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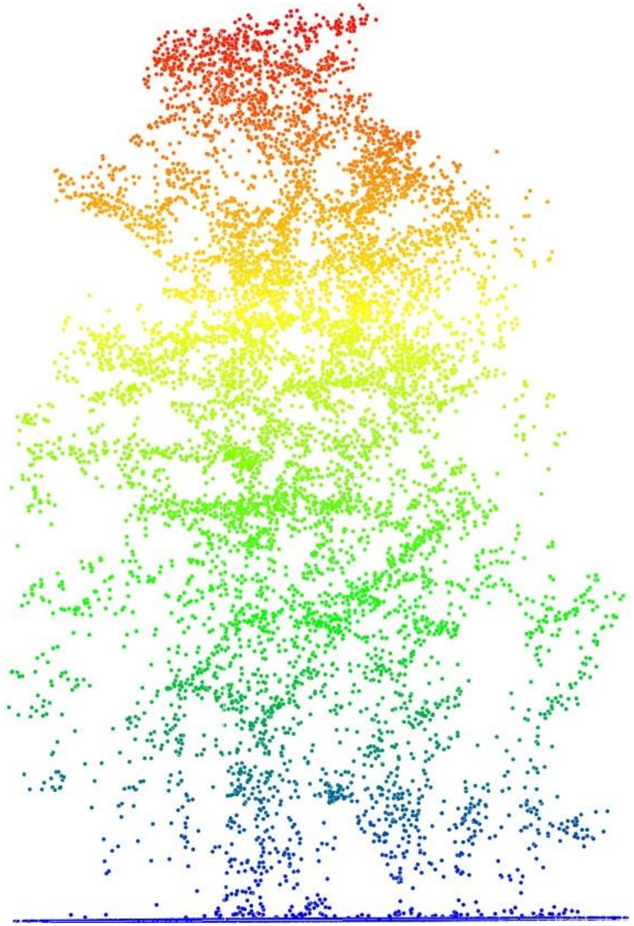
Institute for Biodiversity and Ecosystem Dynamics

Measuring vegetation structure with airborne LiDAR

Webinar



Presenters: W. Daniel Kissling, Yifang Shi & Jinhu Wang

13:00 (CEST), 16th October 2025

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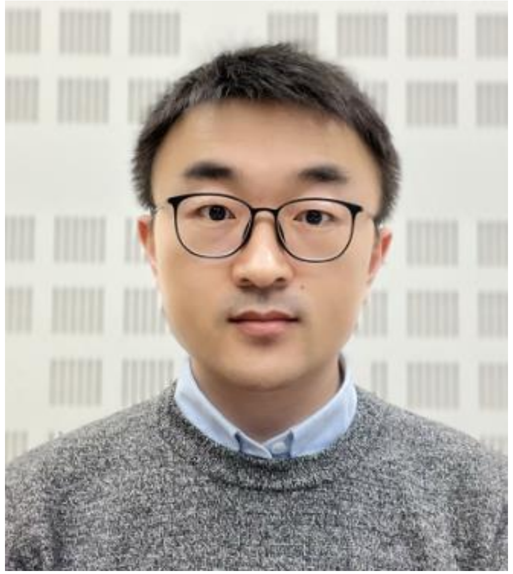
Measuring vegetation structure with airborne LiDAR

W. Daniel Kissling
Associate Professor of Quantitative Biodiversity
Ecology & biodiversity science

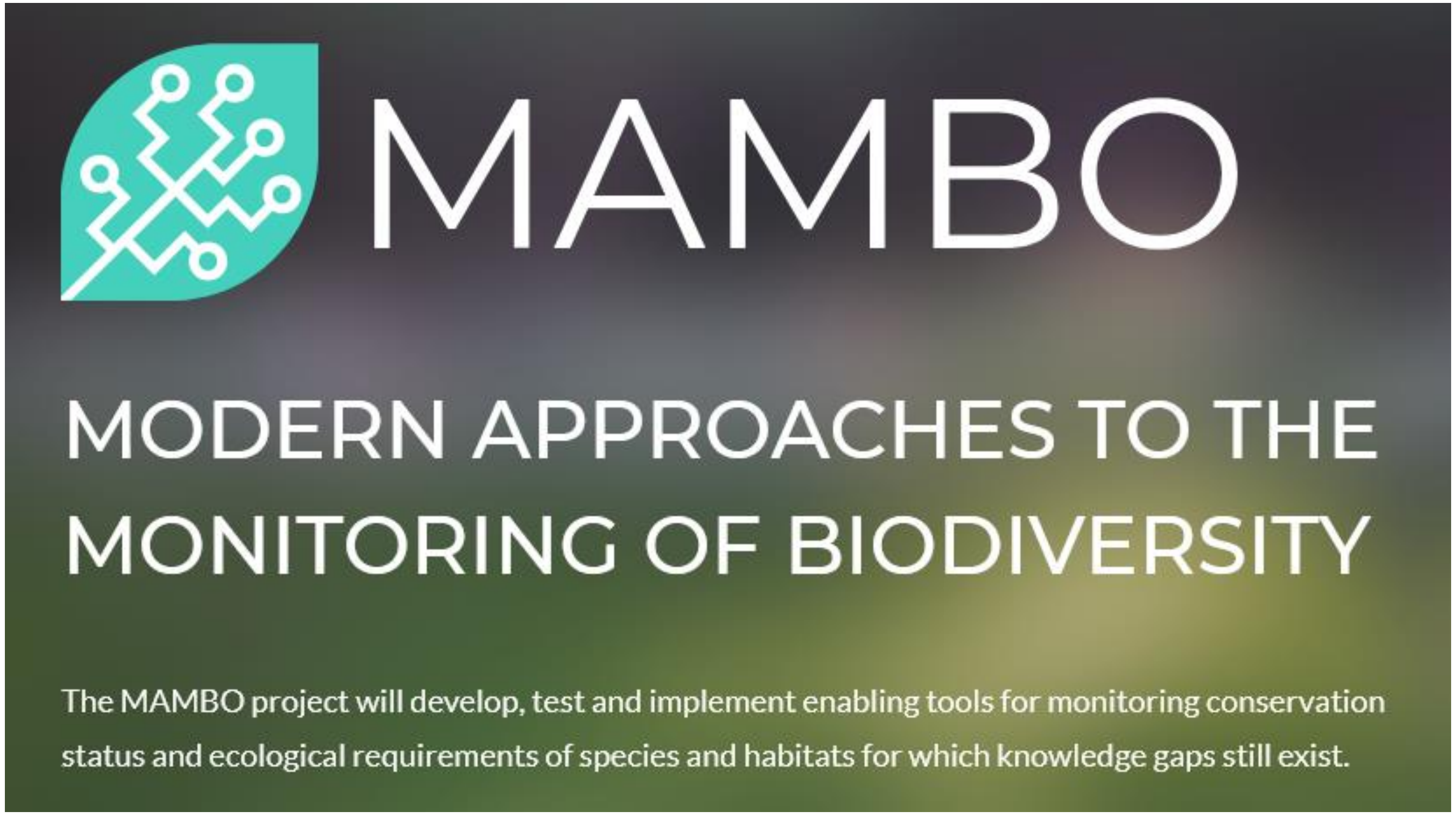
Yifang Shi
Assistant Professor in Land Cover and Land Use Dynamics
Multi-source remote sensing



Jinhu Wang
LiDAR scientific developer
Point clouds and 3D object detection

Biodiversity & Macroecology lab (https://www.biomac.org/)

EU project MAMBO



https://www.mambo-project.eu/

WP4

Remote sensing for habitat assessment

- Habitat condition metrics from airborne LiDAR
- Automated execution of workflows

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Program

1. **Introduction to airborne laser scanning** (10 min, W.D. Kissling)
2. **Identifying and mapping individual trees** (10 min, J. Wang)
3. **Mapping 3D vegetation structures** (15 min, Y. Shi)
4. **Measuring trail networks of large herbivores** (15 min, J. Wang)
5. **Wrap-up with available resources** (10 min, W.D. Kissling)

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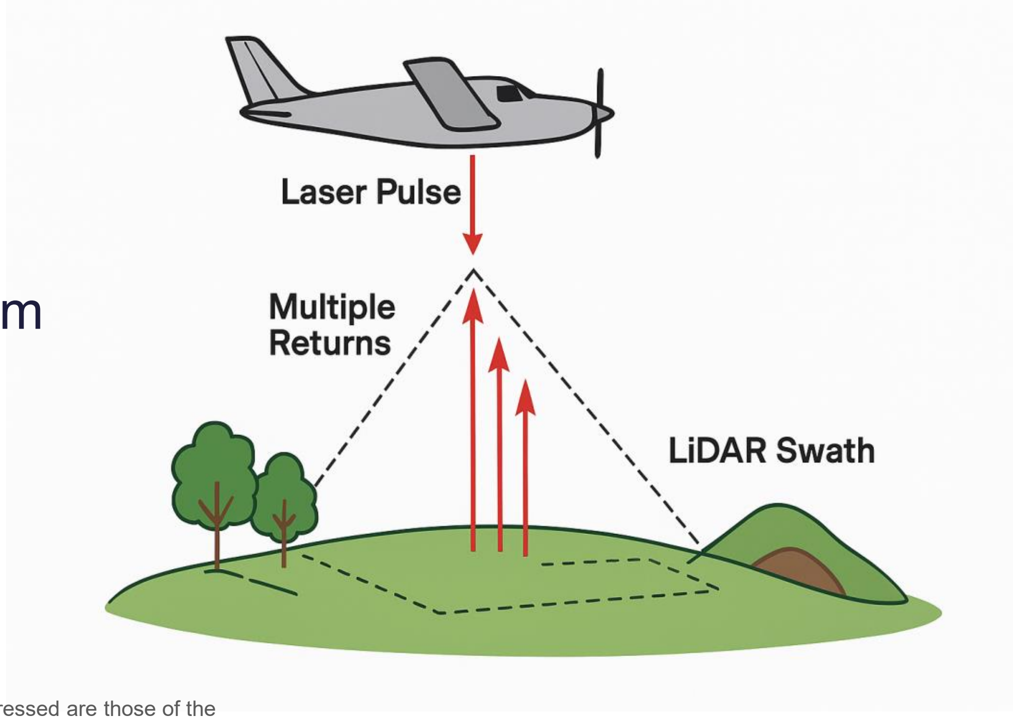
Introduction to airborne laser scanning

W. Daniel Kissling

Associate Professor, Institute for Biodiversity and Ecosystem Dynamics (IBED), University of Amsterdam

16th October 2025



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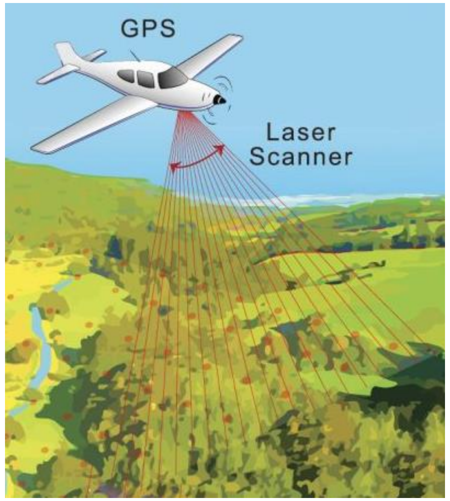
LiDAR (Light Detection And Ranging)

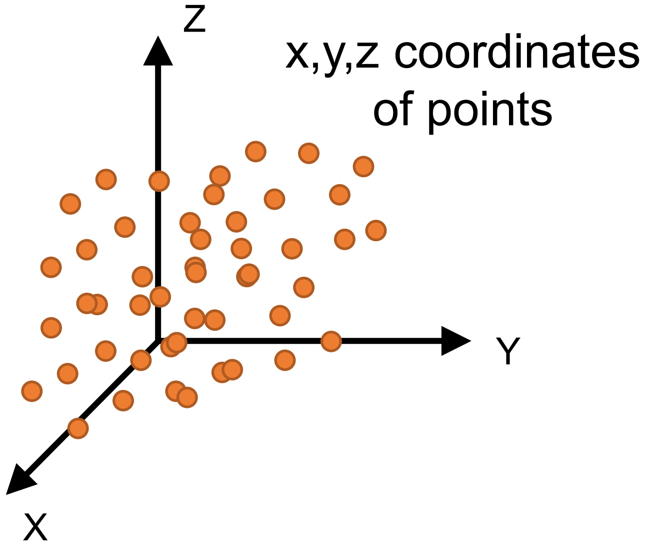
Laser scanner



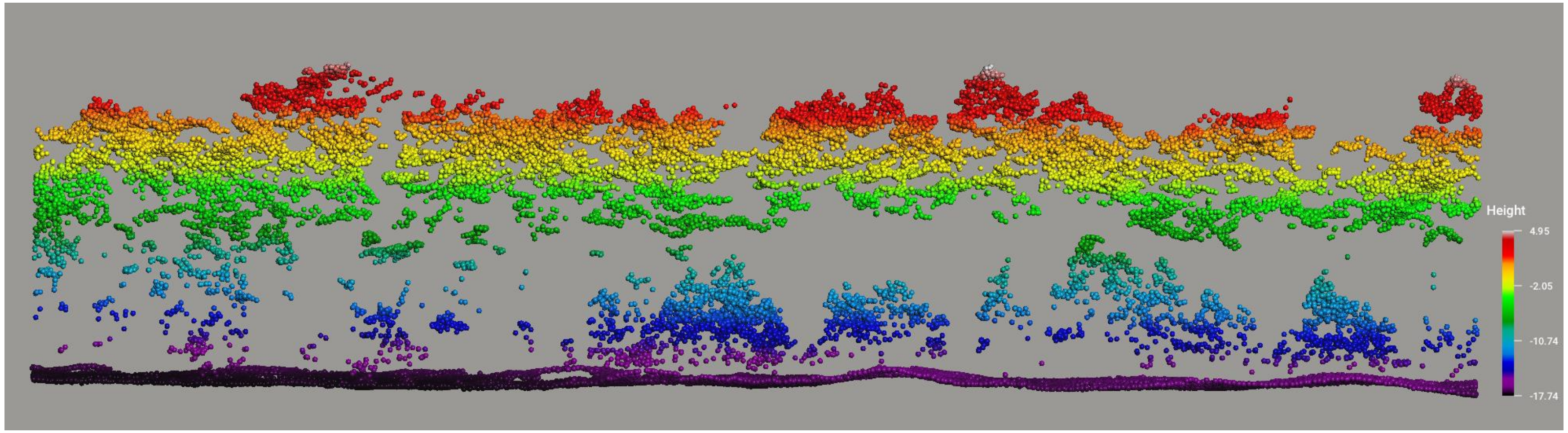
https://www.newport.com/n/lidar

- Pulse of laser light is actively emitted
- Return time is measured and converted into a distance

Recording



Point cloud



Platforms

Ground-based LiDAR platforms

Mobile Laser Scanners (MLS)

Terrestrial Laser Scanners (TLS)

Aerial LiDAR platforms

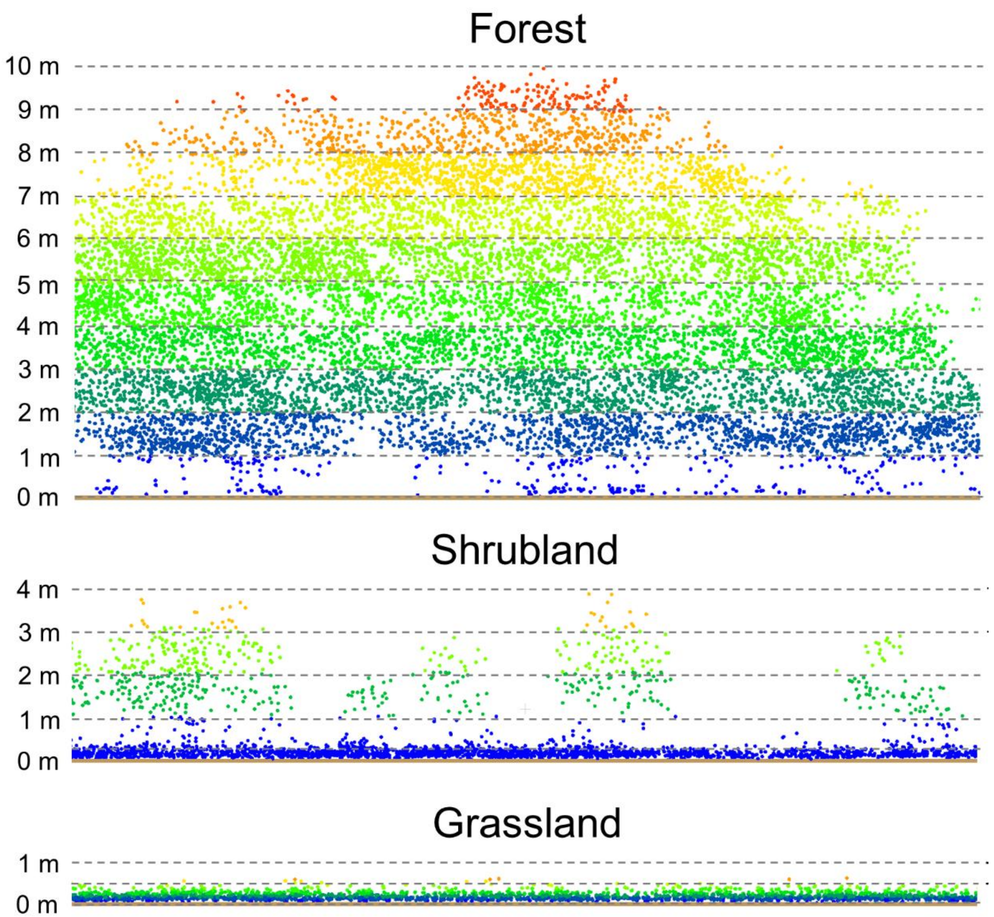
Unmanned aerial vehicles (UAVs)

Airborne Laser Scanners (ALS)

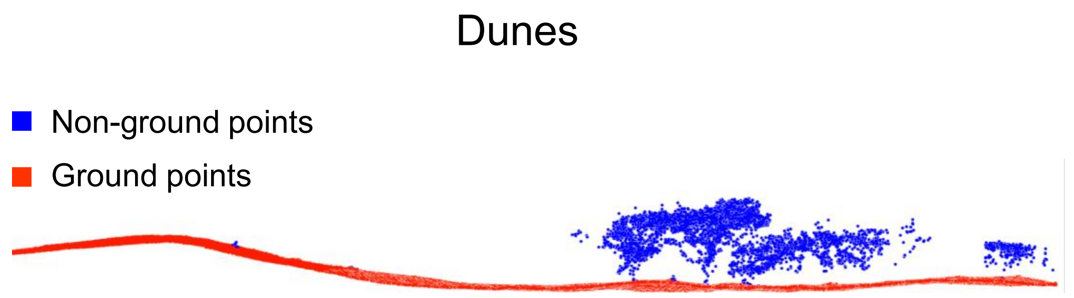
Platforms

	Ground-based LiDAR platforms		Aerial LiDAR platforms	
	Mobile Laser Scanners (MLS)	Terrestrial Laser Scanners (TLS)	Unmanned aerial vehicles (UAVs)	Airborne Laser Scanners (ALS)
				
Point density	1,000–50,000 points/m²	1,000–50,000 points/m²	100–10,000 points/m²	1–100 points/m²
Coverage	Small areas (~100 m range)	Localized (~5–300 m range)	Small nature reserves	Whole countries
Viewpoint	Ground level, understory, upper canopy hidden	Understory/trunk/branch details, poor for top canopy	Top canopy, terrain, branches	Canopy surface, terrain, understory features

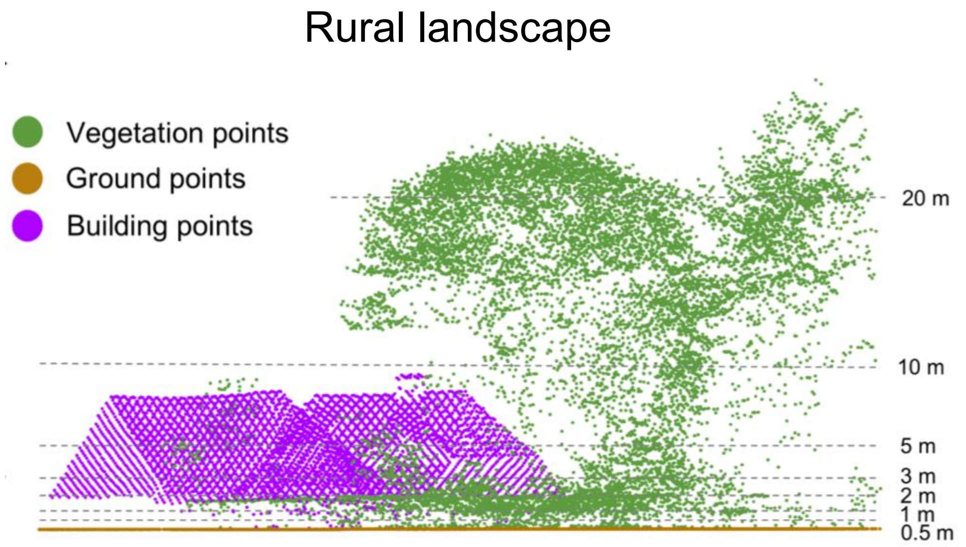
Examples of ALS data in different habitats



Kissling & Shi 2023 *Diversity and Distributions* https://doi.org/10.1111/ddi.13760



Natura 2000 site ‘Kennemerland-Zuid’ (site code NL1000012), The Netherlands



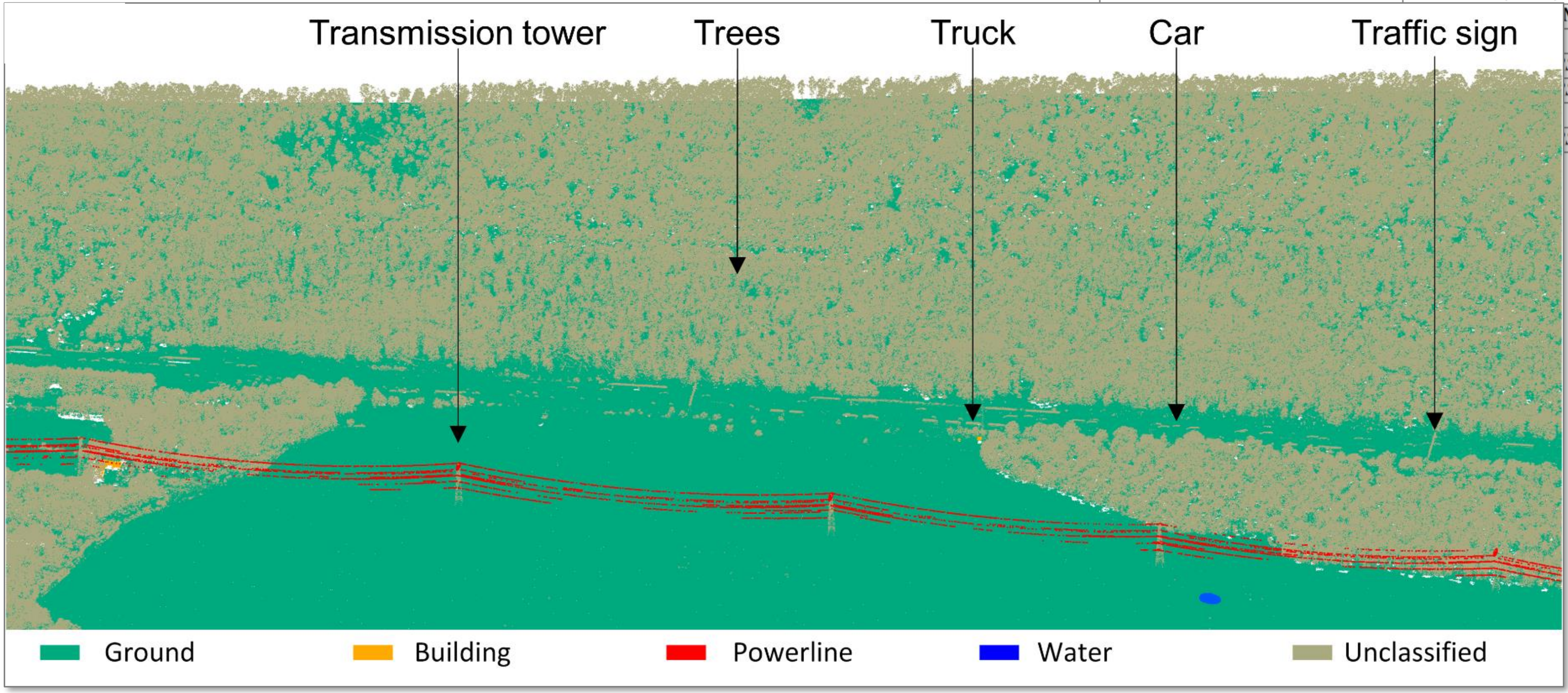
Kissling & Shi 2023 *Diversity and Distributions*
https://doi.org/10.1111/ddi.13760

Point classification

ASPRS Standard Point Classes (Point Data Record Formats)

Classification Value (Bits 0:4)	Meaning
0	Created, Never Classified
1	Unclassified[2]
2	Ground
3	Low Vegetation
4	Medium Vegetation
5	High Vegetation
6	Building
7	Low Point (Noise)
	Mass Point)
	S Definition
	S Definition
	S Definition

<u>Point classes available from most data providers (example: AHN4 dataset from the Netherlands)</u>

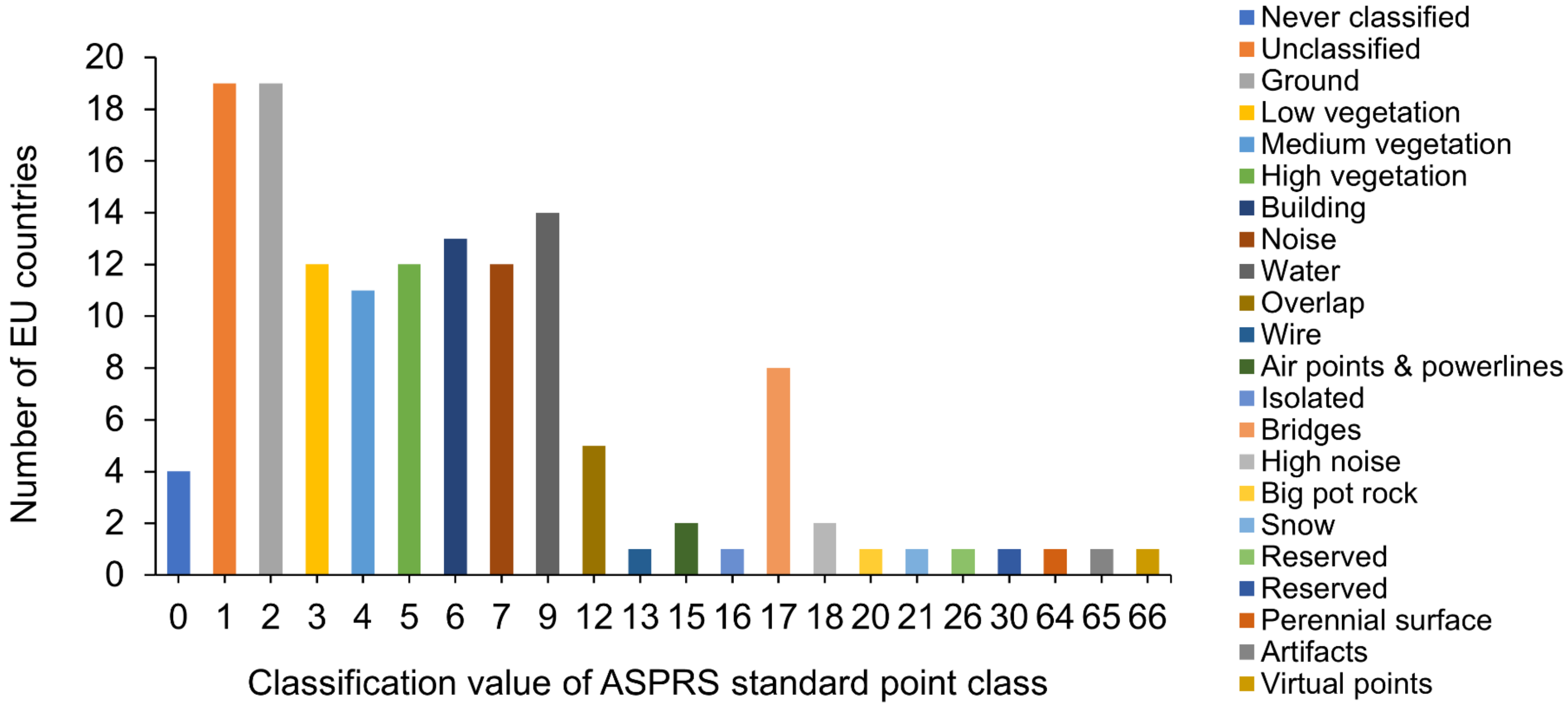


Natura 2000 site ‘De Veluwe’ (site code NL9801023), The Netherlands

Kissling et al. 2024 *Ecological Indicators* https://doi.org/10.1016/j.ecolind.2024.112970

Point classification

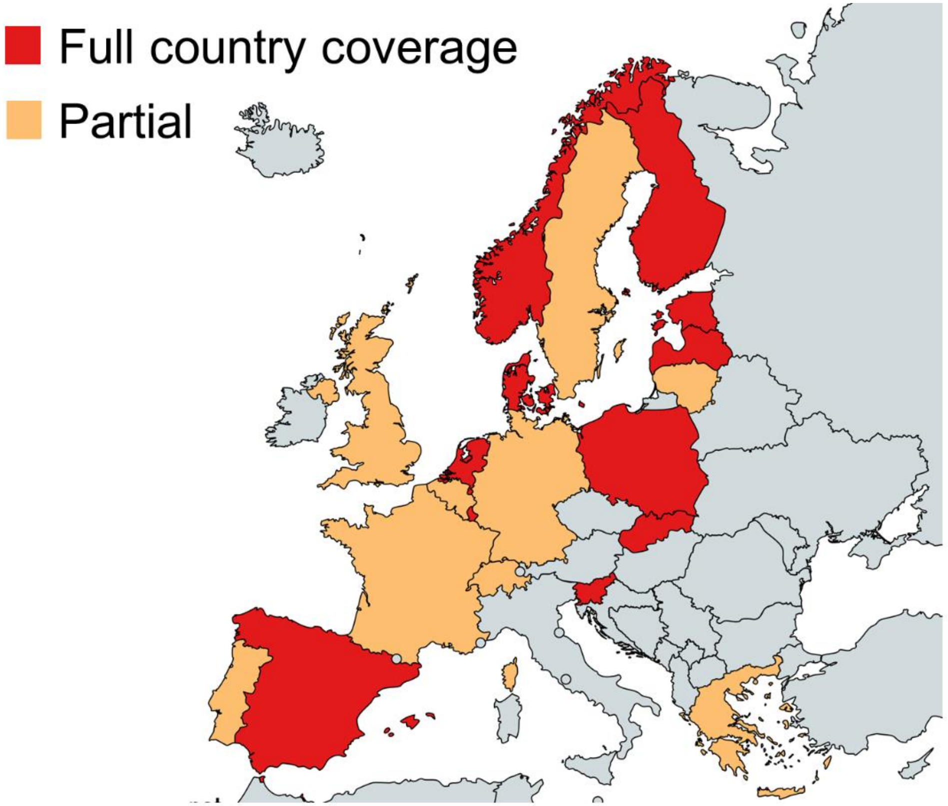
<u>Available point classes across open-access (sub)national ALS point clouds in Europe</u>



Kissling et al. 2024 *Ecological Indicators* https://doi.org/10.1016/j.ecolind.2024.112970

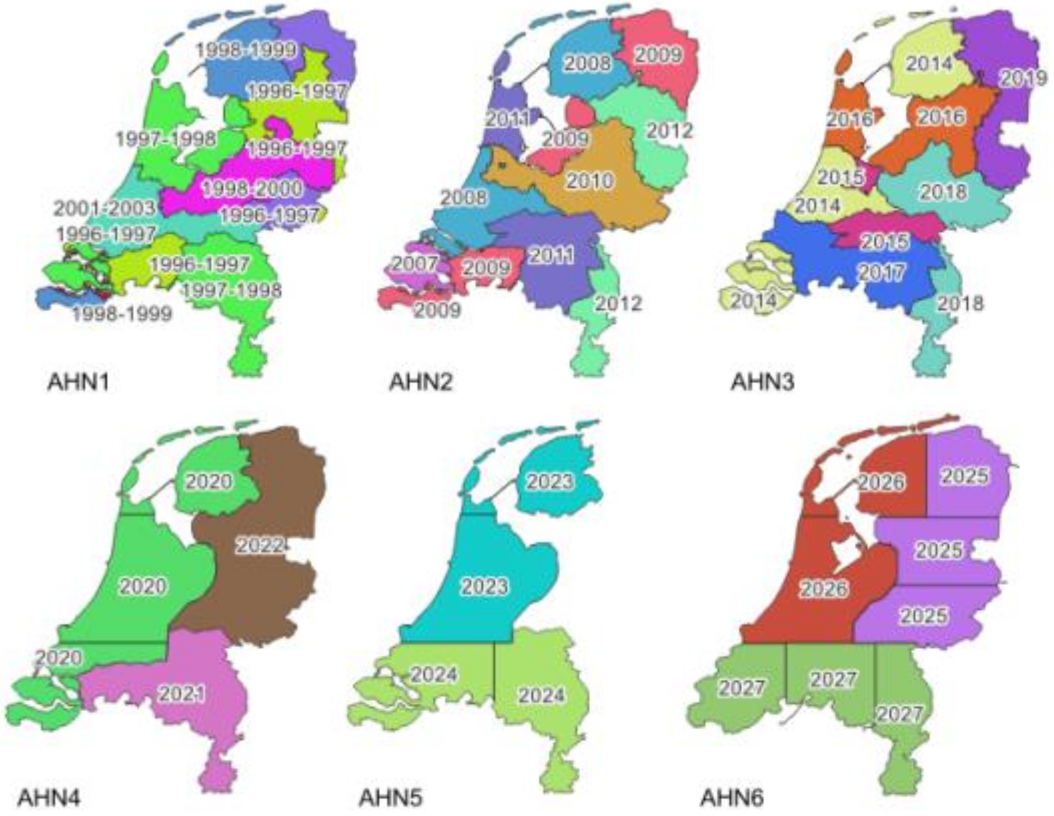
ALS data availability in Europe

<u>Geographic coverage of open-access (sub)national ALS point clouds across Europe</u>



See Supplementary Data 1 (Appendix A and Table A1) in Kissling et al. 2024 *Ecological Indicators*
https://doi.org/10.1016/j.ecolind.2024.112970

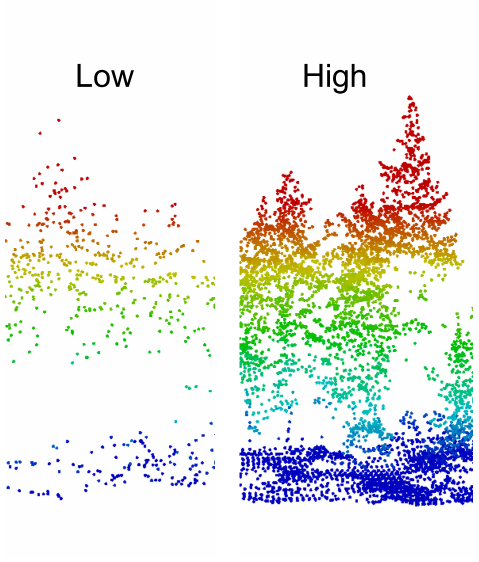
<u>Multi-temporal national ALS point clouds (The Netherlands)</u>



https://www.ahn.nl/dataroom

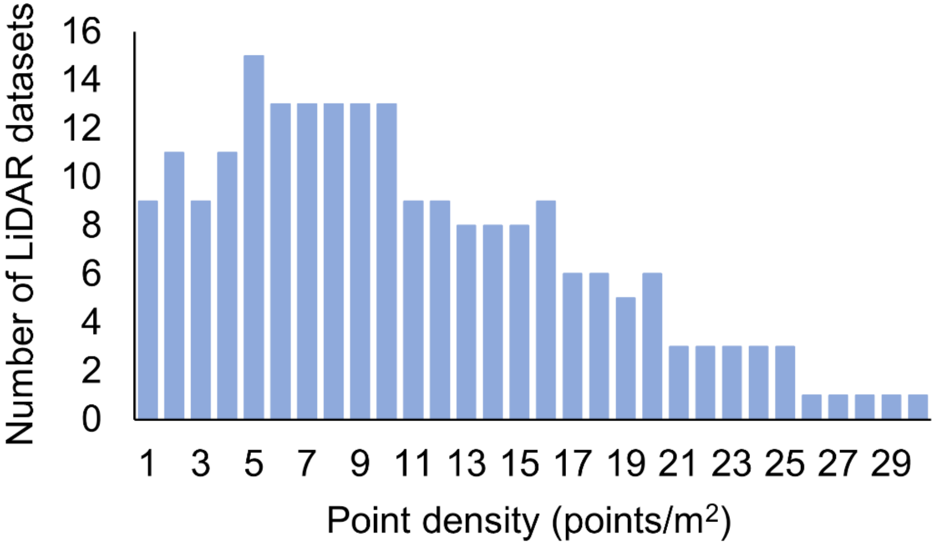
Point density

Point densities



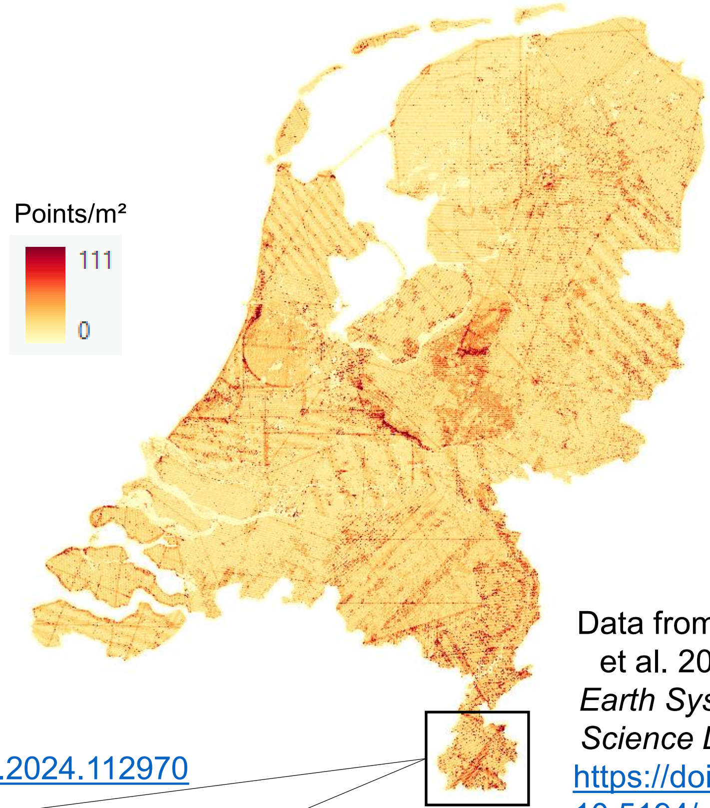
Bakx et al. 2019 *Diversity and Distributions*
https://doi.org/10.1111/ddi.12915

Average point densities available across open-access (sub)national ALS point clouds in Europe

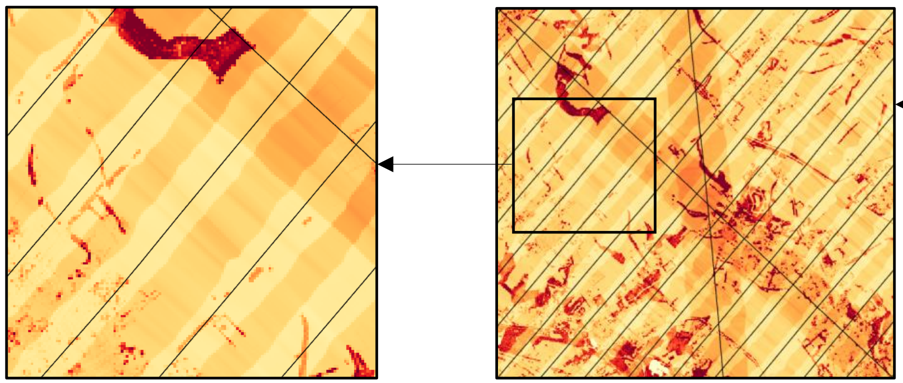


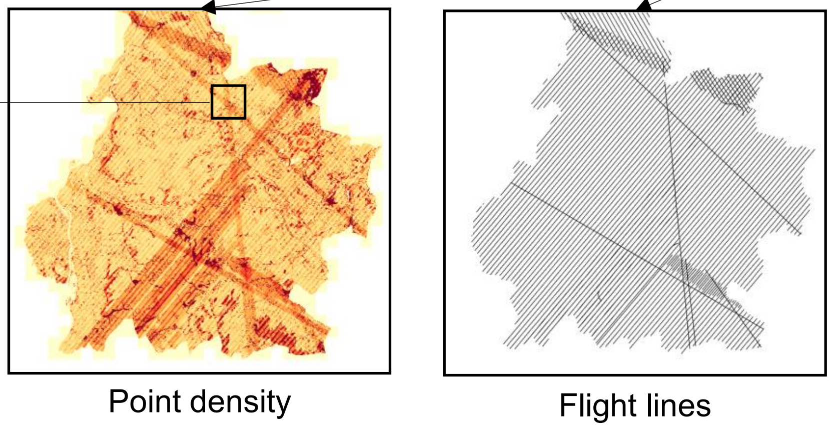
Kissling et al. 2024 *Ecological Indicators* https://doi.org/10.1016/j.ecolind.2024.112970

Variability of point densities within national ALS datasets (AHN3, The Netherlands)



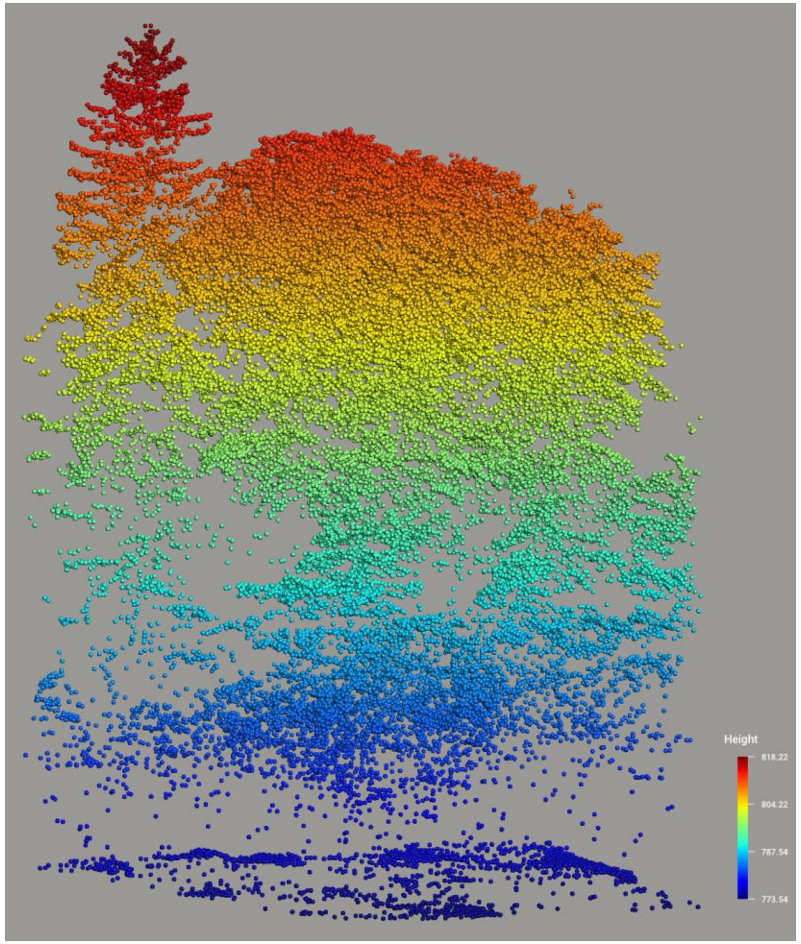
Data from Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025





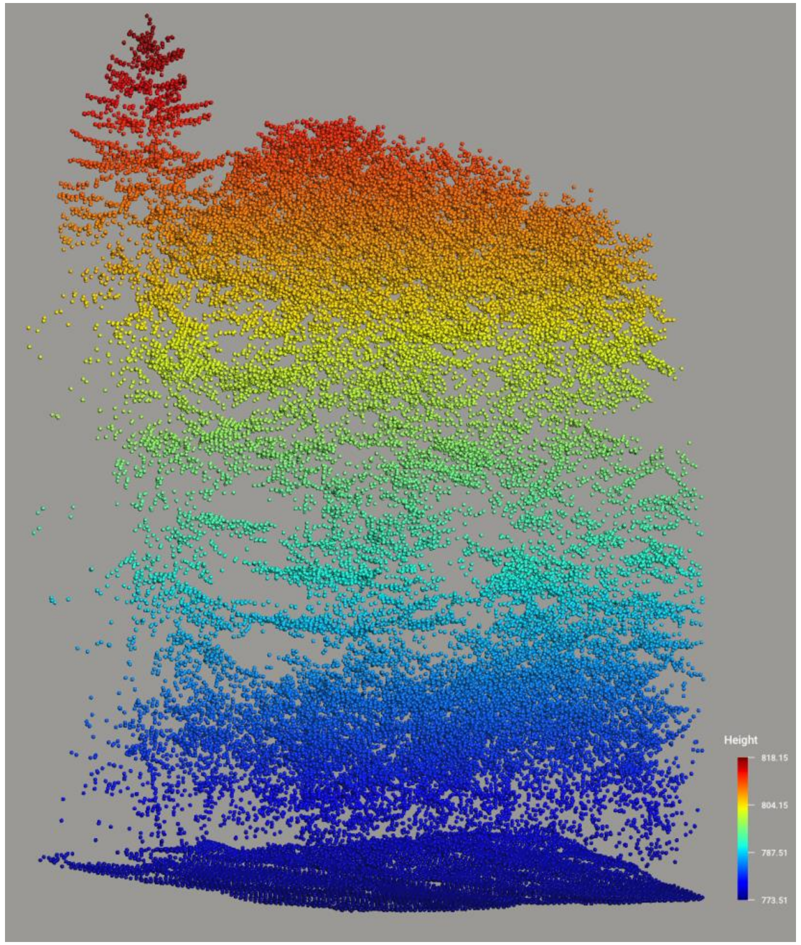
Acquisition time

<u>Leaf-on</u>



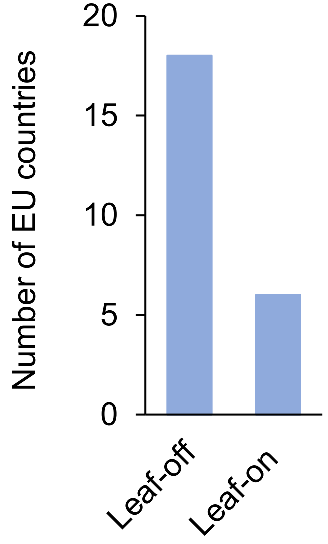
- ➢ More points in upper canopy layer
- ➢ Less points in lower layers
- ➢ Less points on ground

<u>Leaf-off</u>



- ➢ Fewer points in upper canopy layer
- ➢ More points in lower layers
- ➢ More points on ground

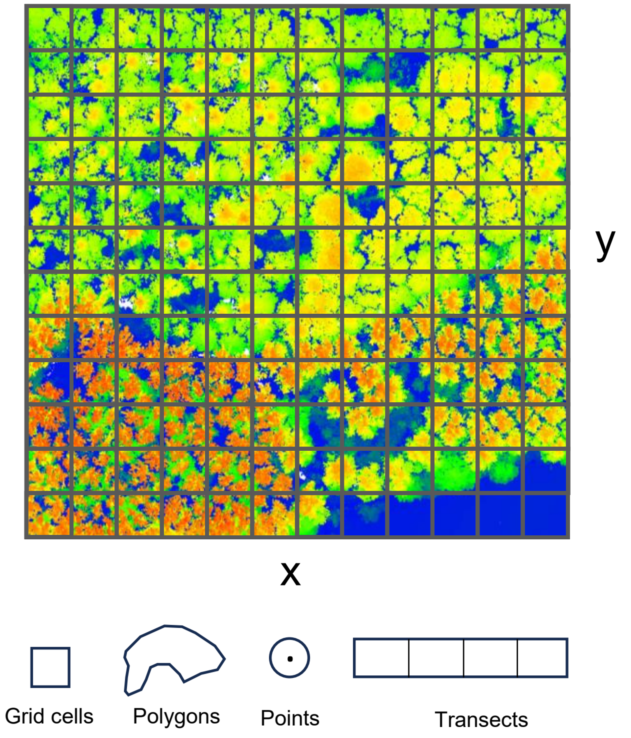
<u>Season of data acquisition across open-access (sub)national ALS point clouds in Europe</u>



Kissling et al. 2024 *Ecological Indicators*
https://doi.org/10.1016/j.ecolind.2024.112970

Processing approaches

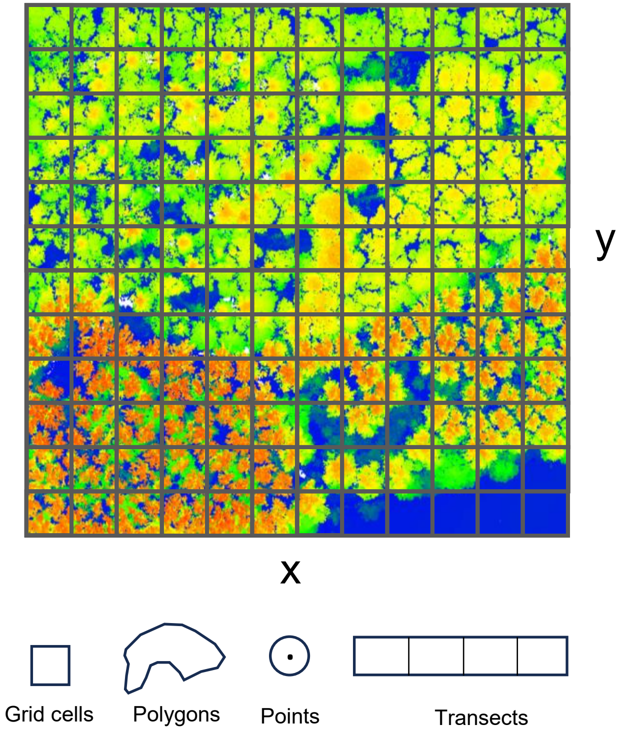
Area-based approach



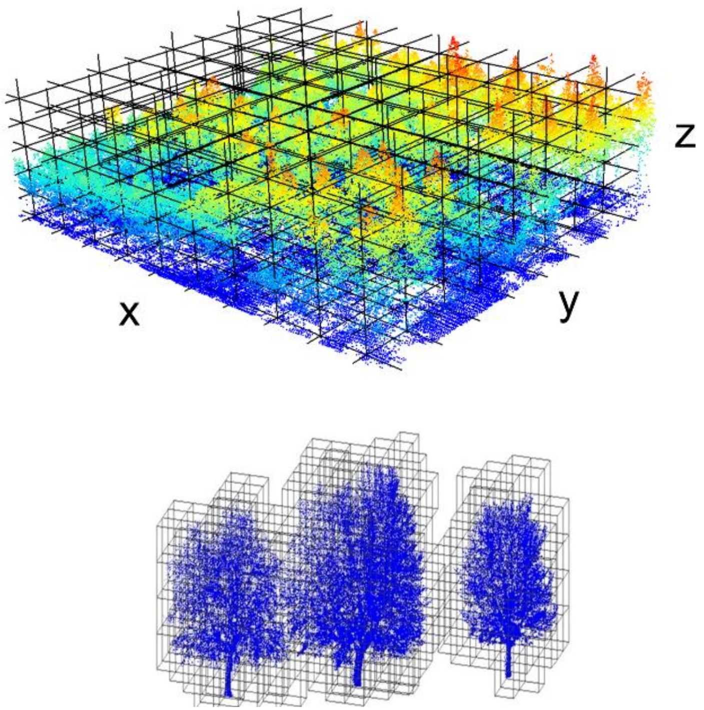
Bakx et al. 2019 *Diversity and Distributions* https://doi.org/10.1111/ddi.12915

Processing approaches

Area-based approach



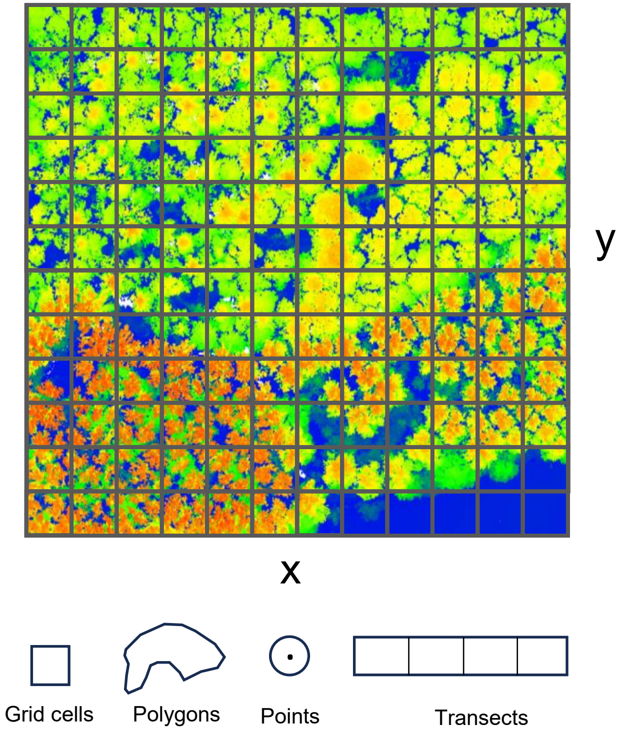
Voxel-based approach



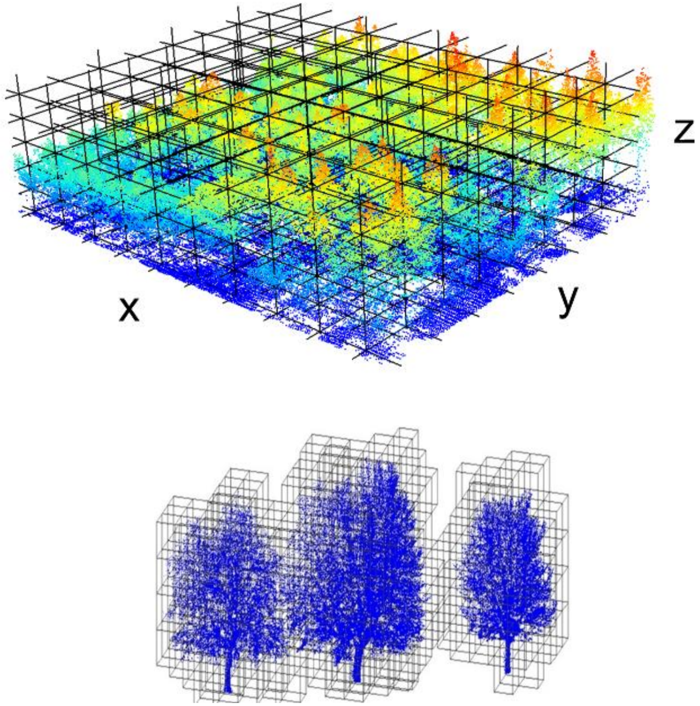
Bakx et al. 2019 *Diversity and Distributions* https://doi.org/10.1111/ddi.12915

Processing approaches

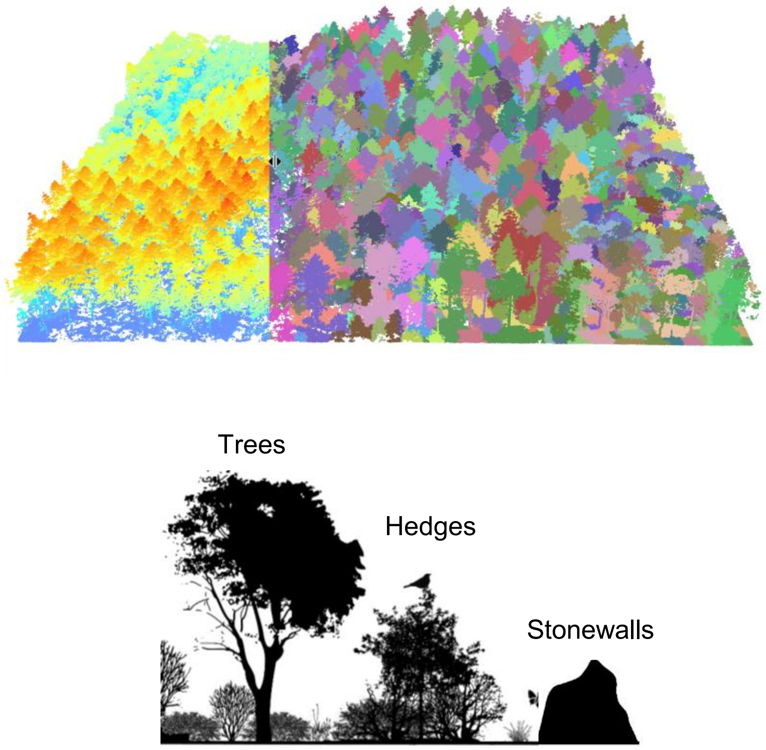
<u>Area-based approach</u>



<u>Voxel-based approach</u>



<u>Object-based approach</u>



Bakx et al. 2019 *Diversity and Distributions* https://doi.org/10.1111/ddi.12915

Program

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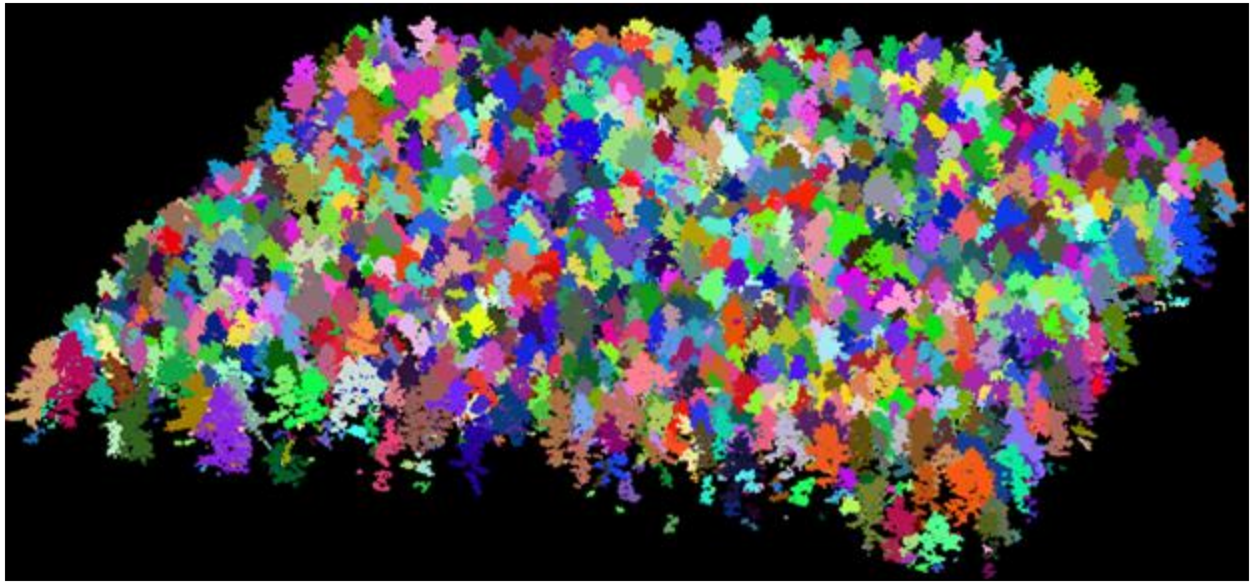
Tree individualization with airborne LiDAR data

Jinhu Wang

16th October 2025



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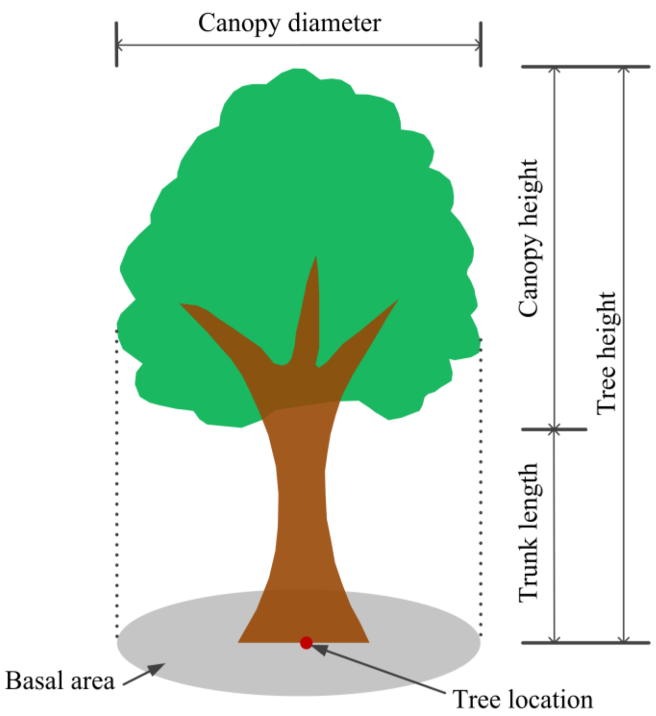
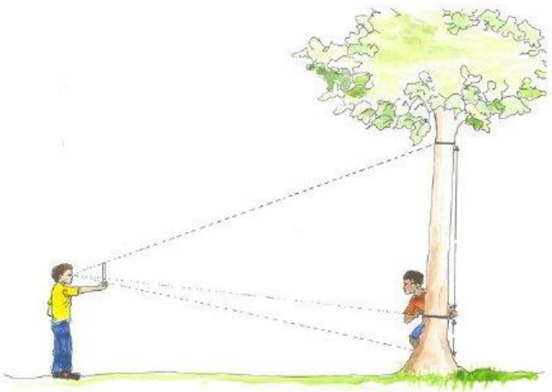
Background

Accurate individual tree metrics are foundational for understanding large-scale forest ecosystems



Key metrics:

- *tree height*
- *crown size*
- *canopy height*
- *basal area*
- *...*

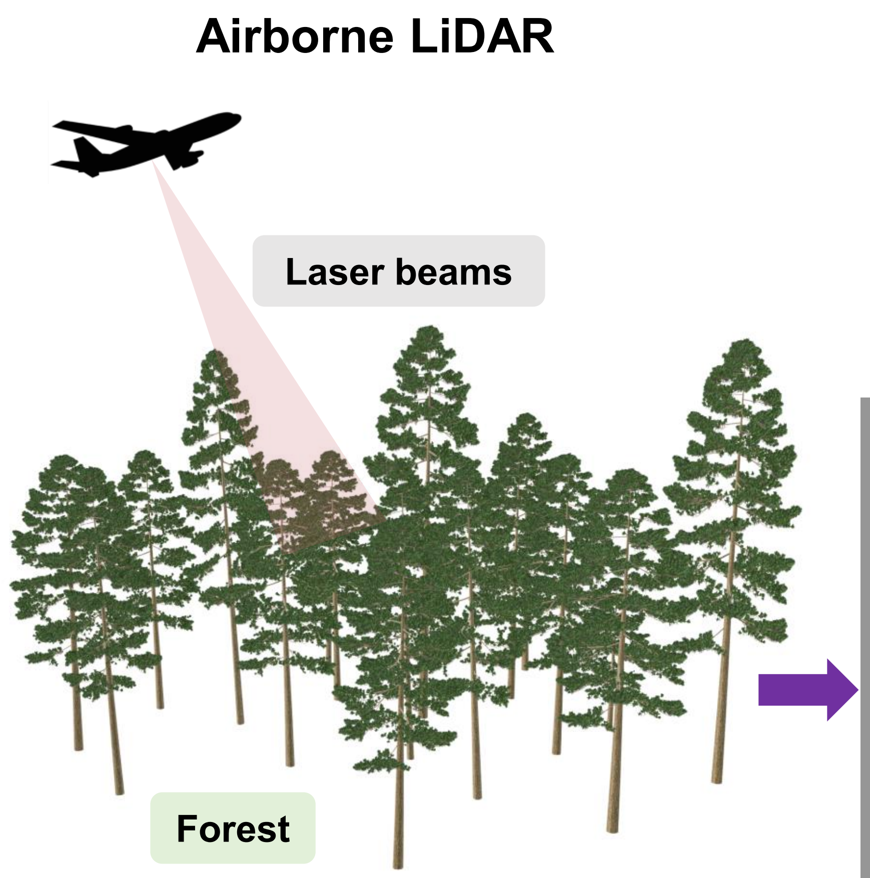


Traditional manual field forest inventories are expensive, inefficient, labor intensive, etc.

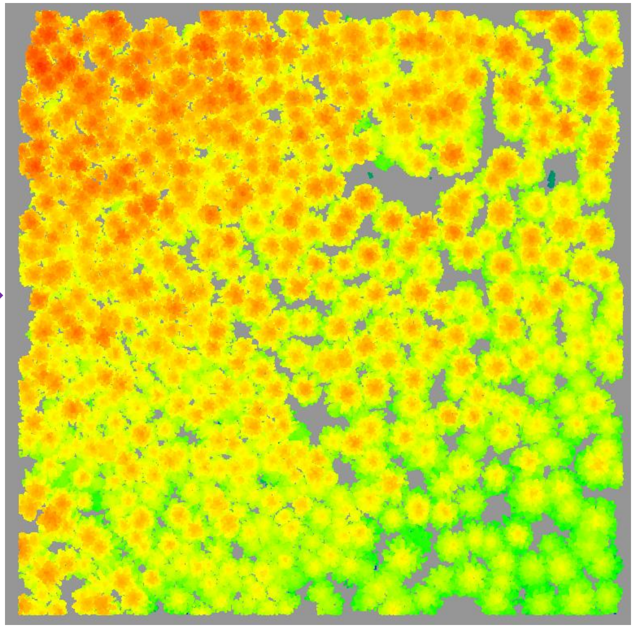
Background

Advantages:

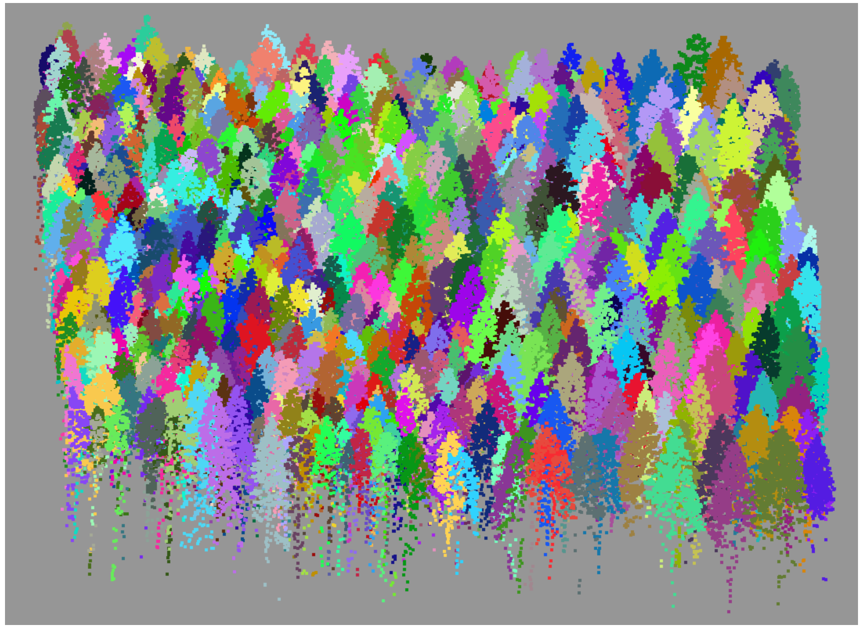
- Capture precise and detailed 3D forest structure
- Survey vast and remote forest areas
- Reduce fieldwork and labour costs
- Produce consistent and repeatable data



Top view of tree points (100m*100m)



Side view of individualized trees (100m*100m)



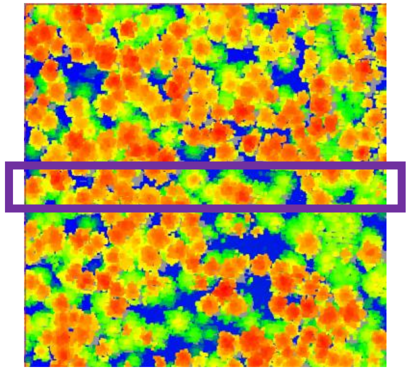
Background

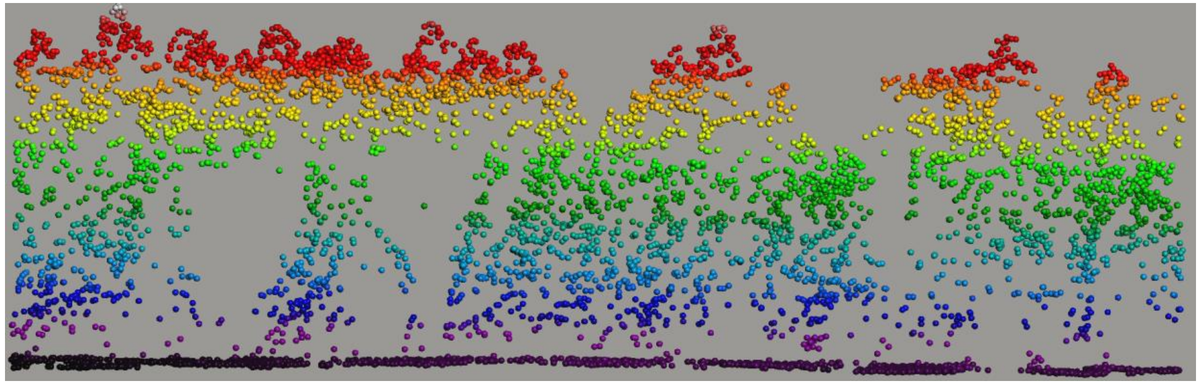
Examples of airborne LiDAR data of forests

Top view (100m*100m)

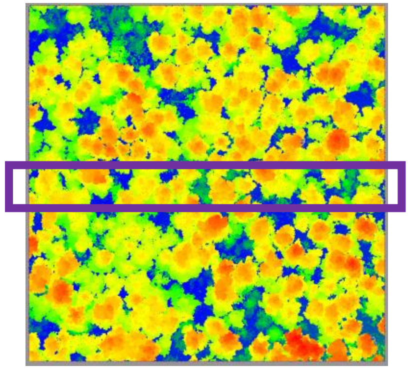
Side view (10m*100m)

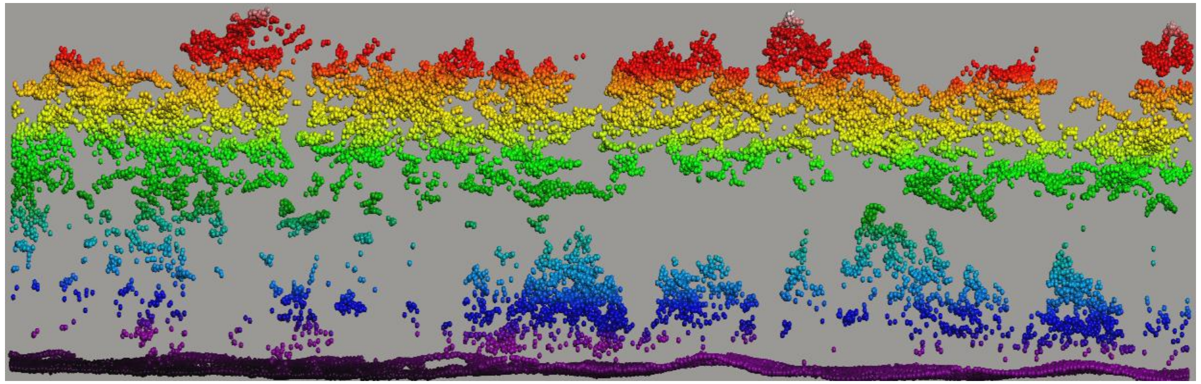
Białowieża (PLC200004)



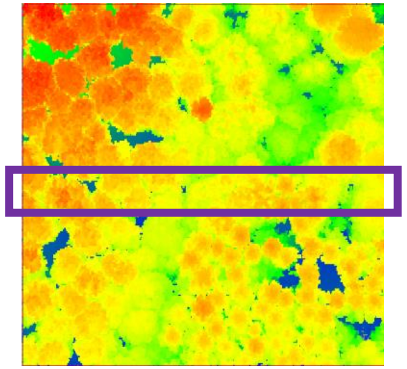


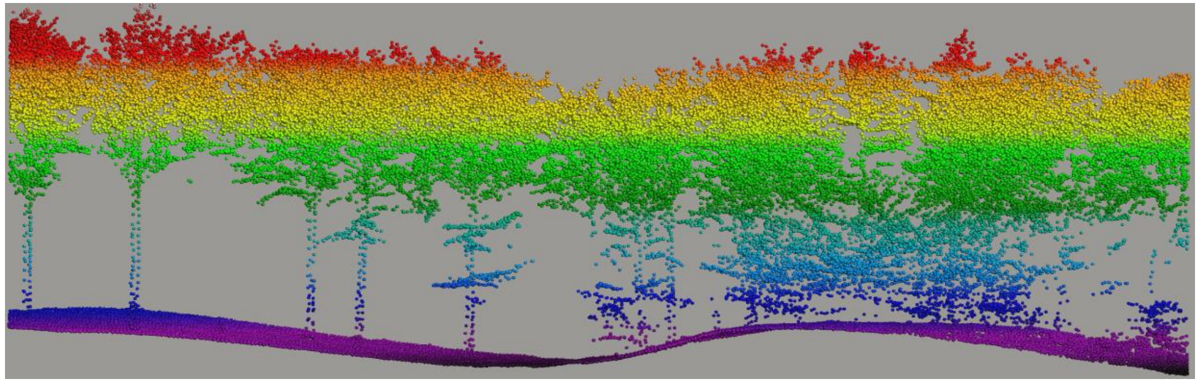
Veluwe (NL9801023)





Silkeborgskovene (DK00DY262)





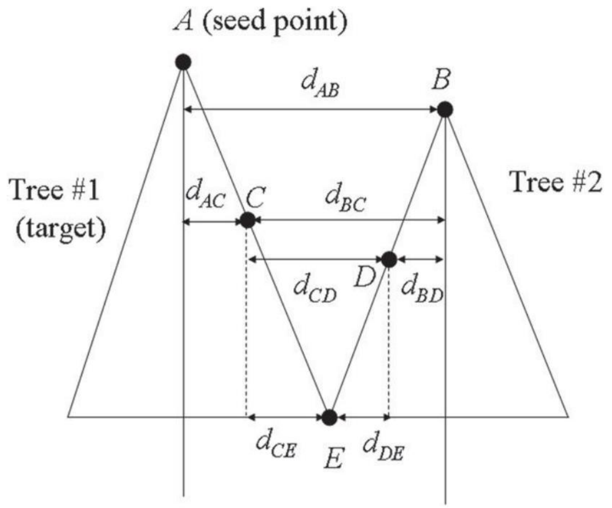
Existing methods

Categorized by algorithmic approach:

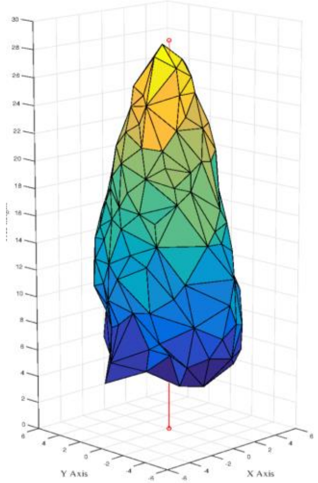
1: Geometric/Rule-based methods

Apply spatial or morphological rules from tree structure to LiDAR data

Pre-defined criteria to canopy gap, crown shape, etc.

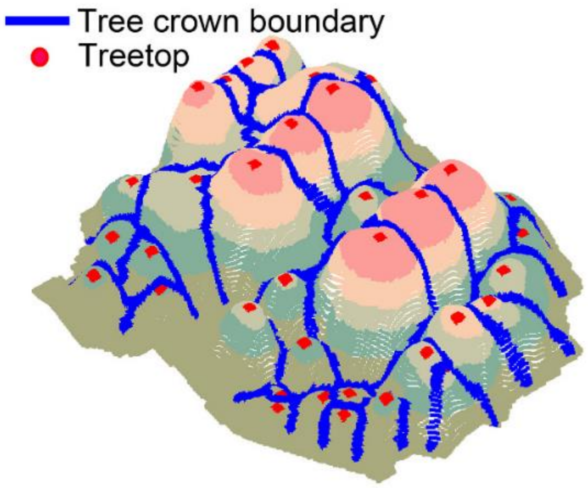


Li et al. 2012 *Photo. Eng. Re. Sens.*



Harikumar et al. 2017 *IEEE Trans. Geosci. Remote Sens.*

Canopy height model with watershed algorithms



Yun et al. 2021 *Remote Sens. Env.*

Pros:

- Computationally efficient
- Interpretable

Cons:

- Overlapping crowns
- Irregular tree shapes
- Understory trees
- Sensitive to parameter tuning

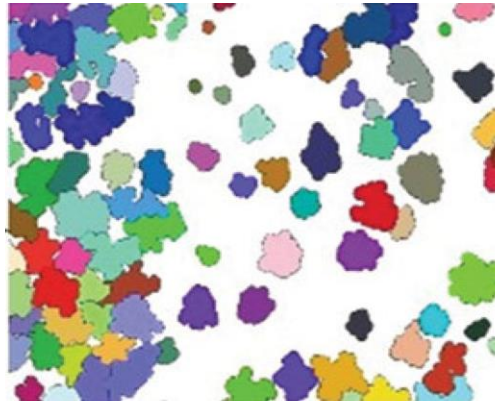
Existing methods

Categorized by algorithmic approach:

2: Clustering-based methods

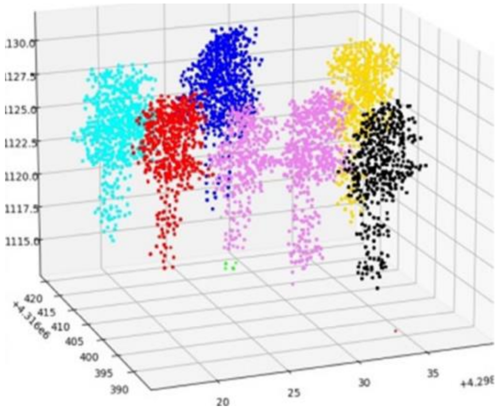
Group points/pixels/voxels based on similarity or distance metrics

Distance-based clustering
(k-means)



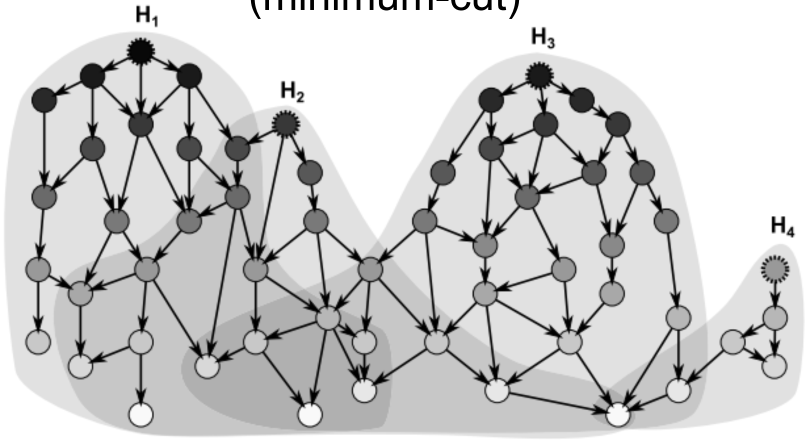
Ayrey et al. 2017 *Can. J. Remote Sens*.

Density-based clustering
(DBSCAN)



Chen et al. 2021
Open Geosci.

Graph-based clustering
(minimum-cut)



Strîmbu et al. 2017 *ISPRS J. Photo. Remote Sens.*

Pros:

- Flexible
- Require minimal prior knowledge

Cons:

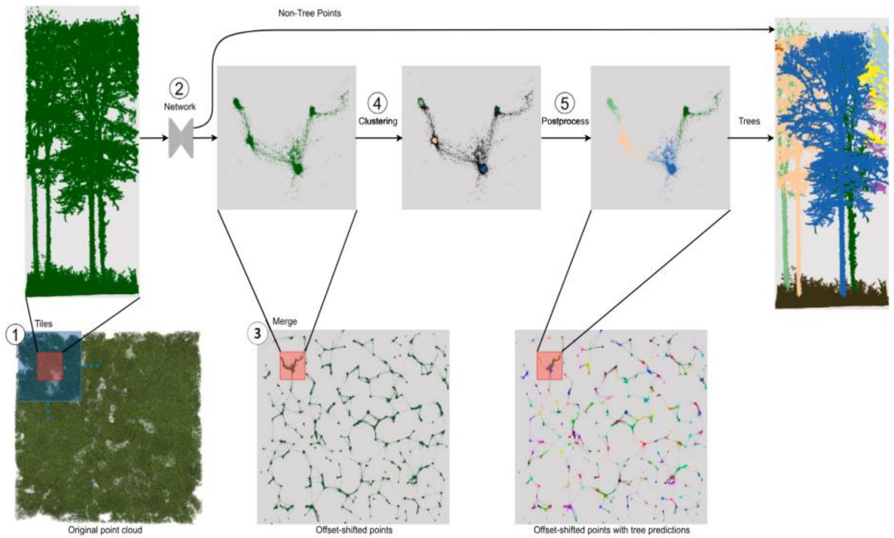
- Sensitive to thresholds
- Difficult to get optimal clusters

Existing methods

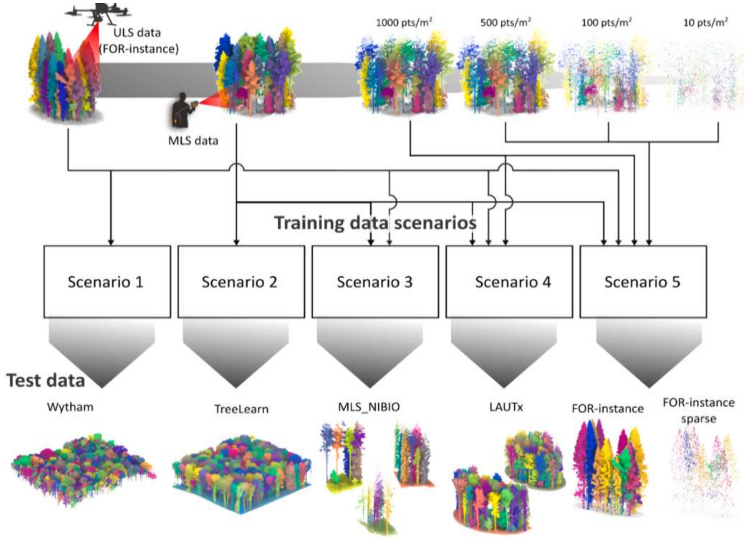
Categorized by algorithmic approach:

3: Machine learning-based methods

Train deep convolutional networks to model tree characteristics for individualization



Henrich et al. 2024
Ecological Informatics



Wielgosz et al. 2024 *Remote Sensing of Environment*

Pros:

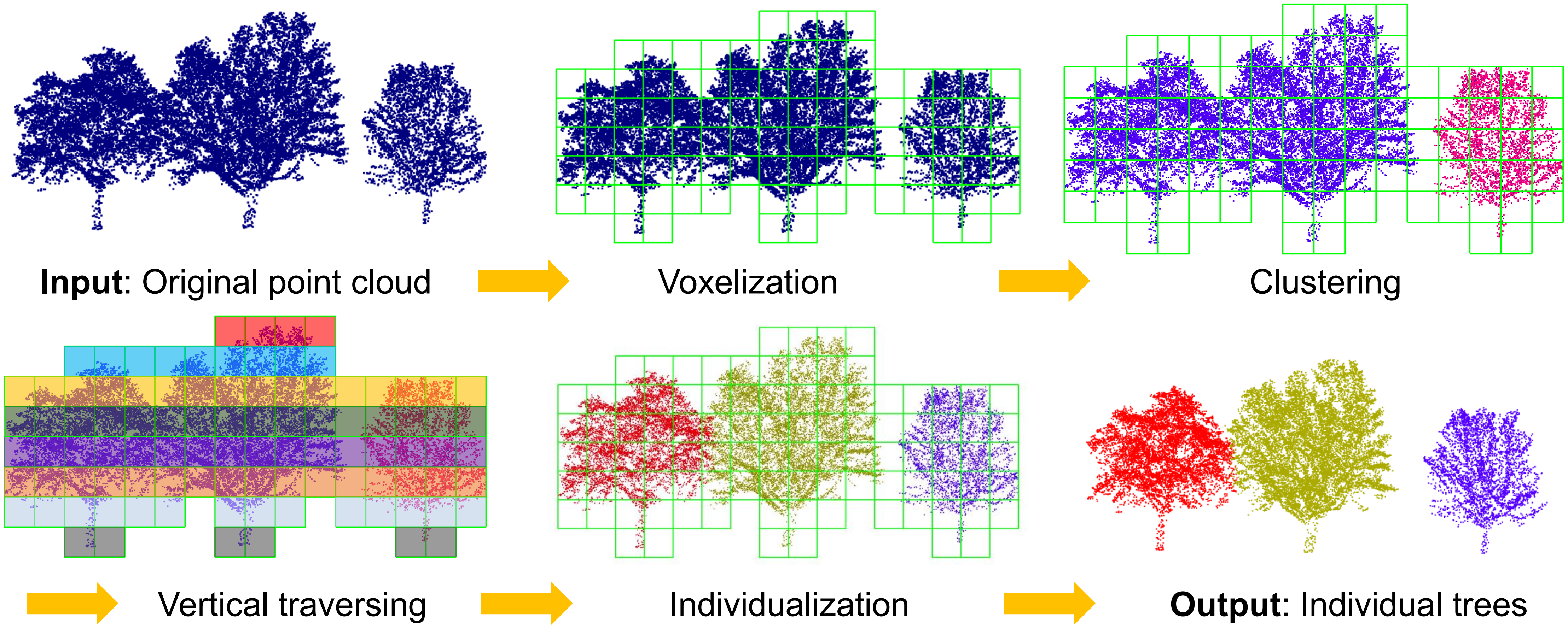
- End-to-end models
- Achieve high accuracy when trained on sufficient annotated data

Cons:

- Require substantial training datasets and computational resources
- Less interpretable & transferable
- Few available training datasets for ALS

Methodology

Tree individualization using voxel clustering and adjacency analysis

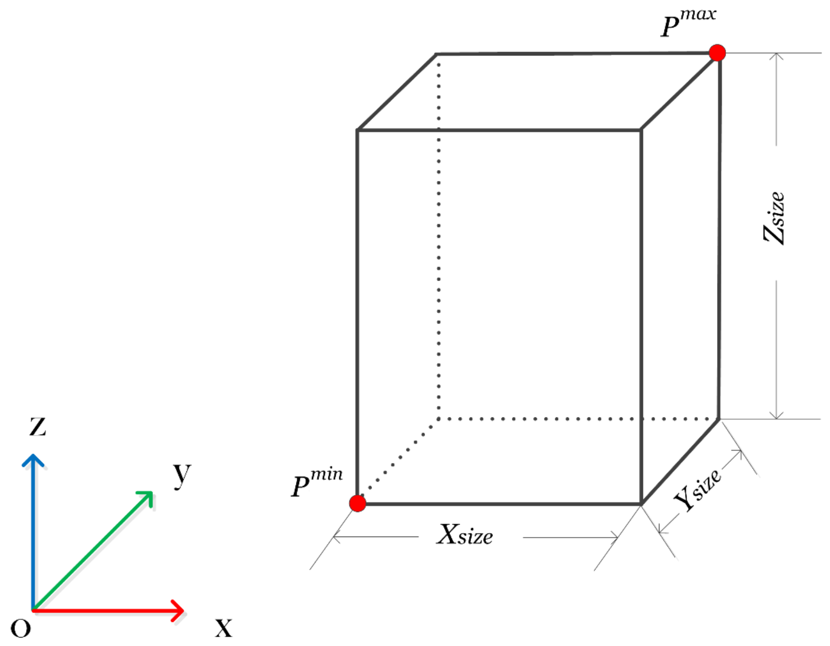


Wang et al. 2018 *The Photogrammetric Record* https://doi.org/10.1111/phor.12247

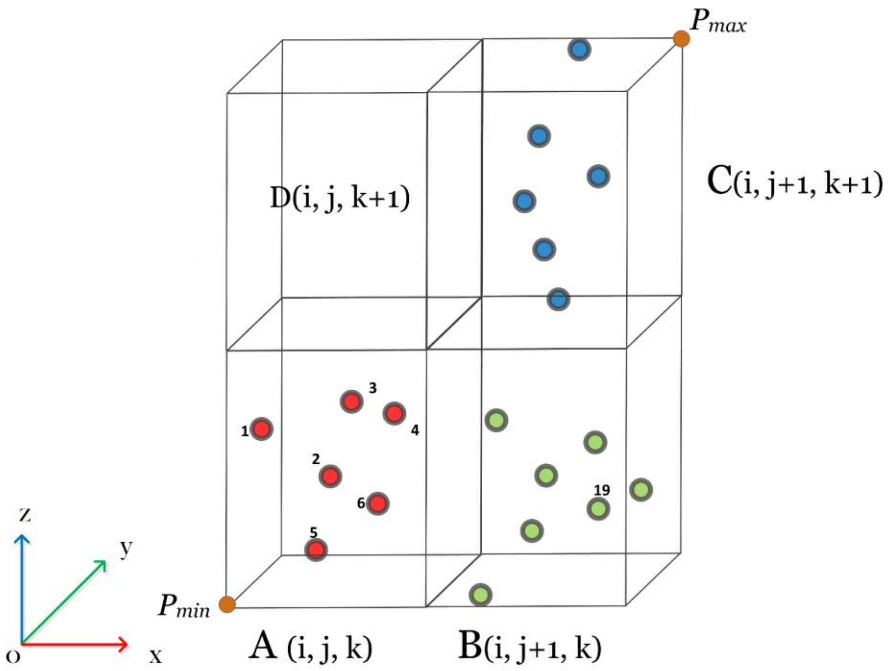
Methodology

Tree individualization using voxel clustering and adjacency analysis

Voxelization of point cloud



Voxel structure



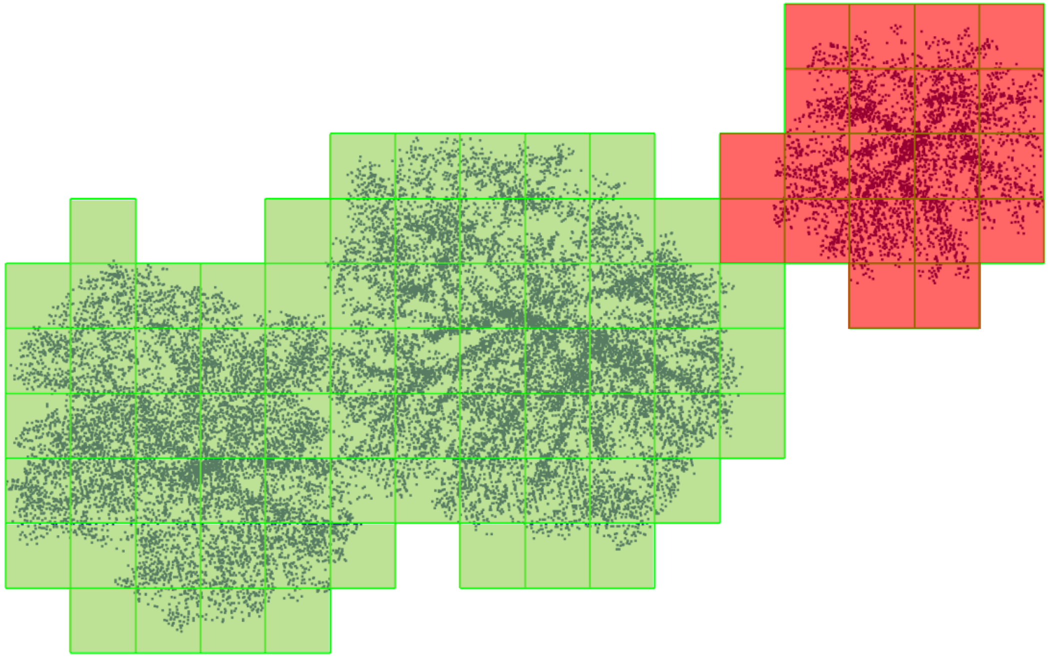
Voxelization of tree points

Wang et al. 2018 *The Photogrammetric Record* https://doi.org/10.1111/phor.12247

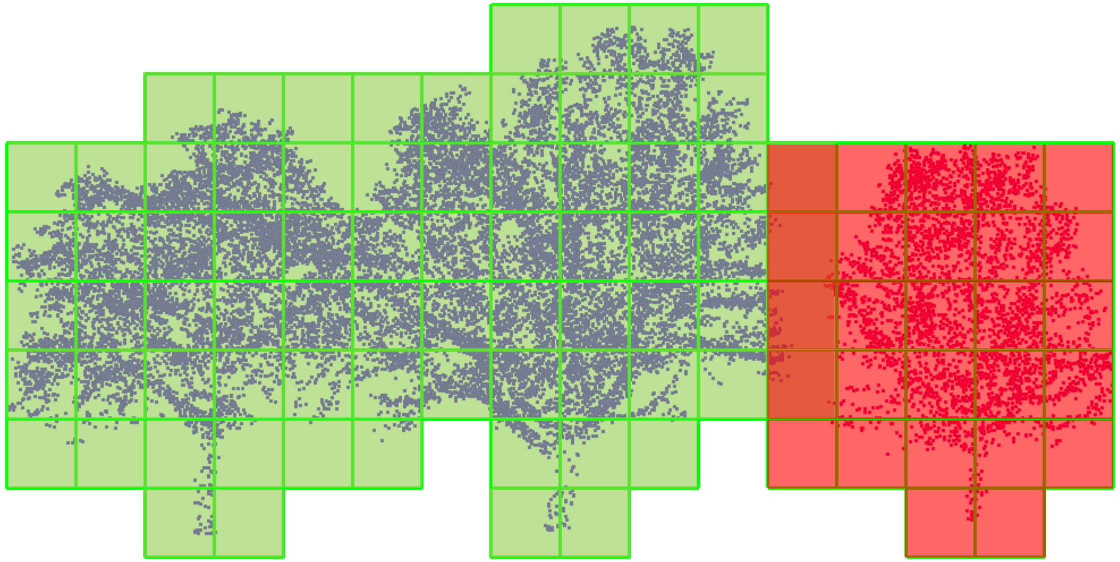
Methodology

Tree individualization using voxel clustering and adjacency analysis

Clustering based on voxel-face connectivity



Face-adjacent voxel clustering (top view)



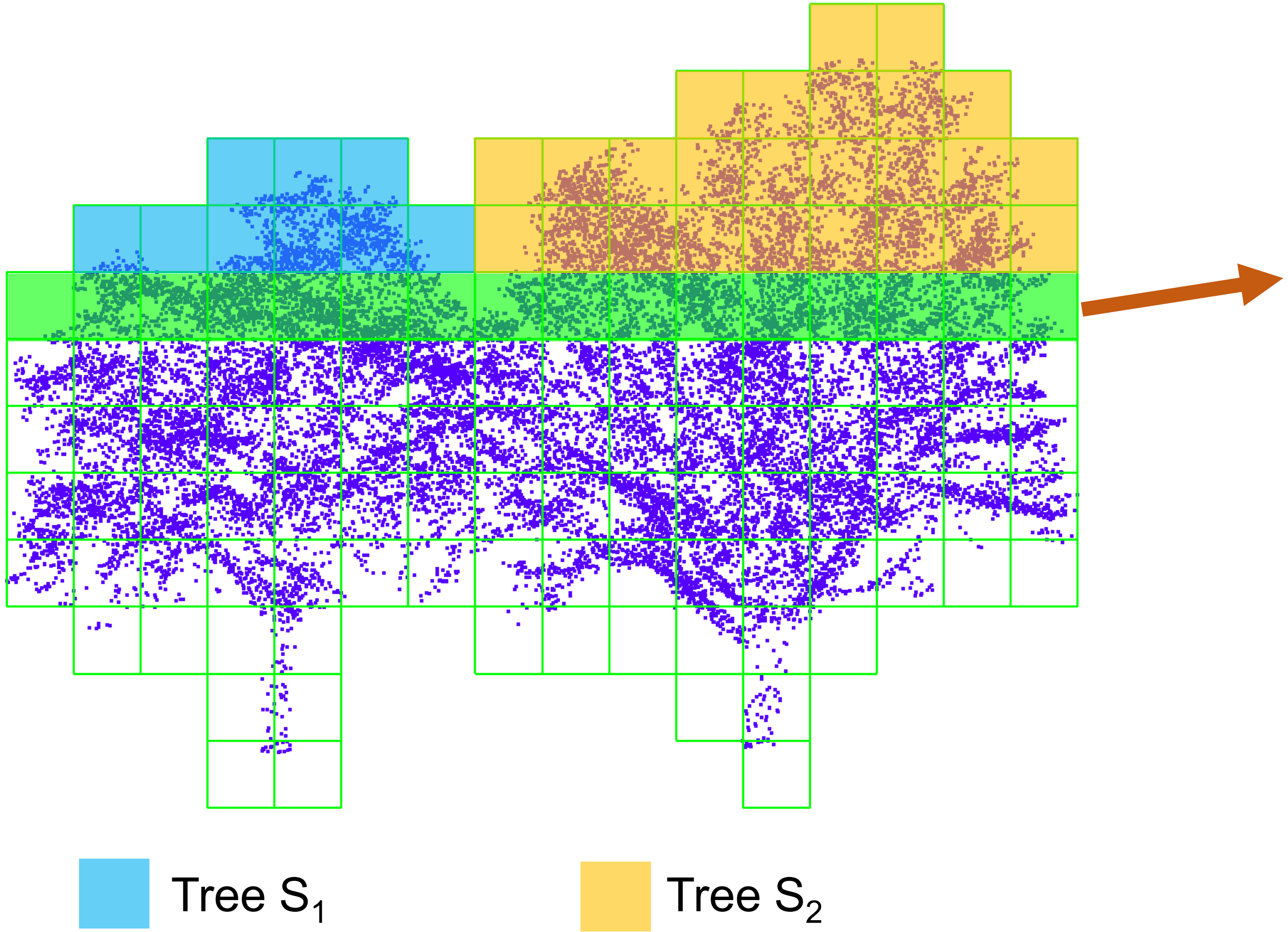
Face-adjacent voxel clustering (side view)

Wang et al. 2018 *The Photogrammetric Record* https://doi.org/10.1111/phor.12247

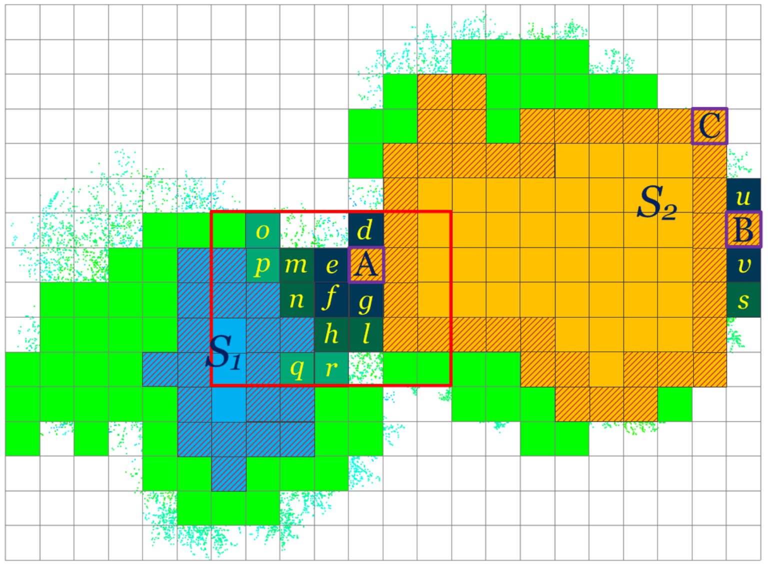
Methodology

Tree individualization using voxel clustering and adjacency analysis

Vertical traversing – top layer downwards



Top view



Adjacency coefficient:

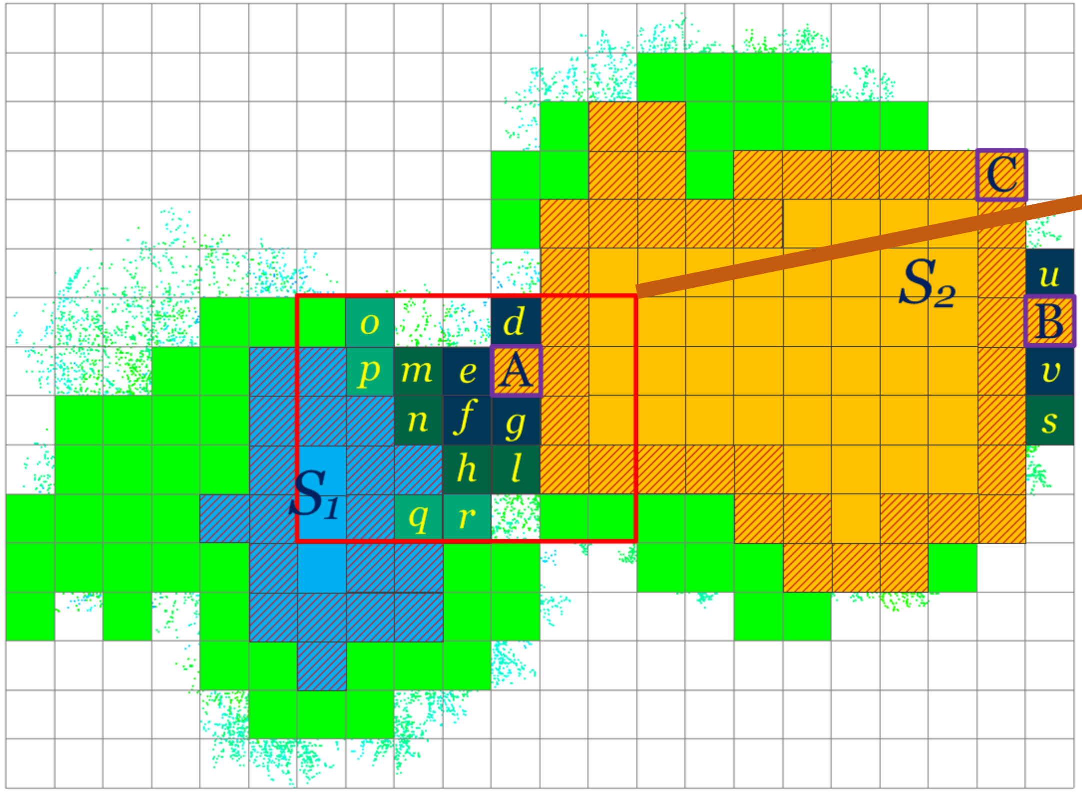
$$c = C^N \times \frac{f_0}{R(k)}$$

Methodology

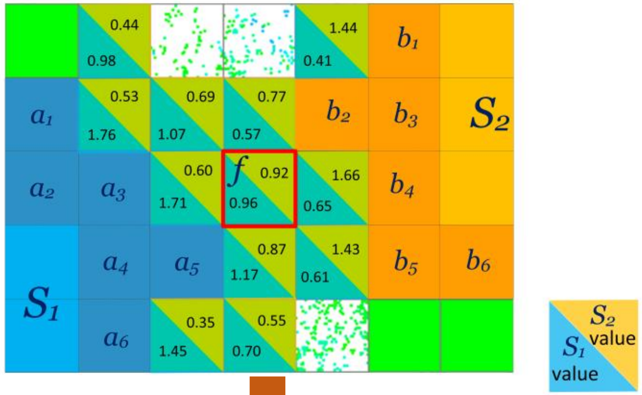
Tree individualization using voxel clustering and adjacency analysis

Voxel adjacency coefficient computation

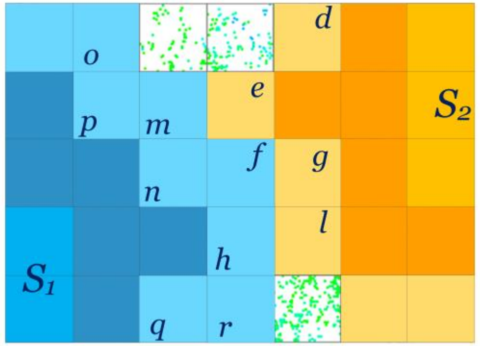
Top view



Computed coefficient



Assign voxel to trees

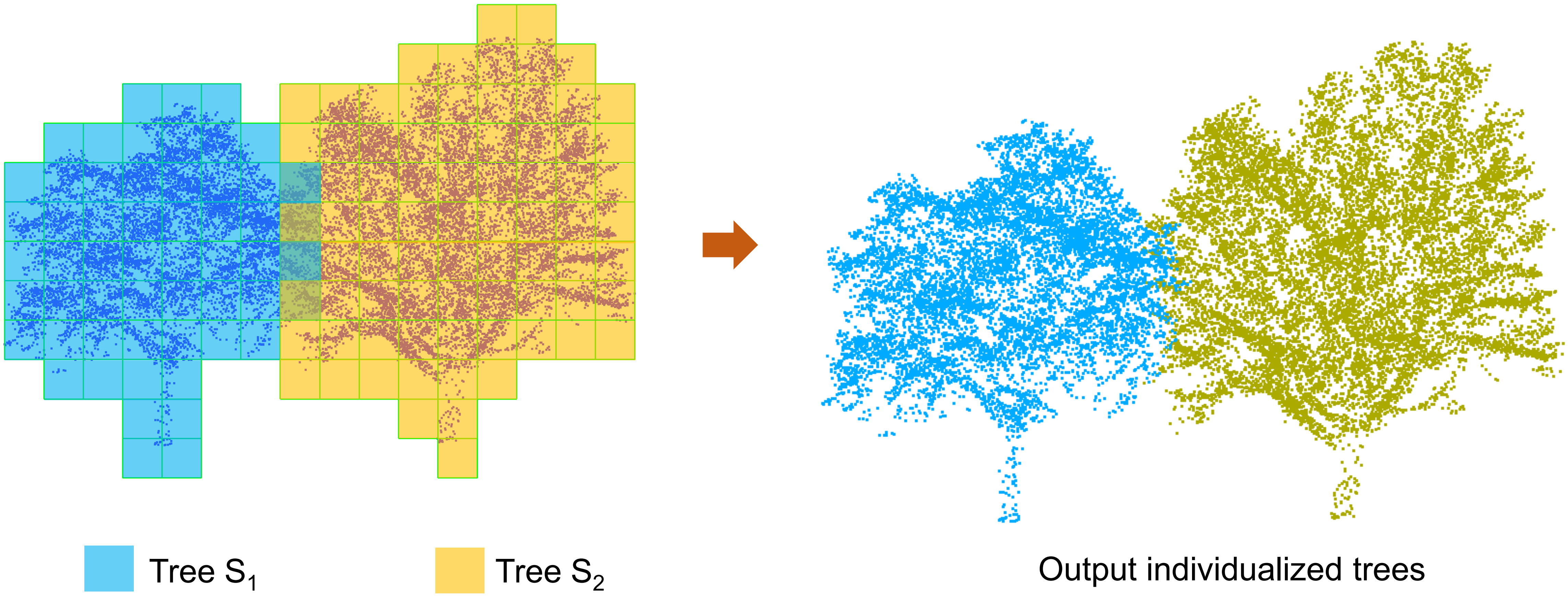


Wang et al. 2018 *The Photogrammetric Record* https://doi.org/10.1111/phor.12247

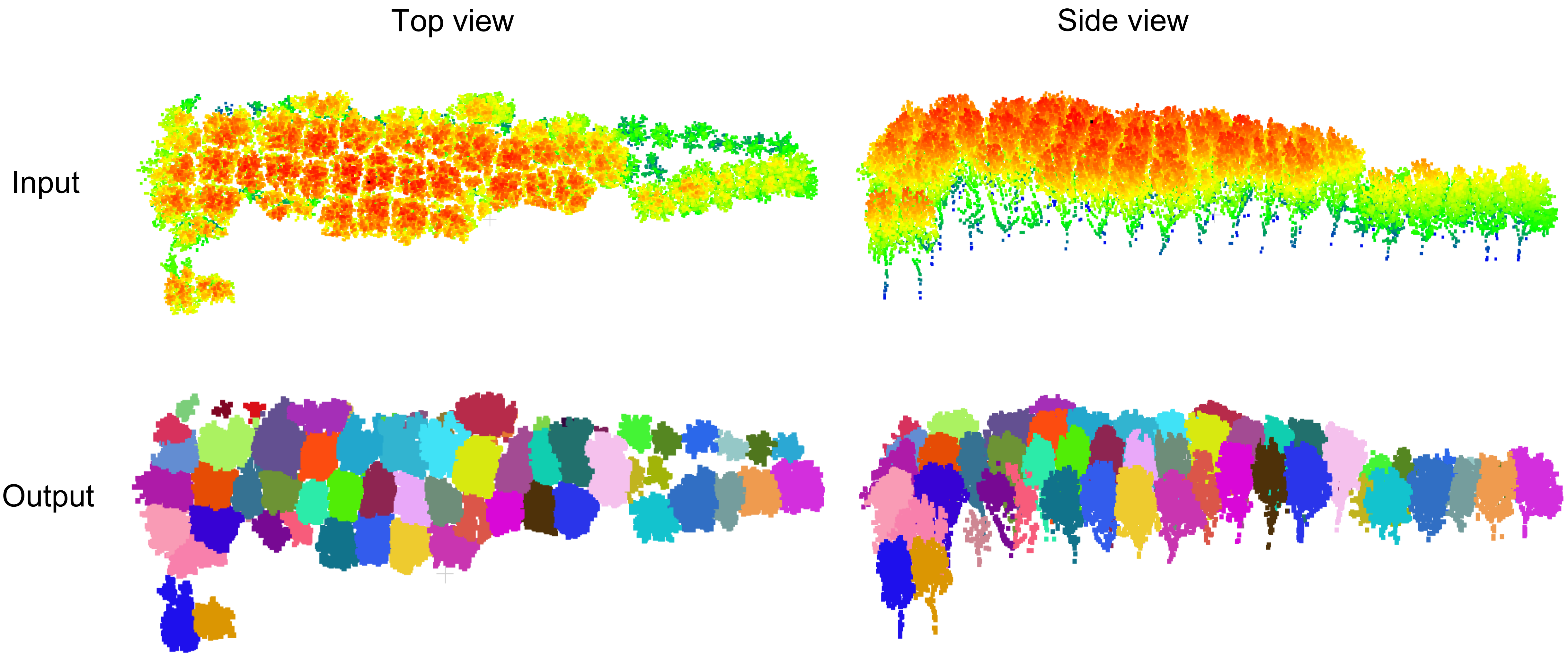
Methodology

Tree individualization using voxel clustering and adjacency analysis

Assign points in voxels to trees

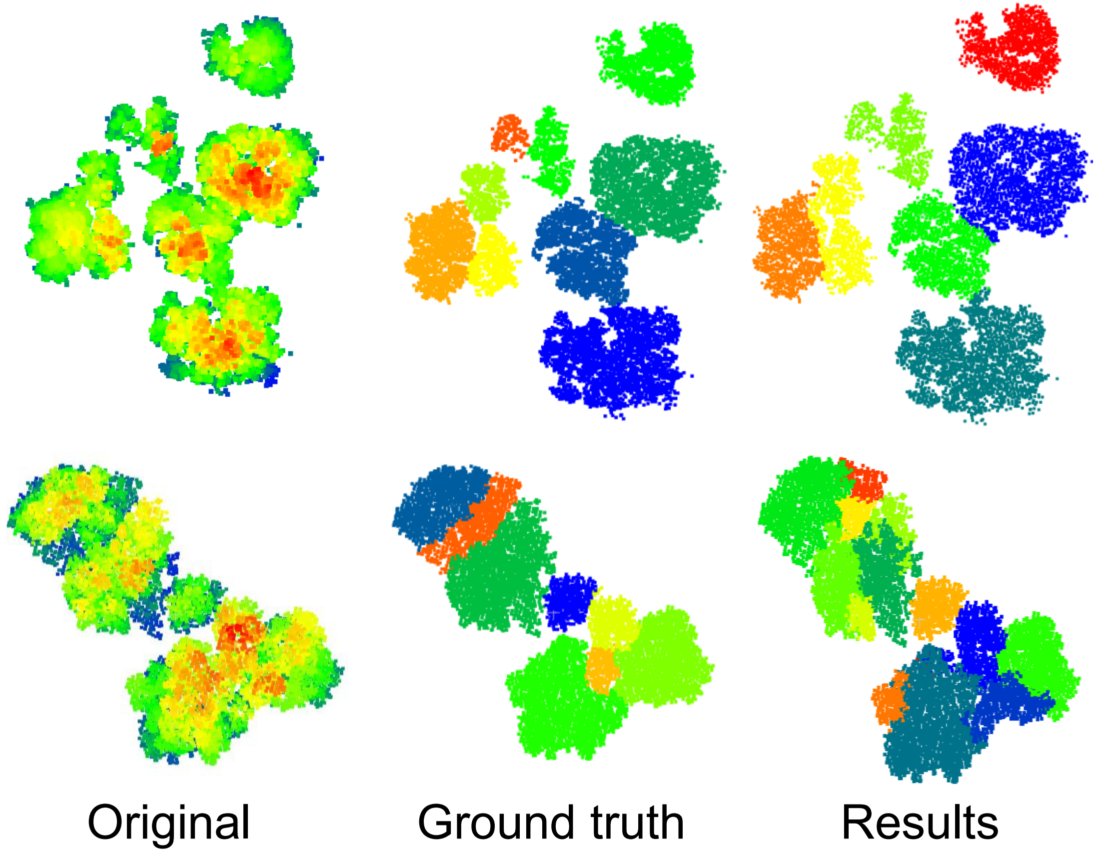


Results



Validation

A total of 20 patches of trees were manually labelled as ground truth

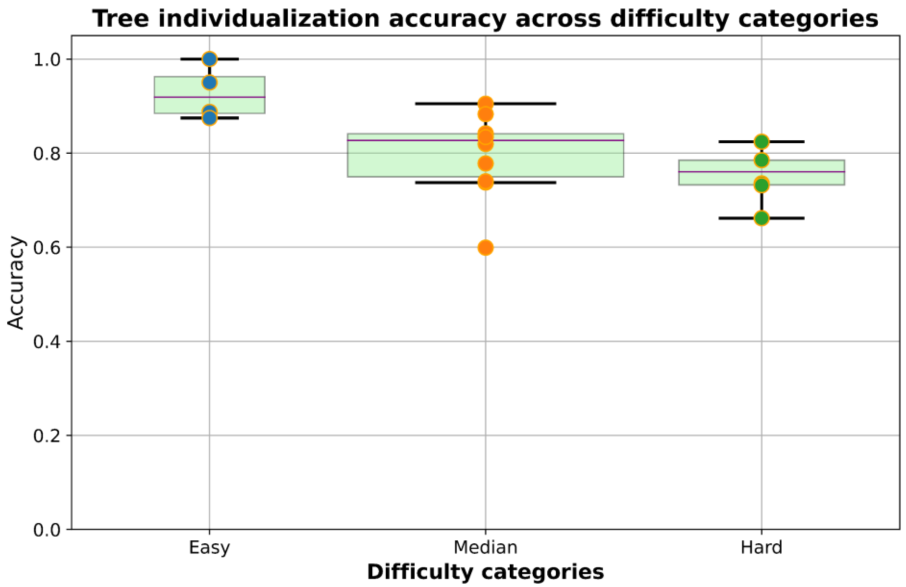


Accuracy metric:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Overall accuracy of the 20 patches:

$$Accuracy = 0.81 \pm 0.09$$



Source code & data: https://github.com/Jinhu-Wang/Tree_Classification_and_Individualization_In_Marsh_Area

Conclusions

- Airborne LiDAR point cloud data allows to delineate individual trees
- Point densities and tree species identity can influence the accuracy of tree individualization
- Individualization is challenging for dense and mixed-species forests
    - Varying tree species and sizes usually cause commissions
    - Fewer points obtained from understory trees, typically leads to omissions

Future work

- Extracting individual tree metrics, i.e. canopy projected area, height, canopy diameter, crown volume, etc.
- Testing transferability of the workflow (large-extent data, varying point densities)
- Modifying current method with new cluster aggregation algorithm

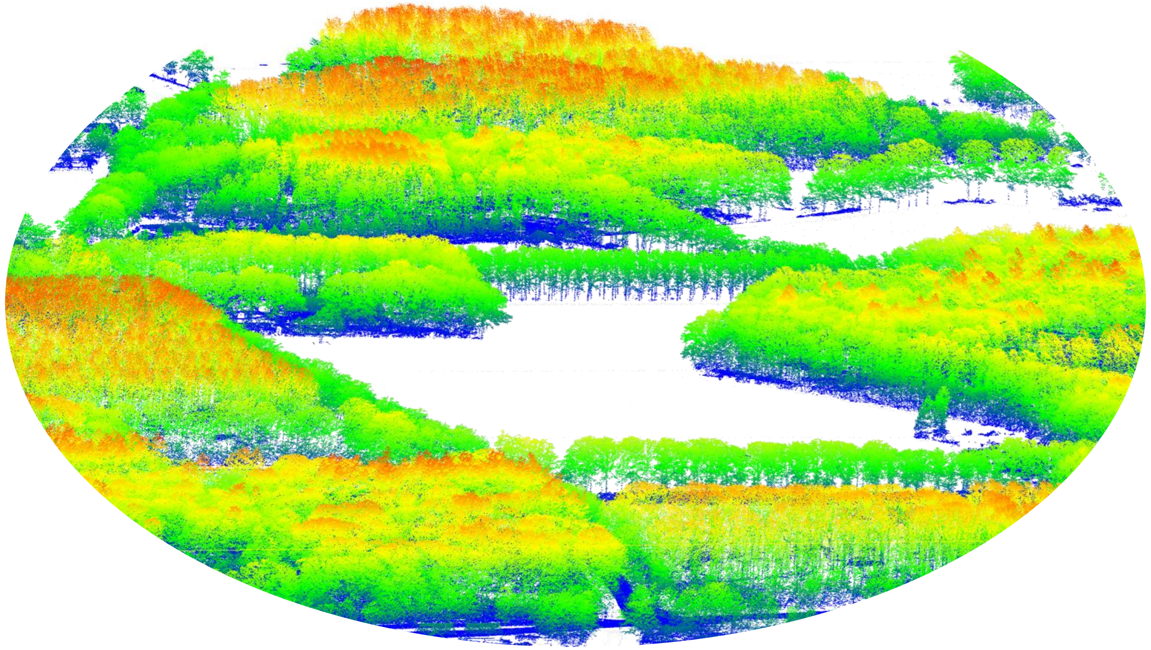
Program

1. **Introduction to airborne laser scanning** (10 min, W.D. Kissling)
2. **Identifying and mapping individual trees** (10 min, J. Wang)
3. **Mapping 3D vegetation structures** (15 min, Y. Shi)
4. **Measuring trail networks of large herbivores** (15 min, J. Wang)
5. **Wrap-up with available resources** (10 min, W.D. Kissling)

University of Amsterdam
Faculty of Science

Institute for Biodiversity and Ecosystem Dynamics

Mapping the spatial distribution of 3D vegetation structures



Yifang Shi

16th October 2025

MAMBO

Funded by the European Union

Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the EU nor the EC can be held responsible for them.

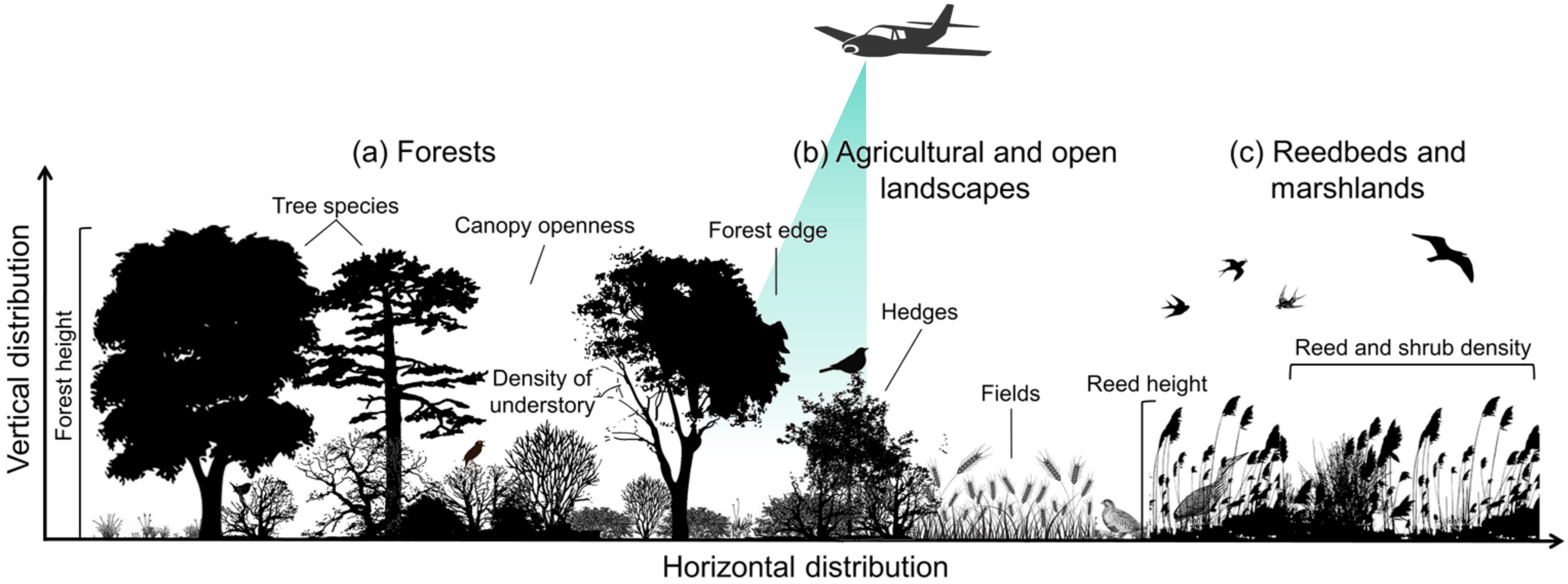
Mapping ecosystem structure using LiDAR

Why quantifying vegetation structure?

- Animal ecology (e.g. habitat, distribution, richness)
- Sustainable forest management
- Biodiversity and ecosystem monitoring

Why LiDAR?

- Precise and spatially contiguous measurement
- Penetrates through canopy (understory and terrain)
- Complementary to other RS data sources

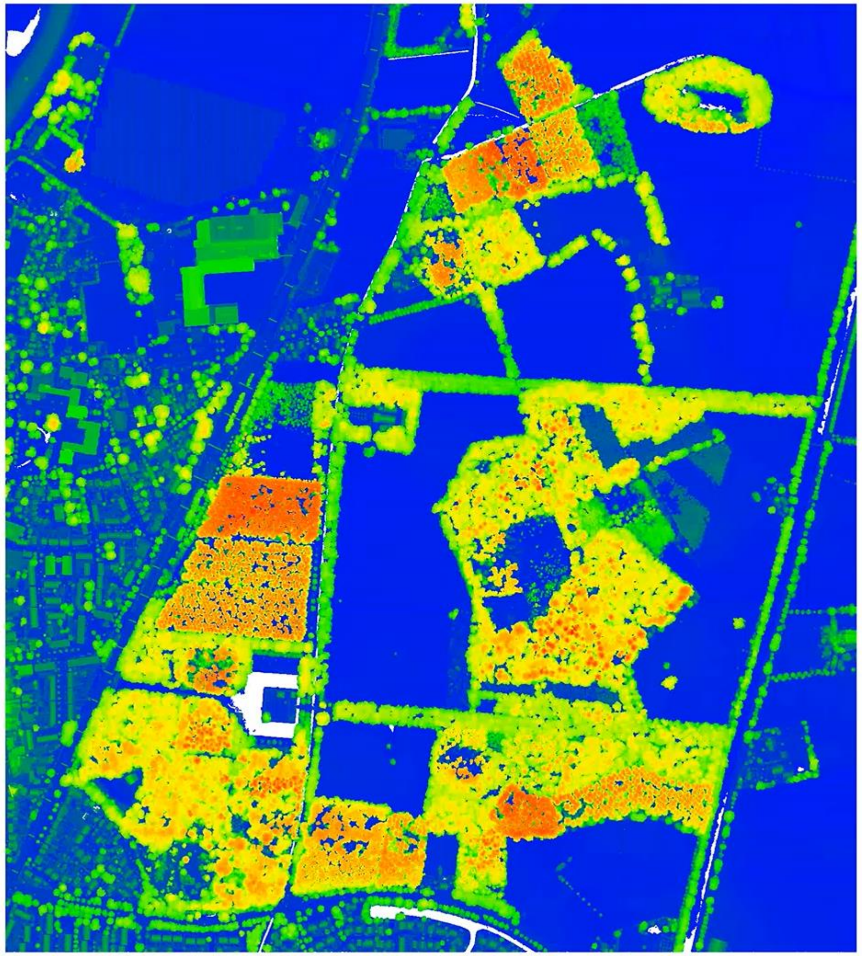


Kissling et al. 2017 *Research Ideas and Outcomes* https://doi.org/10.3897/rio.3.e14939

Mapping ecosystem structure using LiDAR

Google Earth Pro Image

Airborne LiDAR point cloud



How do we characterize 3D point cloud?

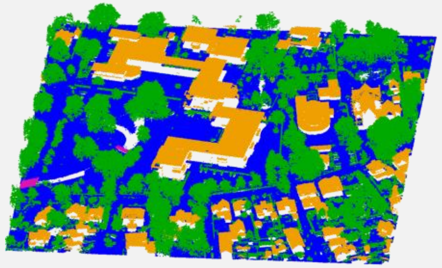
Raw point cloud

ASPRS point data format

Item
X
Y
Z
Intensity
Return Number
Number of Returns (Given Pulse)
Scan Direction Flag
Edge of Flight Line
Classification
Scan Angle Rank (-90 to +90) – Left Side
User Data
Point Source ID
GPS Time

Preprocessing

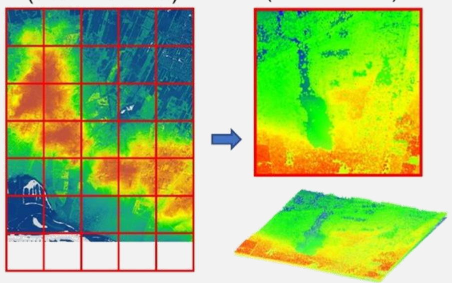
(re-) Classification



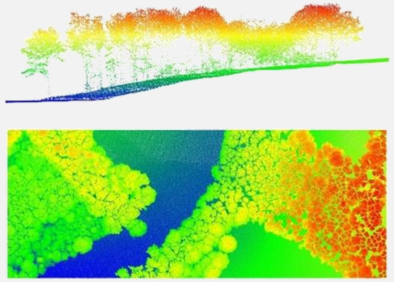
Re-tiling

Single raw LAZ tile (5 km × 6.5 km)

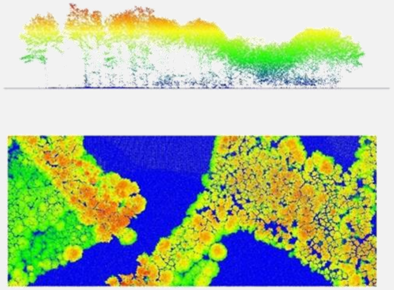
Single re-tiled file (1 km × 1 km)



Normalization

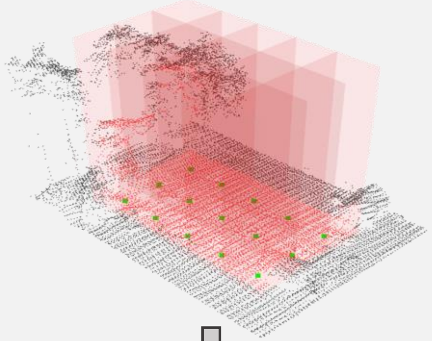


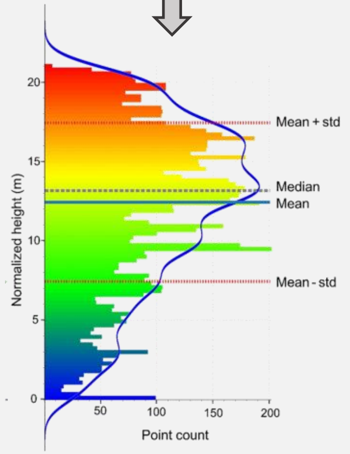
Subtract ground elevation



Metrics extraction

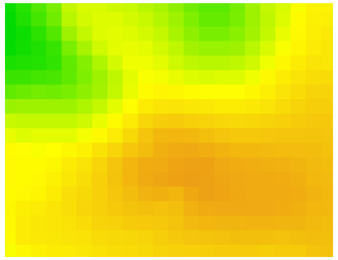
Define geometry volume



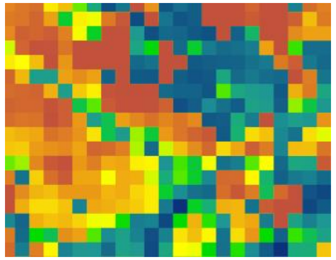


Metrics Output

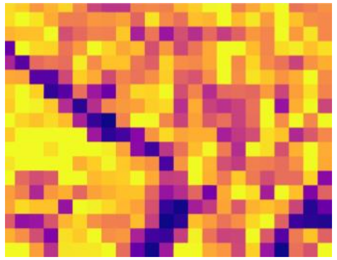
Digital Terrain Model



Vegetation height



Canopy openness

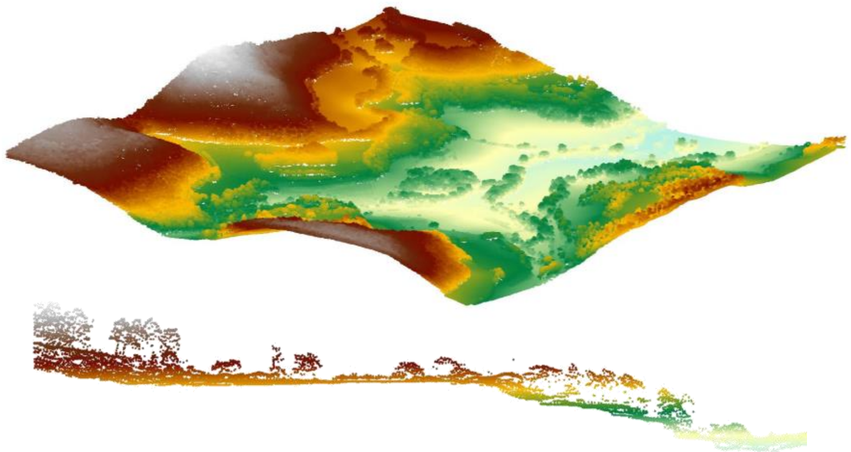


ASPRS: LAS Specification 1.4-R15, 2019.

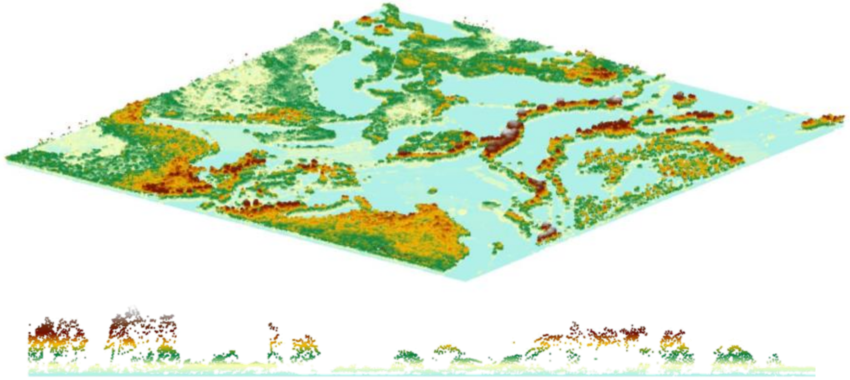
Kissling et al. 2022 *Ecological Informatics* https://doi.org/10.1016/j.ecoinf.2022.101836

Normalization

Raw point cloud



Normalized point cloud



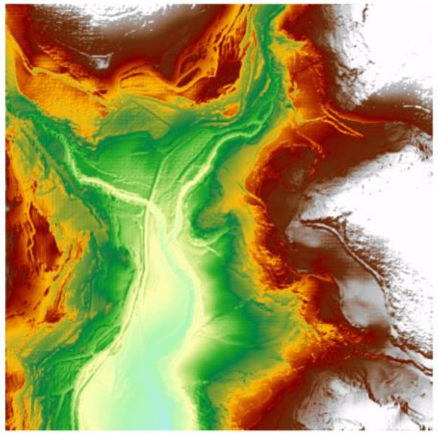
Data source: [Country-wide ALS campaign from Spain]
Location: Barcelona
Collected year: 2017

(1) Normalizing using a DTM

Methods to generate a DTM

- Triangular irregular network (TIN)
- Kriging algorithm
- Invert distance weighting

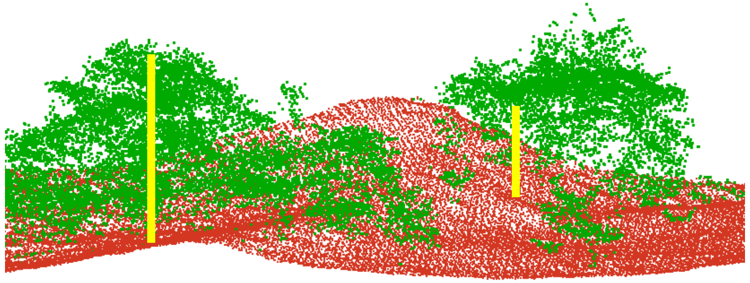
Digital Terrain Model



(2) Normalizing without using a DTM

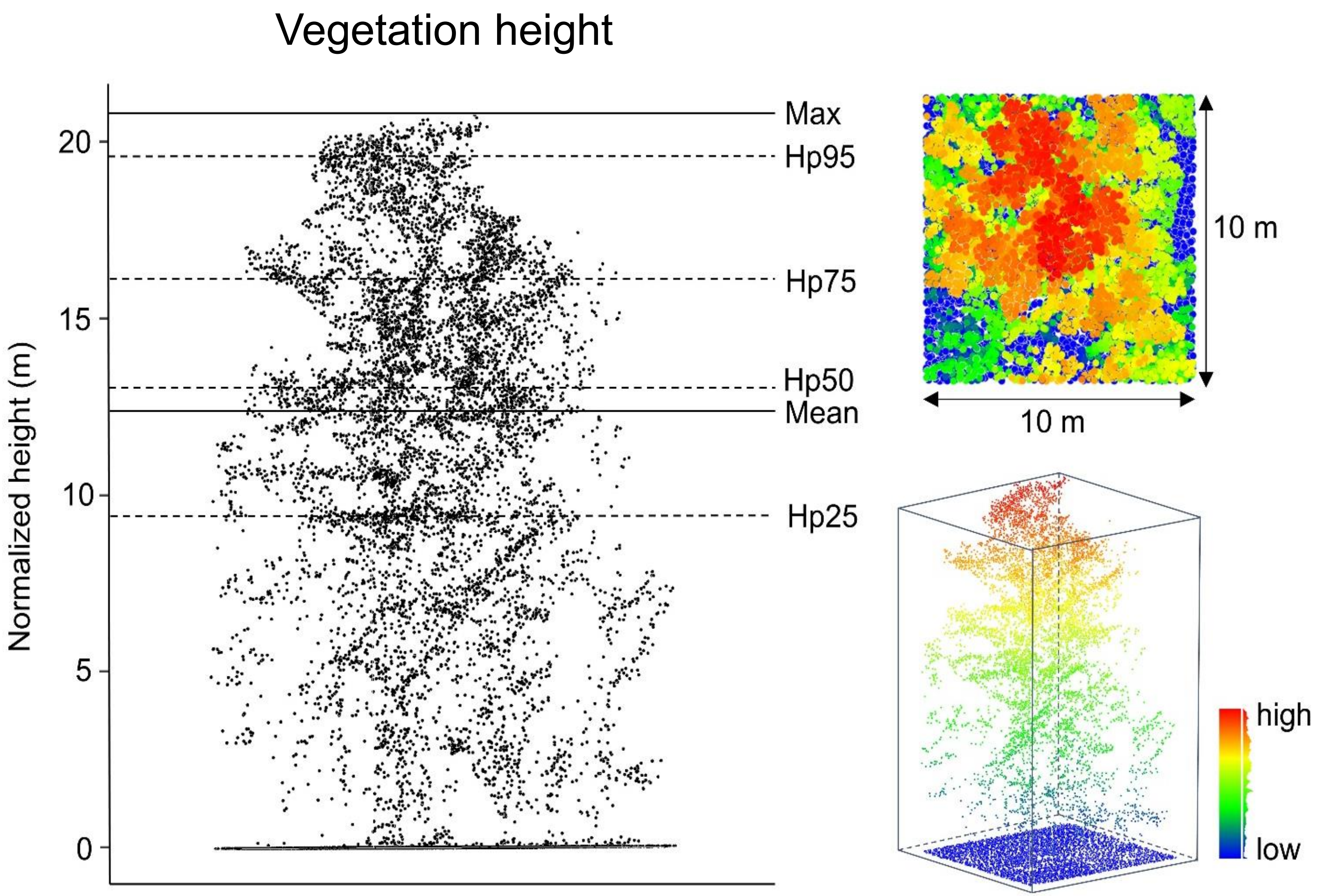
Interpolating the elevation of non-ground points using the exact position of ground points beneath

- Vegetation points
- Ground points



What are the metrics?

LiDAR metrics of vegetation structure



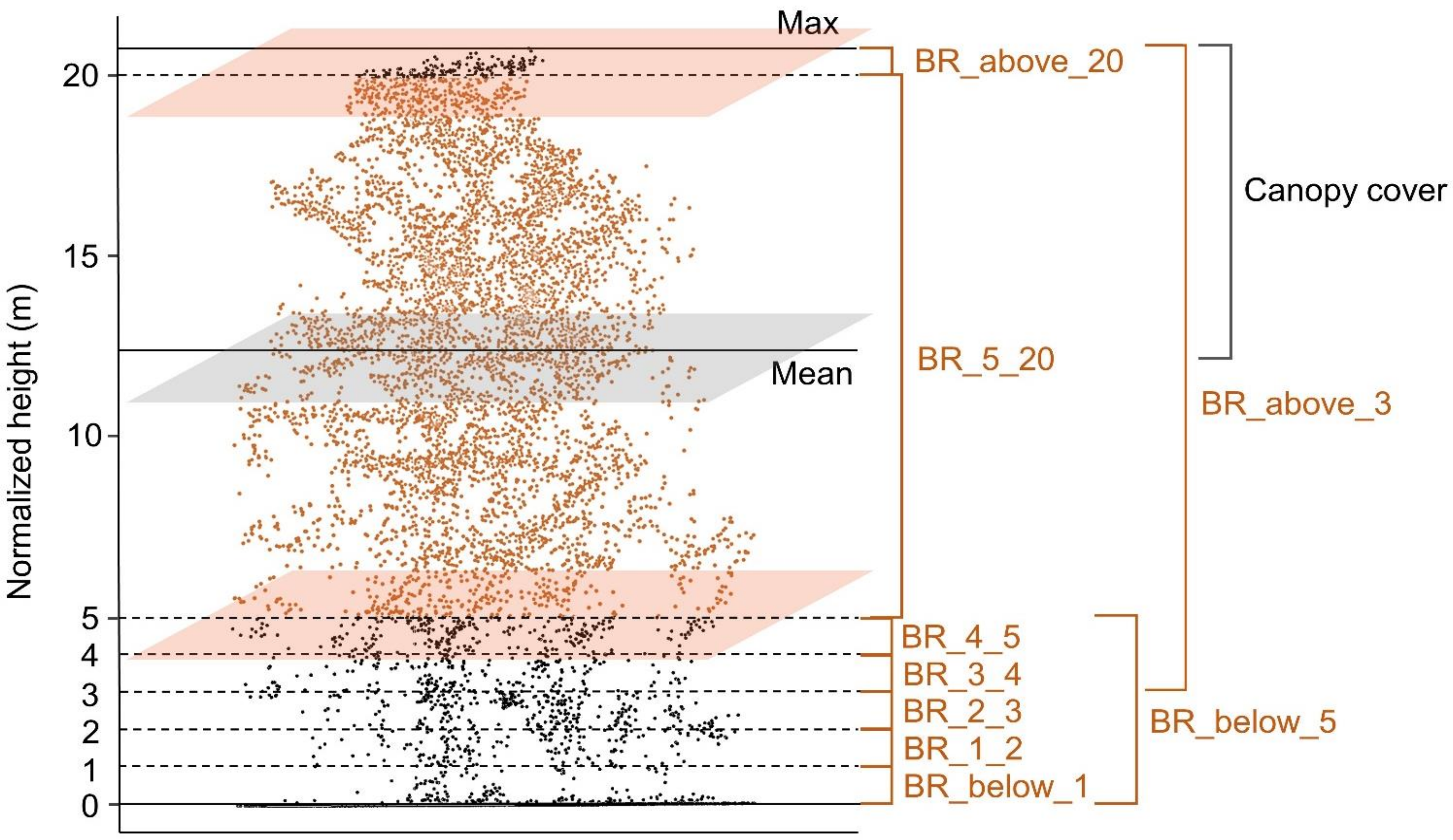
percentile of normalized z within a cell

- Maximum vegetation height
- Mean of vegetation height
- 25th percentile of vegetation height
- 50th percentile of vegetation height
- 75th percentile of vegetation height
- 95th percentile of vegetation height

Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025

LiDAR metrics of vegetation structure

Vegetation cover



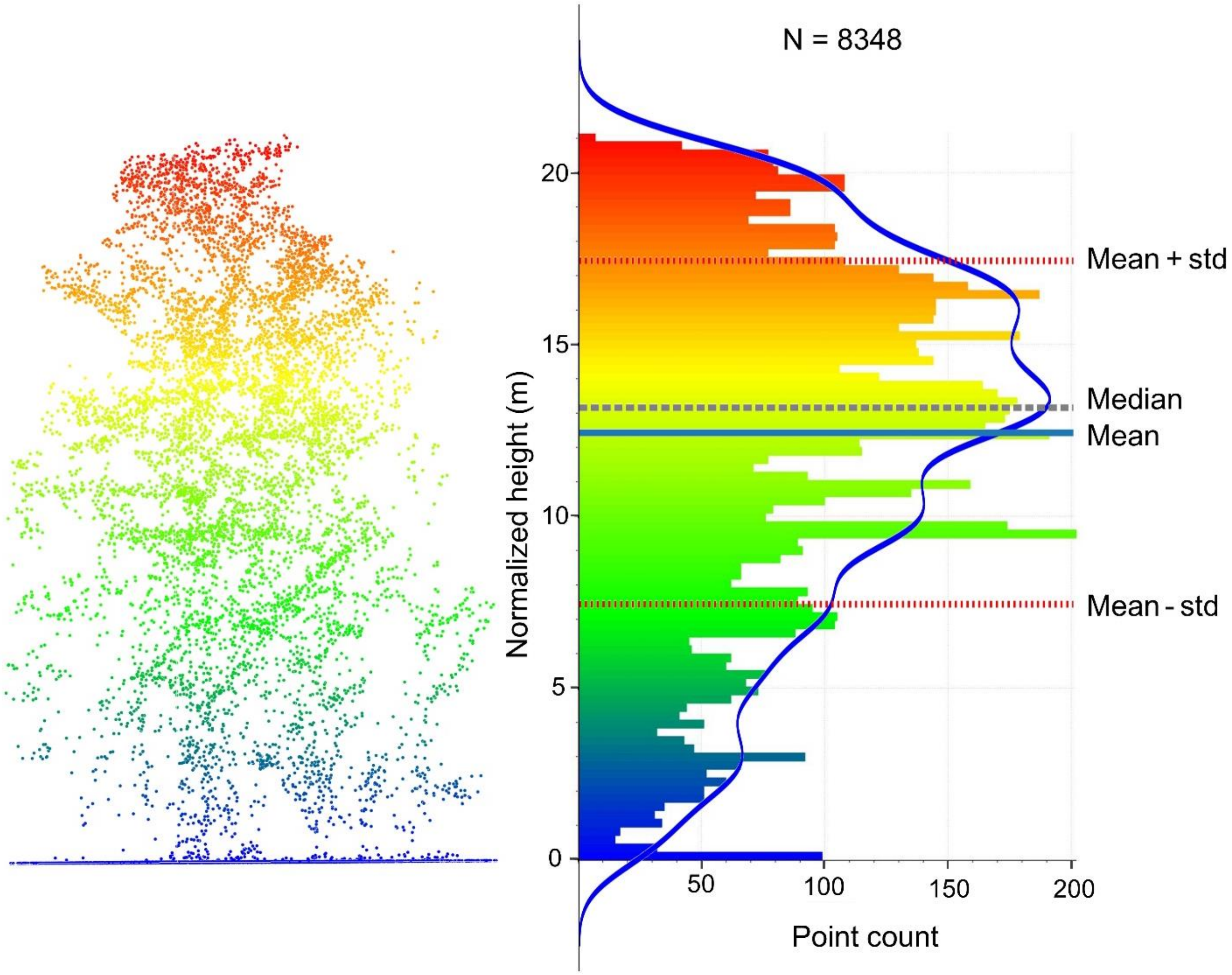
Ratio of number of vegetation points within a given height layer to the total number of vegetation points within a cell

- Density of vegetation points below 1 m
- Density of vegetation points between 1–2 m
- Density of vegetation points between 2–3 m
- Density of vegetation points above 3 m
- Density of vegetation points between 3–4 m
- Density of vegetation points between 4–5 m
- Density of vegetation points below 5 m
- Density of vegetation points between 5–20 m
- Density of vegetation points above 20 m
- Canopy cover above mean height
- Pulse penetration ratio (N_{ground}/N_{total})

Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025

LiDAR metrics of vegetation structure

Vegetation vertical variability

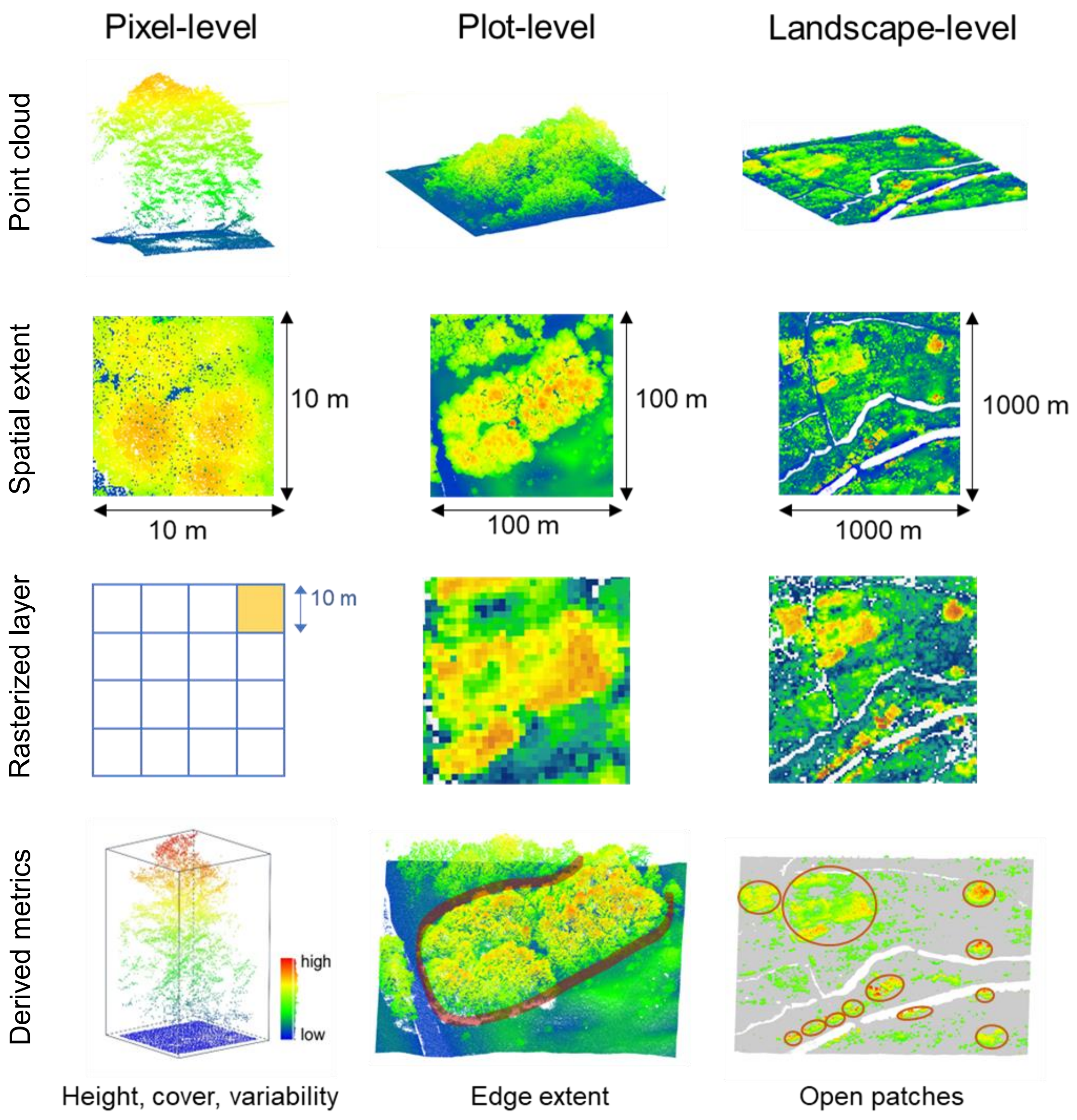


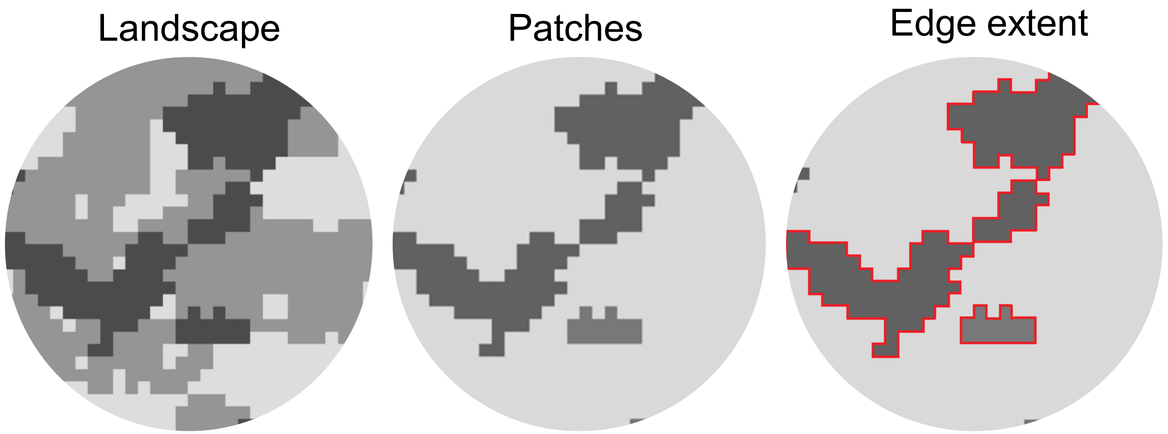
Vertical variability variation of normalized z within a cell

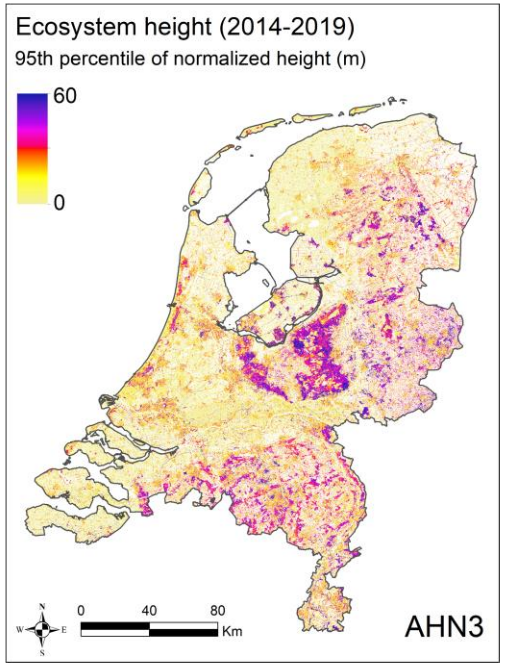
- Coefficient of variation of vegetation height
- Standard deviation of vegetation height
- Variance of vegetation height
- Kurtosis of vegetation height
- Skewness of vegetation height
- Shannon index (Entropy_z)

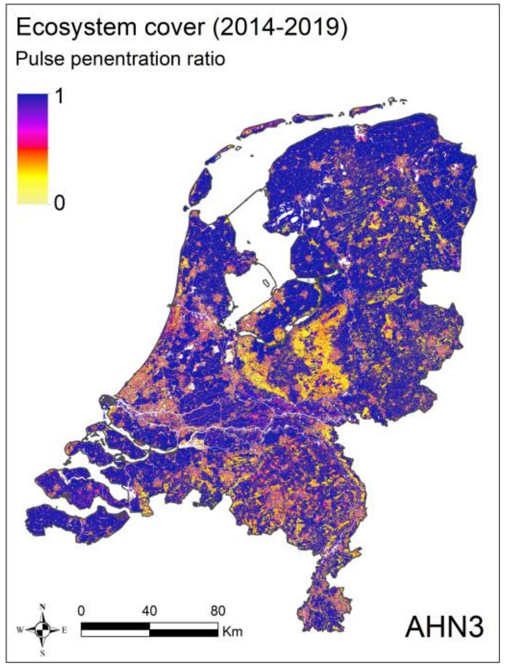
Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025

LiDAR metrics and derivatives at different level





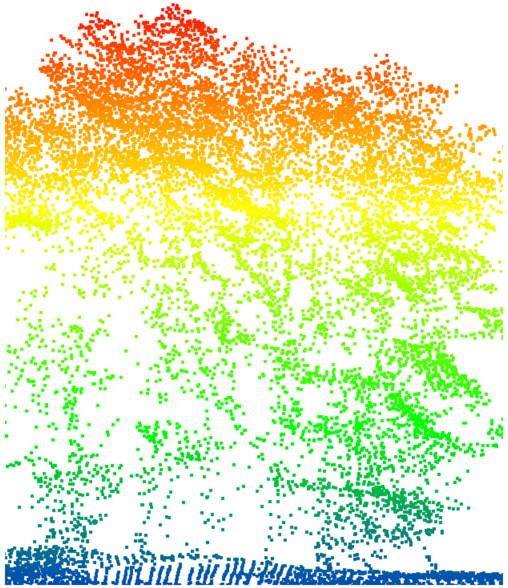




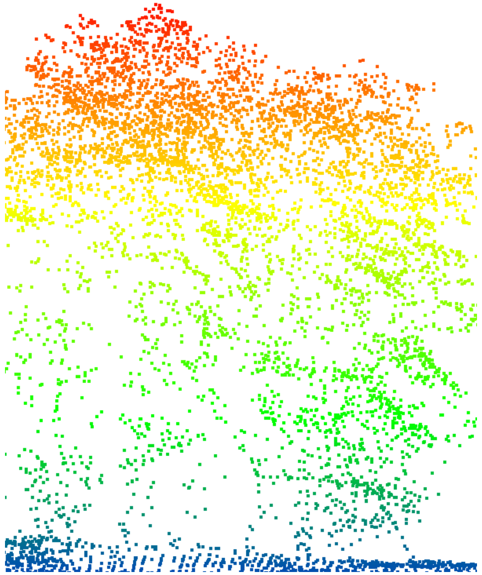
Kissling et al. 2023 *Data in Brief* https://doi.org/10.1016/j.dib.2022.108798

Are the metrics robust?

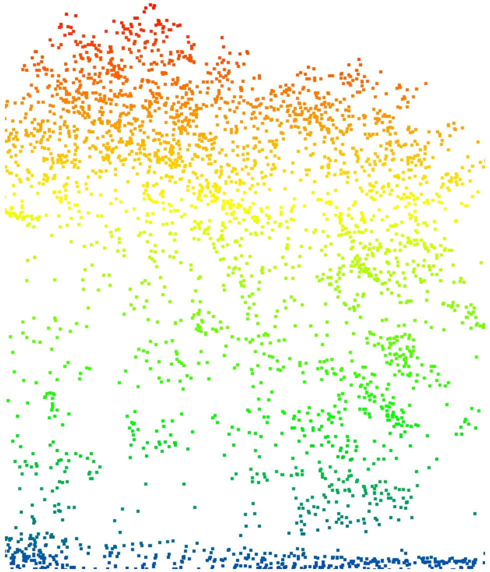
Robustness of LiDAR metrics



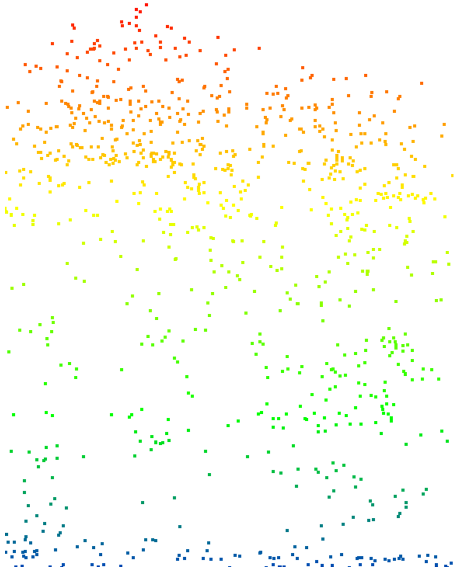
Original



$^{1}/_{2}$ density



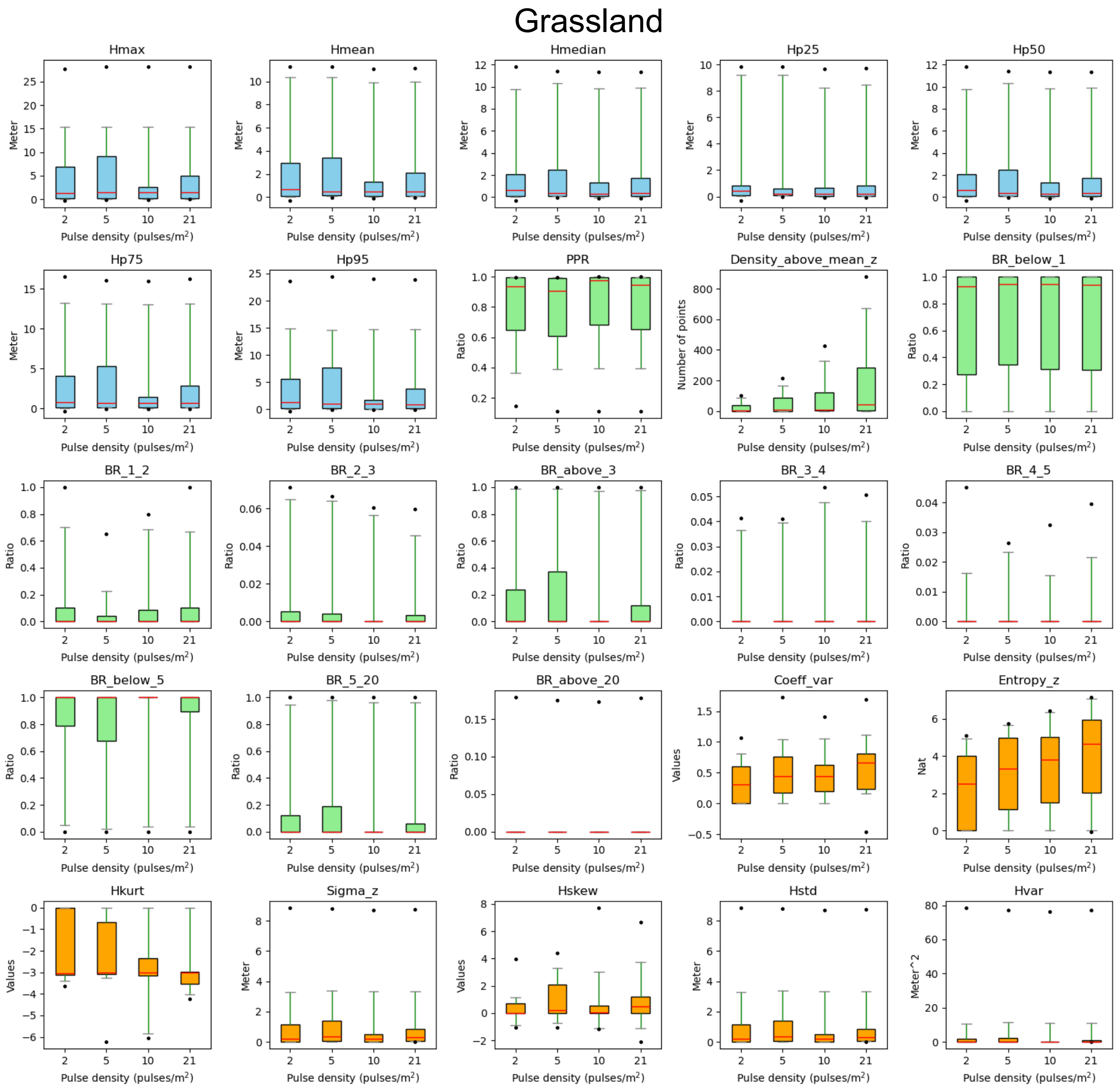
$^{1}/_{4}$ density



$^{1}/_{8}$ density

Are the LiDAR metrics robust towards varying point densities?

Robustness of LiDAR metrics



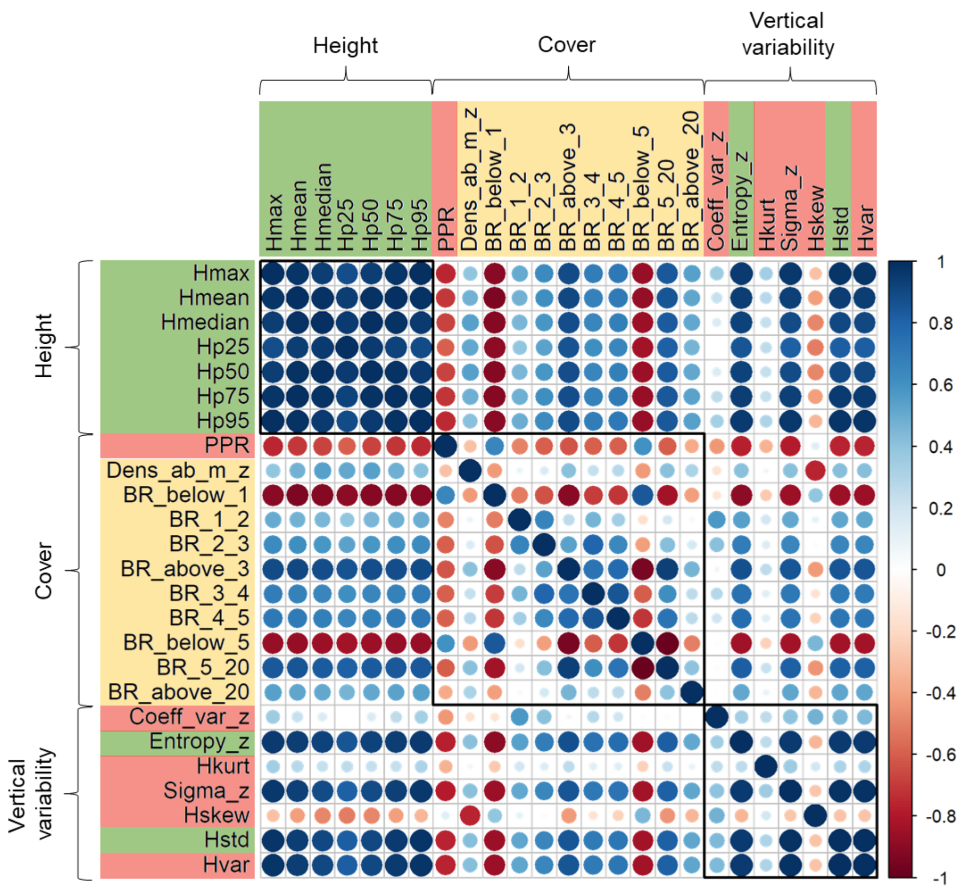
Sensitivity analysis of the LiDAR metrics in relation to the varying pulse densities across different habitats (i.e. woodland, shrubland, dunes, grassland, marshes)

- Almost all metrics in all habitats are robust (at 10 m resolution)
- There are exceptions:
  - *Canopy cover* and *Shannon index* in all habitats
  - *Coefficient of variation of vegetation height* in grasslands and shrublands
  - Some metrics in grasslands showed larger variability

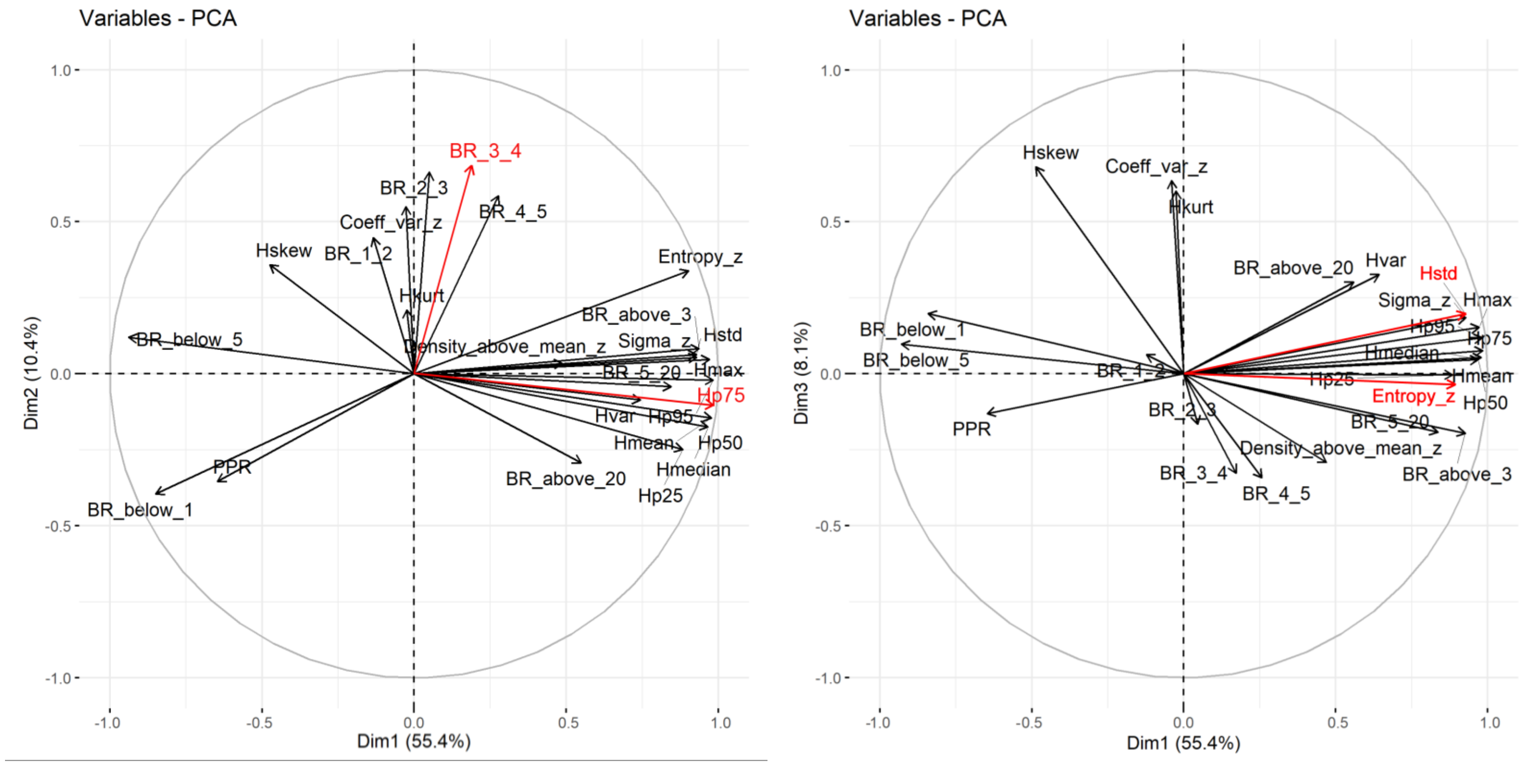
Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025

Which metrics are most essential?

Covariation among LiDAR metrics



Principal Component Analysis (PCA) among 25 LiDAR metrics



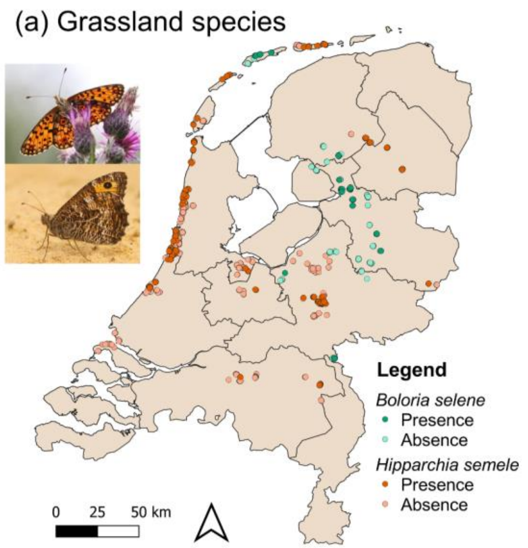
- All height metrics are highly correlated (r ≥ 0.8)
- Some metrics of cover and variability are also highly correlated with height metrics.

- Dim 1: Height metrics explain ~ 55% variation (e.g. Hp75)
- Dim 2: Cover metrics explain ~ 10% variation (e.g. BR_3_4)
- Dim 3: Vertical variability metrics explain ~ 8% variation (e.g. Hskew)

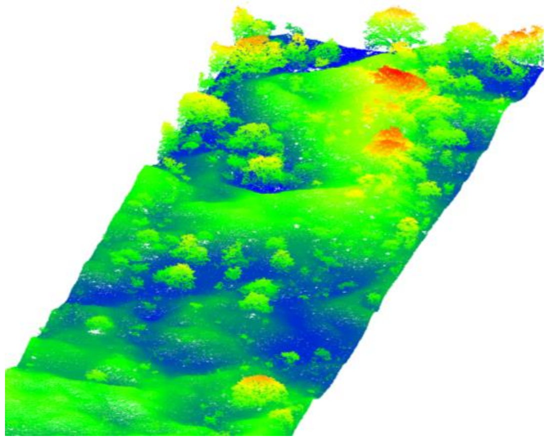
Kissling & Shi 2023 *Diversity and Distributions* https://doi.org/10.1111/ddi.13760

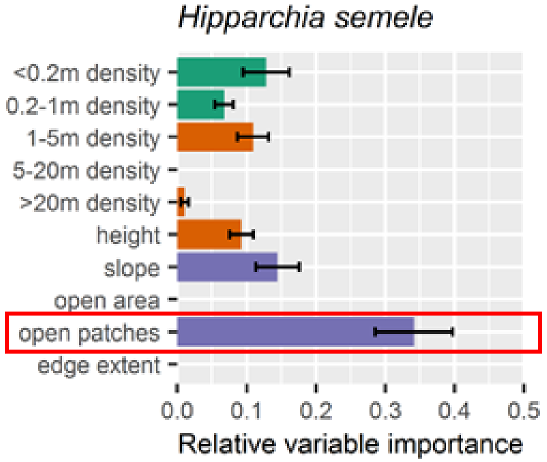
How can the metrics be used?

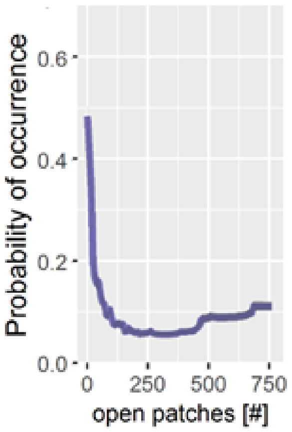
Habitat preferences of threatened butterflies

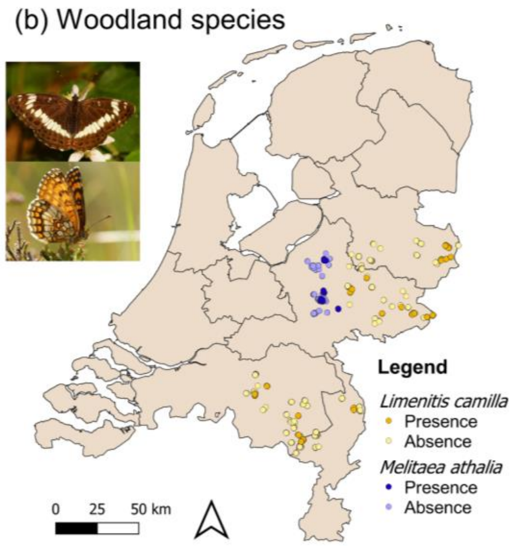


Hipparchia semele
Dry open grasslands; dunes & heather

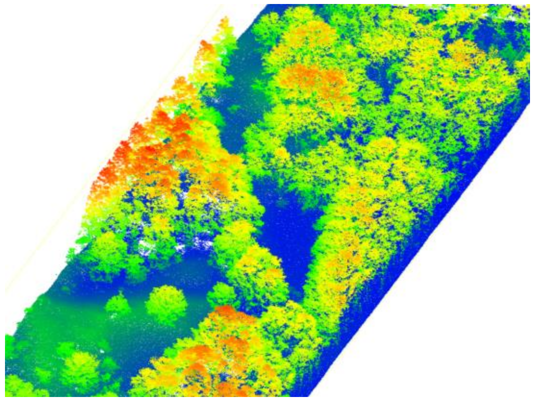


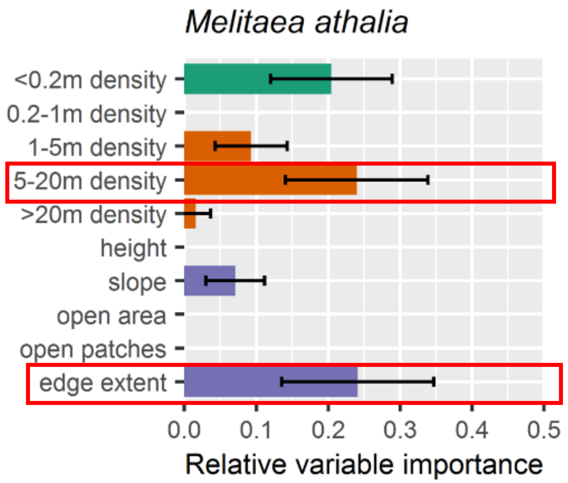


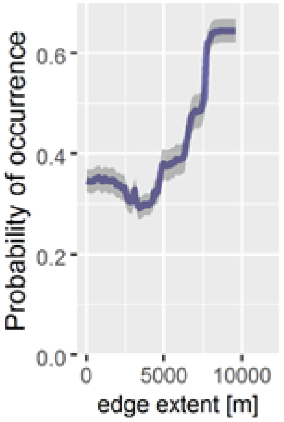




Melitaea athalia
Clearings in dry forest habitat

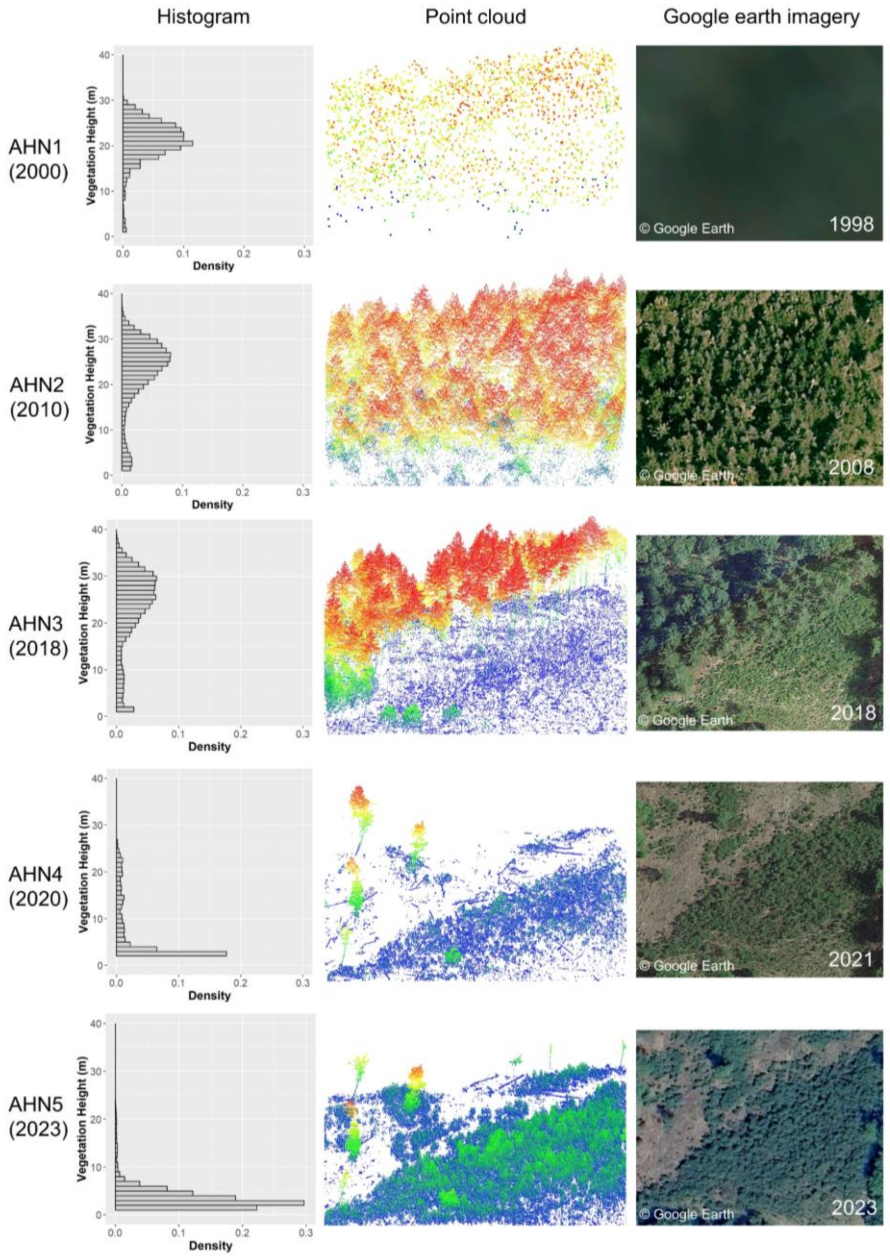




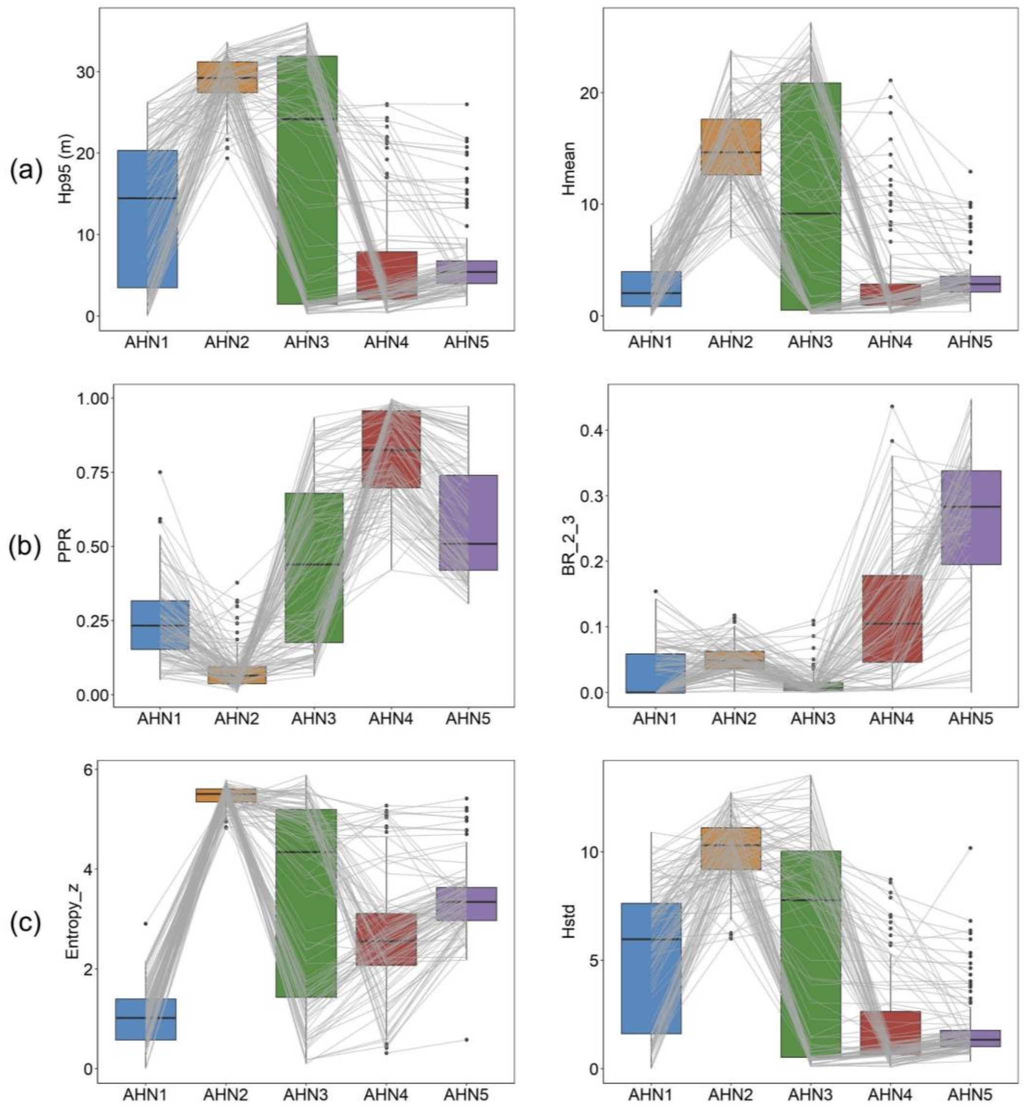


de Vries et al. 2021 *Diversity and Distributions* https://doi.org/10.1111/ddi.13272

Vegetation structural change over time



LiDAR metrics derived from multi-temporal AHN datasets capturing the changes of the vegetation structure in a 100 m × 100 m sample area



Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025

Take home message

- Airborne LiDAR provides detailed information on vegetation structure across spatial scales.
- Landscape metrics can be derived from fine-scale LiDAR metrics
- Most LiDAR metrics are robust towards varying point density, but some metrics have more variability in specific habitats
- LiDAR offers great potential for predictive habitat distribution modelling
- Multi-temporal LiDAR data capture ecosystem structural dynamics

Program

1. **Introduction to airborne laser scanning** (10 min, W.D. Kissling)
2. **Identifying and mapping individual trees** (10 min, J. Wang)
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4. **Measuring trail networks of large herbivores** (15 min, J. Wang)
5. **Wrap-up with available resources** (10 min, W.D. Kissling)

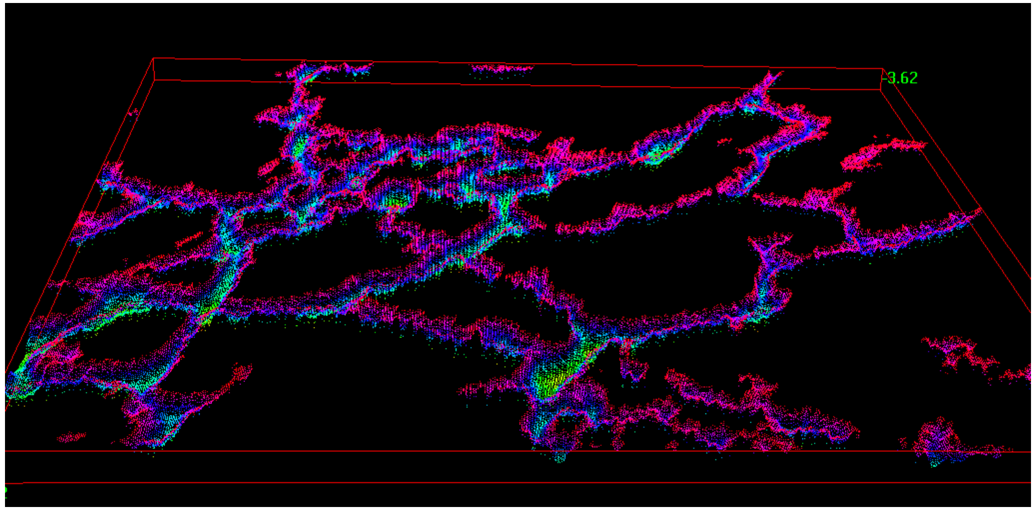
UNIVERSITY OF AMSTERDAM
Faculty of Science

IBED Institute for Biodiversity and Ecosystem Dynamics

Delineation of red deer trails in reedbeds with airborne LiDAR data

Jinhu Wang

16th October 2025



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Background

<u>Herbivores as ecosystem engineers</u>

Red deer, *horses*, and *cattle* are introduced into nature reserves to shape the landscape through grazing, browsing and trampling

Consequences:

- Creation of trails

  Fragmented reedbeds, open patches

- Impacts on biodiversity

  Habitat fragmentation affects species (e.g. breeding birds)

➢ Delineating trails is key to evaluate their impact on ecosystems and biodiversity

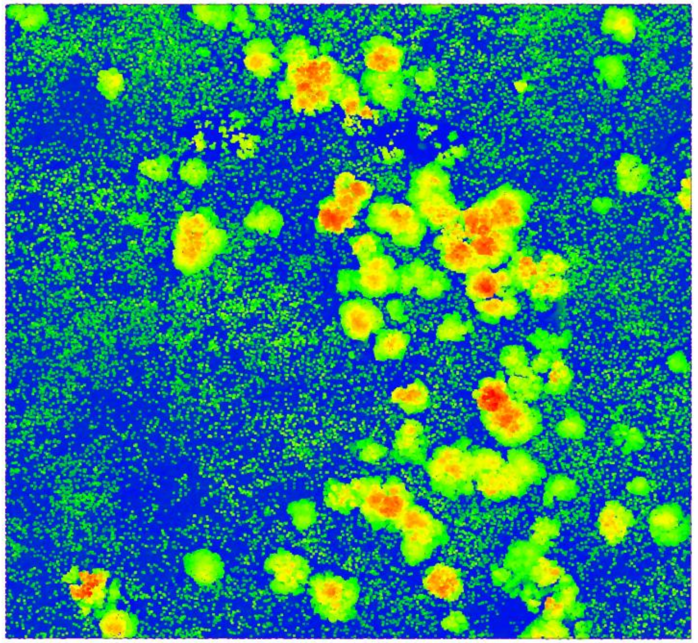
Background

<u>Traditional mapping methods are difficult</u>

Manual in-situ mapping or from aerial photos is challenging:

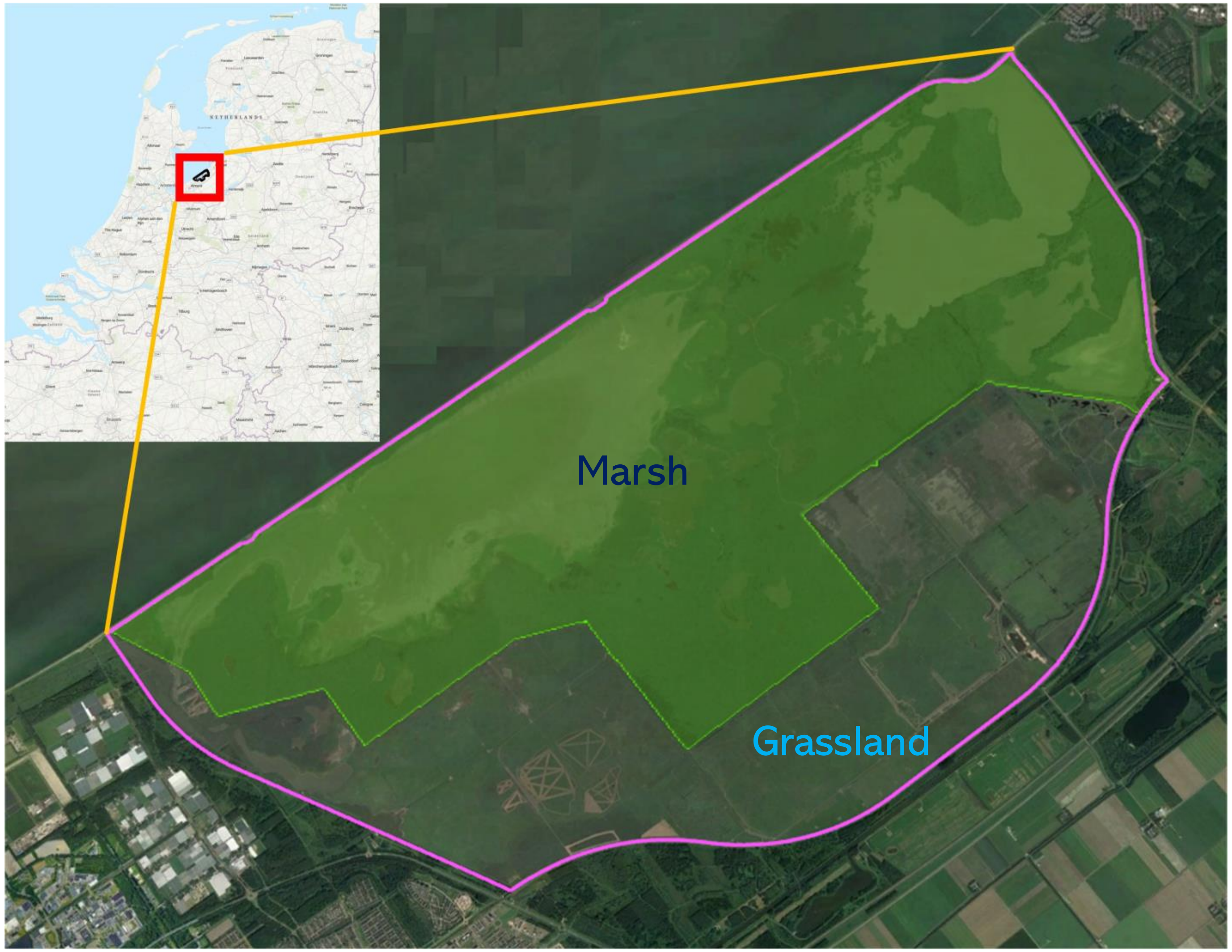
- Generally inaccessible on foot
- Sometimes invisible from 2D images
- Large-scale mapping is impractical

Trails are typically linear features and can be delineated from airborne LiDAR data



Background

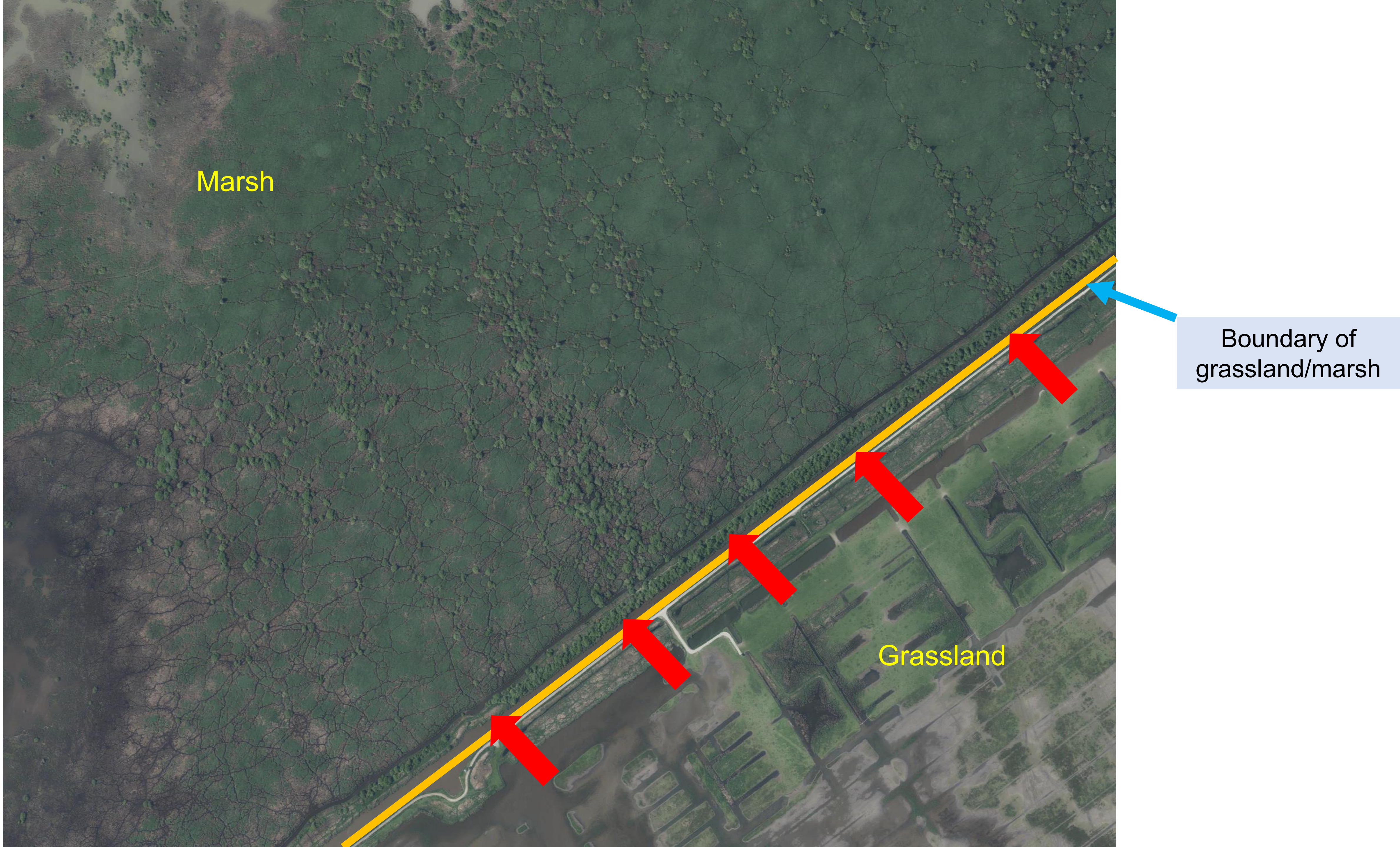
Study area: Oostvaardersplassen



- Natura 2000 site (code: NL9802054)
- Marsh area ~ 36 km^2
- Grassland area ~20 km^2
- Cattle and horses were introduced in 1983/84
- Red deer were introduced in 1992

Background

Red deer walk across the grassland/marsh boundary to look for shrubs and trees to forage on


Marsh
Grassland
Boundary of grassland/marsh

Background

Consequences of red deer in reedbeds:

Alter vertical vegetation structure

- Trampled reedbeds

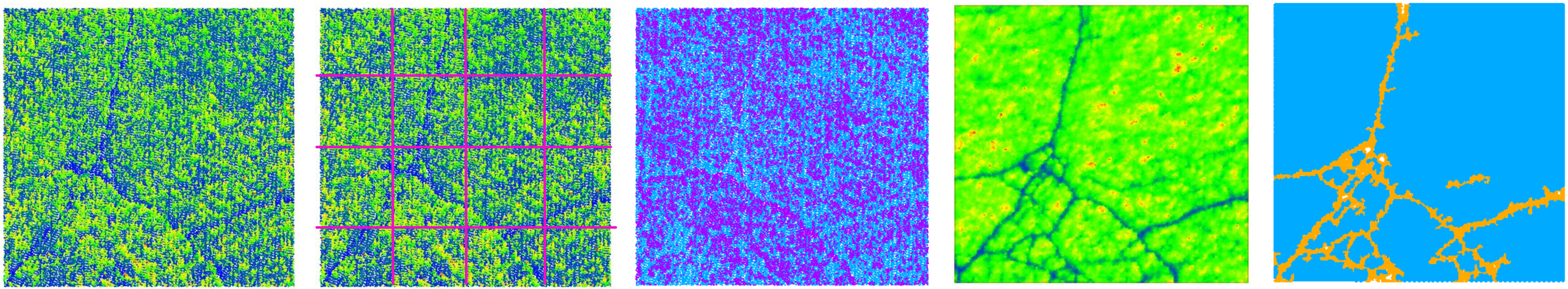
Create vegetation patches

- Fragmented reedbeds

Affect breeding songbirds

- Higher/lower densities

Methodology



Original Point Cloud → (1) Pre-Processing → (2) Terrain filtering → (3) Reconstruct DTMs → (4) Trail extraction

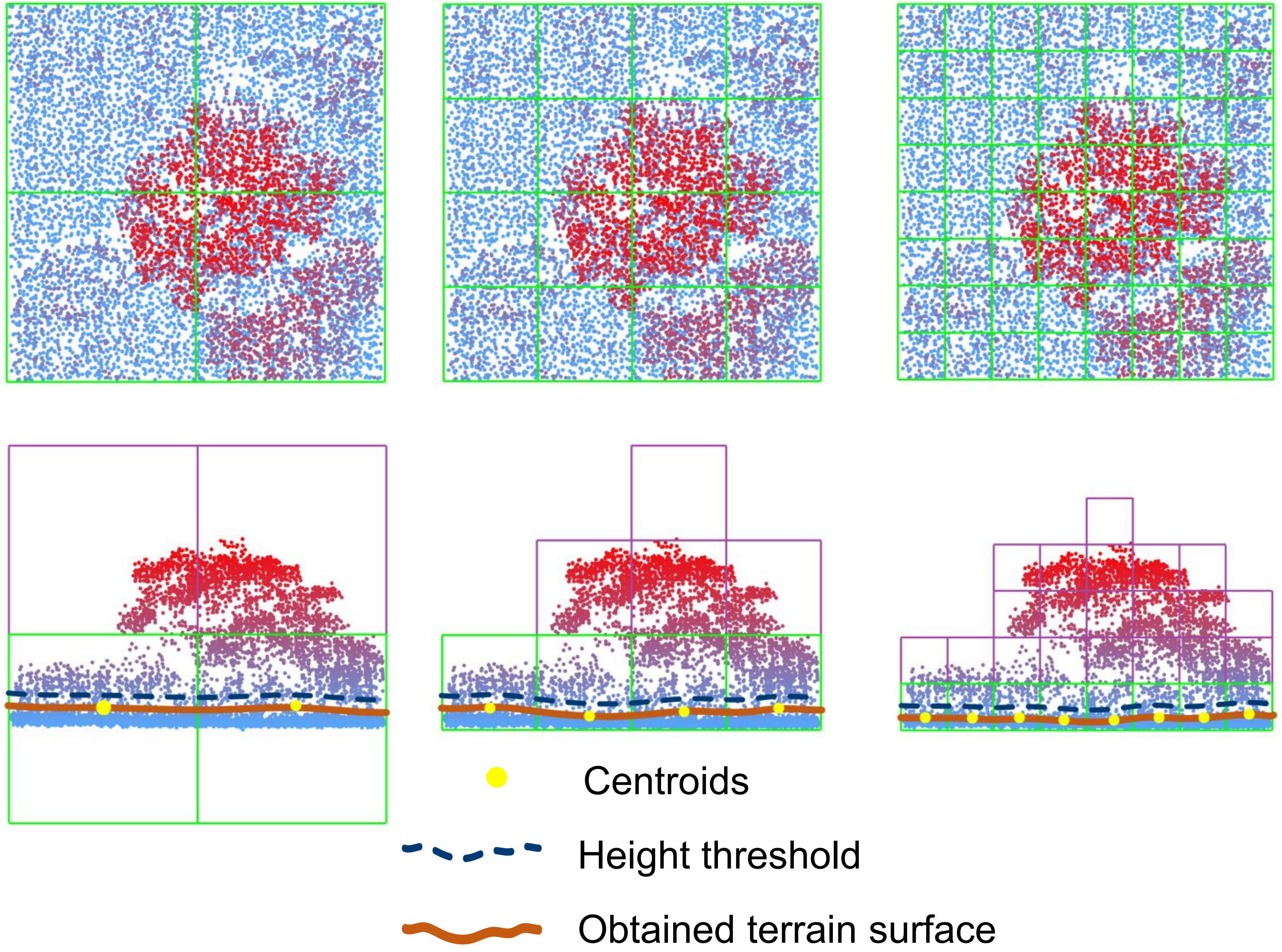
(1) Pre-processing

- Re-tiling - to appropriate plot size
- Clipping - to the boundary polygon of study area
- Outlier removal - mean distance of KNN $P^k = \{p_q \in P \mid (\mu_k - \alpha\sigma_k) \leq \bar{d} \leq (\mu_k + \alpha\sigma_k)\}$

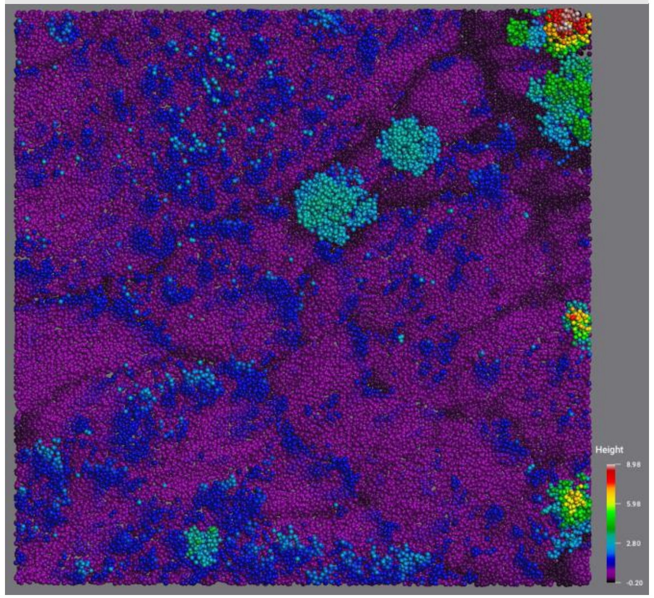
Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

Methodology

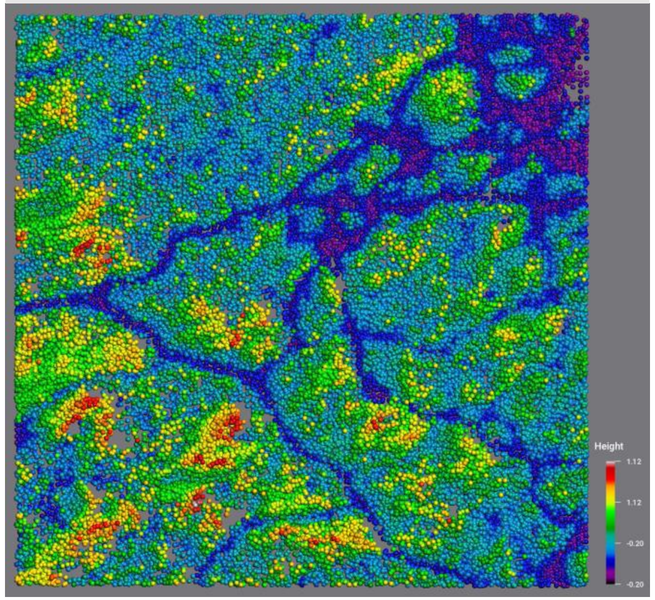
(2) (Near-)terrain filtering



Before filtering



After filtering



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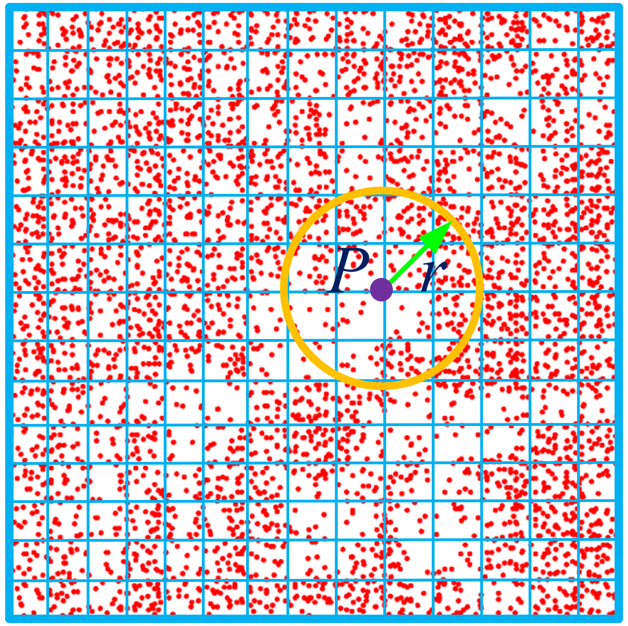
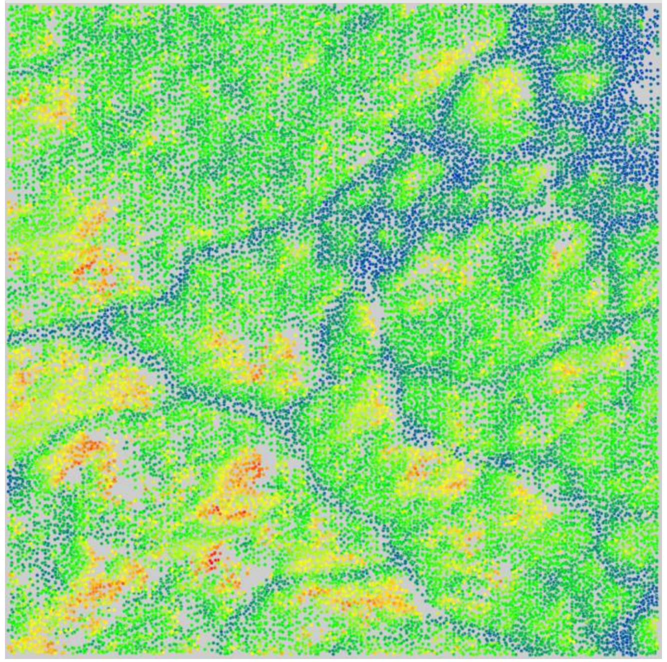
Methodology

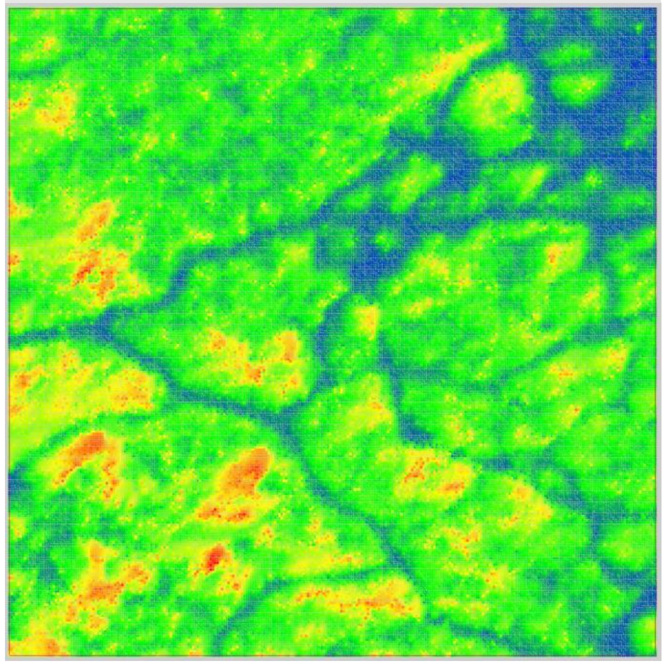
(3) Reconstruct DTM



Near-terrain points



Generated DTM



Inverse distance weight interpolation:

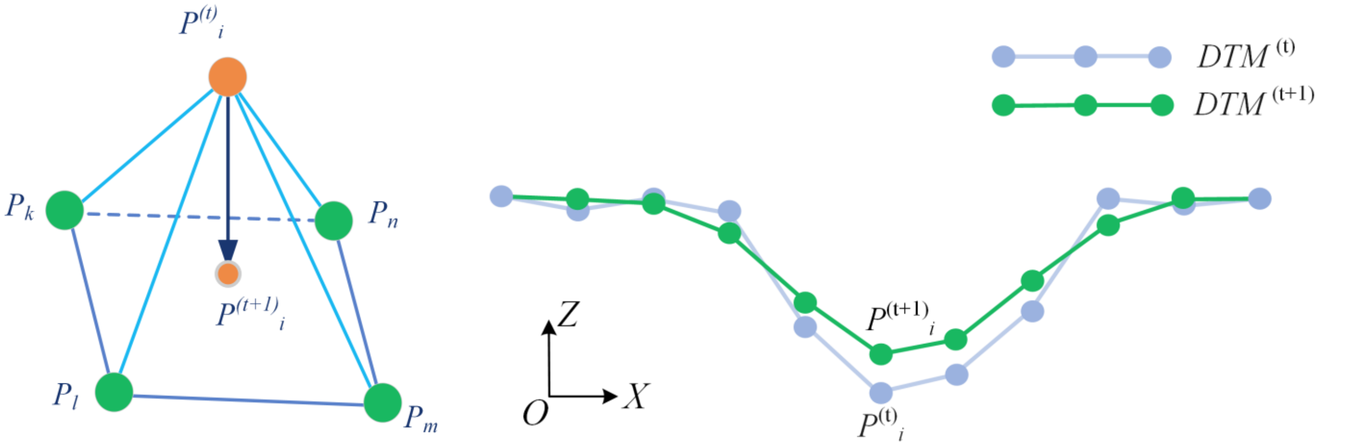
$$H_p = \frac{\sum \frac{H_i}{d_i}}{\sum \frac{1}{d_i}}$$

Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

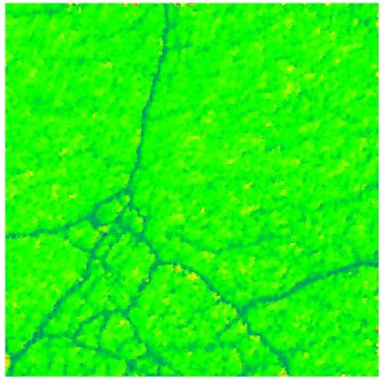
Methodology

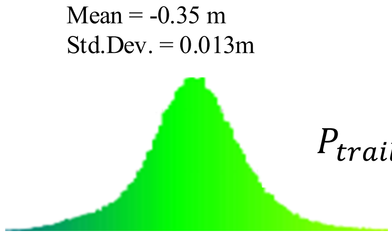
(4) Trail extraction

4.1 Laplacian smoothing



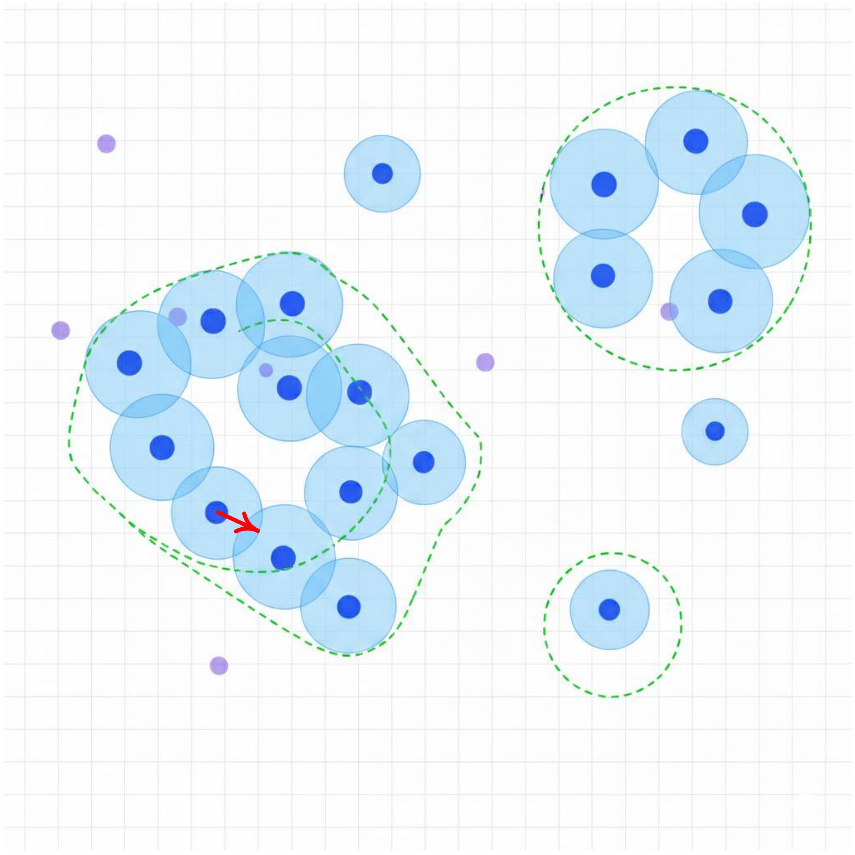
Differentiate DTMs of different iterations: $\Delta \mathrm{H} = \mathrm{DTM}^{(t)} - \mathrm{DTM}^{(t+1)}$





$$P_{trails} = \{p_k \in P \mid \Delta H \leq (\mu_{\Delta H} - \kappa\sigma_{\Delta H})\}$$

4.2 Clustering



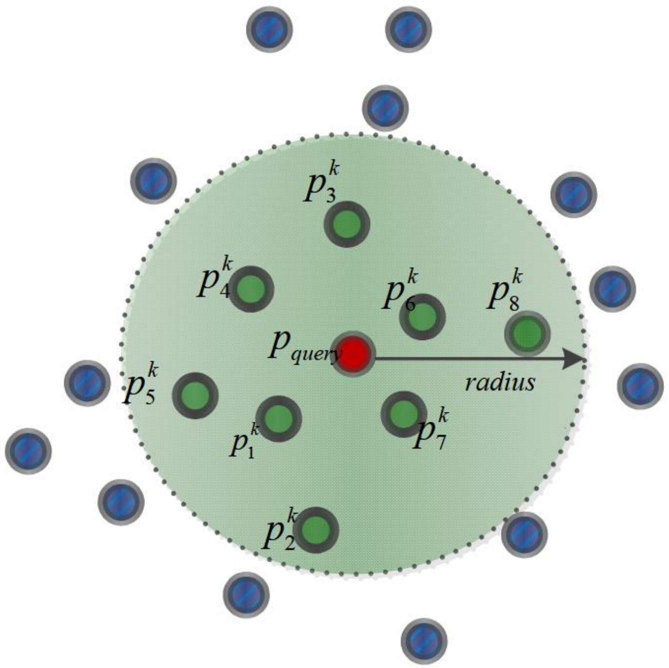
Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

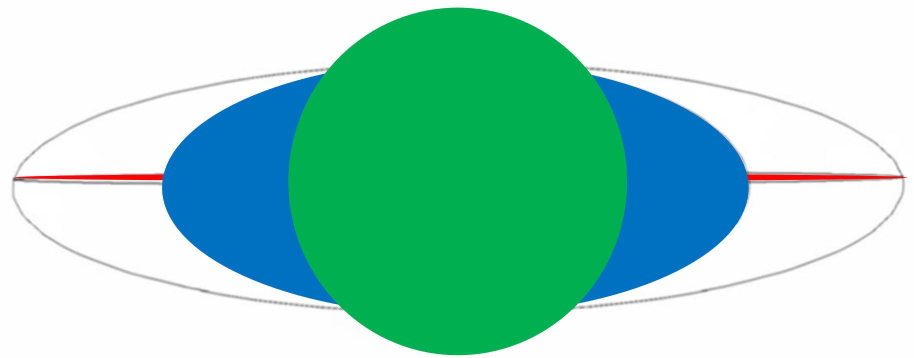
Methodology

(4) Trail extraction

4.3 Tensor Voting

3D neighborhood geometric structure





$$M = \sum_{i=1}^{3} \lambda_i \, e_i e_i^T$$

$$= \quad \boldsymbol{S} + \boldsymbol{P} + \boldsymbol{B}$$

S is the stick tensor

P is the plate tensor

B is the ball tensor

linear feature

planar feature

scatter/saliency feature

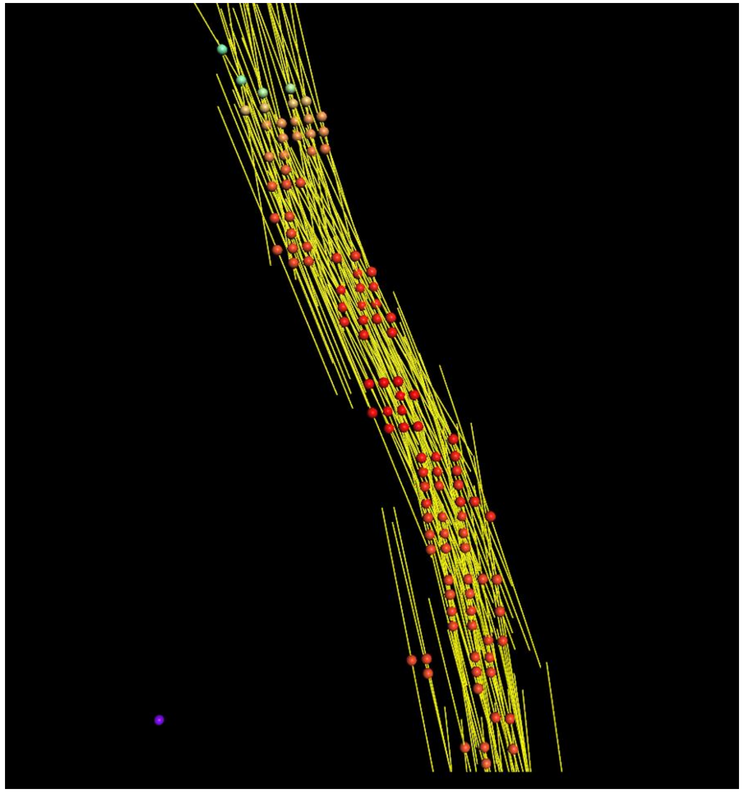
Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

Methodology

(4) Trail extraction

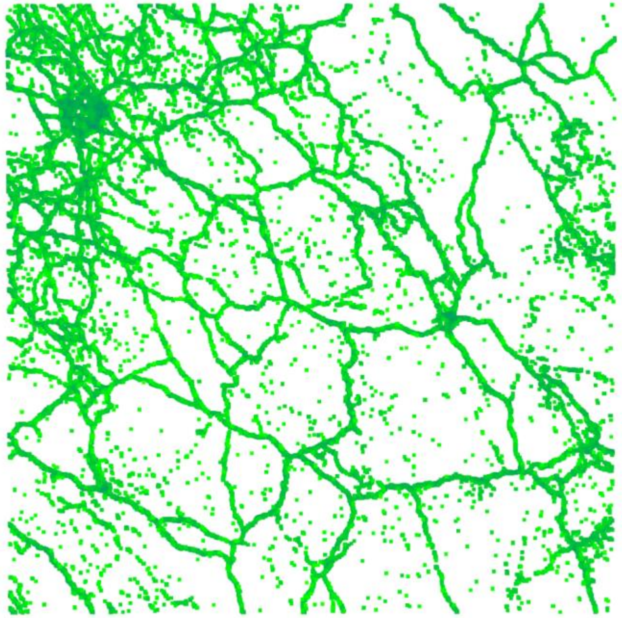
4.3 Tensor Voting

Trail points are typically linear features



Results after clustering:

- Isolated points
- Gaps
- Non-linear clusters



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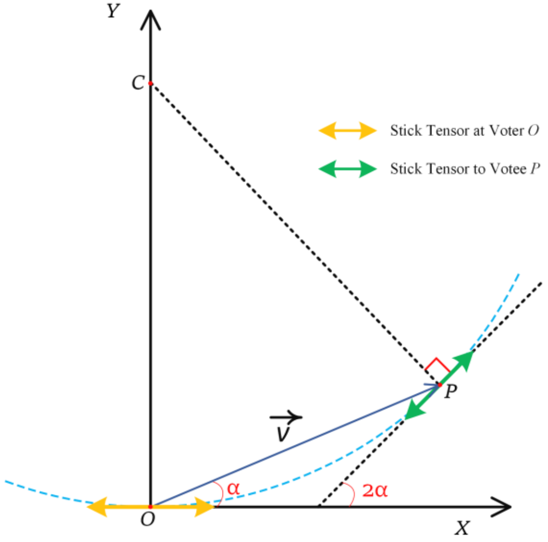
Methodology

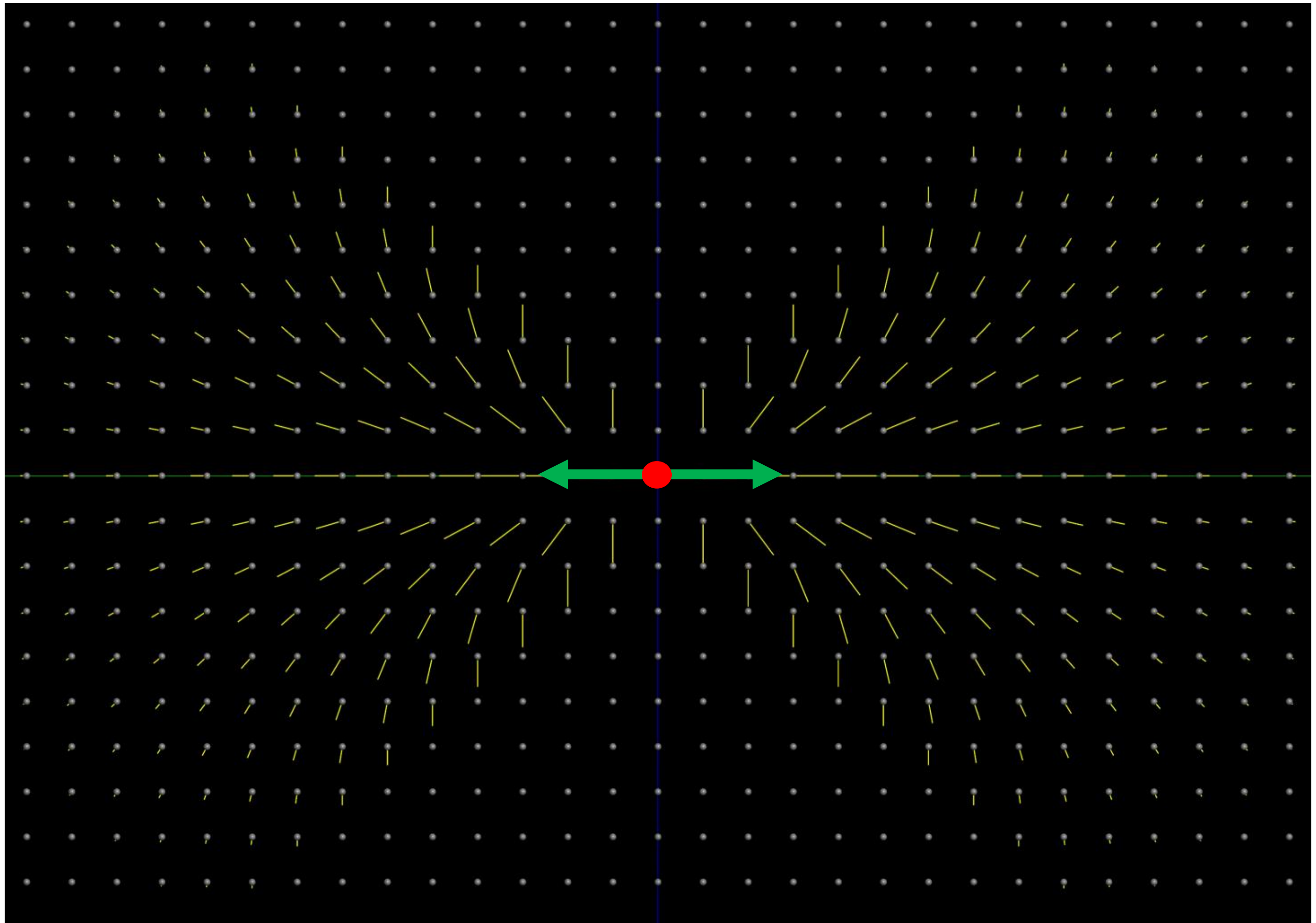
(4) Trail extraction

4.3 Tensor Voting

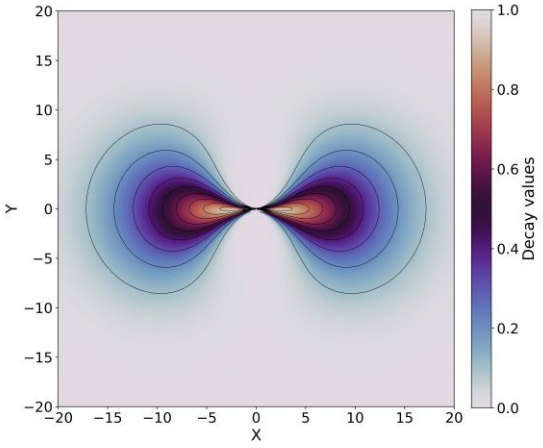
Voting direction:



Casting linearity to neighboring points



Voting weight:



Voter

Voting stick tensor

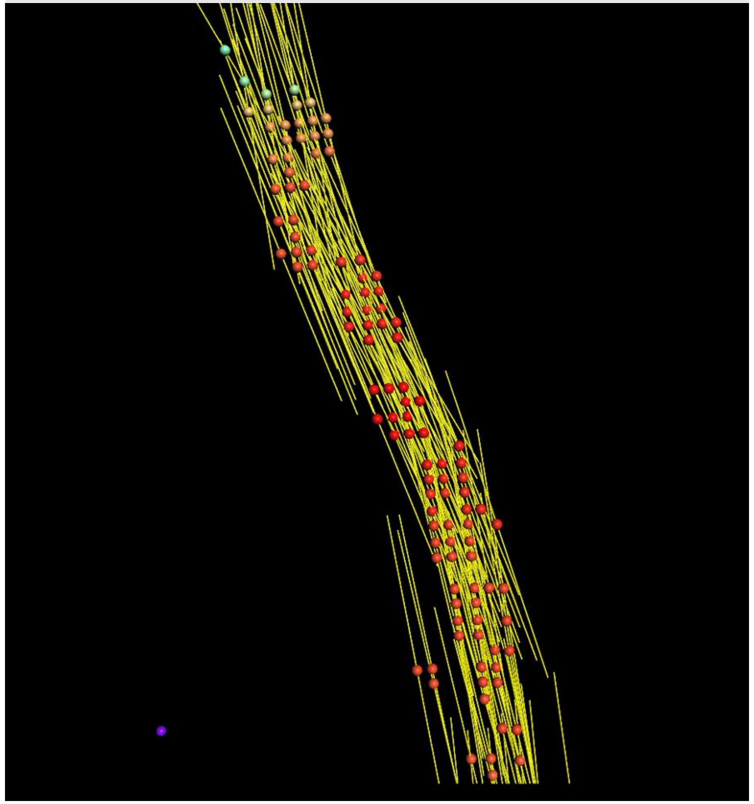
Methodology

(4) Trail extraction

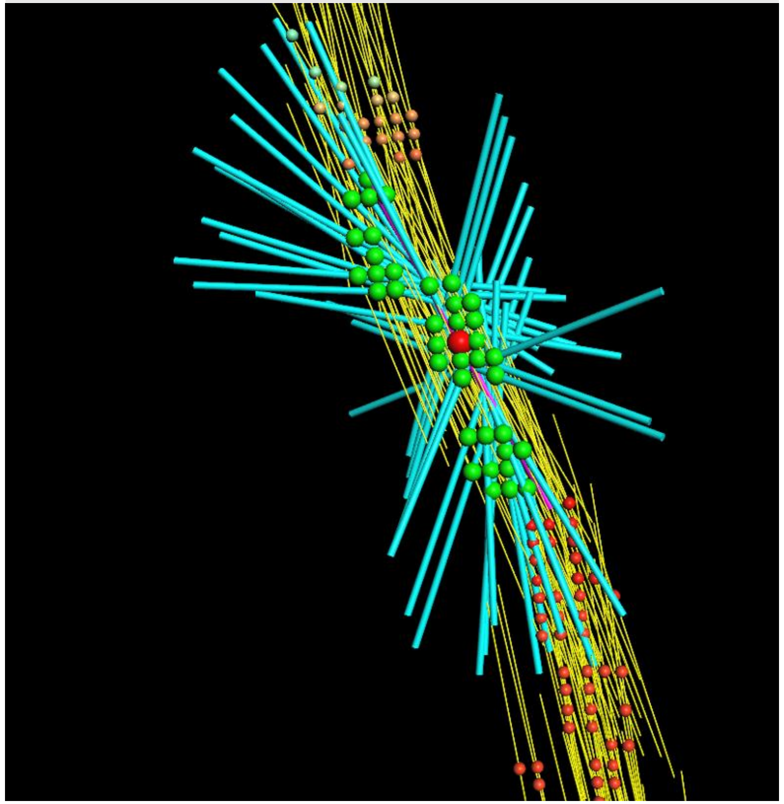
4.3 Tensor Voting

Votee accumulate the votes from neighboring points

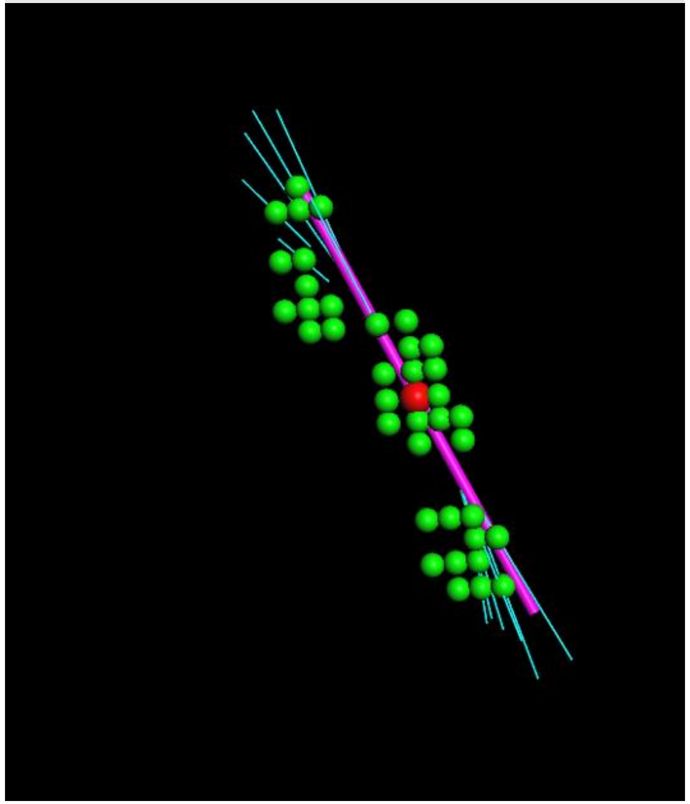
Linear features



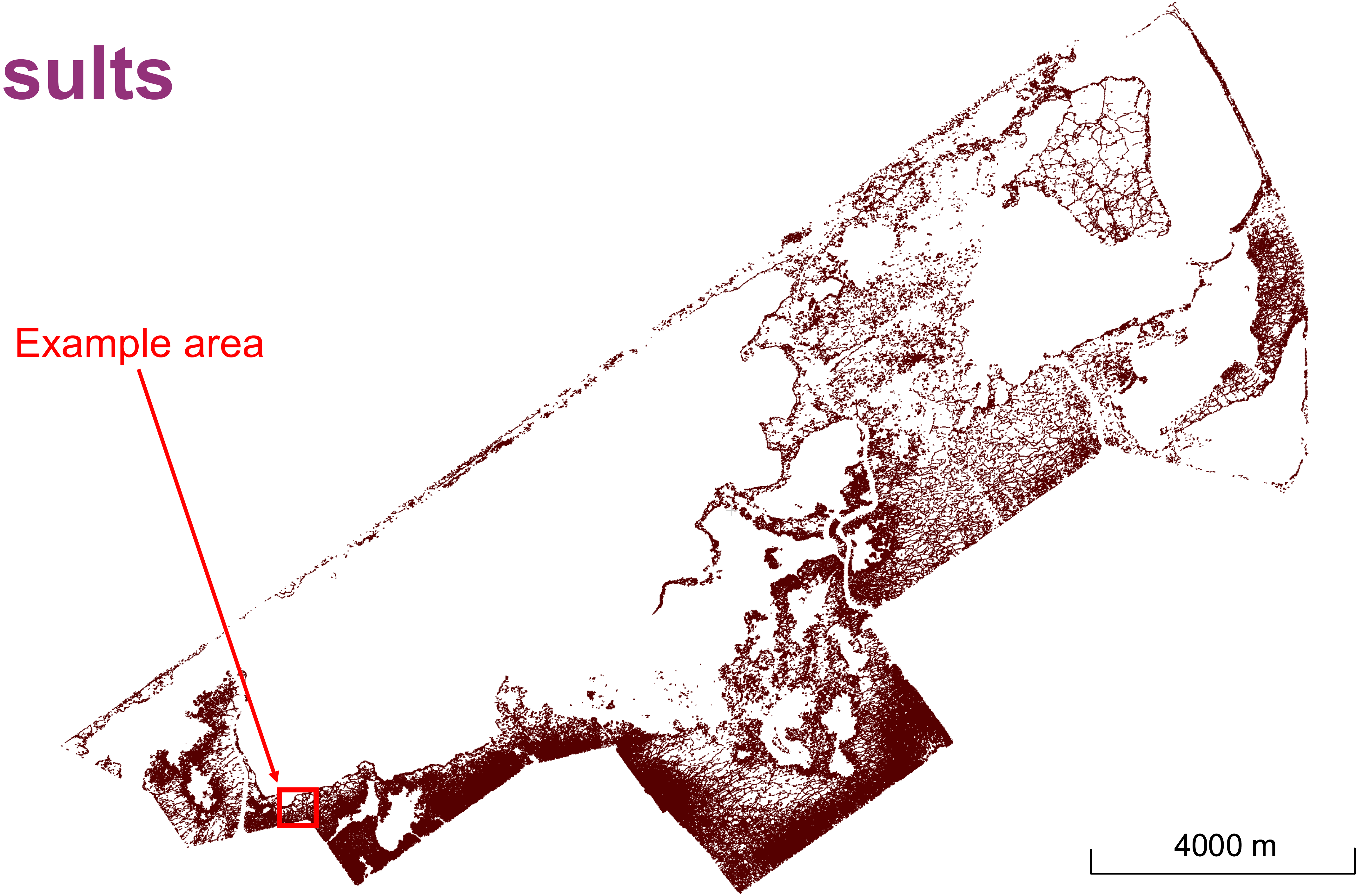
Casting directions to neighbors



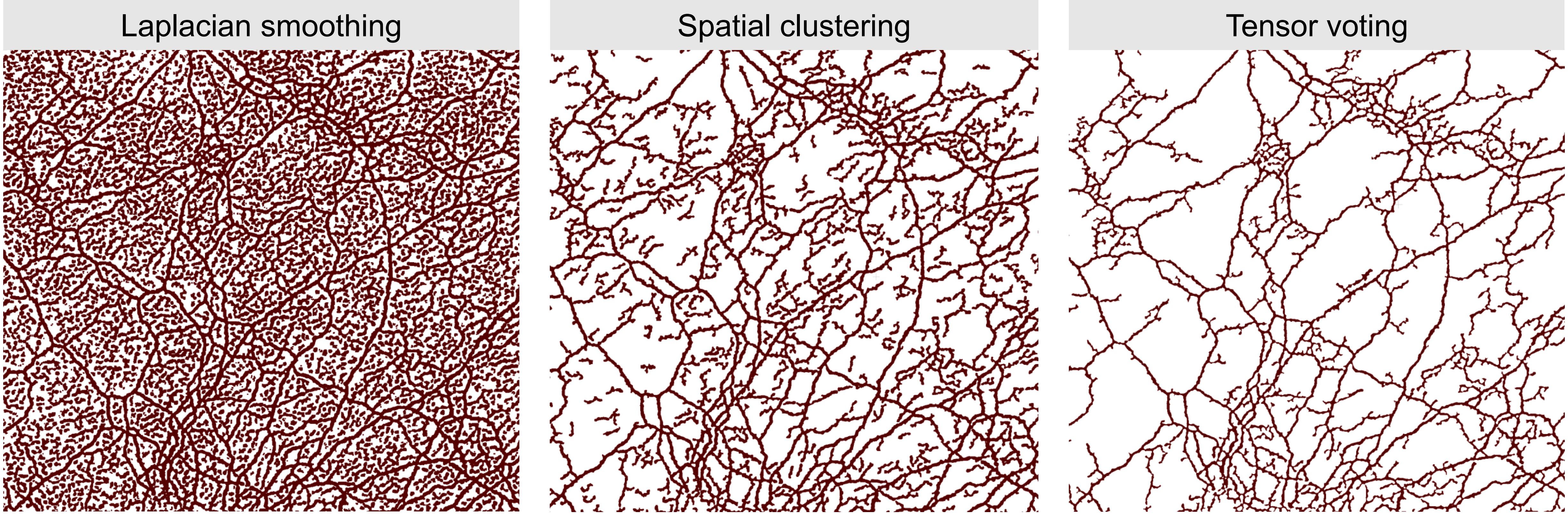
Accumulate votes



Results



Results



Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

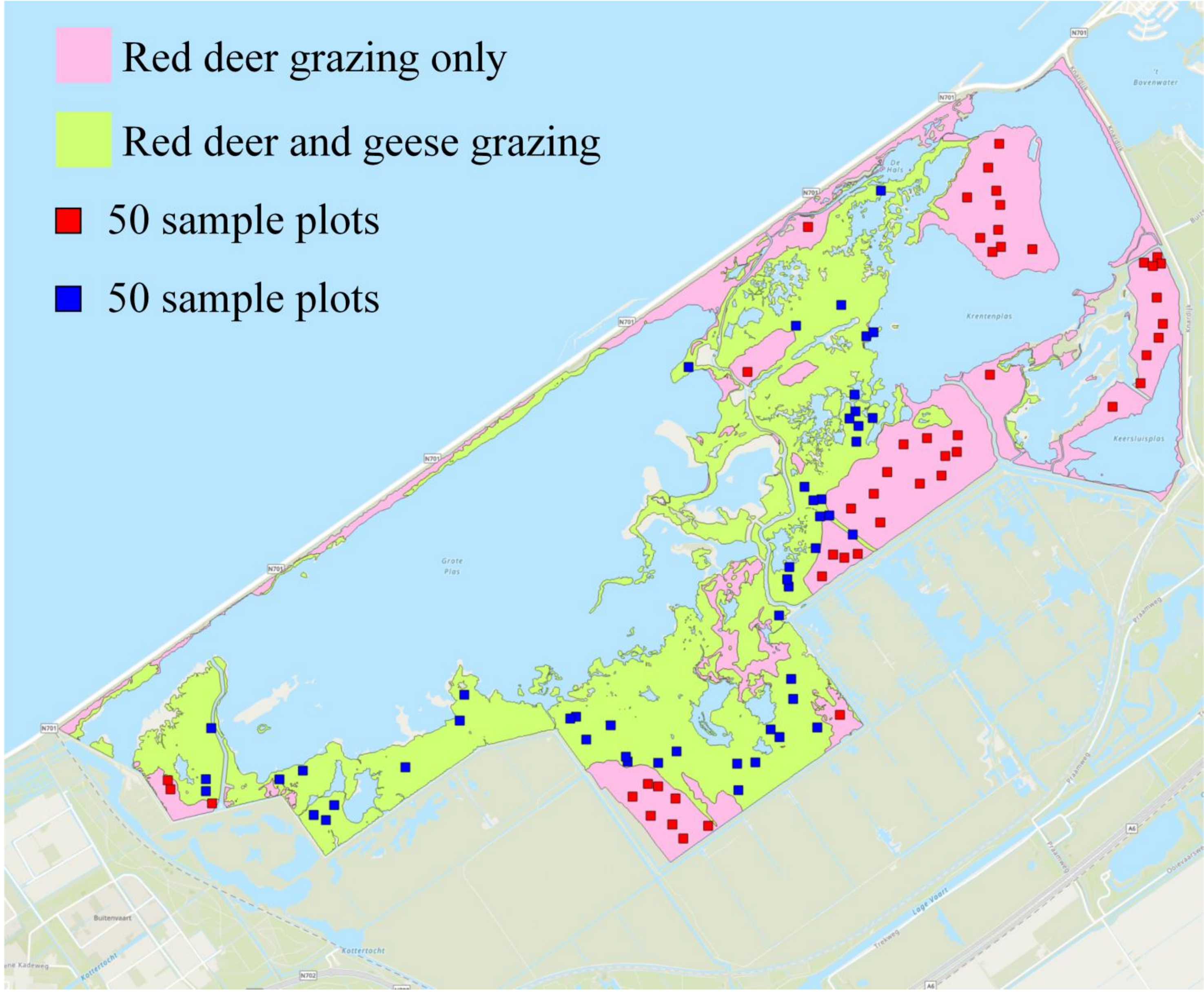
Validation

<u>Data for validation:</u>

- ~500,000,000 points in total
- 100 randomly placed plots
- 30 m square plots
- In two areas with different grazing
- Manually labelled ground truth
- A total of 9,000,000 labelled grid cells

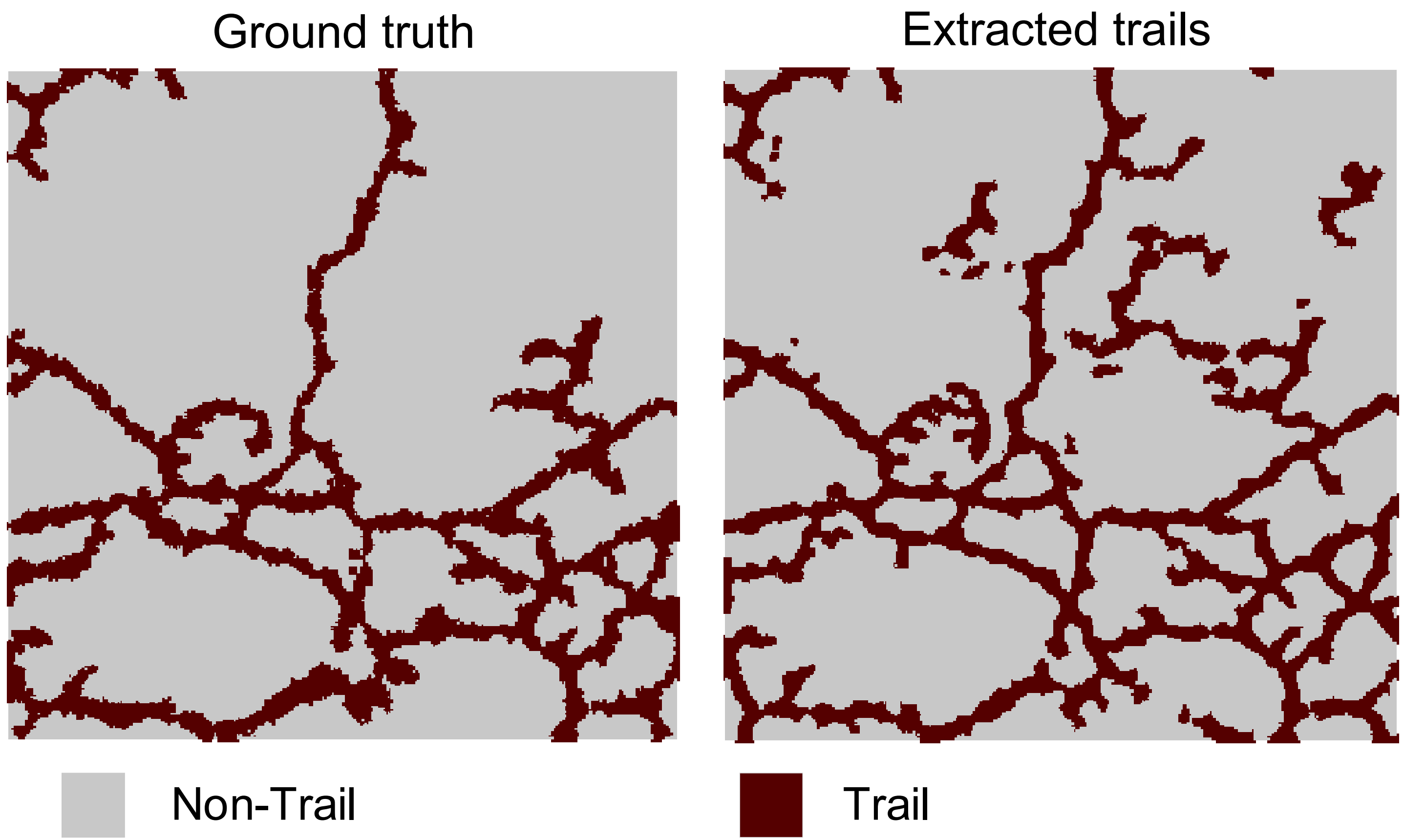
Accuracy metric:

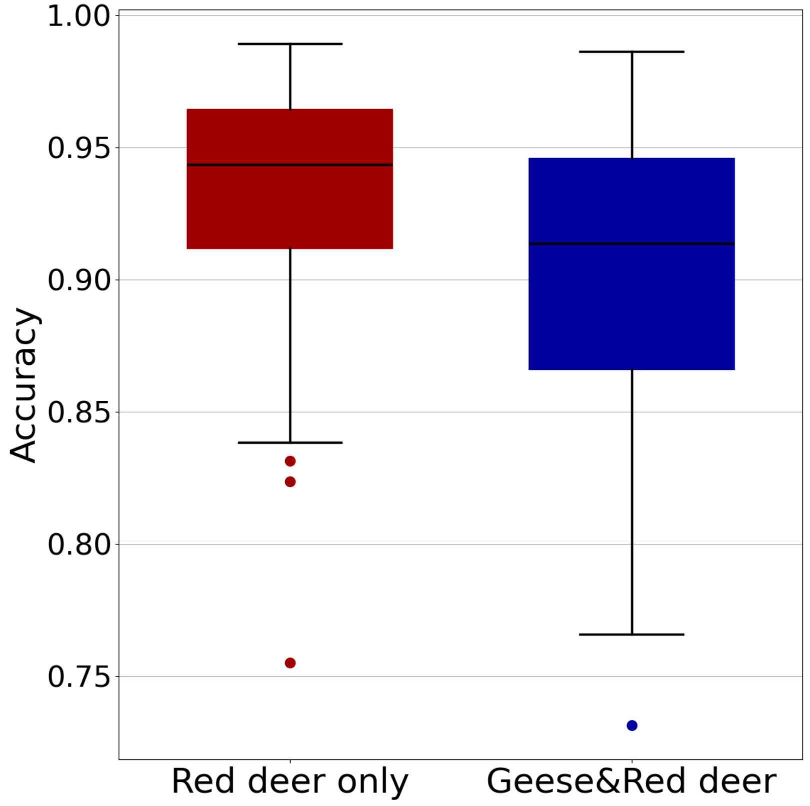
$$Acc = \frac{TP + TN}{TN + TN + FP + FN}$$



Wang et al. 2025 *Front. in Remote Sens.* https://doi.org/10.3389/frsen.2025.1599128

Validation





Area of red deer grazing only:
$Acc = 0.93 \pm 0.05$ (range: 0.75-0.98).

Area of red deer and geese grazing :
$Acc = 0.90 \pm 0.06$ (range: 0.73–0.98)

Source code: https://github.com/Jinhu-Wang/Extracting-ungulate-trails-in-wetlands-using-3D-point-clouds-obtained-from-airborne-laser-scanning

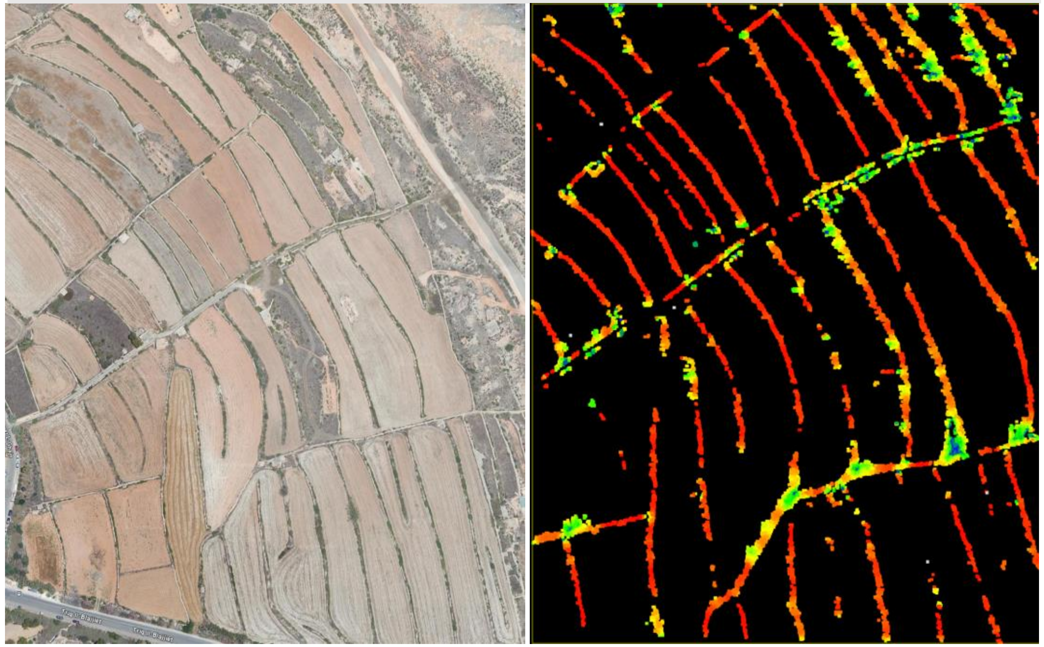
Conclusions

- Trails created by red deer in reedbed habitat can be delineated by airborne LiDAR data
- Laplacian-based method uses the topographic shape of trails, but not its linearity feature
- Sparse 3D tensor voting encodes the “linear” feature to aggregate trails
- Difficulties exist for tensor voting in dense “trail” areas, since trails have local planar feature
- Workflow requires specialized knowledge (point cloud data processing)

Future work

- Apply the workflow to different LiDAR data (e.g. multi-temporal or other study areas)
- Test deep learning-based methods for trail delineation
- Adapt workflow to extract other linear features (e.g. stonewalls or treelines)

Stonewall delineation at Marsaskala, Malta



Treeline extraction at Maasheggen, the Netherlands

Program

1. **Introduction to airborne laser scanning** (10 min, W.D. Kissling)
2. **Identifying and mapping individual trees** (10 min, J. Wang)
3. **Mapping 3D vegetation structures** (15 min, Y. Shi)
4. **Measuring trail networks of large herbivores** (15 min, J. Wang)
5. **Wrap-up with available resources** (10 min, W.D. Kissling)

MAMBO

University of Amsterdam
Faculty of Science

UNIVERSITY OF AMSTERDAM
Faculty of Science

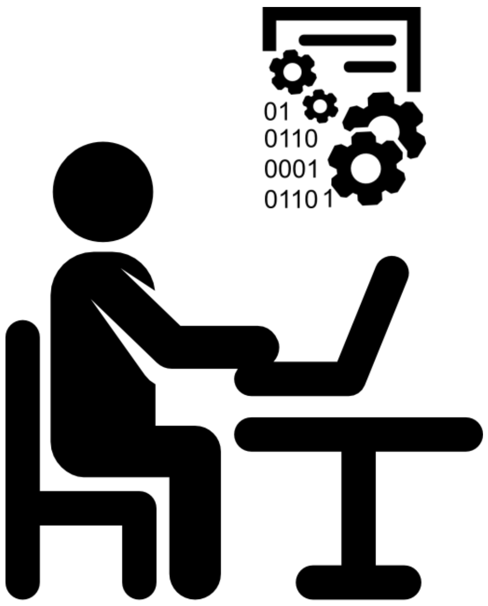
Institute for Biodiversity and Ecosystem Dynamics

Wrap-up with available resources

W. Daniel Kissling

Associate Professor, Institute for Biodiversity and Ecosystem Dynamics (IBED), University of Amsterdam

16th October 2025



MAMBO

Funded by the European Union

Software for LiDAR data

https://github.com/r-lidar/lidR

https://lastools.github.io/

https://cloudcompare.org/

⇒ Very good for visualisation and processing smaller amounts of data (study sites)

⇒ Not all are open source

⇒ Usually do not provide reproducible end-to-end workflows for processing massive (multi-terabyte) LiDAR point clouds

Laserchicken software

SoftwareX 12 (2020) 100626

Contents lists available at ScienceDirect

SoftwareX

journal homepage: www.elsevier.com/locate/softx

ELSEVIER

Original software publication

Laserchicken—A tool for distributed feature calculation from massive LiDAR point cloud datasets

C. Meijer [a,*], M.W. Grootes [a], Z. Koma [b], Y. Dzigan [a], R. Gonçalves [a], B. Andela [a], G. van den Oord [a], E. Ranguelova [a], N. Renaud [a], W.D. Kissling [b]

[a] Netherlands eScience Center, Science Park 140, 1098 XG Amsterdam, The Netherlands
[b] Institute for Biodiversity and Ecosystem Dynamics (IBED), University of Amsterdam, P.O. Box 94240, 1090 GE Amsterdam, The Netherlands

Meijer et al. 2020 *SoftwareX* https://doi.org/10.1016/j.softx.2020.100626

- Open-source Python tool for extracting statistical properties of 3D point clouds

- Designed for efficient, scalable, distributed processing of multi-terabyte datasets

User manual: https://laserchicken.readthedocs.io/en/latest/

Source code (GitHub): https://github.com/eEcoLiDAR/laserchicken

Tutorial as Jupyter notebook (GitHub): https://github.com/eEcoLiDAR/laserchicken/blob/master/tutorial.ipynb

Table 1
Features currently implemented in Laserchicken..

Feature name	Formal description	Example of use	References
Point density	$\frac{N}{V}$ where V is the target volume or area	Point cloud spatial distribution	
Pulse penetration ratio	$\frac{N_{\text{ground}}}{N_{\text{total}}}$	Tree species classification	[17]
Echo ratio	$100 \cdot \frac{N_{3D}}{N_{2D}}$	Roof detection	[18]
Skewness	$\frac{1}{\sigma^3} \cdot \sum \frac{(Z_i - \bar{Z})^3}{N}$	Vegetation, ground, and roof classification and detection	[19]
Kurtosis	$\frac{1}{\sigma^4} \cdot \sum \frac{(Z_i - \bar{Z})^4}{N}$	Vegetation, ground, and roof classification and detection	[19]
Standard deviation	$\sqrt{\sum \frac{(Z_i - \bar{Z})^2}{N-1}}$	Classification of reed within wetland	[20]
Variance	$\sum \frac{(Z_i - \bar{Z})^2}{N-1}$	Classification of reed within wetland	[20]
Sigma Z	$\sqrt{\sum \frac{(R_i - \bar{R})^2}{N-1}}$ where R_i is the residual after plane fitting		Adapted from [20]
Minimum Z	Z_{min}	Simple digital terrain model in wetlands	[20]
Maximum Z	Z_{max}	Height and structure of forests	[21]
Mean Z	$\frac{1}{N} \cdot \sum Z_i$	Height and structure of forests	[21]
Median Z	Z_{median}	Height and structure of forests	[21]
Range Z	$\lvert Z_{\text{max}} - Z_{\text{min}} \rvert$	Height and structure of forests	[21]
Percentiles Z	Height of every 10$^{\text{th}}$ percentile.	Height and structure of forests	[21]
Eigenvalues	$\lambda_1, \lambda_2, \lambda_3$, with $\lvert\lambda_1\rvert \geq \lvert\lambda_2\rvert \geq \lvert\lambda_3\rvert$	Classification of urban objects	[22]
Normal vector	eigen vector $\vec{v_3}$	Roof detection	[23]
Slope	$\tan(\arccos(\vec{v_3} \cdot \vec{k}))$, where $\vec{k} = [0, 0, 1]^T$	Planar surface detection	[24]
Entropy Z	$-\sum_i P_i \cdot \log_2 P_i$, with $P_i = \frac{N_i}{\sum_j N_j}$ and N_i points in bin i	Foliage height diversity	[25]
Coefficient variance Z	$\frac{1}{\bar{Z}} \cdot \sqrt{\sum \frac{(Z_i - \bar{Z})^2}{N-1}}$	Urban tree species classification	[8]
Non-ground density absolute mean	$\frac{100}{N_{\text{non-ground}}} \cdot \sum_{i \in \text{non-ground}} [Z_i > \bar{Z}_{\text{non-ground}}]$	Urban tree species classification	[8]
Band ratio	$\frac{N_{Z_i < Z < Z_j}}{N_{\text{tot}}}$ with Z_i and Z_j provided by user	Height and vertical structure of vegetation	

Workflow Laserfarm

Ecological Informatics 72 (2022) 101836

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

ELSEVIER

Laserfarm – A high-throughput workflow for generating geospatial data products of ecosystem structure from airborne laser scanning point clouds

W. Daniel Kissling [a,b,*], Yifang Shi [a,b], Zsófia Koma [a,c], Christiaan Meijer [d], Ou Ku [d], Francesco Nattino [d], Arie C. Seijmonsbergen [a], Meiert W. Grootes [d]

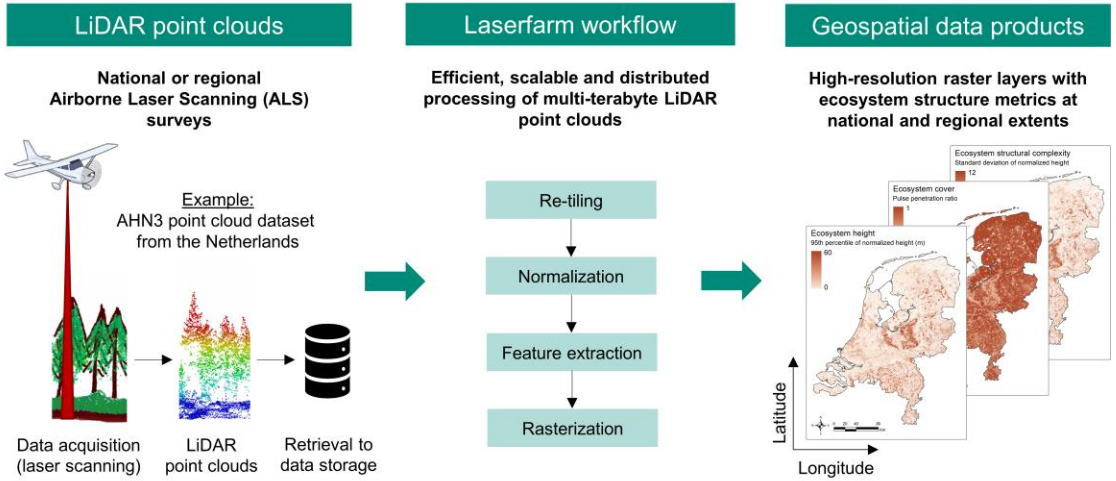
User manual: https://laserfarm.readthedocs.io/en/latest/

Current version:
On PyPI (https://pypi.org/project/laserfarm/) or Zenodo (https://doi.org/10.5281/zenodo.3842780)

All code produced during the development of Laserfarm (GitHub):
https://github.com/eEcoLiDAR/Laserfarm

Examples of Jupyter Notebooks (WorkflowHub):
https://workflowhub.eu/projects/302#workflows

- Reproducible end-to-end workflow with retiling, normalization, feature extraction and rasterization
- Designed for efficient, scalable, distributed processing of multi-terabyte LiDAR point clouds
- Available as Jupyter Notebook (Python)



Kissling et al. 2022 *Ecological Informatics*
https://doi.org/10.1016/j.ecoinf.2022.101836

Other code examples

Tree individualisation:

- C++ code on GitHub (https://github.com/Jinhu-Wang/Tree_Classification_and_Individualization_In_Marsh_Area)

Processing country-wide or multi-site LiDAR datasets (Netherlands or from different EU sites):

- Jupyter notebooks for country-wide (AHN1-AHN4) ALS data on GitHub (https://github.com/ShiYifang/AHN)
- Laserfarm applications for European demonstration sites (https://workflowhub.eu/projects/302#workflows)

Trail extraction:

- C++ code for extracting ungulate trails (https://github.com/Jinhu-Wang/Extracting-ungulate-trails-in-wetlands-using-3D-point-clouds-obtained-from-airborne-laser-scanning)

Retiling and clipping large LAZ files:

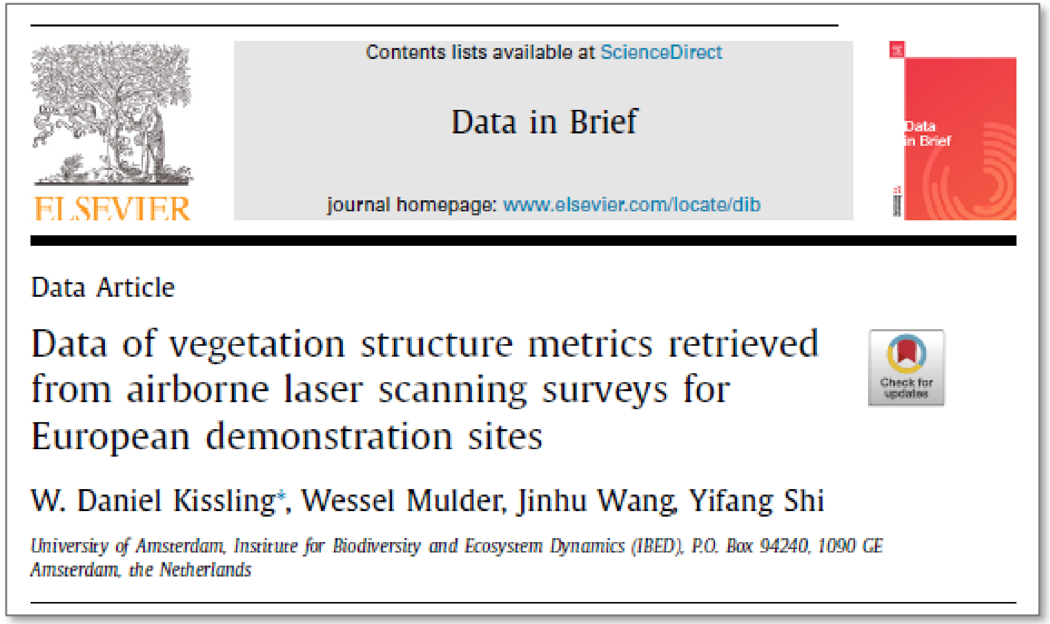
- C++ code for retiling large LAZ files to smaller tiles and clipping 3D LiDAR point clouds of LAS/LAZ format with polygons of ESRI shapefiles (https://github.com/Jinhu-Wang/Retile_Clip_LAZ)

Assessing robustenss of LiDAR metrics:

- Code for testing the robustness of LiDAR vegetation metrics to varying point densities (https://github.com/Jinhu-Wang/Testing-the-robustness-of-LiDAR-vegetation-metrics-to-varying-point-densities)

Datasets

Vegetation structure metrics for seven demonstration sites in five European countries:


Contents lists available at ScienceDirect

Data in Brief

journal homepage: www.elsevier.com/locate/dib

ELSEVIER

Data Article

Data of vegetation structure metrics retrieved from airborne laser scanning surveys for European demonstration sites

W. Daniel Kissling*, Wessel Mulder, Jinhu Wang, Yifang Shi

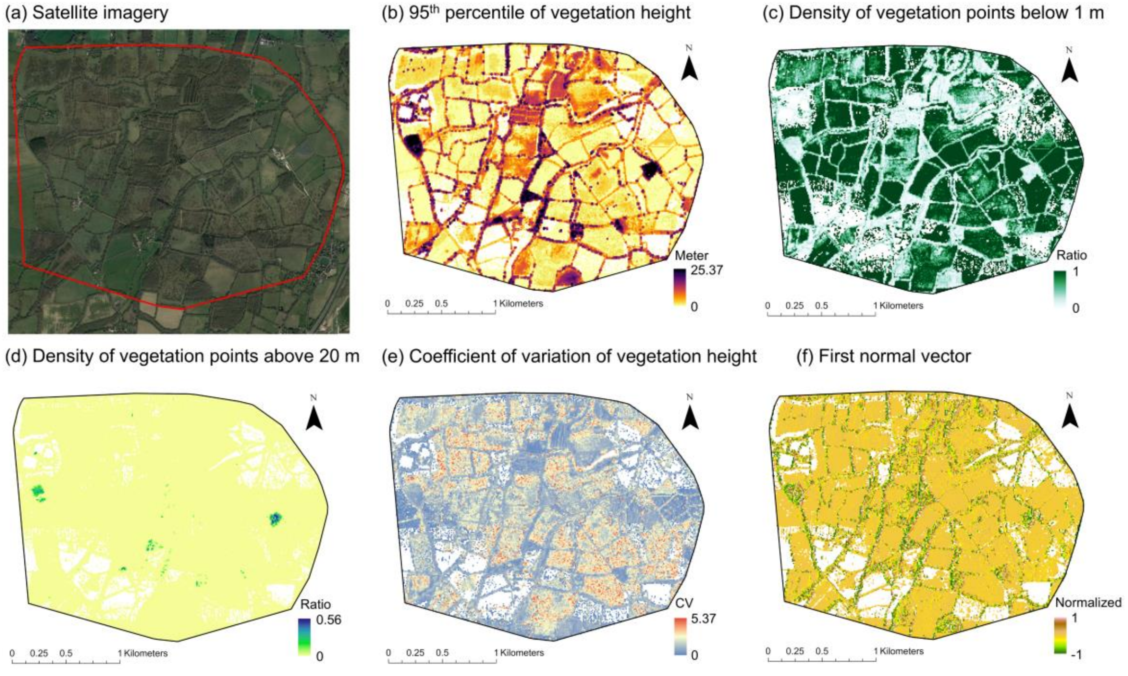
University of Amsterdam, Institute for Biodiversity and Ecosystem Dynamics (IBED), P.O. Box 94240, 1090 GE Amsterdam, the Netherlands

Kissling et al. 2025 *Data in Brief* https://doi.org/10.1016/j.dib.2025.111548
Zenodo: https://zenodo.org/records/14745310

- 35 LiDAR metrics, 10 m resolution
- Include habitat types such as forests, broadleaf and conifer woodlands, small plan- tations, dry and wet grasslands, marshes, reedbeds, arable fields, farmland, scrublands and mediterranean garigue

Includes seven sites:

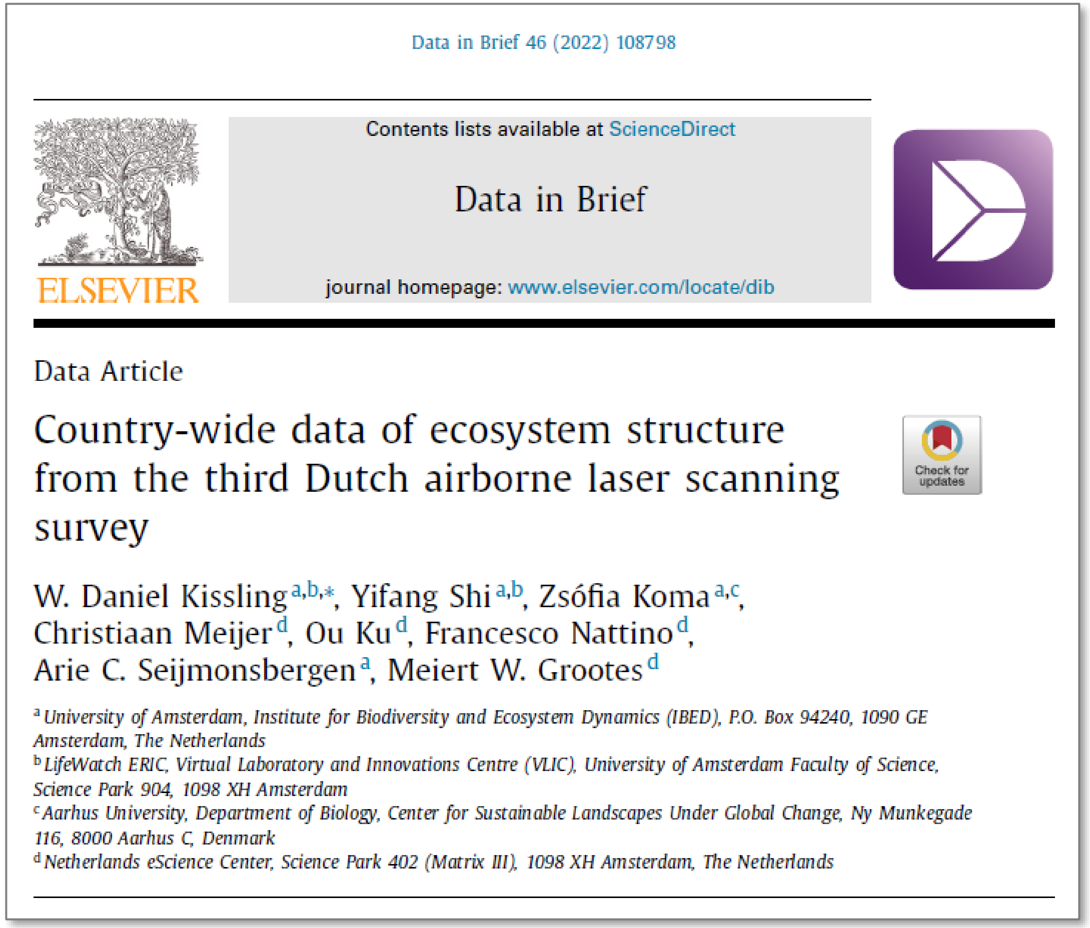
- Mols Bjerge National Park (Denmark)
- Reserve Naturelle Nationale du Bagnas (France)
- Oostvaardersplassen (Netherlands)
- Salisbury Plain (United Kingdom)
- Knepp Estate (United Kingdom)
- Monks Wood (United Kingdom)
- Island of Comino (Malta)



Example Knepp Estate in the United Kingdom

Datasets

Vegetation structure metrics for 3rd Dutch ALS campaign (AHN3):


Data in Brief 46 (2022) 108798

Contents lists available at ScienceDirect

Data in Brief

ELSEVIER

journal homepage: www.elsevier.com/locate/dib

Data Article

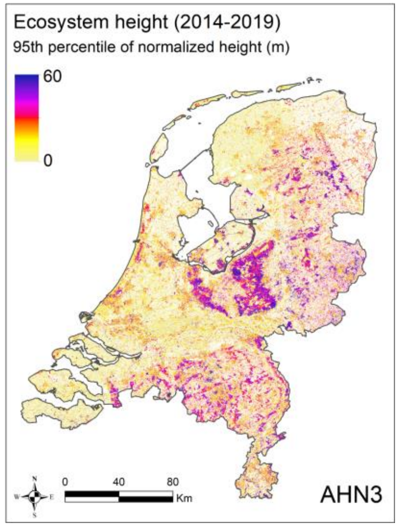
Country-wide data of ecosystem structure from the third Dutch airborne laser scanning survey

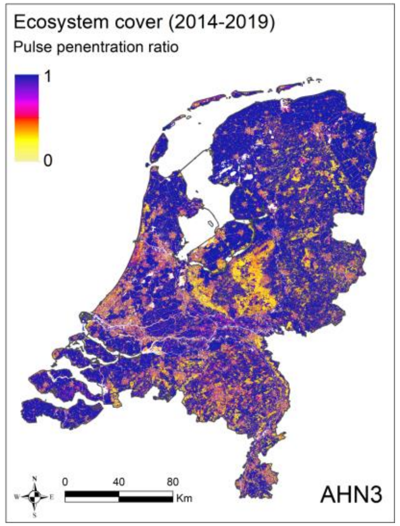
W. Daniel Kissling[a,b,*], Yifang Shi[a,b], Zsófia Koma[a,c], Christiaan Meijer[d], Ou Ku[d], Francesco Nattino[d], Arie C. Seijmonsbergen[a], Meiert W. Grootes[d]

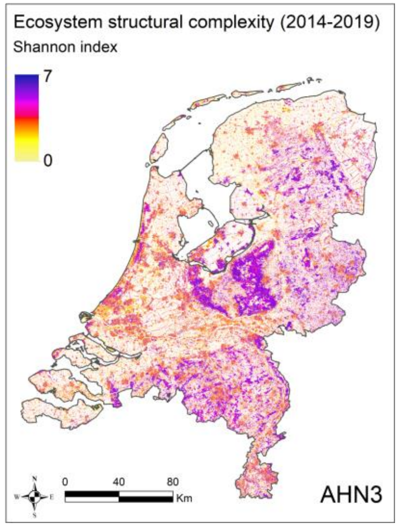
[a] University of Amsterdam, Institute for Biodiversity and Ecosystem Dynamics (IBED), P.O. Box 94240, 1090 GE Amsterdam, The Netherlands
[b] LifeWatch ERIC, Virtual Laboratory and Innovations Centre (VLIC), University of Amsterdam Faculty of Science, Science Park 904, 1098 XH Amsterdam
[c] Aarhus University, Department of Biology, Center for Sustainable Landscapes Under Global Change, Ny Munkegade 116, 8000 Aarhus C, Denmark
[d] Netherlands eScience Center, Science Park 402 (Matrix III), 1098 XH Amsterdam, The Netherlands

Kissling et al. 2023 *Data in Brief* https://doi.org/10.1016/j.dib.2022.108798
Zenodo: https://zenodo.org/records/13692080

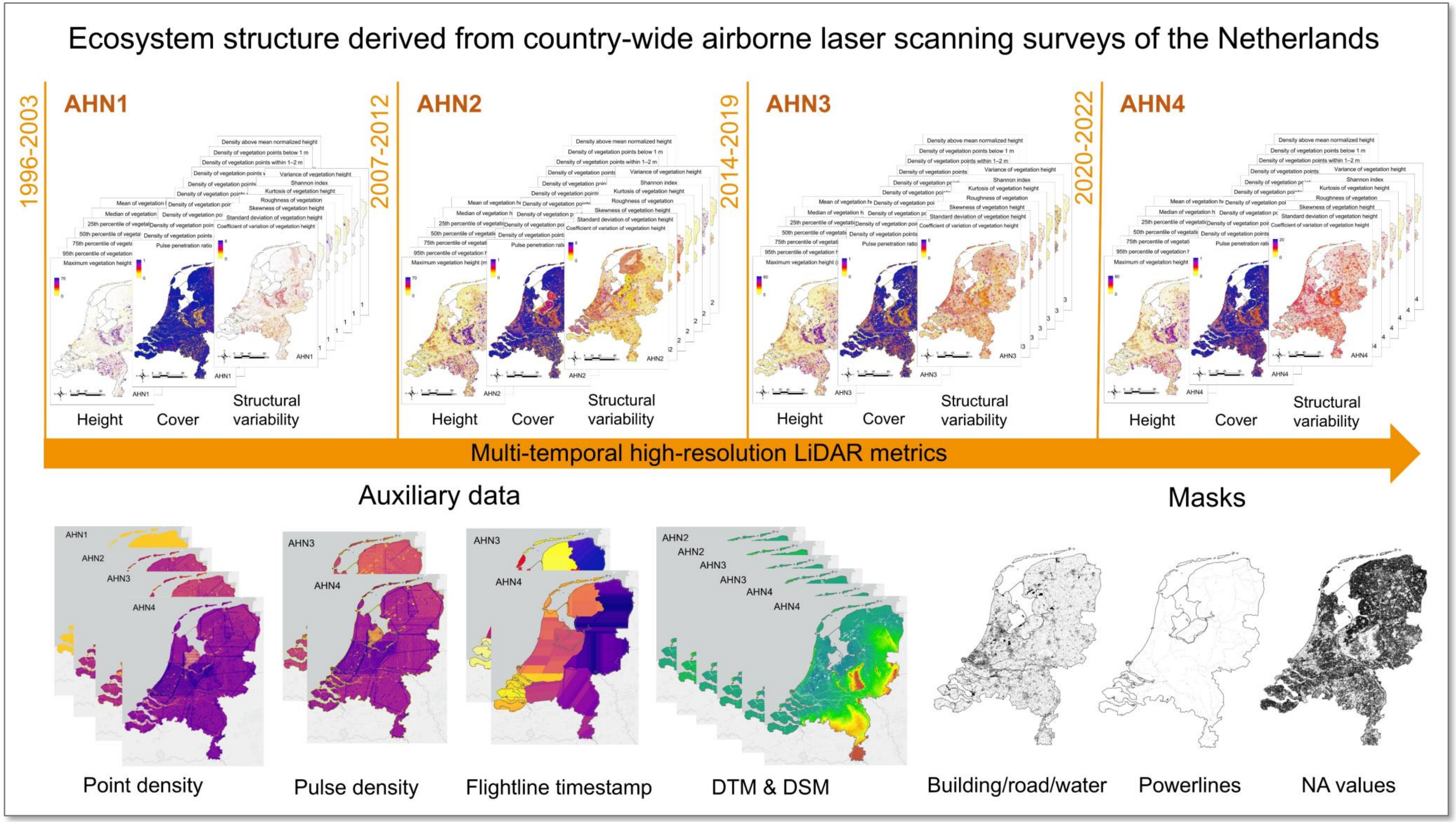
- 10 m resolution raster layers of ecosystem structure (GeoTIFF files)
- 25 LiDAR metrics of ecosystem height, cover and structural complexity
- Can be readily used by ecologists in a geographic information system (GIS) or analytical open-source software such as R







Datasets



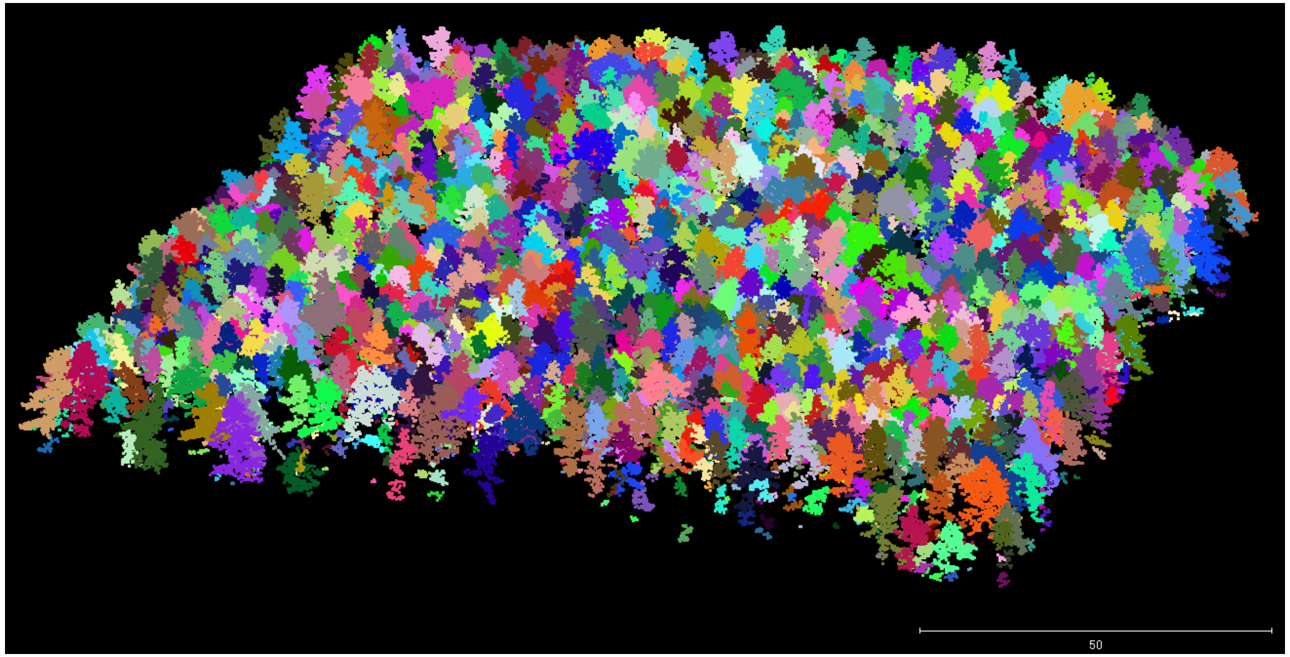
Shi et al. 2025 *Earth System Science Data* https://doi.org/10.5194/essd-17-3641-2025
Zenodo: https://zenodo.org/records/15261042

Datasets

Extracted trails in the Oostvaardersplassen nature reserve

Wang et al. 2025 *Zenodo*
https://doi.org/10.5281/zenodo.14987500

Ground truth data for tree classification and tree individualization



GitHub: https://github.com/Jinhu-Wang/Tree_Classification_and_Individualization_In_Marsh_Area?tab=readme-ov-file#validation-data

Most recent publications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Original Articles

Towards consistently measuring and monitoring habitat condition with airborne laser scanning and unmanned aerial vehicles

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ABSTRACT

Indicators of habitat condition are essential for tracking conservation progress, but measuring biotic, abiotic and landscape characteristics at fine resolution over large spatial extents remains challenging. In this *viewpoint* article, we provide a comprehensive synthesis of the challenges and solutions for consistently measuring and monitoring habitat condition with remote sensing using airborne Light Detection and Ranging (LiDAR) and affordable Unmanned Aerial Vehicles (UAVs) over multiple sites and transnational or continental extents. Key challenges include variability in sensor characteristics and survey designs, non-transparent pre-processing workflows, heterogeneous and complex data, issues with the robustness of metrics and indices, limited model generalizability and transferability across sites, and difficulties in handling big data, such as managing large volumes and utilizing parallel or distributed computing. We suggest that a collaborative cloud virtual research environment (VRE) for habitat condition research and monitoring could provide solutions, including tools for data discovery, access, and data standardization, as well as geospatial processing workflows for airborne LiDAR and UAV data. A VRE would also improve data management, metadata standardization, workflow reproducibility, and transferability of structure-from-motion algorithms and machine learning models such as random forests and convolutional neural networks. Along with best practices for data collection and adopting FAIR (findability, accessibility, interoperability, reusability) principles and open science practices, a VRE could enable more consistent and transparent data processing and metric retrieval, e.g., for Natura 2000 habitats. Ultimately, these improvements would support the development of more reliable habitat condition indicators, helping prevent habitat degradation and promoting the sustainable use of natural resources.

1. Introduction

Habitat condition can be measured by quantifying the biotic, abiotic and landscape characteristics of an ecosystem (Turner and Gardner, 2015). A good habitat condition allows species to meet their needs for resources, shelter, and successful reproduction and promotes the conservation of habitats with their wild fauna and flora, including the diversity, distribution and abundance of a variety of animals, plants and other organisms (Moeslund et al., 2019; Nagendra et al., 2013; Tews et al., 2004; Turner and Gardner, 2015). Indicators of habitat condition can be derived from measurements of vegetation structure, cover and composition (Lorimer, 2024; Magee et al., 2019), topography (Assmann et al., 2022; Davies and Asner, 2014; Moeslund et al., 2013), microclimate (Zellweger et al., 2019), soil heterogeneity (Guerra et al., 2021), hydrology (Rolls et al., 2018), biotic resources such as deadwood (Seibold et al., 2015), dung, litter, carcasses and flower abundance (Brunbjerg et al., 2017; Sookhan et al., 2024), and landscape elements such as hedgerows, tree lines, stonewalls and flower strips (Albrecht et al., 2021; Broughton et al., 2021). Habitat extent and condition continue to decline at alarming rates, facing deteriorating trends from changes in land use, eutrophication, unsustainable management practices and other human-induced pressures, which contributes substantially to the ongoing loss of biodiversity (Diaz et al., 2019). While some habitats show improvements, progress is generally not sufficient to meet conservation targets and policy goals (European Environment Agency, 2020; Leclère et al., 2020; Moersberger et al., 2024). Effective

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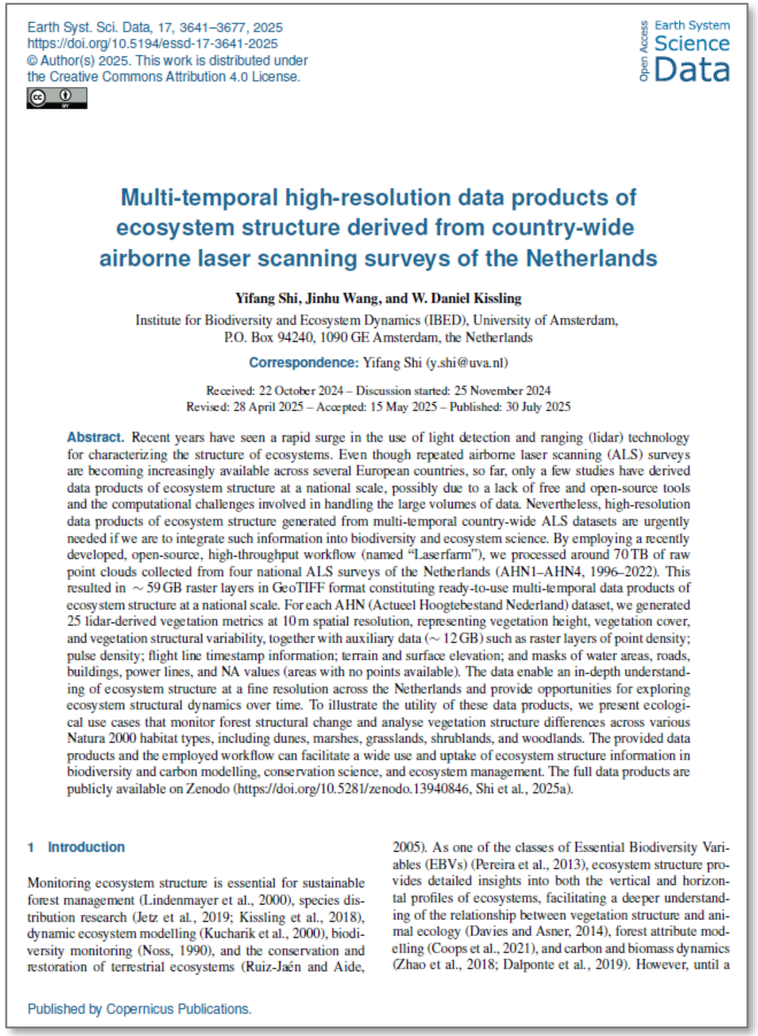
Earth Syst. Sci. Data, 17, 3641–3677, 2025
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Open Access Earth System Science Data

Multi-temporal high-resolution data products of ecosystem structure derived from country-wide airborne laser scanning surveys of the Netherlands

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Abstract. Recent years have seen a rapid surge in the use of light detection and ranging (lidar) technology for characterizing the structure of ecosystems. Even though repeated airborne laser scanning (ALS) surveys are becoming increasingly available across several European countries, so far, only a few studies have derived data products of ecosystem structure at a national scale, possibly due to a lack of free and open-source tools and the computational challenges involved in handling the large volumes of data. Nevertheless, high-resolution data products of ecosystem structure generated from multi-temporal country-wide ALS datasets are urgently needed if we are to integrate such information into biodiversity and ecosystem science. By employing a recently developed, open-source, high-throughput workflow (named "Laserfarm"), we processed around 70 TB of raw point clouds collected from four national ALS surveys of the Netherlands (AHN1–AHN4, 1996–2022). This resulted in ~ 59 GB raster layers in GeoTIFF format constituting ready-to-use multi-temporal data products of ecosystem structure at a national scale. For each AHN (Actueel Hoogtebestand Nederland) dataset, we generated 25 lidar-derived vegetation metrics at 10 m spatial resolution, representing vegetation height, vegetation cover, and vegetation structural variability, together with auxiliary data (~ 12 GB) such as raster layers of point density; pulse density; flight line timestamp information; terrain and surface elevation; and masks of water areas, roads, buildings, power lines, and NA values (areas with no points available). The data enable an in-depth understanding of ecosystem structure at a fine resolution across the Netherlands and provide opportunities for exploring ecosystem structural dynamics over time. To illustrate the utility of these data products, we present ecological use cases that monitor forest structural change and analyse vegetation structure differences across various Natura 2000 habitat types, including dunes, marshes, grasslands, shrublands, and woodlands. The provided data products and the employed workflow can facilitate a wide use and uptake of ecosystem structure information in biodiversity and carbon modelling, conservation science, and ecosystem management. The full data products are publicly available on Zenodo (https://doi.org/10.5281/zenodo.13940846, Shi et al., 2025a).

1 Introduction

Monitoring ecosystem structure is essential for sustainable forest management (Lindenmayer et al., 2000), species distribution research (Jetz et al., 2019; Kissling et al., 2018), dynamic ecosystem modelling (Kucharik et al., 2000), biodiversity monitoring (Noss, 1990), and the conservation and restoration of terrestrial ecosystems (Ruiz-Jaén and Aide, 2005). As one of the classes of Essential Biodiversity Variables (EBVs) (Pereira et al., 2013), ecosystem structure provides detailed insights into both the vertical and horizontal profiles of ecosystems, facilitating a deeper understanding of the relationship between vegetation structure and animal ecology (Davies and Asner, 2014), forest attribute modelling (Coops et al., 2021), and carbon and biomass dynamics (Zhao et al., 2018; Dalponte et al., 2019). However, until a

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A workflow for extracting ungulate trails in wetlands using 3D point clouds obtained from airborne laser scanning

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Ungulates and other mammalian herbivores can create trails in dense vegetation by trampling and browsing. This can affect vegetation structure and result in the fragmentation of closed, high vegetation, with subsequent impacts on biodiversity. Manually mapping trails in the field or from aerial photographs can be challenging and time-consuming, especially in inaccessible or difficult-to-access habitats such as wetlands and if trails occur beneath the canopy of woody plants (i.e., trees and shrubs) or in other tall vegetation (e.g., reed). Airborne laser scanning (ALS) provides an alternative method because Light Detection and Ranging (LiDAR) can record returns from both the canopy and the ground, as some laser pulses pass through gaps in the vegetation, resulting in highly accurate and dense three-dimensional (3D) point clouds. Here, we present a workflow for extracting ungulate trails using 3D point clouds obtained from country-wide ALS surveys, illustrated by red deer trampling in reedbeds within a 36 km^2 marsh area of a Dutch nature reserve. The workflow starts by pre-processing to retile the LiDAR point clouds to designated tiles and removes outliers from the raw data. The (near-)terrain points are then segmented using an iterative filtering algorithm, and digital terrain models are generated with a user-defined resolution. Finally, trail cells are extracted by thresholding the residuals from iterative Laplacian smoothing and then refined by sparse 3D structure tensor voting. The parameters of the workflow were optimized with comprehensive sensitivity analyses. Applying the workflow resulted in a classification of trail and non-trail grid cells at 10 cm resolution across the study area. Compared to manually labeled ground truths, the results showed an overall accuracy of 93% and 90% in regions of red deer grazing only and both geese and red deer grazing, respectively. To test its transferability, the workflow could be applied to other LiDAR data (e.g., ALS surveys from another flight campaign in the same study area or in a different country), to other nature areas (e.g., other rewilding sites or other wetlands), and to other ungulate species (e.g., domesticated livestock or other native large herbivores).

KEYWORDS
ecosystem structure, grazing pressure, habitat condition, large mammals, light detection and ranging, nature conservation, vegetation structure, reedbed

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Examples of ecological applications

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RESEARCH ARTICLE

Diversity and Distributions WILEY

Identifying fine-scale habitat preferences of threatened butterflies using airborne laser scanning

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Editor: Reid Tingley

Abstract

Aim: Light Detection And Ranging (LiDAR) is a promising remote sensing technique for ecological applications because it can quantify vegetation structure at high resolution over broad spatial extents. Using country-wide airborne laser scanning (ALS) data, we test to what extent fine-scale LiDAR metrics capturing low vegetation, medium-to-high vegetation and landscape-scale habitat structures can explain the habitat preferences of threatened butterflies at a national extent.

Location: The Netherlands.

Methods: We applied a machine-learning (random forest) algorithm to build species distribution models (SDMs) for grassland and woodland butterflies in wet and dry habitats using various LiDAR metrics and butterfly presence–absence data collected by a national butterfly monitoring scheme. The LiDAR metrics captured vertical vegetation complexity (e.g., height and vegetation density of different strata) and horizontal heterogeneity (e.g., vegetation roughness, microtopography, vegetation openness and woodland edge extent). We assessed the relative variable importance and interpreted response curves of each LiDAR metric for explaining butterfly occurrences.

Results: All SDMs showed a good to excellent fit, with woodland butterfly SDMs performing slightly better than those of grassland butterflies. Grassland butterfly occurrences were best explained by landscape-scale habitat structures (e.g., open patches, microtopography) and vegetation height. Woodland butterfly occurrences were mainly determined by vegetation density of medium-to-high vegetation, open patches and woodland edge extent. The importance of metrics generally differed between wet and dry habitats for both grassland and woodland species.

Main conclusions: Vertical variability and horizontal heterogeneity of vegetation structure are key determinants of butterfly species distributions, even in low-stature habitats such as grasslands, dunes and heathlands. The information content of low vegetation LiDAR metrics could further be improved with country-wide leaf-on ALS data or surveys from drones and terrestrial laser scanners at specific sites. LiDAR

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DOI: 10.1111/ddi.12915

BIODIVERSITY REVIEW

WILEY Diversity and Distributions

Use and categorization of Light Detection and Ranging vegetation metrics in avian diversity and species distribution research

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Funding information
Netherlands eScience Center.

Editor: Damaris Zurell

Abstract

Aim: Vegetation structure is a key determinant of animal diversity and species distributions. The introduction of Light Detection and Ranging (LiDAR) has enabled the collection of massive amounts of point cloud data for quantifying habitat structure at fine resolution. Here, we review the current use of LiDAR-derived vegetation metrics in diversity and distribution research of birds, a key group for understanding animal–habitat relationships.

Location: Global.

Methods: We review 50 relevant papers and quantify where, in which habitats, at which spatial scales and with what kind of LiDAR data current studies make use of LiDAR metrics. We also harmonize and categorize LiDAR metrics and quantify their current use and effectiveness.

Results: Most studies have been conducted at local extents in temperate forests of North America and Europe. Rasterization is currently the main method to derive LiDAR metrics, usually from airborne laser scanning data with low point densities (<10 points/m^2) and small footprints (<1 m diameter). Our metric harmonization suggests that 40% of the currently used metric names are redundant. A categorization scheme allowed to group all metric names into 18 out of 24 theoretically possible classes, defined by vegetation part (total vegetation, single trees, canopy, understorey, and other single layers as well as multi-layer) and structural type (cover, height, horizontal variability and vertical variability). Metrics related to canopy cover, canopy height and canopy vertical variability are currently most often used, but not always effective.

Main conclusions: Light Detection and Ranging metrics play an important role in understanding animal space use. Our review and the developed categorization scheme may facilitate future studies in the selection, prioritization and ecological interpretation of LiDAR metrics. The increasing availability of airborne and spaceborne LiDAR data and the development of voxel-based and object-based approaches will further allow novel ecological applications, also for open habitats and other vertebrate and invertebrate taxa.

ECOGRAPHY

Research

Niche separation of wetland birds revealed from airborne laser scanning

Zsófia Koma, Meiert W. Grootes, Christiaan W. Meijer, Francesco Nattino, Arie C. Seijmonsbergen, Henk Sierdsema, Ruud Foppen and W. Daniel Kissling

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Ecography
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Numerous organisms depend on the physical structure of their habitats, but incorporating such information into ecological niche analyses has been limited by the lack of adequate data over broad spatial extents. The increasing availability of high-resolution measurements from country-wide airborne laser scanning (ALS) surveys – a light detection and ranging (LiDAR) technology – now provides unprecedented opportunities for characterizing habitat structure. Here, we use country-wide ALS data in combination with presence–absence observations of birds from a national monitoring scheme in the Netherlands to quantify niche filling, niche overlap and niche separation of three closely-related wetland birds (great reed warbler, Eurasian reed warbler and Savi's warbler). We developed a workflow to derive LiDAR metrics capturing different aspects of vertical and horizontal vegetation structure and used a principal component analysis (PCA), niche equivalency and niche similarity tests to analyse the fine-scale breeding habitat niches of these warbler species in the Netherlands. The widespread Eurasian reed warbler almost completely filled the available wetland habitat space (93%) whereas the two other species showed considerably less niche filling (64% and 74%, respectively). Substantial niche overlap occurred among all species, but each species occupied a distinct part of the habitat space. The great reed warbler mainly occurred in tall and vertically complex wetland vegetation and was absent in areas with large proportions of reedbeds. The Eurasian reed warbler occupied all parts of the wetland habitat space, whereas the Savi's warbler mainly occurred in large homogenous reedbeds with low vegetation height. Our results demonstrate that broad-scale ecological niche analyses can incorporate the fine-scale 3D habitat preference of species with unprecedented detail (e.g. 10 m resolution), and thus go much beyond quantifying the climate niche and 2D habitat information from land cover maps. This is important to identify habitat features and priorities for biodiversity conservation in wetlands and other habitats.

Keywords: *Acrocephalus*, active remote sensing, ecological niche, landscape ecology, *Locustella*, wetland restoration

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Koma et al. 2021 Ecography
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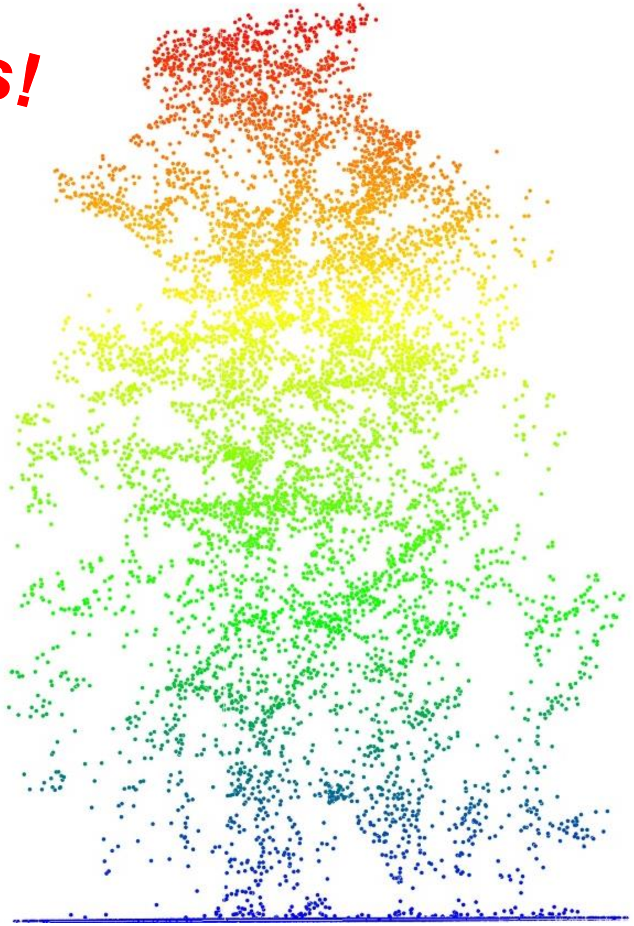
University of Amsterdam
Faculty of Science

Institute for Biodiversity and Ecosystem Dynamics

Measuring vegetation structure with airborne LiDAR

Thanks!



We plan an in-person (3-4 day) workshop and training course on ‘Scaling up LiDAR workflows for ecological applications across Europe’ (February 2026)

If you are interested, contact us or leave your details (full name) in the chat with ‘course’.

Questions & answers (15-30 min)

MAMBO

Funded by the European Union

Views and opinions expressed are those of the author(s) only and do not necessarily reflect those of the European Union or the European Commission. Neither the EU nor the EC can be held responsible for them.