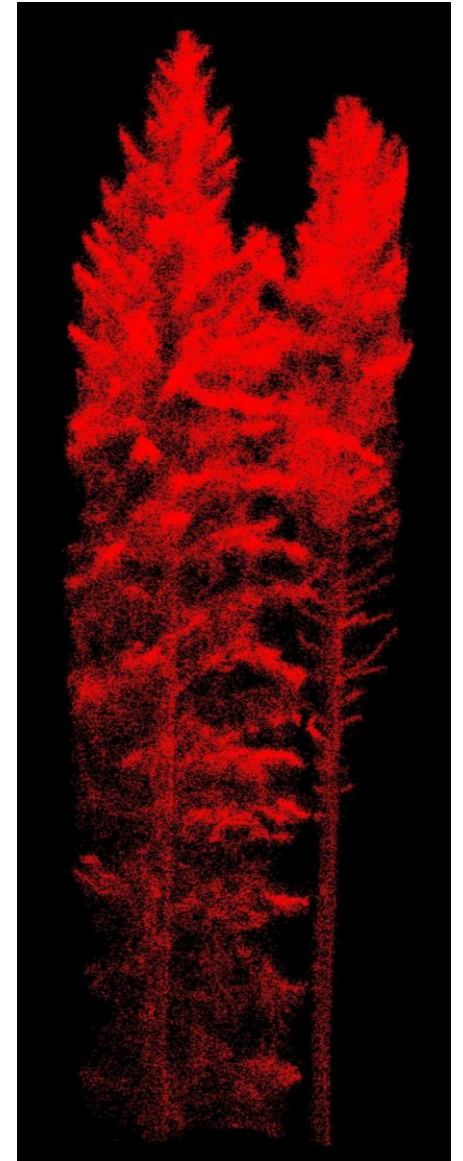
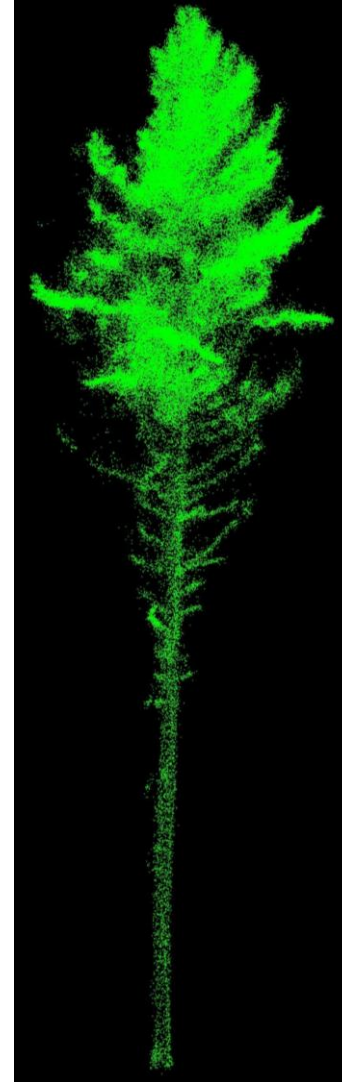
Typically, errors come from missing smaller trees, and mis-grouping multiple trees together.

Training on **manual** labels of aerial imagery seems to artificially inflate performance, likely due to biases towards easily identifiable canopy trees.

Defining success in instance segmentation: IoU



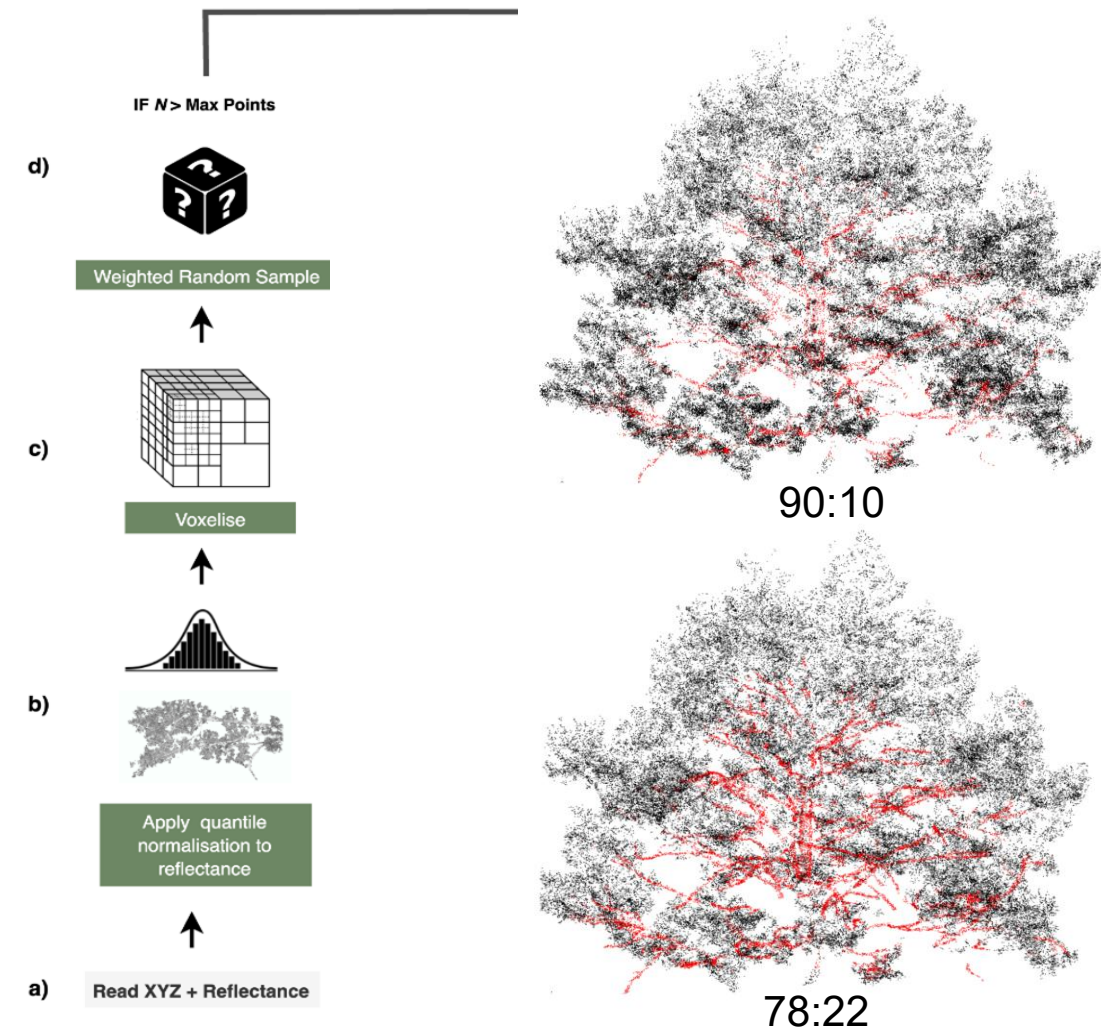
$\text{IoU} > 0.5$:
a “success”
(*by ML standards*)



New ecological evaluation: leaf-wood segmentation

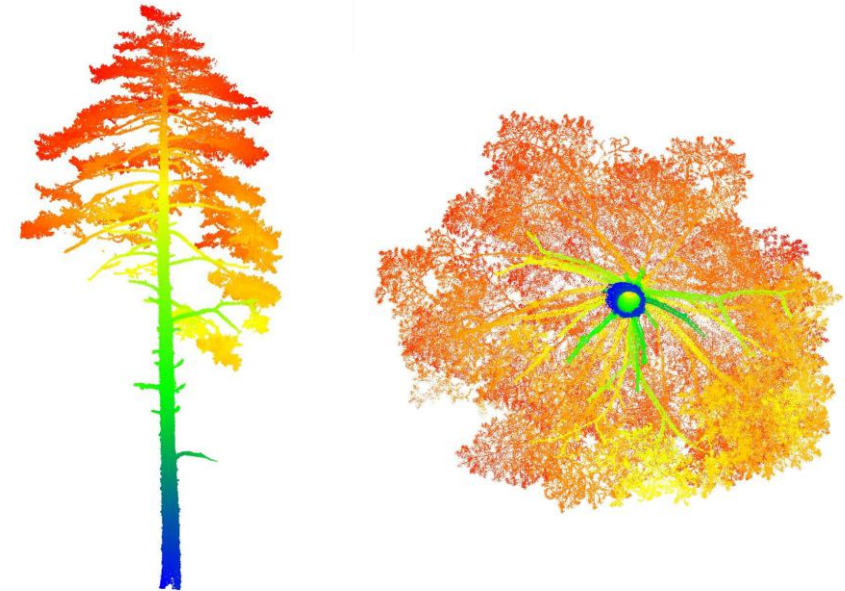


We tailored existing architecture *and* performance metrics to target hard to classify, rare, small features (wood).
Trained on three biome data (boreal/temperate/Mediterranean) and binary classification.



Downsampling to try to retain more of the rare class (wood).
Adding reflectance to the x-y-z information

Evaluation in the hard to classify areas (twigs) by weighting accuracy by path length



Improved *ecologically relevant* performance vs benchmark (retrained)



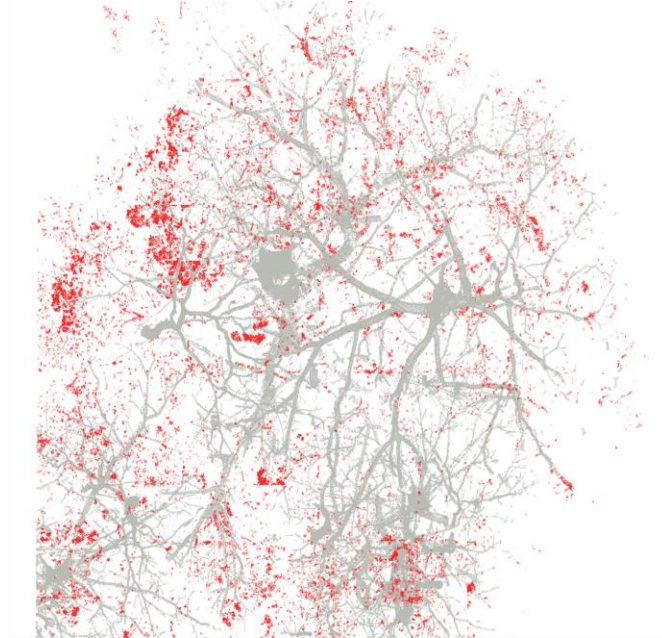
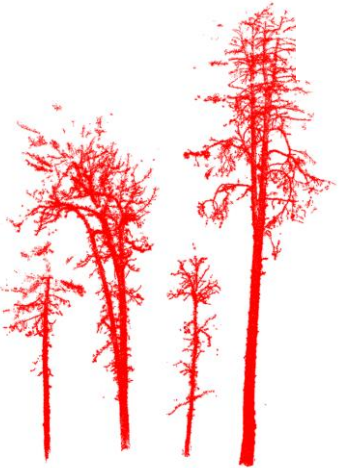
PointsToWood, Owen *et al* (2025)

Benchmark method

Finland



Spain



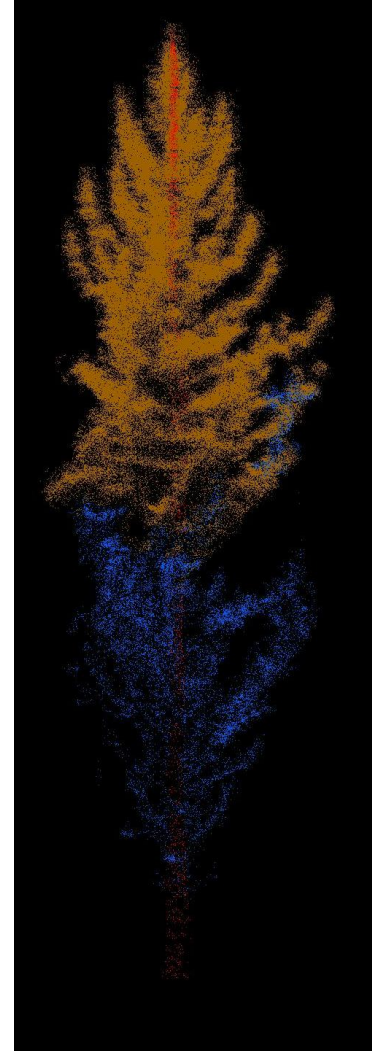
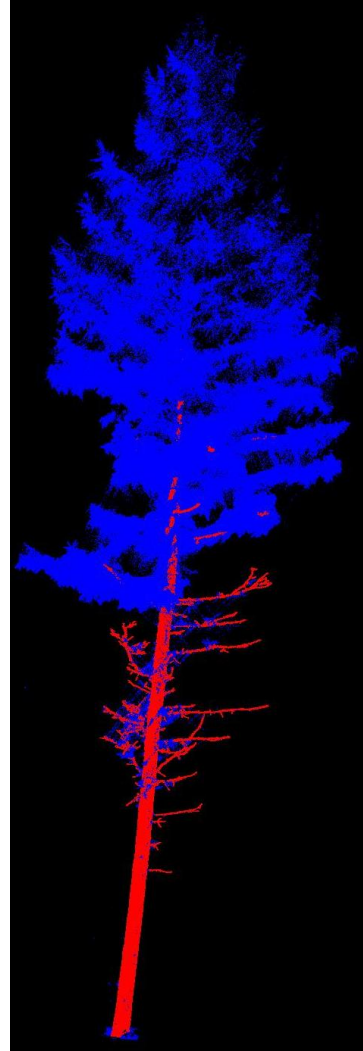
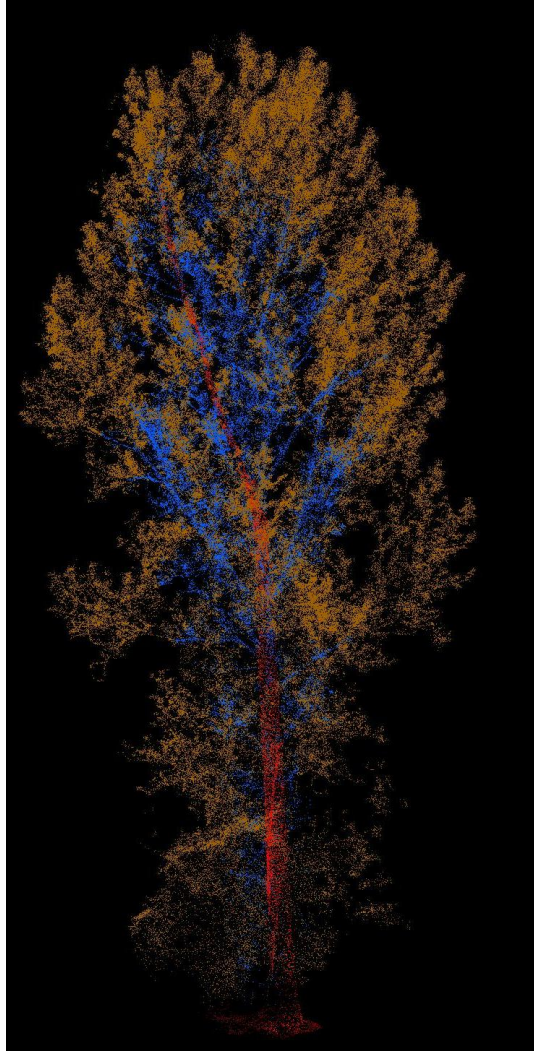
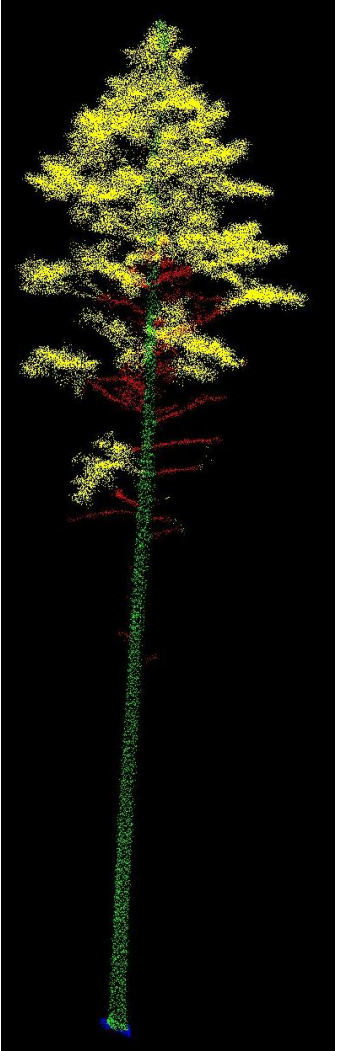
Clear improvement on small element classification (twigs)

← **grey** shows our predictions; **red** shows false labels by benchmark method

Fine details matter for crown reconstruction, but represent a *tiny* fraction of the total points, making evaluation difficult.

Balanced accuracy **weighted by pathlength** highlights improvements in rare, messy, and hard to classify extremities that are hidden by standard metrics.

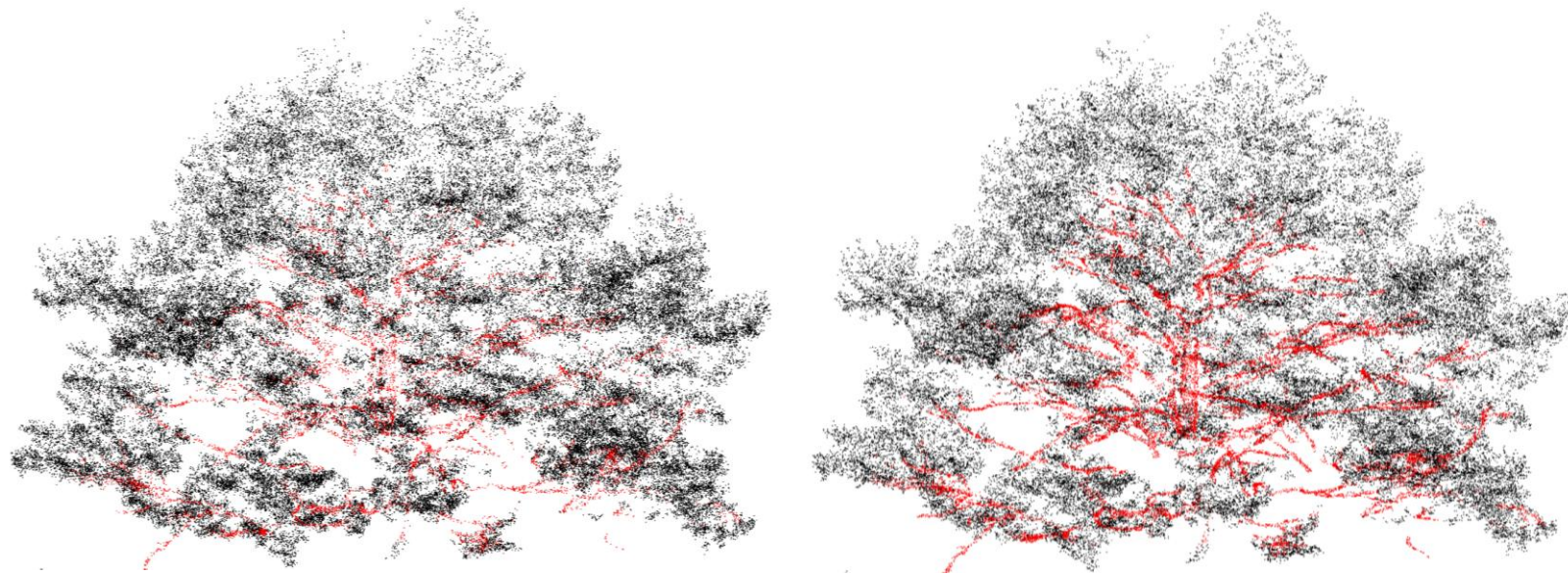
The state of benchmark datasets (*good labels are gold dust*)



Better
models will
do **worse** on
poor
'benchmark'
datasets

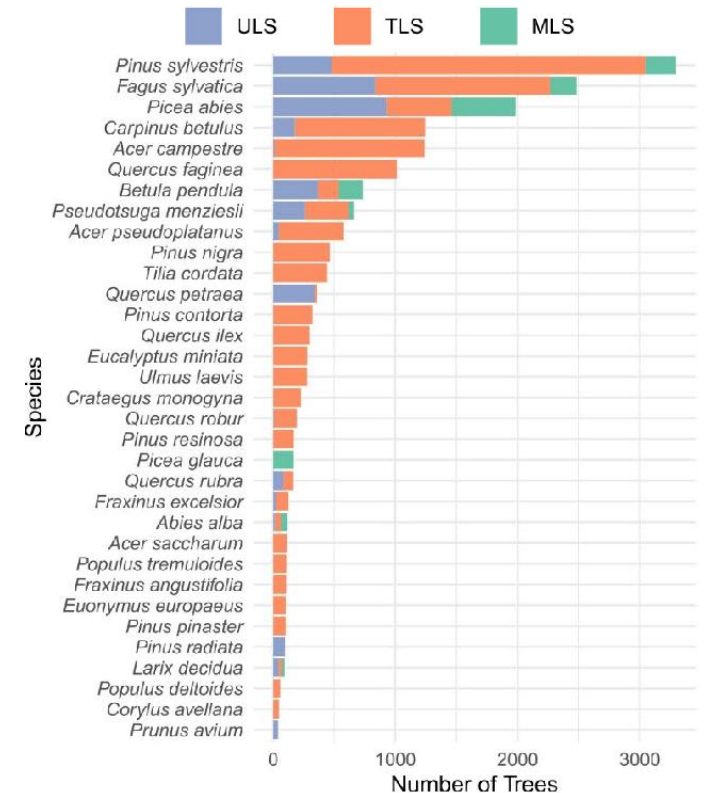
Ecological tasks need ecological metrics of success. But our data brings structural challenges: uneven classes are the norm

High density data cannot be ingested into networks. Standard downsampling loses key details



Owen *et al.* PointsToWood (arXiv & in review)

Rare species are undersampled but crucial for biodiversity monitoring.



Puliti, Lines *et al.*

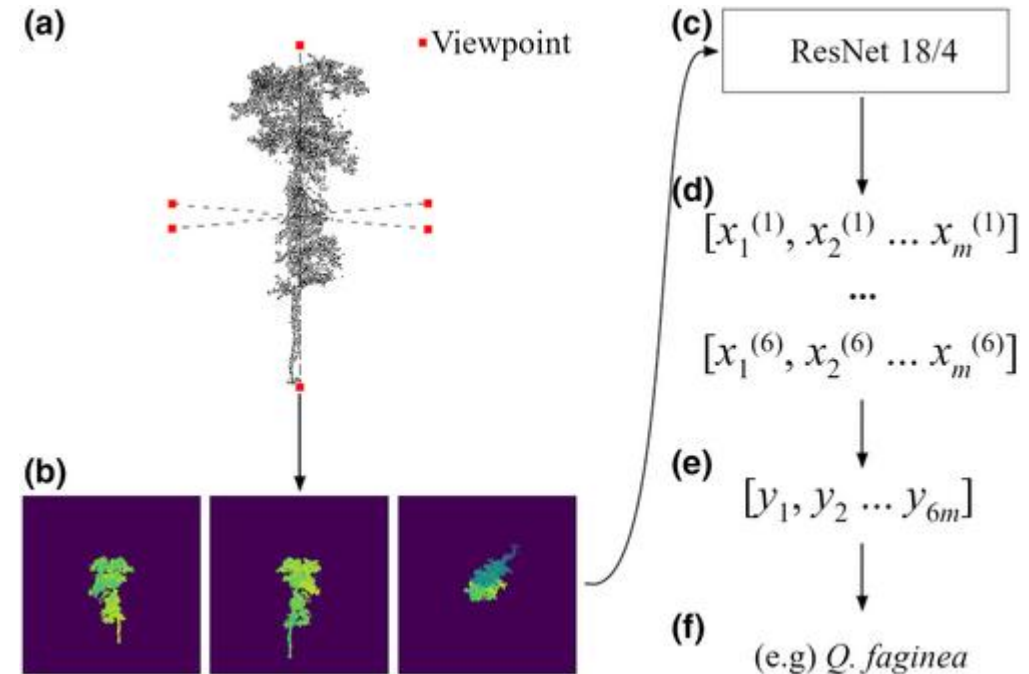
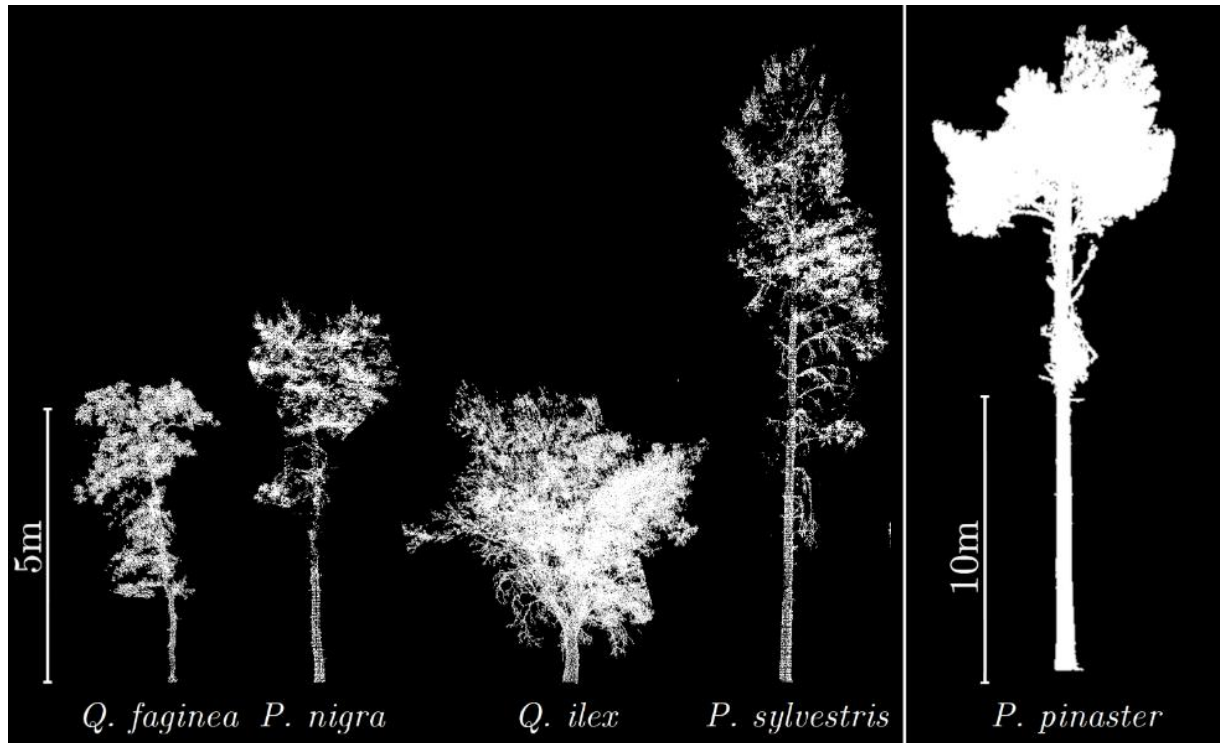
FOR-species20k (MEE, 2025)

and its very time consuming to manually label millions of points

What will help?



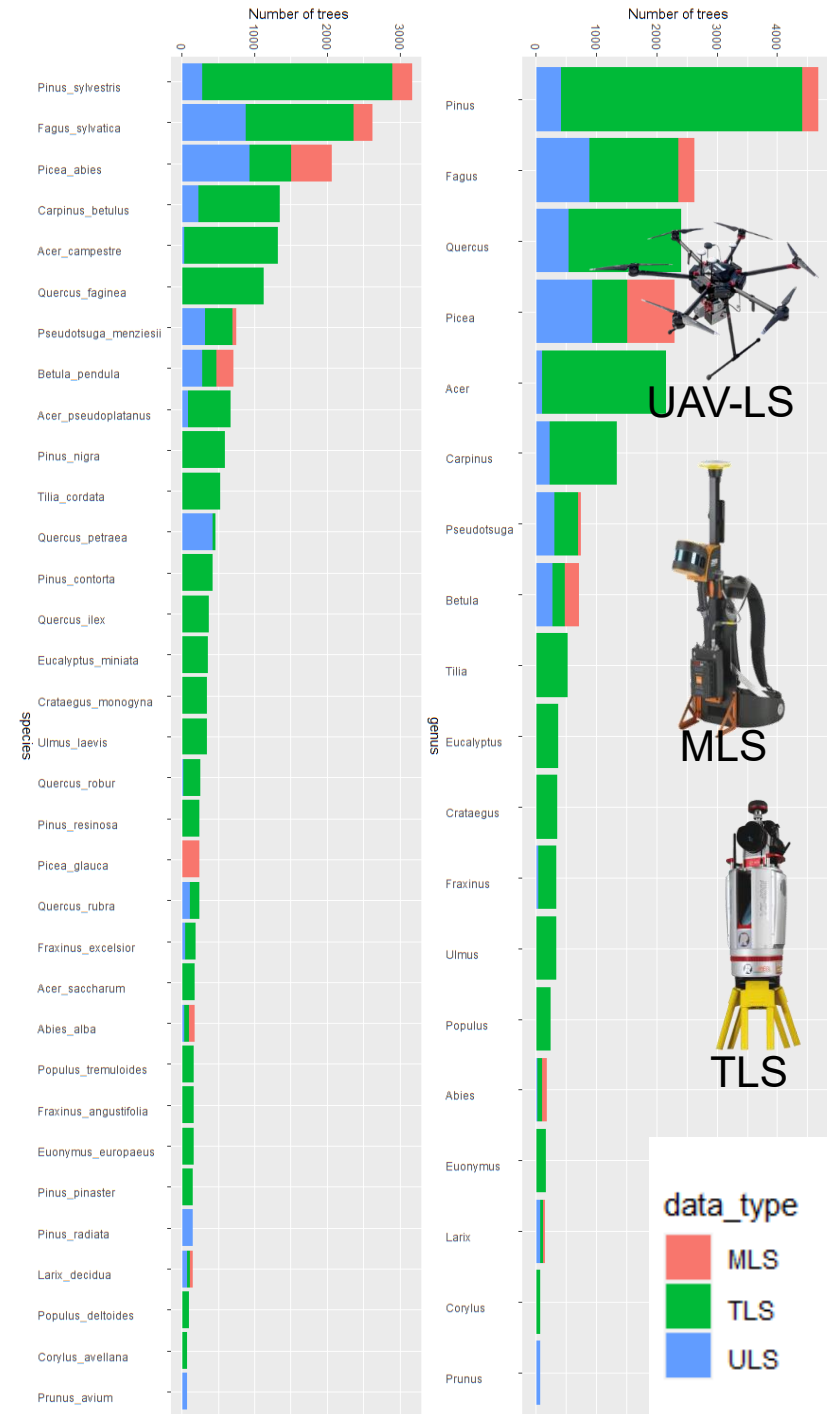
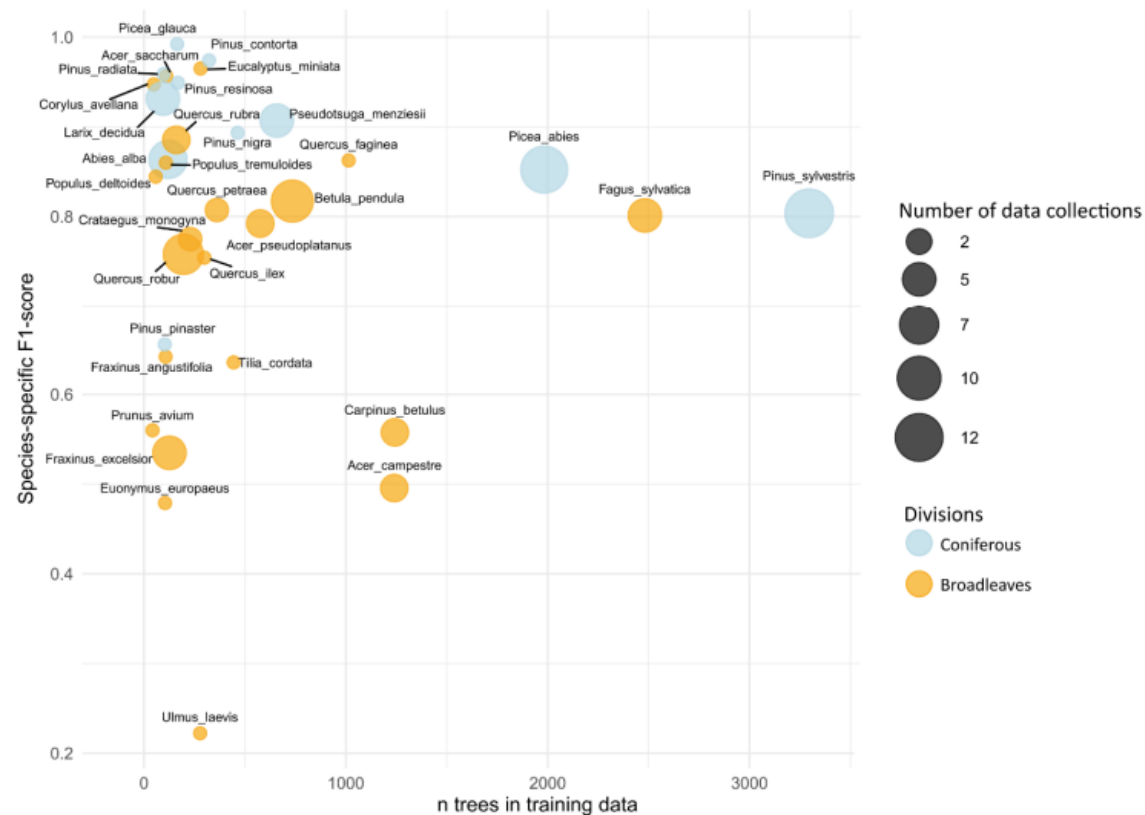
Monitoring diversity: tree species identification with AI



CNN for species classification, with camera projections and SimpleView
Allen et al. (2022)

Towards broad 3D point cloud tree species identification

More data probably helps, but there are likely other limits on performance



Community sourced benchmarking for data diversity

3dtrees.earth

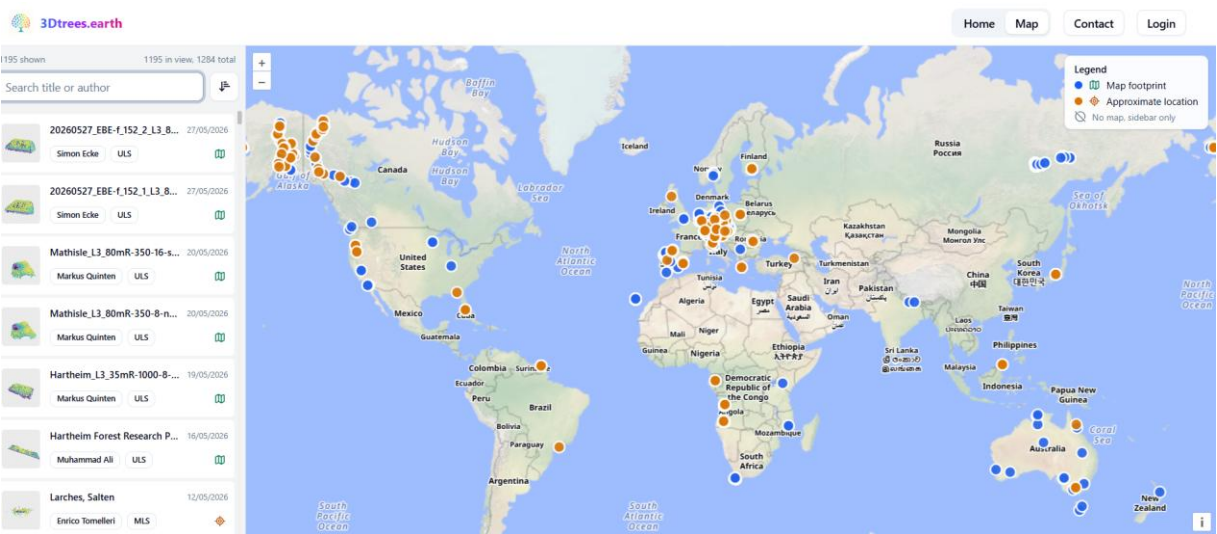
Build *the* Global Forest Reference

Researchers worldwide are sharing high-quality 3D forest data to advance science, AI, and sustainability. Explore what's already here, or contribute your own.

1,320 datasets | 446 contributors | 8,292 ha covered

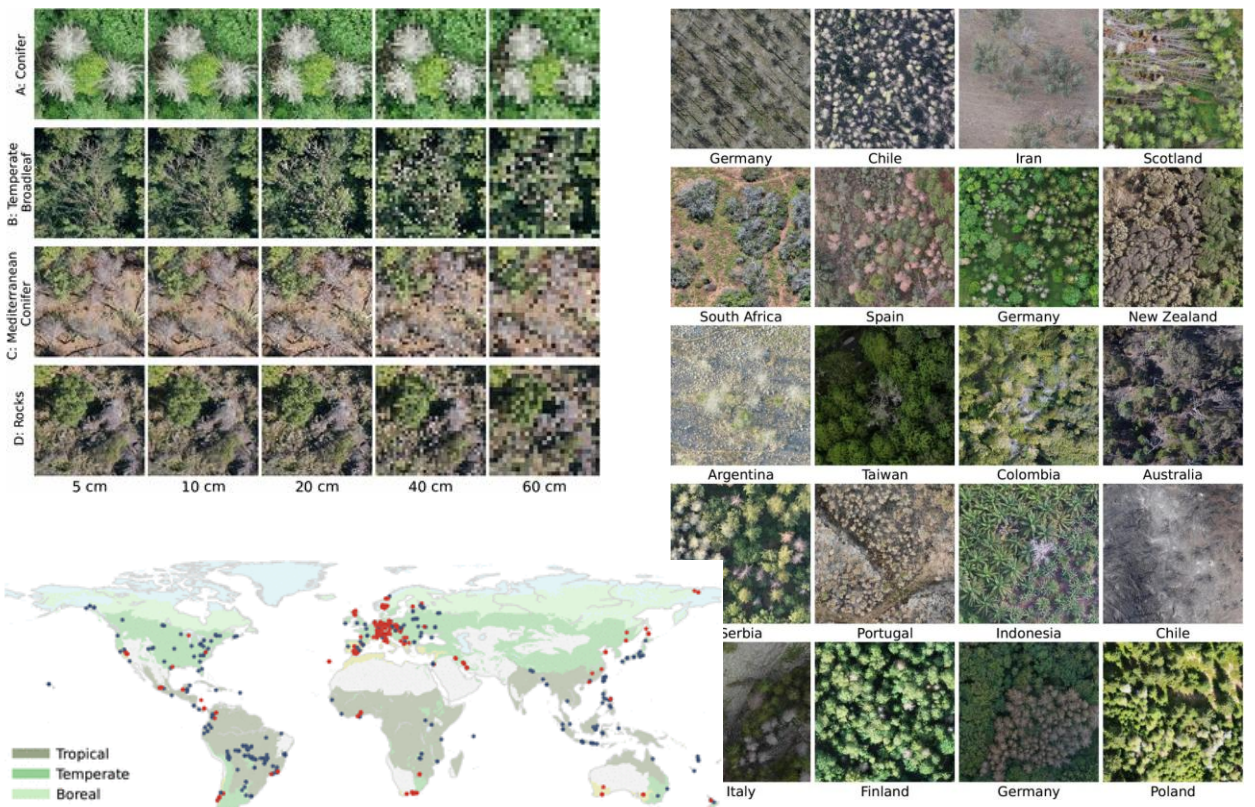
Start contributing →

Explore the map



Vajna-Jehle, Gerberding,
Kattenborn et al. *in progress*

deadtrees.earth



87 institutions, >300k ha
Mosig et al. 2026 RSE

How do we get to the point of trusting outputs?

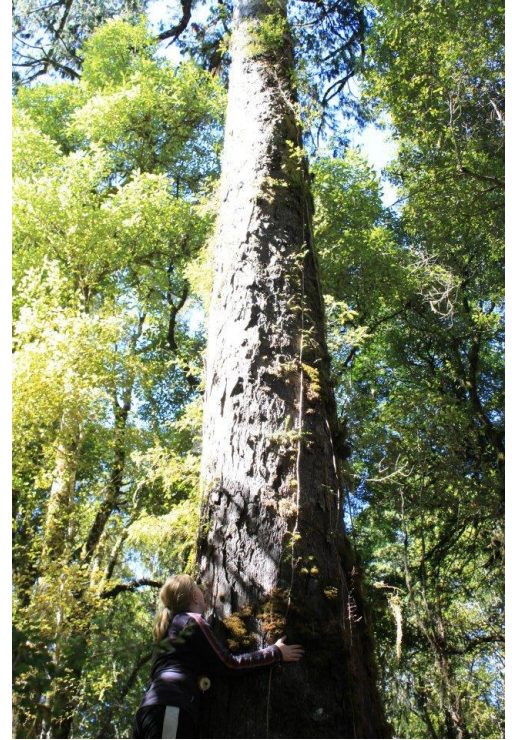
Forests and sensors are diverse and data is hard to label: progress is only possible by working together as a community.

However, not all labelled data is good enough for use and we should be strict on what gets used for benchmarking.

There is enough open data to demonstrate:

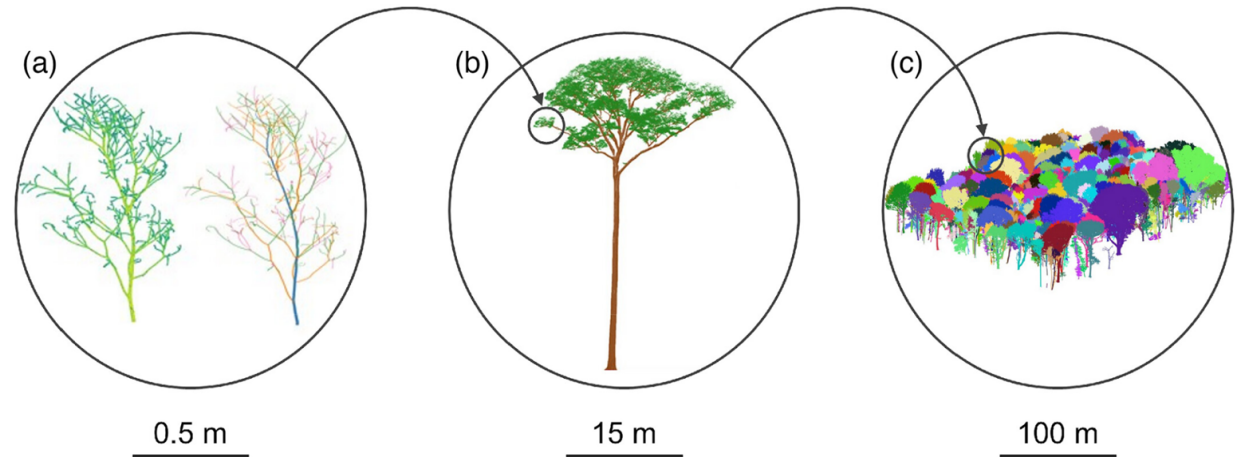
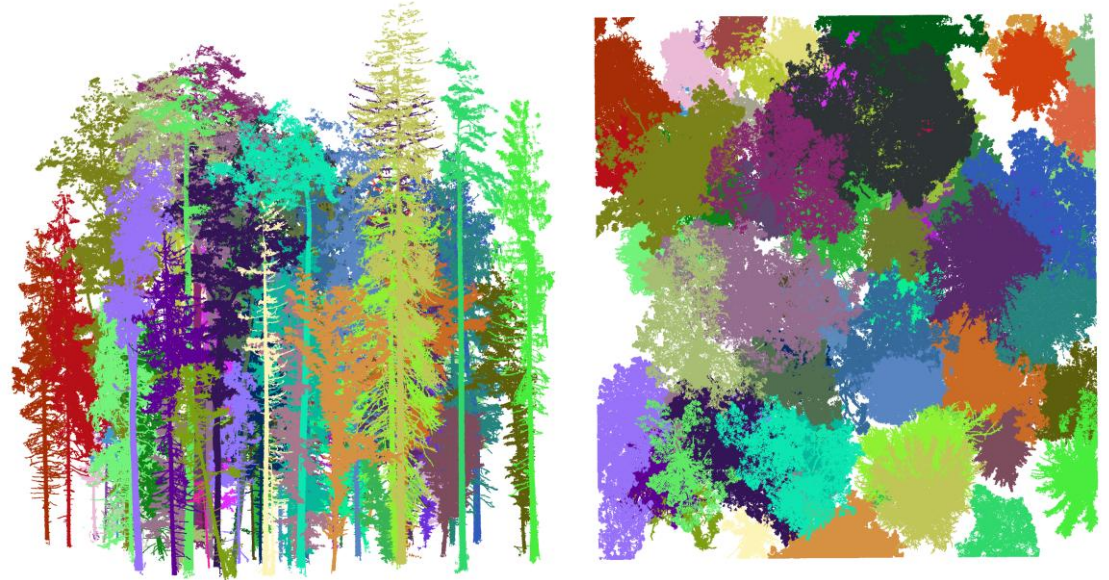
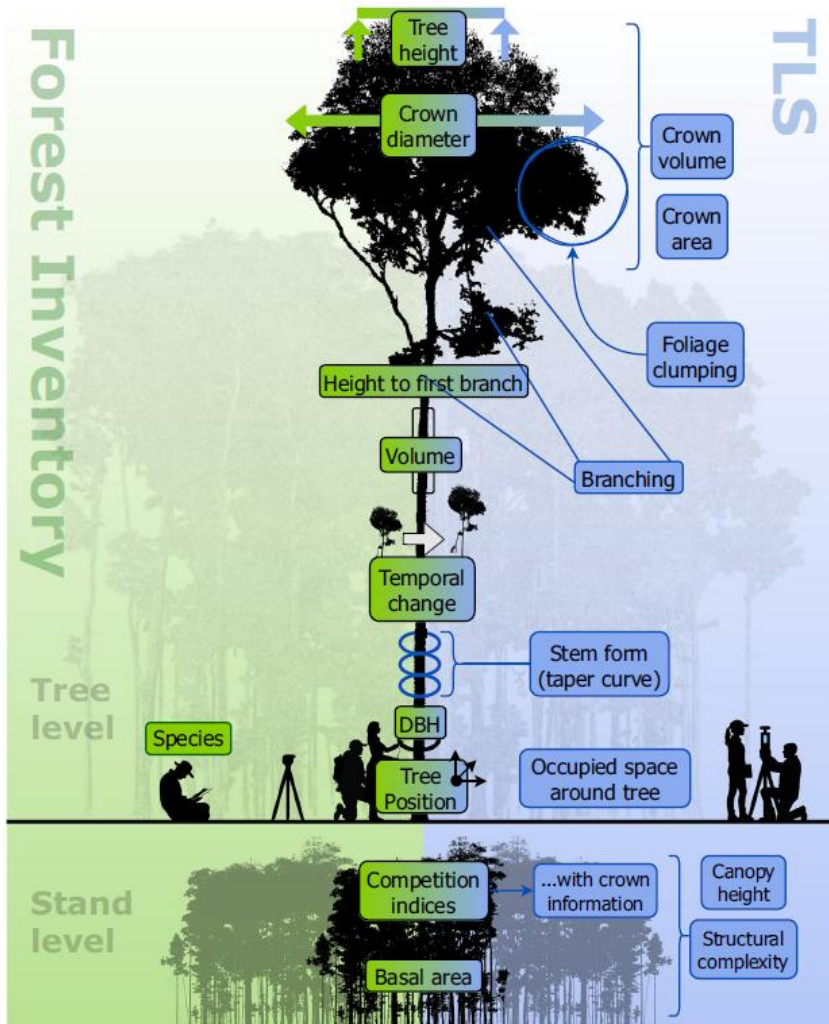
- Real usefulness of tools for *tasks (not just F1 scores)*, **and**
- Improvements over other methods

And demonstrating these should be required by us a scientists, reviewers and editors.



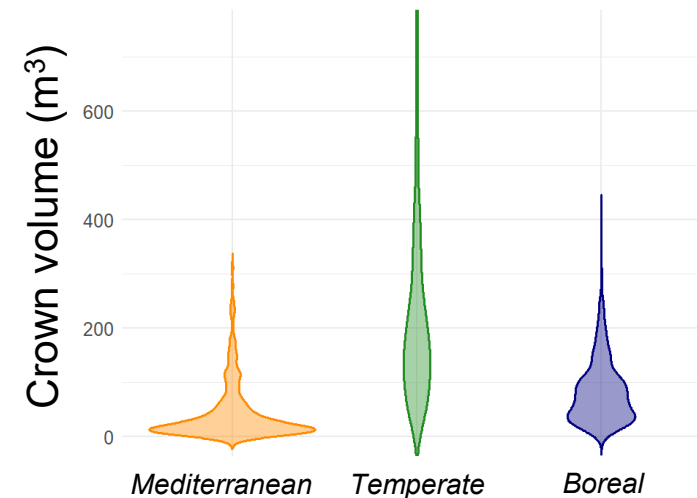
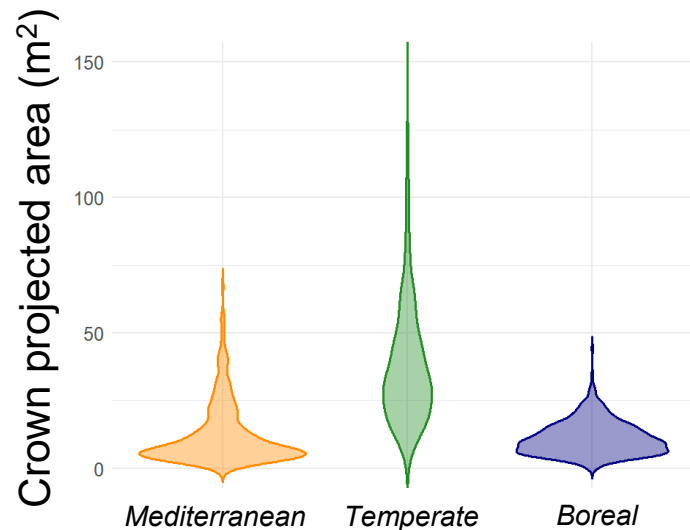
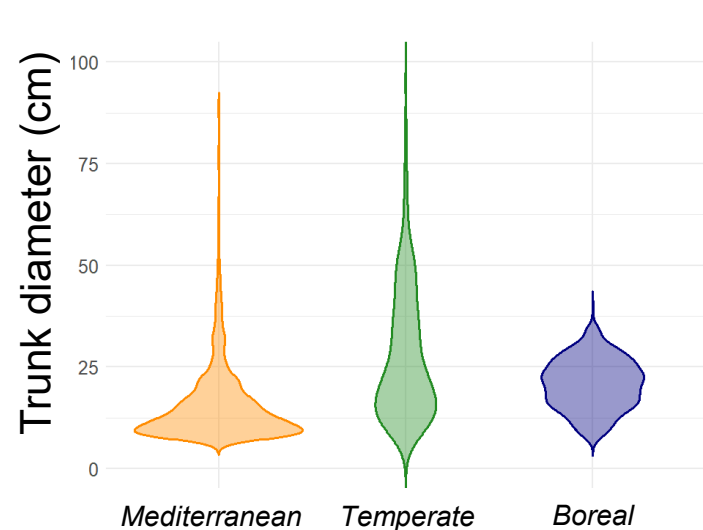


Are high resolution data worth it?

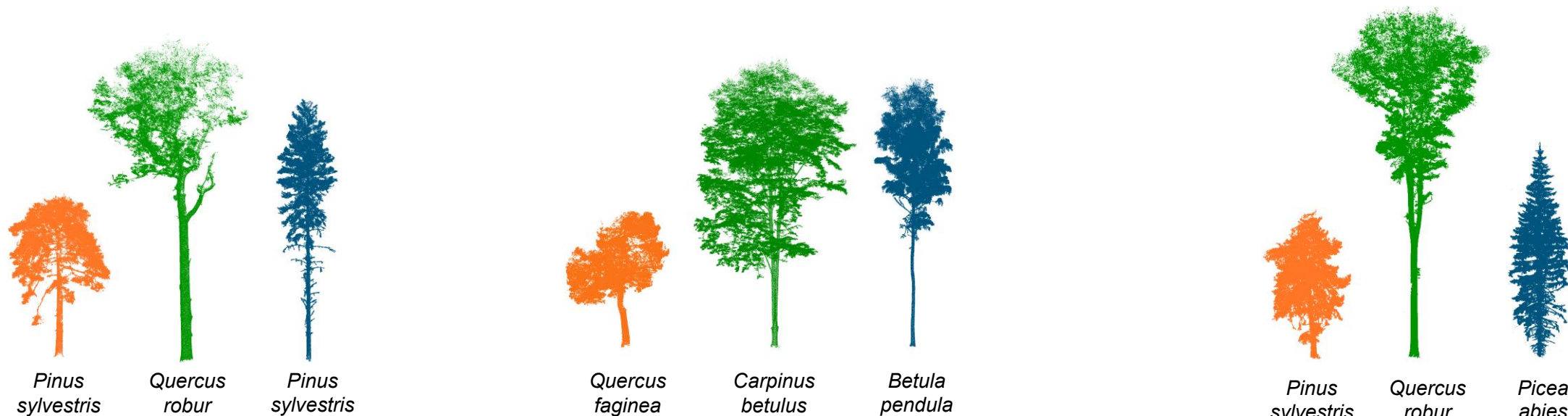


Integration of remote sensing and traditional methods (Maeda et al. 2026)

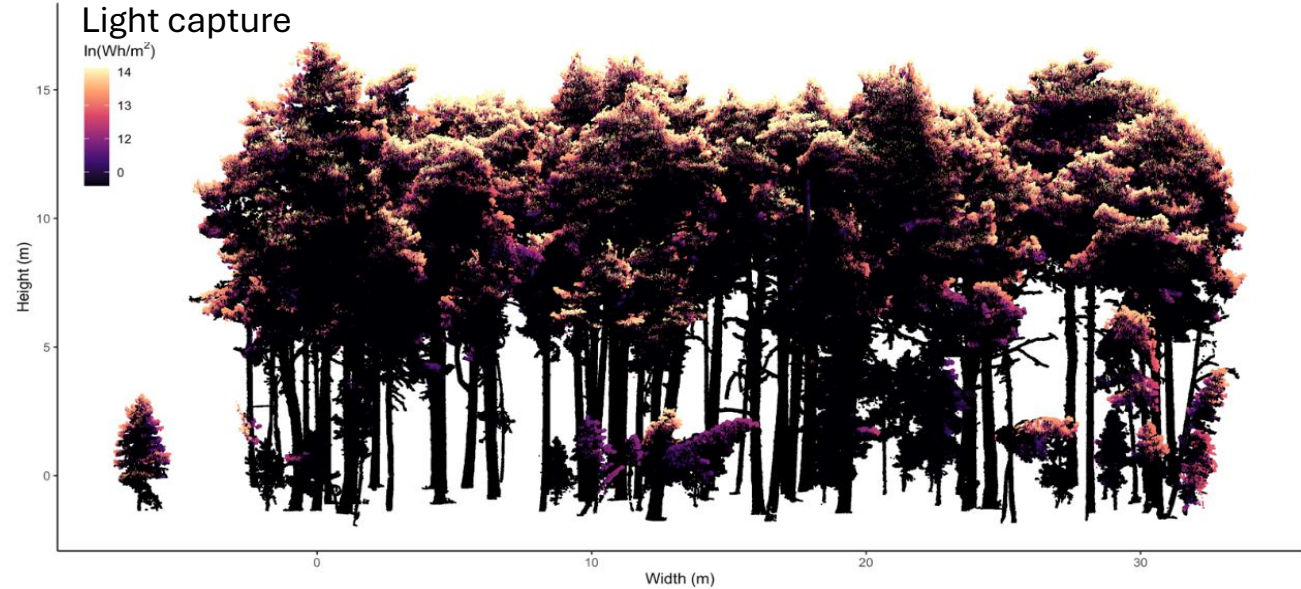
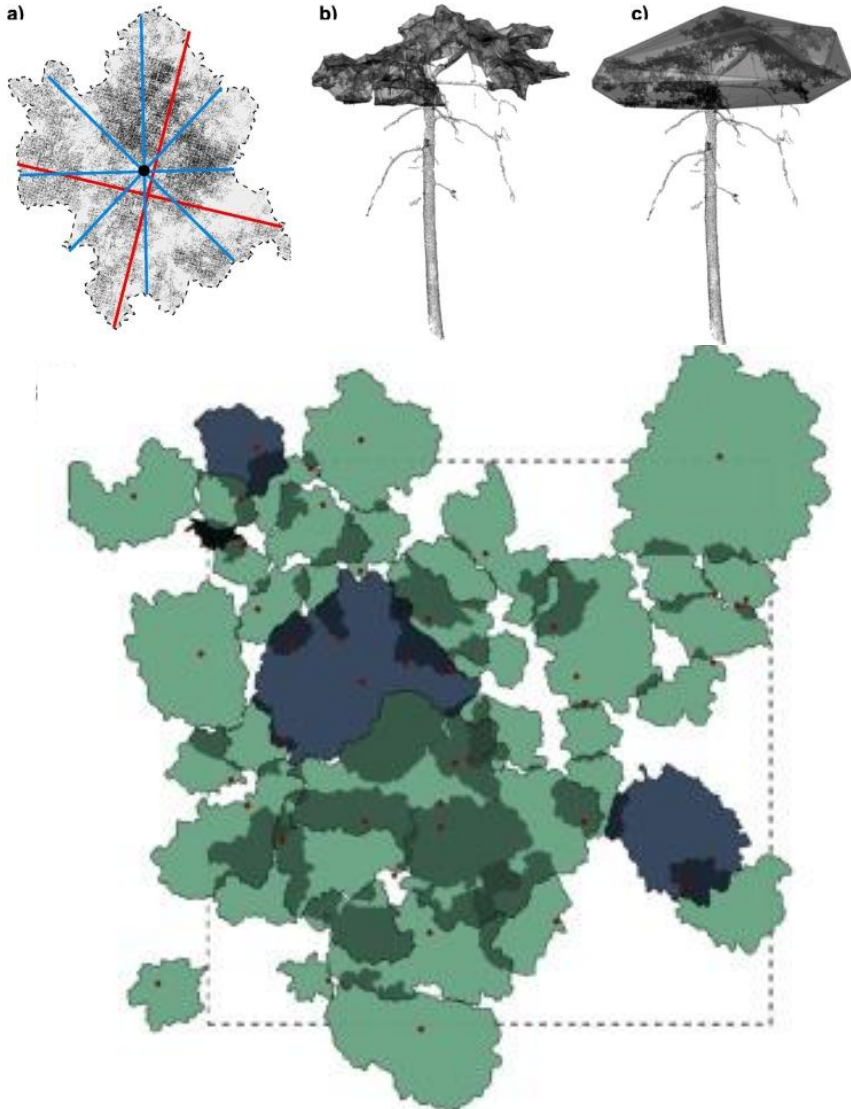
Exploring the diversity of tree and forest structures



Examples of large individuals



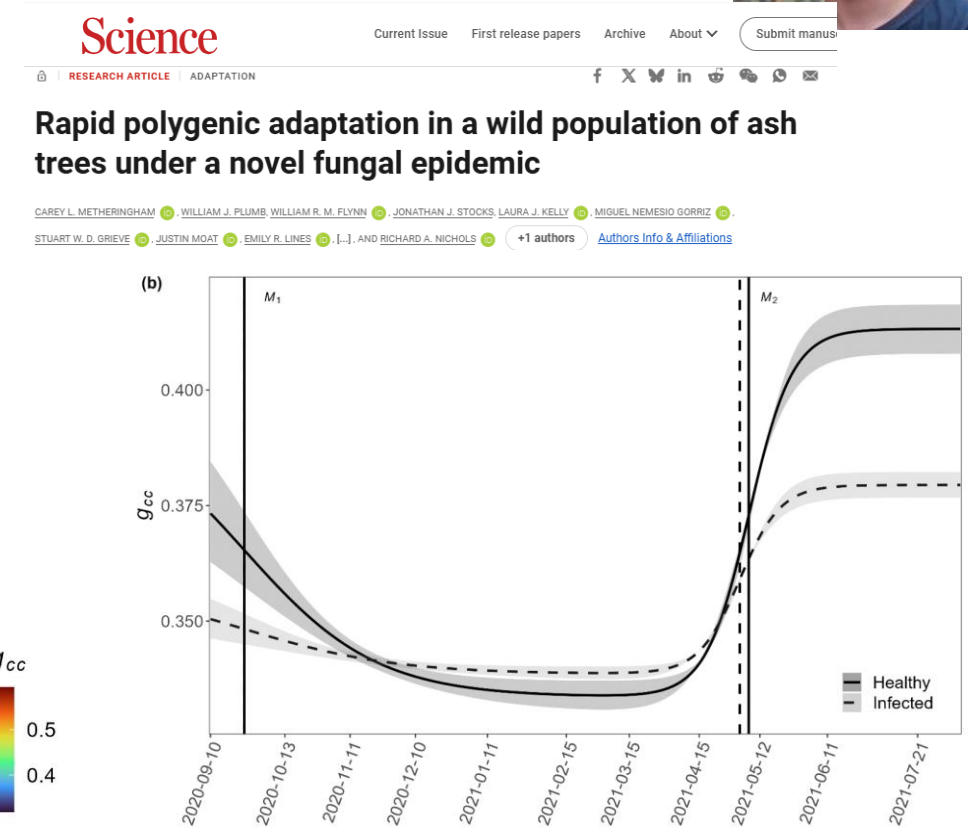
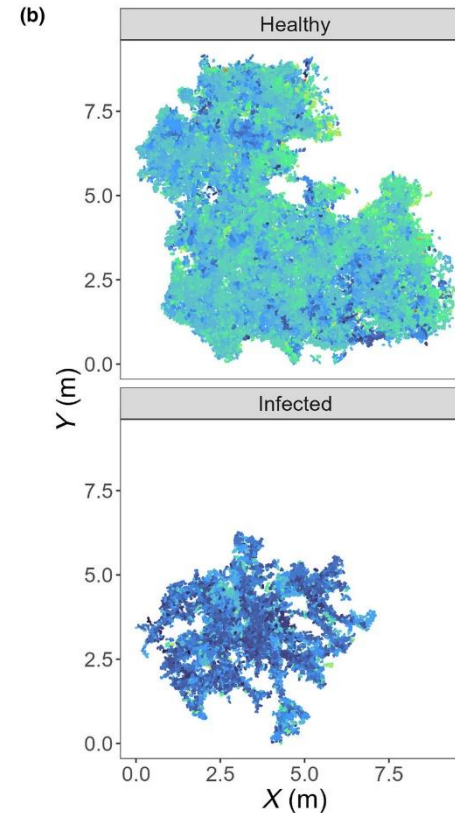
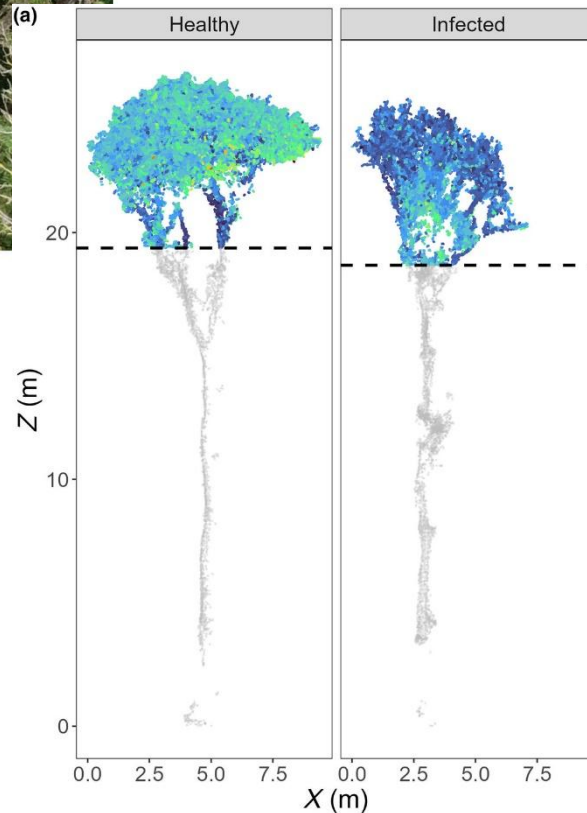
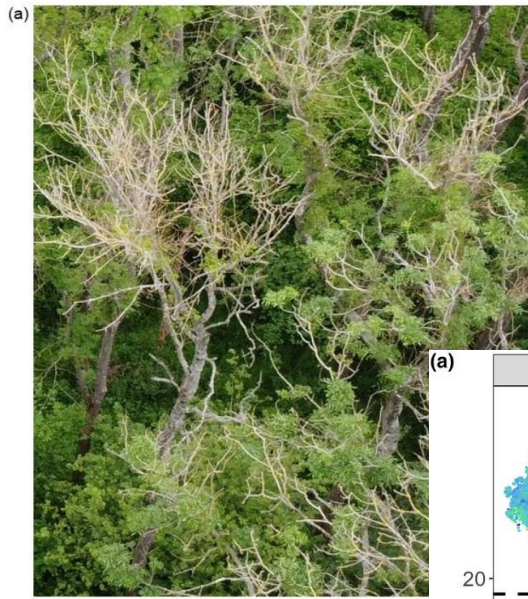
Study structural-functional relationships directly



- Improved allometries for standard field measurements
- Aboveground biomass and carbon
- Leaf area and biomass allocation
- Competition
- Microhabitat and microclimate
- Realistic radiative transfer

Owen et al. (2021),
Owen and Lines (2024)

Spectral-structural-temporal insights into disease



Green-up occurred at a higher rate in trees with higher genomic estimated breeding values & less damage from disease

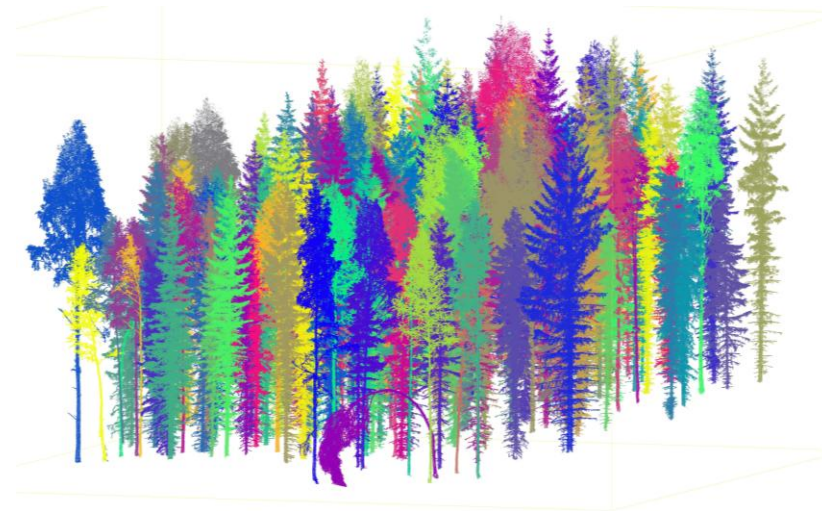
Flynn *et al.* (2024); Metheringham *et al.* (2025)

3D path length analysis shows characteristic greening of ash dieback infected trees

High resolution two and three-dimensional data offer a route towards joint carbon, biodiversity and ecosystem functioning monitoring (direct and proxy) from single data sources.

To do this at scale, we *probably* need deep learning (not yet proven).

With a little more thought we will reach trustworthy implementation.



Research Group



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Future
Leaders
Fellowships



Natural
Environment
Research Council



UNIVERSITY OF CAMBRIDGE



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COST Action CA20118

3DForEcoTech

Three-dimensional forest ecosystem monitoring & better
understanding by terrestrial-based technologies