Rethinking Forest Growth in the LiDAR Era

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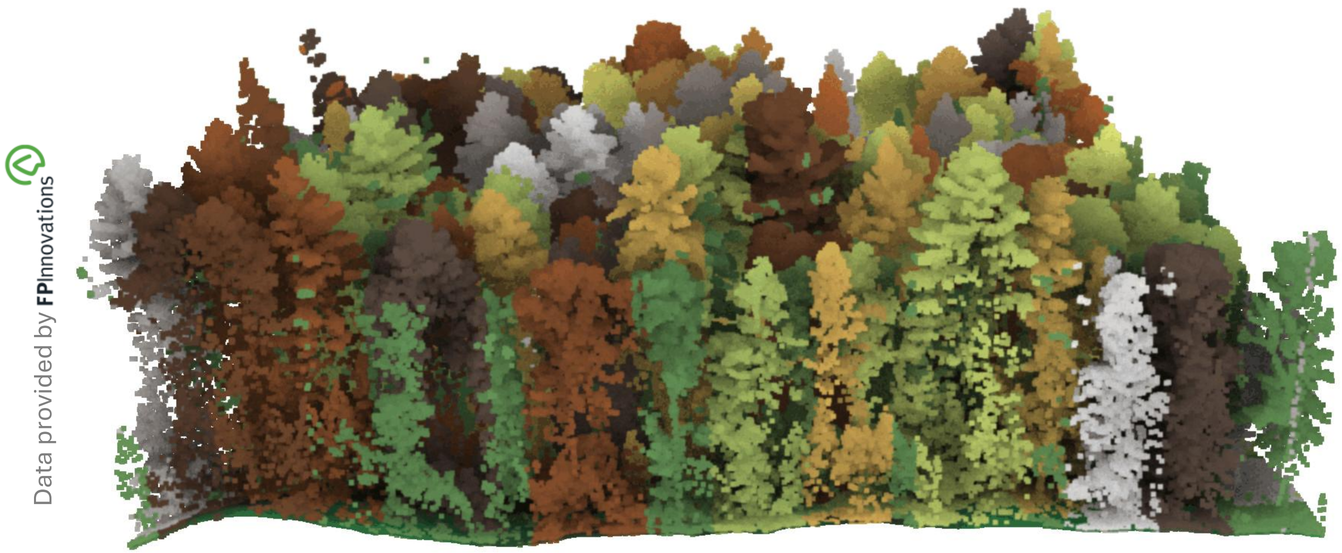
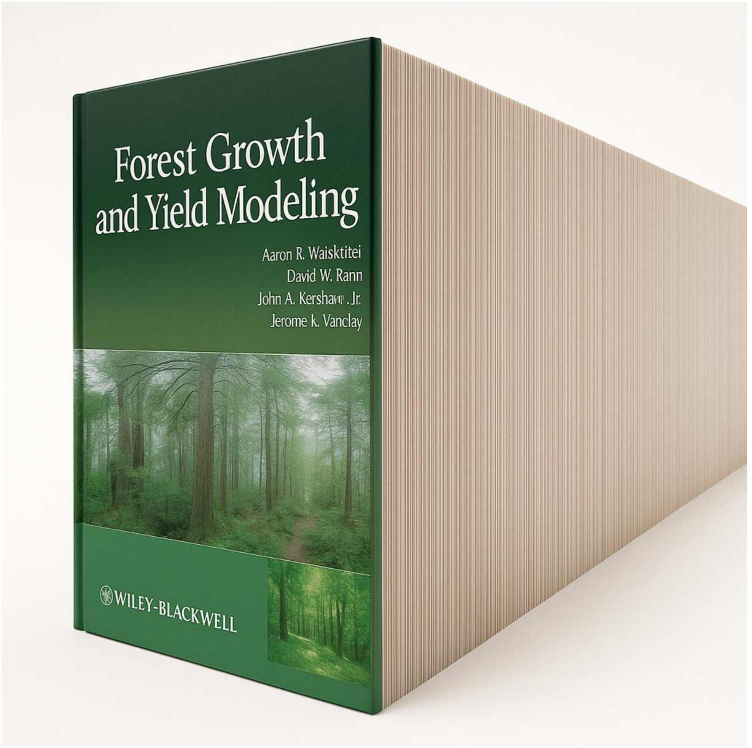
Service canadien des forêts

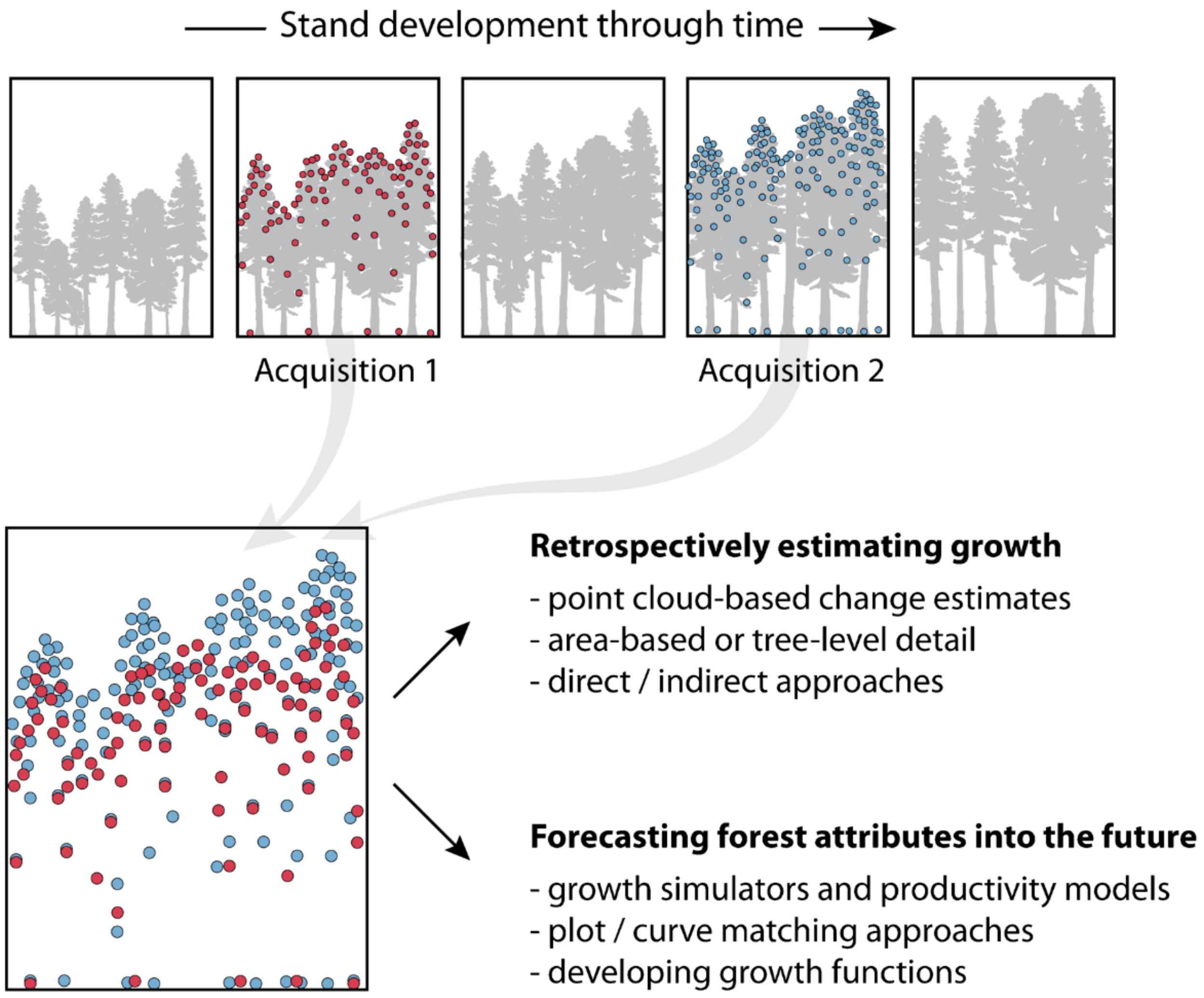
Introduction

- Forest growth is complex, yet essential
- Lidar provides new opportunities to improve models and inventories
- Today: from basics → lidar & growth → future directions





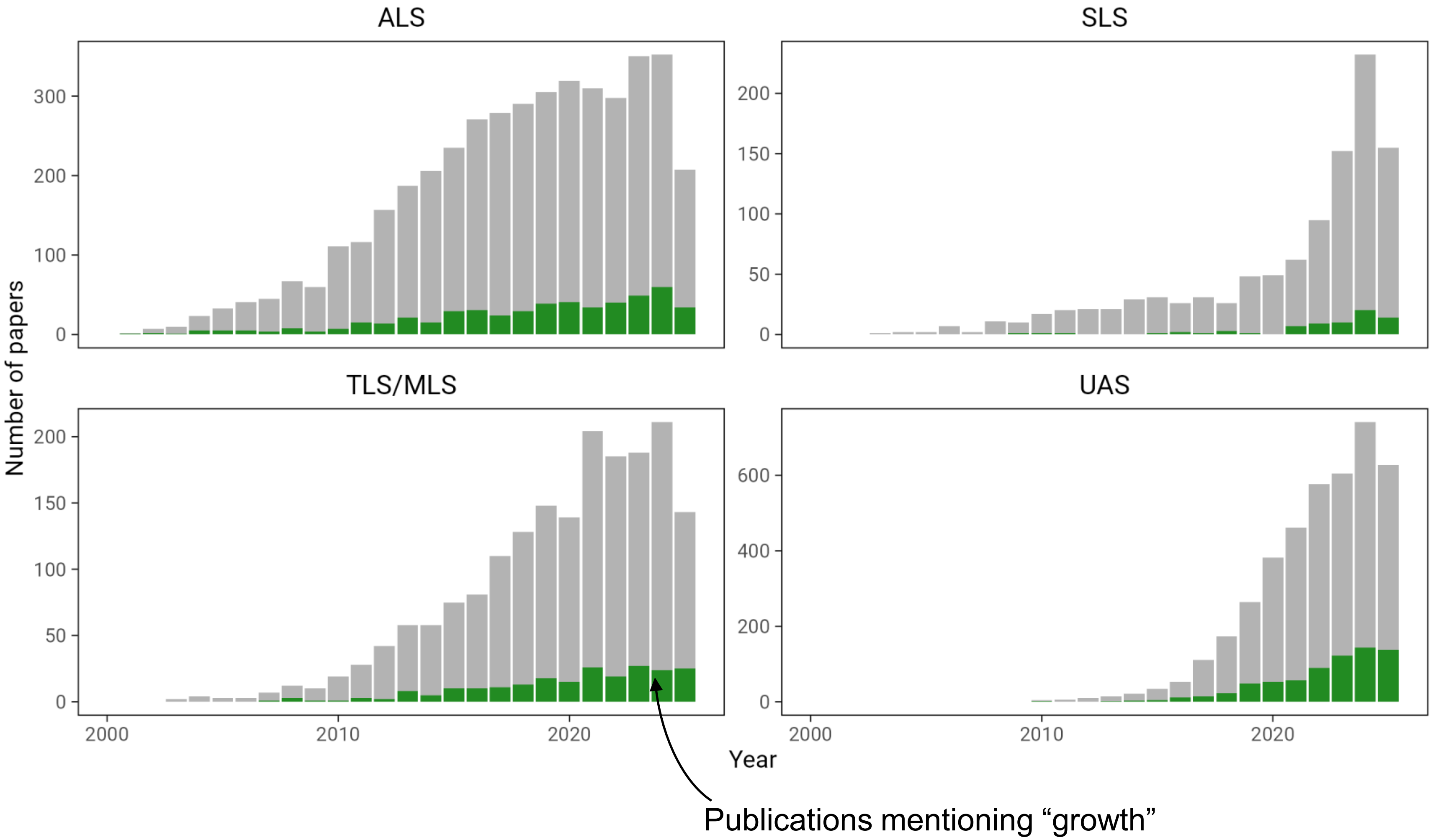
Monitoring vs forecasting



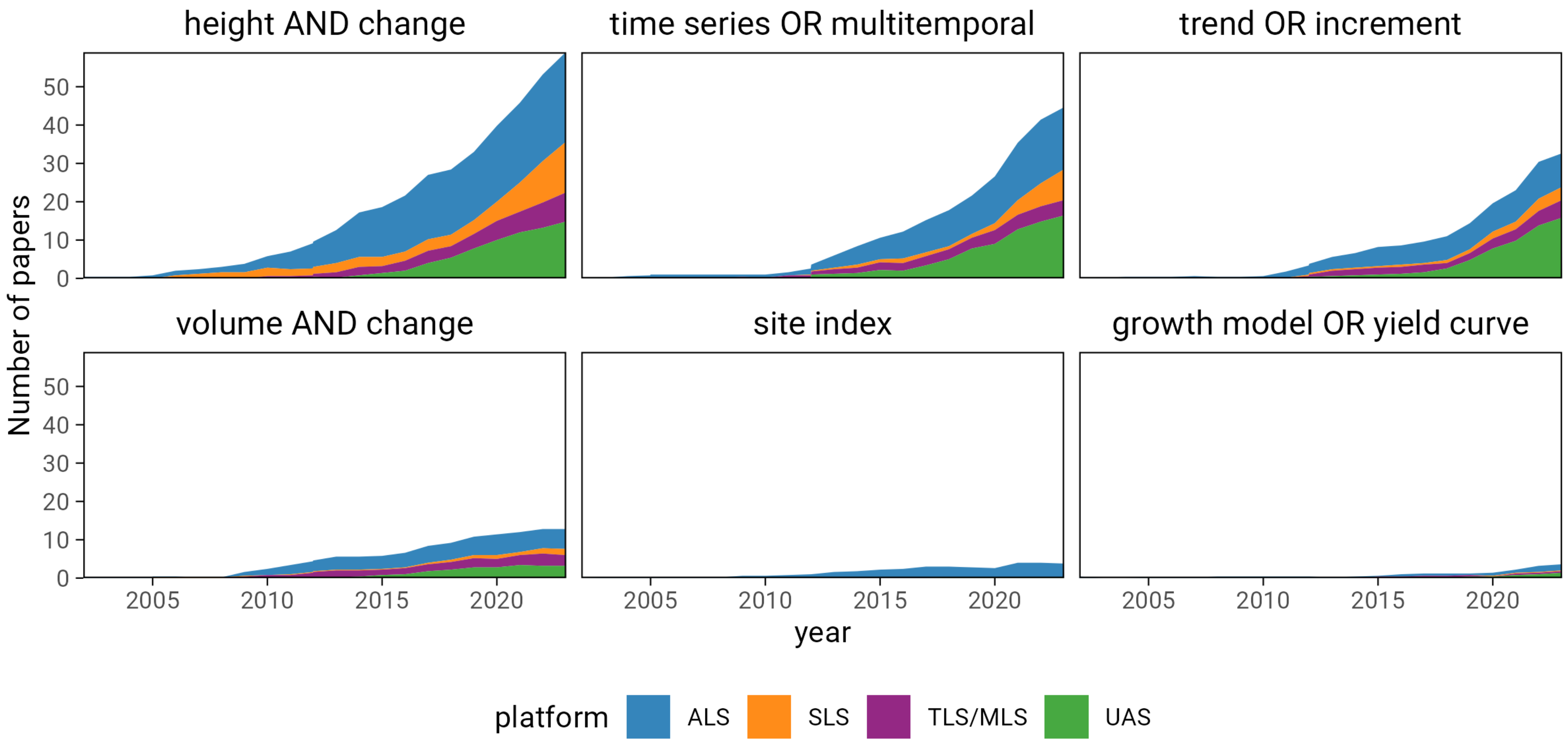
Tompalski, P., Coops, N.C., White, J.C., Goodbody, T.R.H., Hennigar, C.R., Wulder, M.A., Socha, J., Woods, M.E., 2021. Estimating Changes in Forest Attributes and Enhancing Growth Projections: a Review of Existing Approaches and Future Directions Using Airborne 3D Point Cloud Data. Current Forestry Reports. https://doi.org/10.1007/s40725-021-00135-w

How can we use lidar to improve forest monitoring and forecasting of forest attributes?

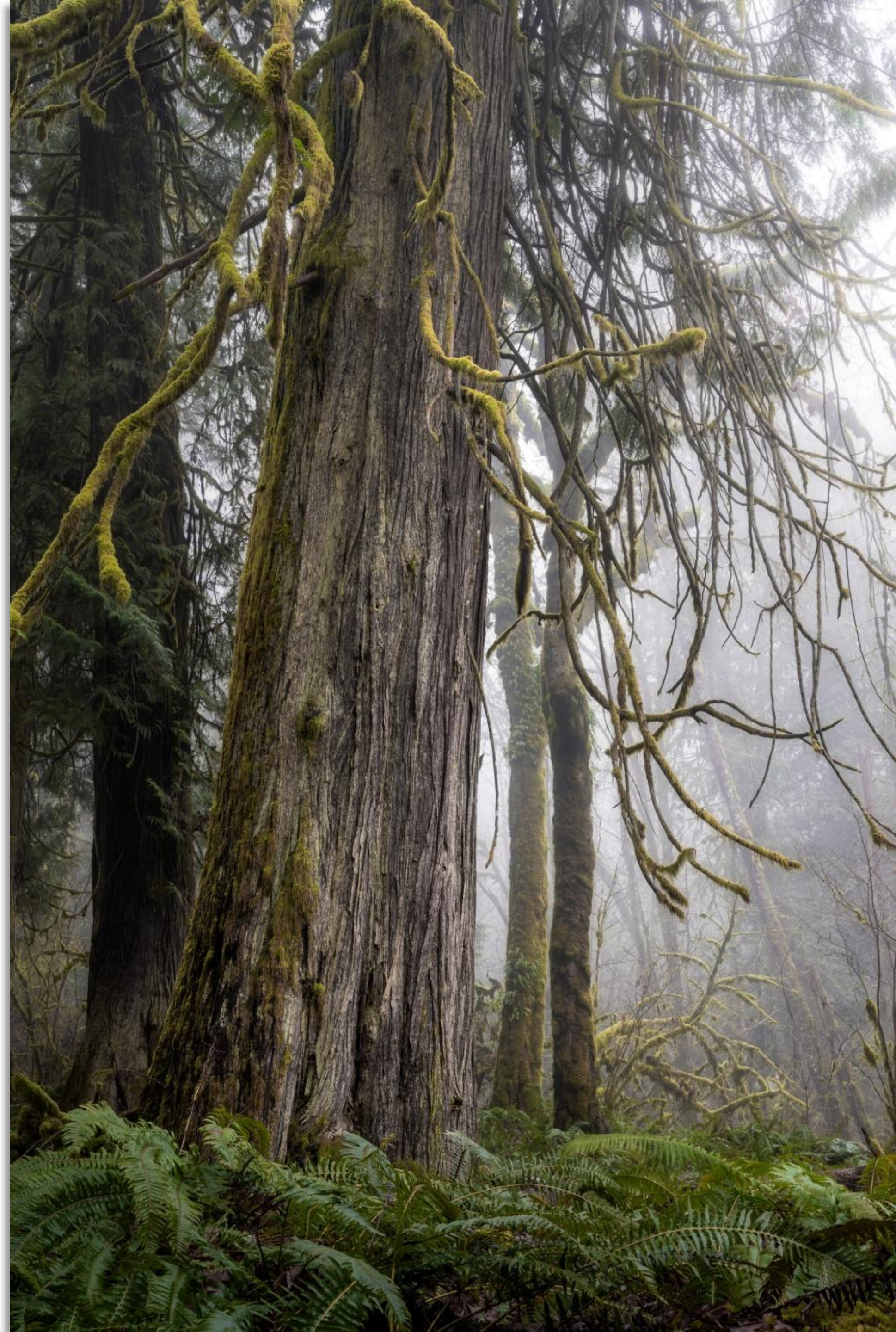
Literature overview

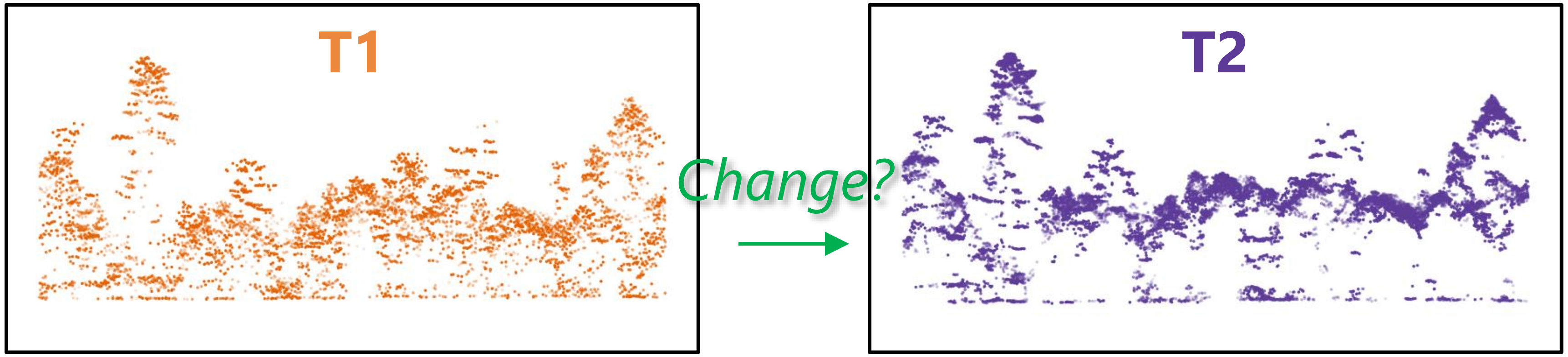


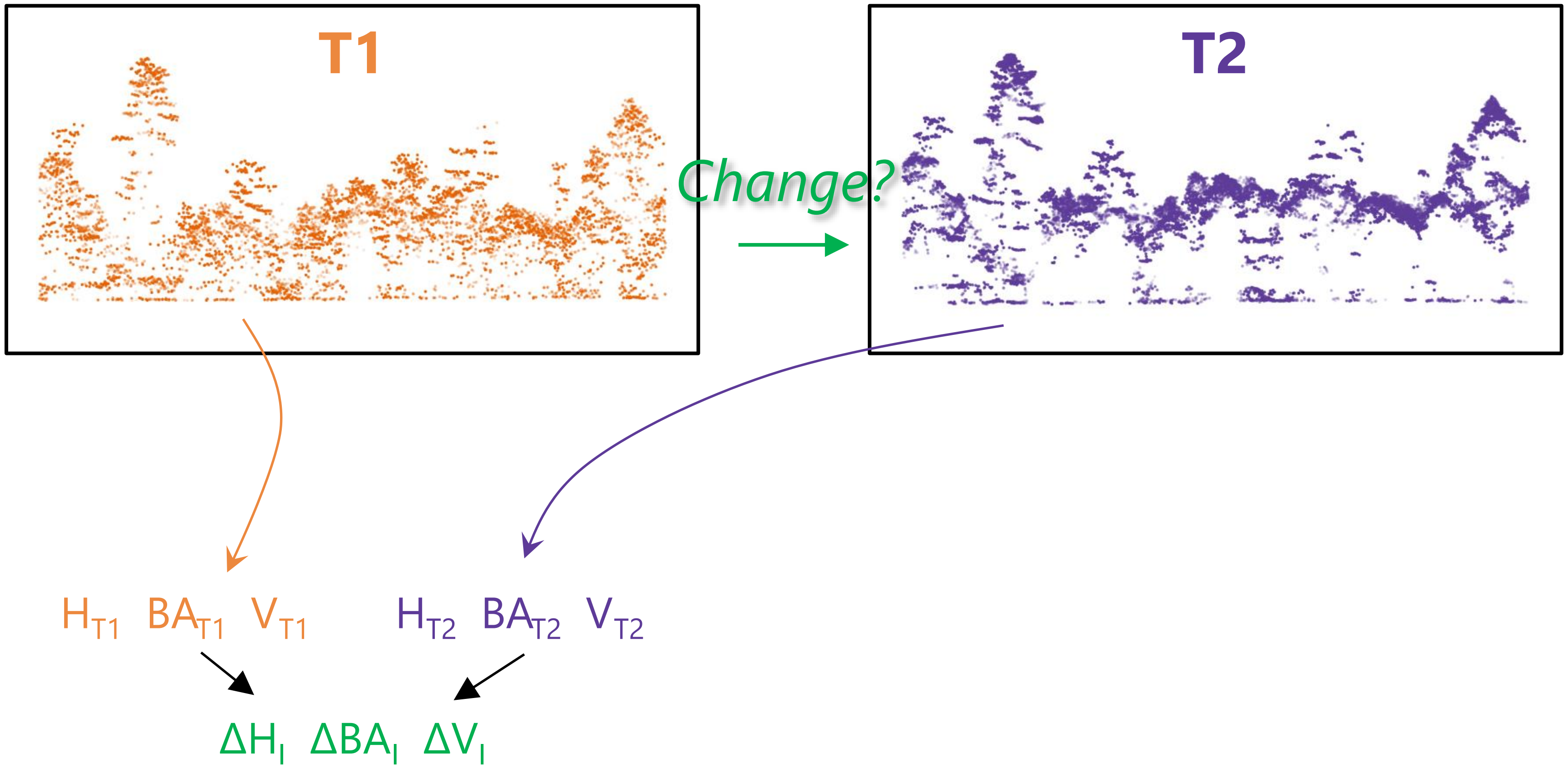
Literature overview

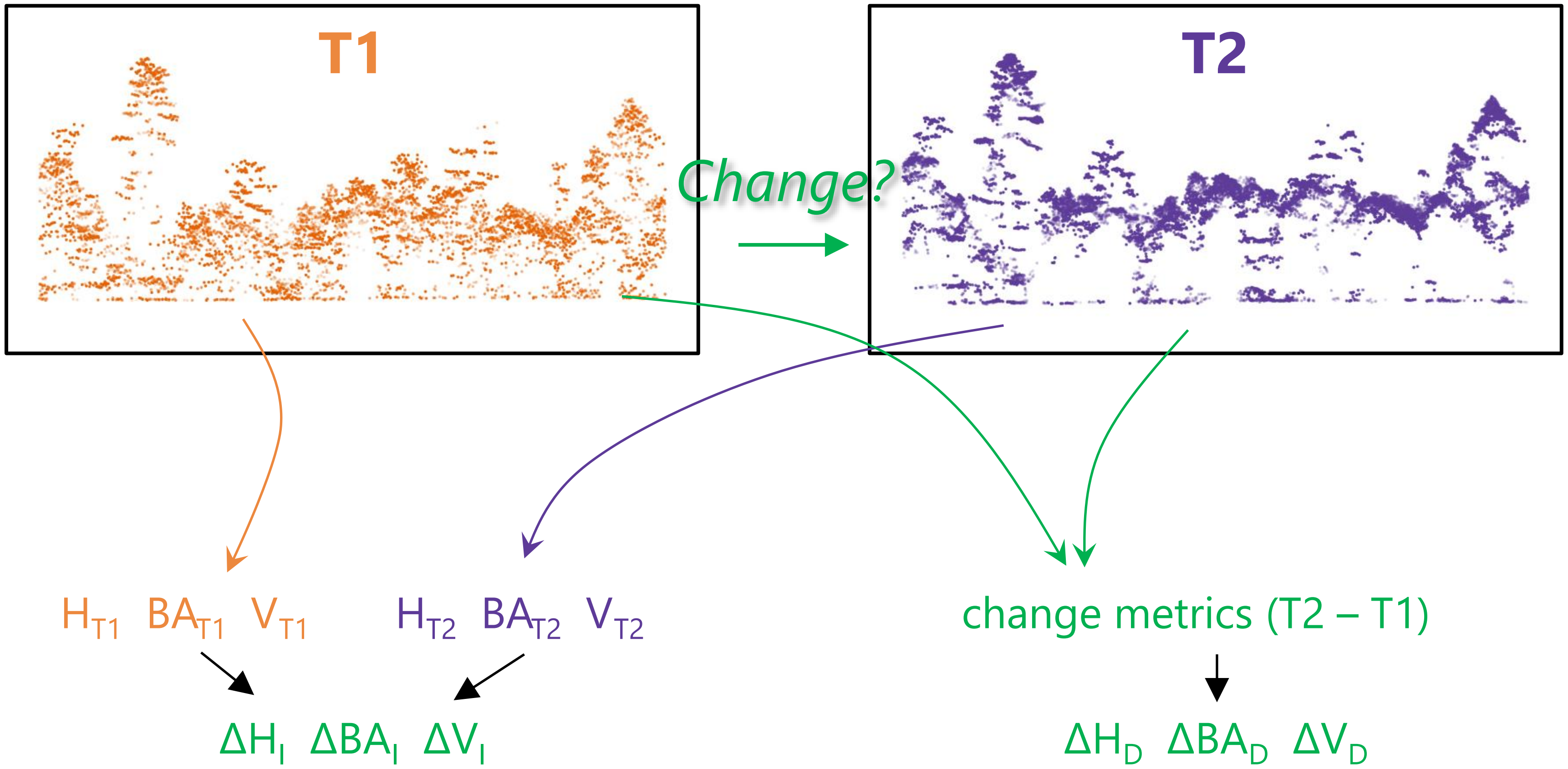


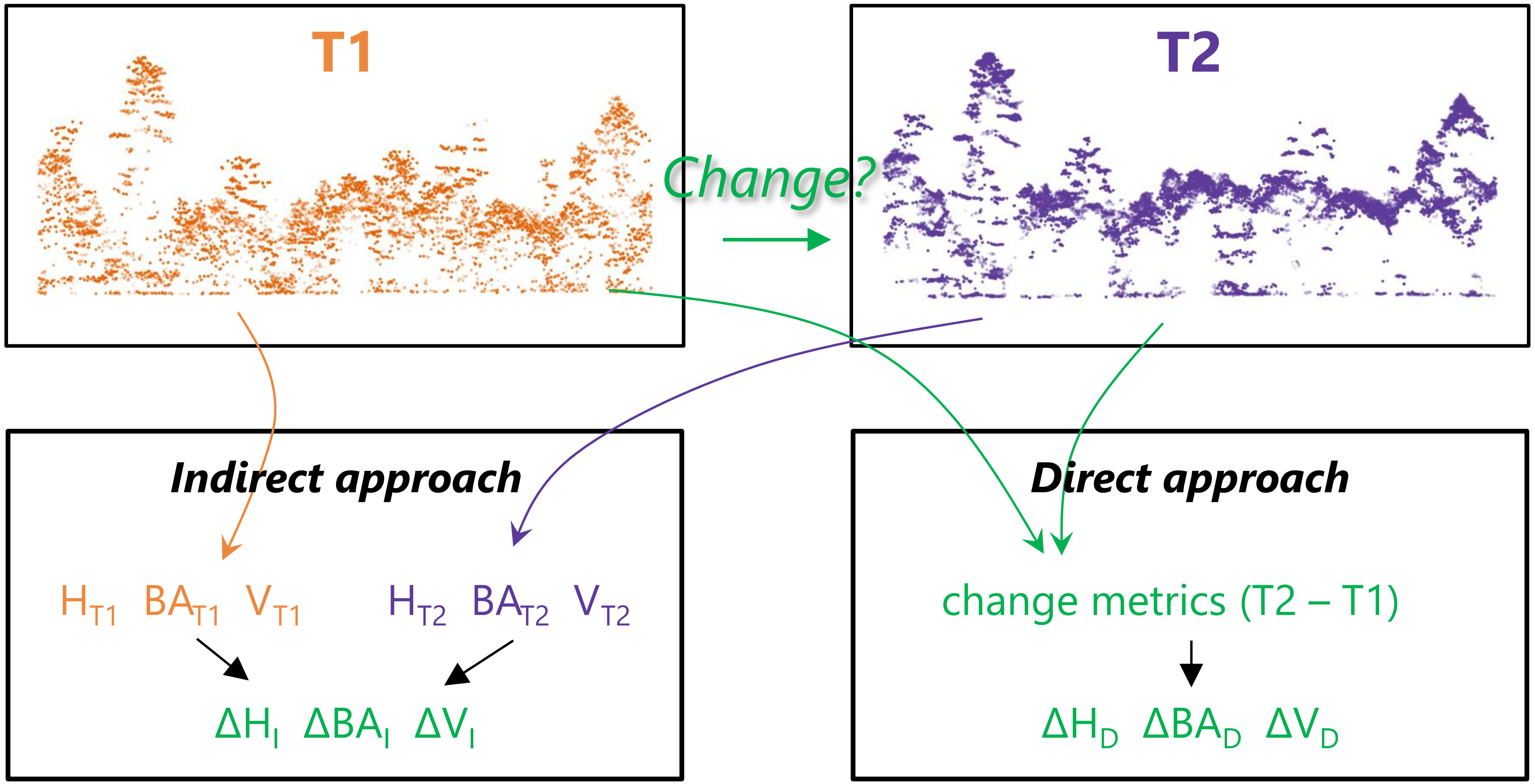
Monitoring



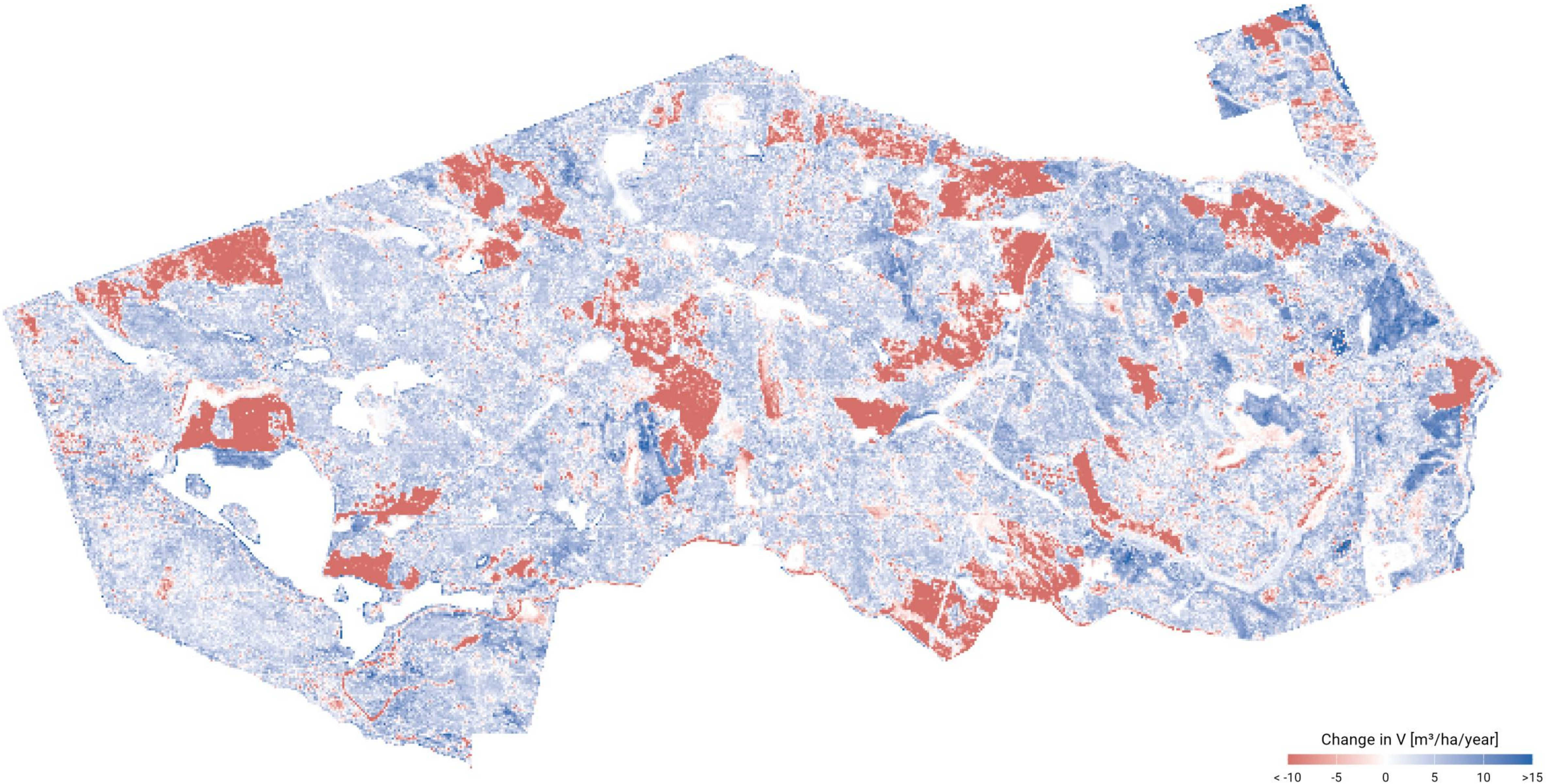

T1
Change?
T2


T1
T2
Change?
H_{T1} BA_{T1} V_{T1}
H_{T2} BA_{T2} V_{T2}
ΔH_I ΔBA_I ΔV_I


T1
T2
Change?
H_{T1} BA_{T1} V_{T1}
H_{T2} BA_{T2} V_{T2}
change metrics (T2 – T1)
ΔH_I ΔBA_I ΔV_I
ΔH_D ΔBA_D ΔV_D

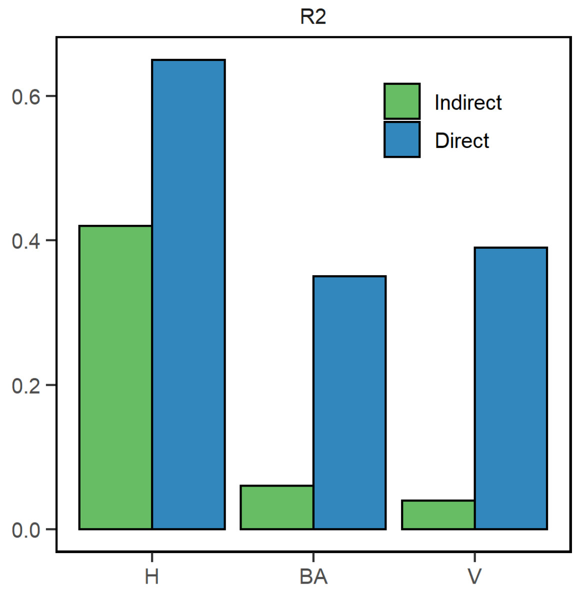


T1
T2
Change?
Indirect approach
H_{T1} BA_{T1} V_{T1}
H_{T2} BA_{T2} V_{T2}
ΔH_I ΔBA_I ΔV_I
Direct approach
change metrics (T2 – T1)
ΔH_D ΔBA_D ΔV_D

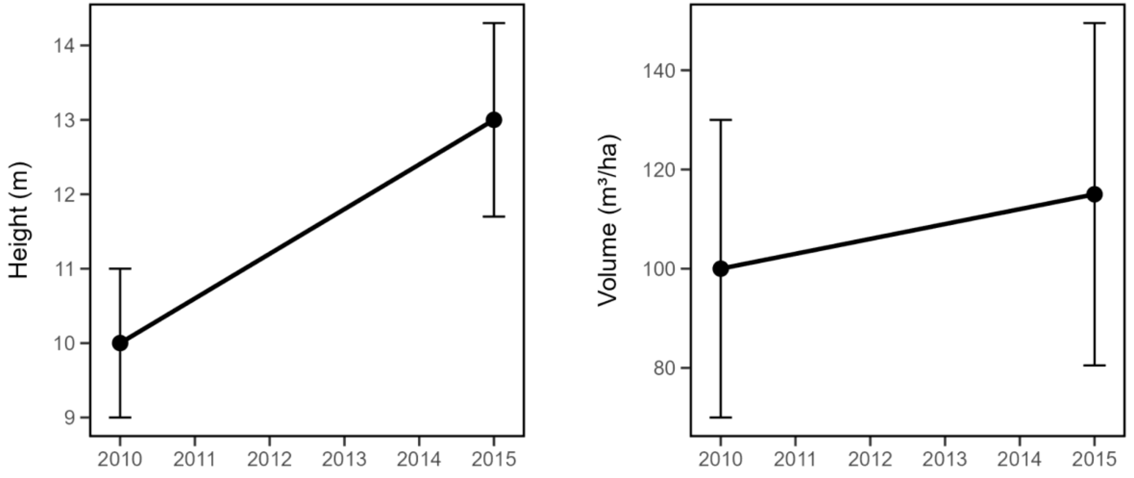

Change in V [m³/ha/year]
< -10
-5
0
5
10
>15

Direct vs indirect

- No consensus in the literature
- Both sensitive to mortality and disturbance
- ΔH - the most accurate
- Time interval is important – growth should exceed the uncertainty in attribute predictions



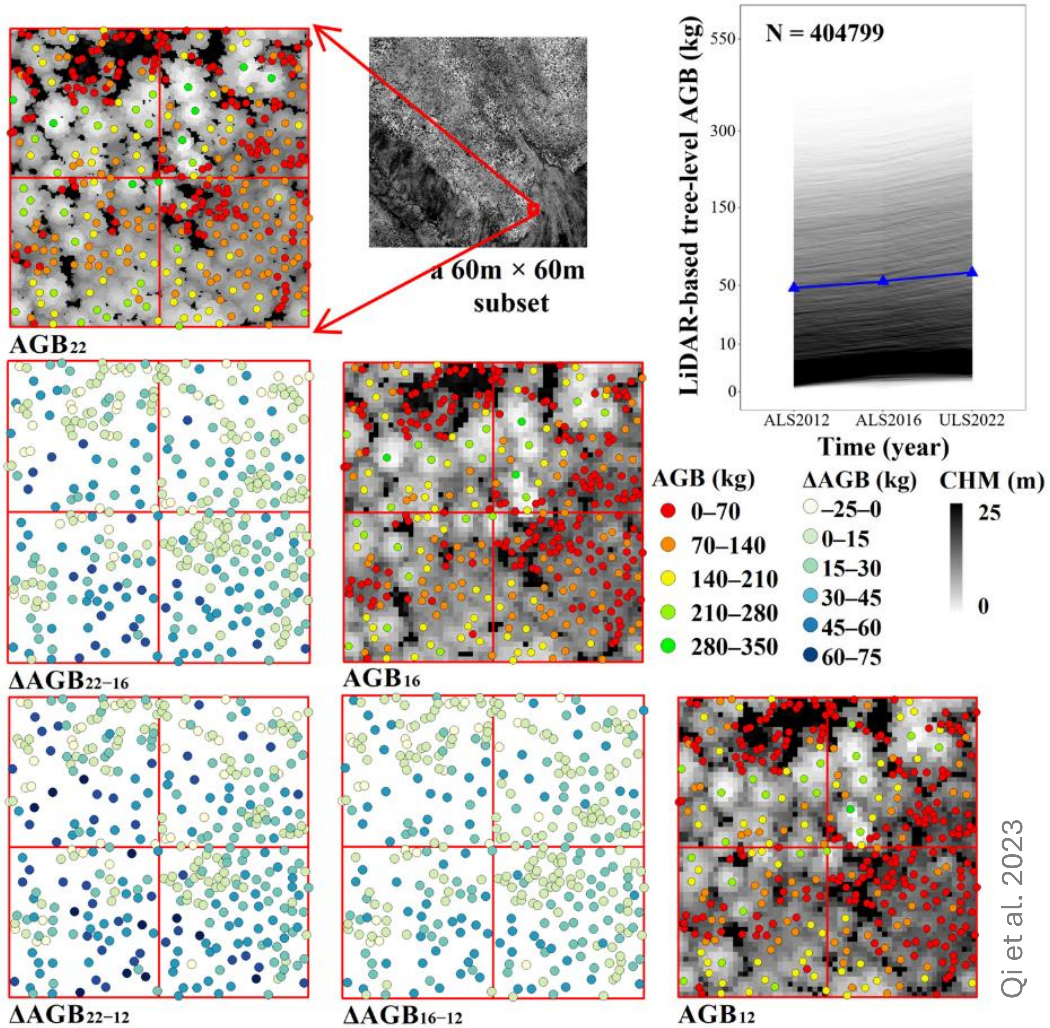
Tompalski et al. 2019



Tompalski, P., Rakofsky, J., Coops, N.C., White, J.C., Graham, A.N. V, Rosychuk, K., 2019. Challenges of Multi-Temporal and Multi-Sensor Forest Growth Analyses in a Highly Disturbed Boreal Mixedwood Forests. Remote Sens. 11, 2102. https://doi.org/10.3390/rs11182102

Change at individual tree level

- Change in tree height (most common), DBH, volume, crown attributes
- Indirect approach more common (T2 – T1)
- More complex than area-based approaches:
  - Tree detection / segmentation
  - Tree-to-tree matching
  - Attribute estimation

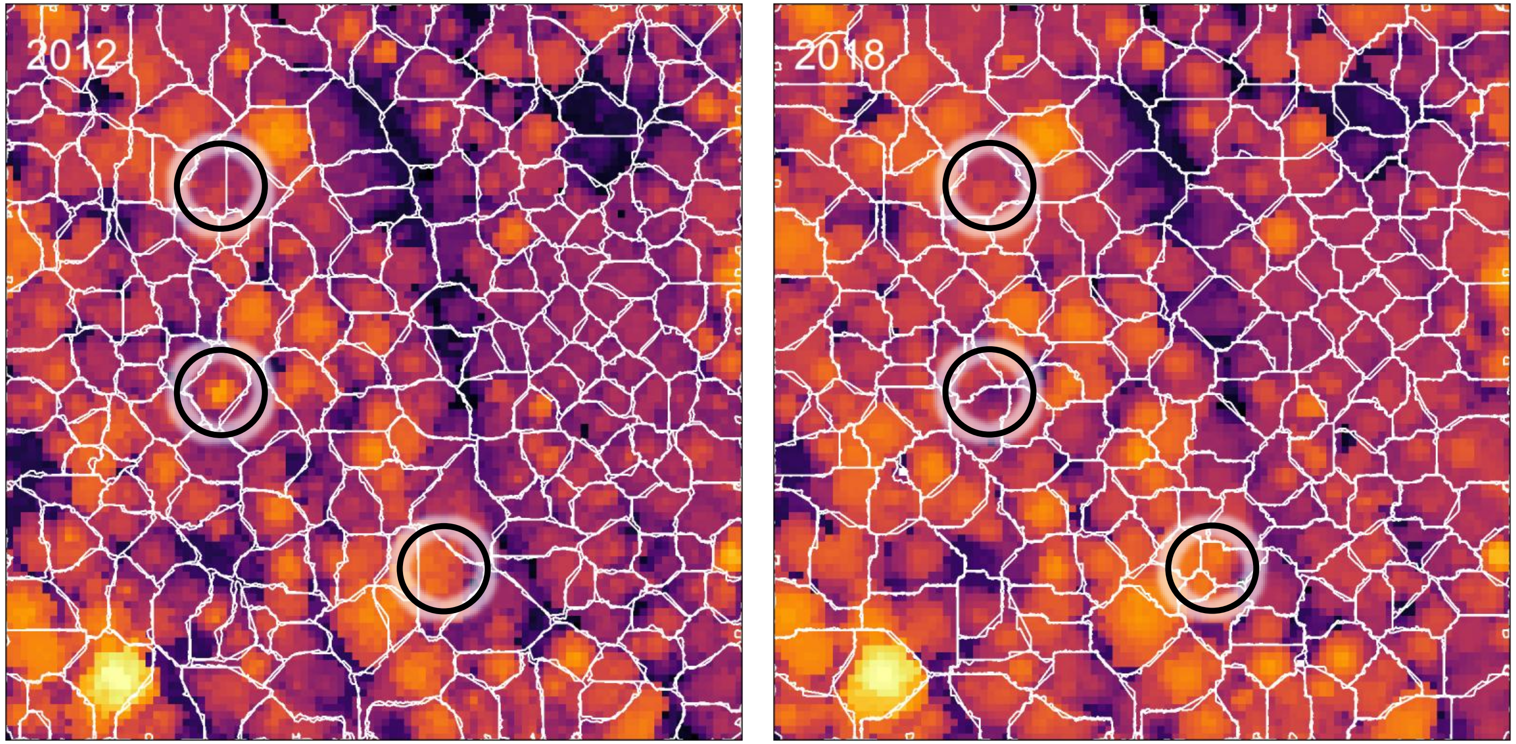


Qi et al. 2023

Qi, Z., Li, S., Pang, Y., Du, L., Zhang, H., Li, Z., 2023. Monitoring Spatiotemporal Variation of Individual Tree Biomass Using Multitemporal LiDAR Data. Remote Sensing 15, 4768. https://doi.org/10.3390/rs15194768

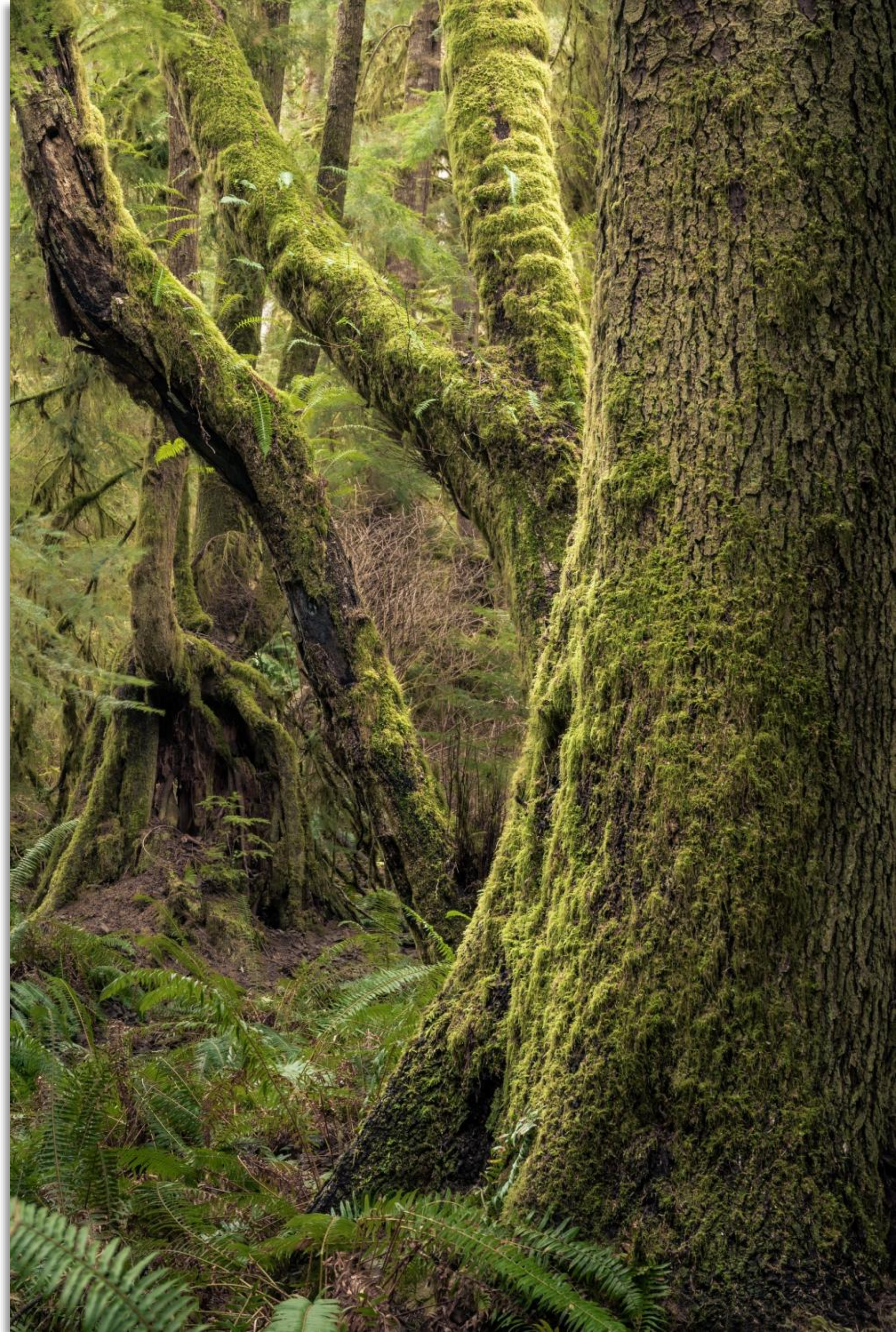
Tree-level challenges

- Tree detection / segmentation independent for each dataset
- Tree-to-tree matching



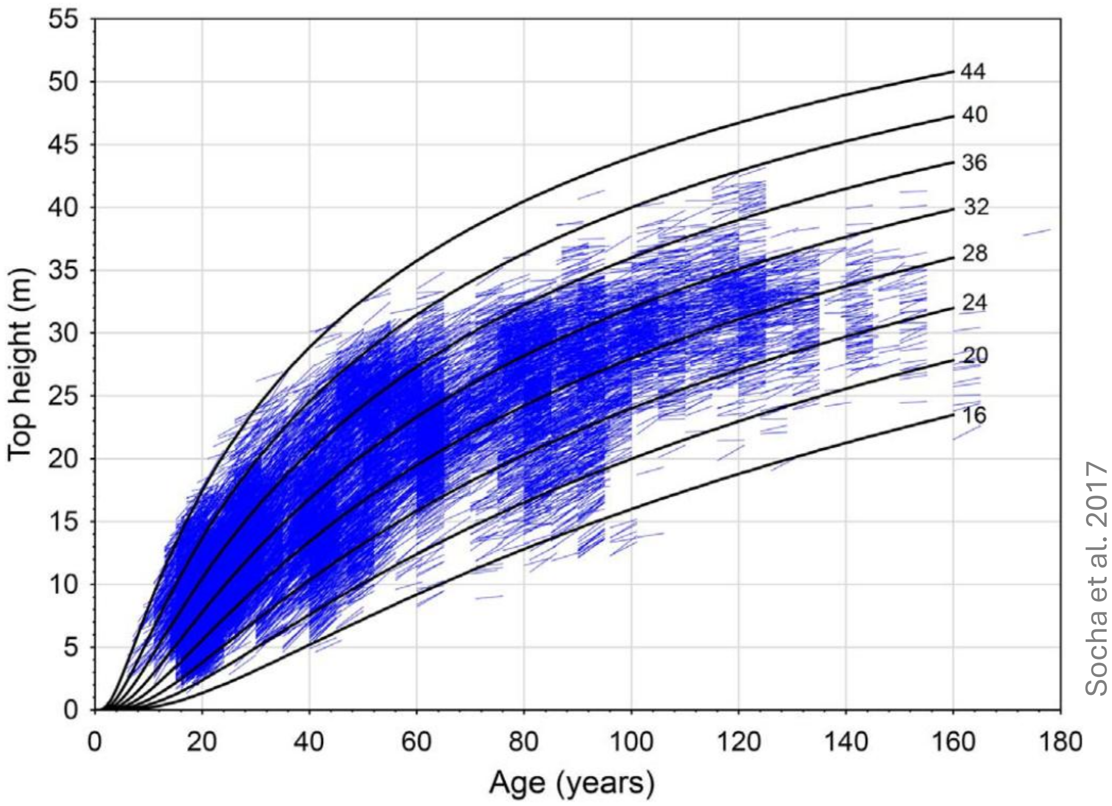
Yu, X., Hyyppä, J., Kukko, A., Maltamo, M., & Kaartinen, H. (2006). Change detection techniques for canopy height growth measurements using airborne laser scanner data. *Photogrammetric Engineering and Remote Sensing*, *72*(12), 1339–1348. https://doi.org/10.14358/PERS.72.12.1339

Forecasting & Model development



Site index

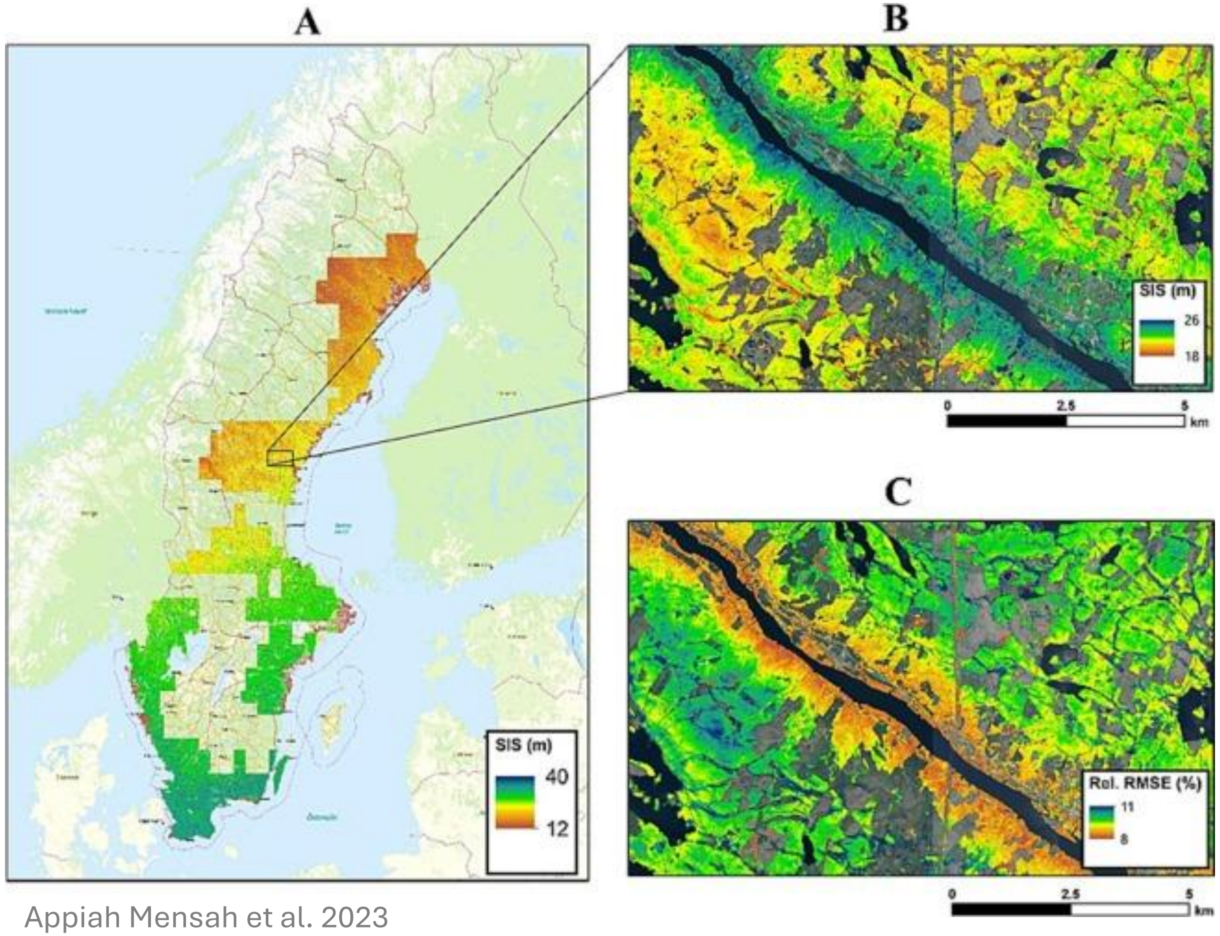
- Bi-temporal ALS → top height (T1, T2)
- SI model (algebraic difference approach (ADA/GADA):
  - Polymorphism
  - Variable asymptotes
- Age, species – existing forest inventory (polygons)



Socha et al. 2017

Socha, J., Pierzchalski, M., Bałazy, R., Ciesielski, M., 2017. Modelling top height growth and site index using repeated laser scanning data. Forest Ecology and Management 406, 307–317. https://doi.org/10.1016/j.foreco.2017.09.039

Site index



Appiah Mensah et al. 2023

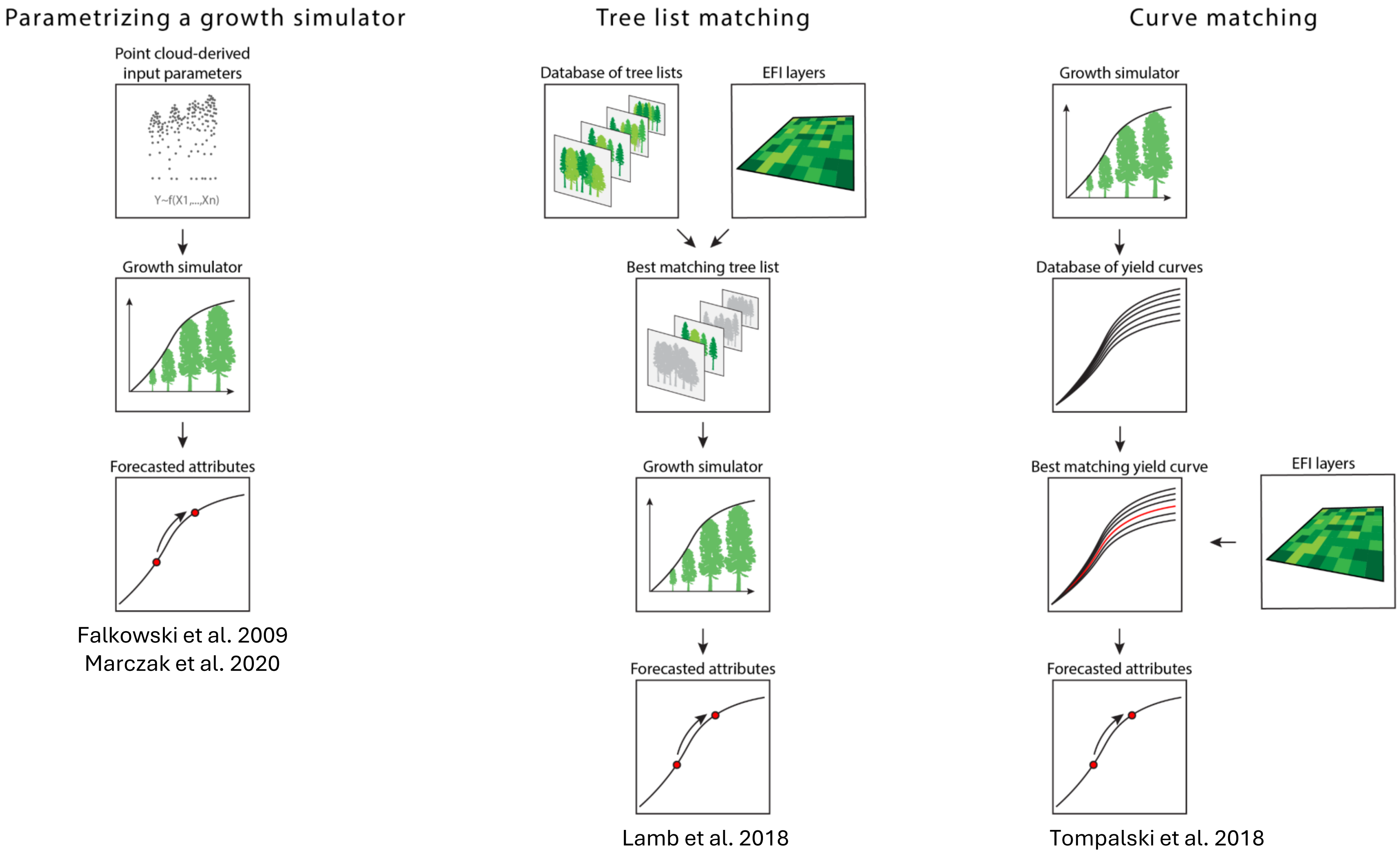
Table 4. Inventory costs, mean net present value losses ($\overline{NPV}_{loss}$), total costs and total costs in per cent of the mean NPV of reference treatment schedules.

Inventory method	Description	Inventory cost (€ ha^{-1})	$\overline{NPV}_{loss}$ (€ ha^{-1})	Total cost (€ ha^{-1})	Total cost %
I	Direct method, bitemporal ALS	5.46	27.87	33.33	1.15
Ii	Direct method, ALS and subsequent DAP	4.56	18.75	23.31	0.80
Iii	Indirect method, bitemporal ALS	5.40	76.18	81.58	2.81
Iv	Indirect method, ALS and subsequent DAP	4.50	52.25	56.75	1.96
V	Single-date ALS	5.40	60.78	66.18	2.28
Vi	Single-date DAP	4.50	56.37	60.87	2.10
Vii	Conventional practices	5.46	58.13	63.59	2.19

Noodermeer et al. 2021

Appiah Mensah, A., Jonzén, J., Nyström, K., Wallerman, J., Nilsson, M., 2023. Mapping site index in coniferous forests using bi-temporal airborne laser scanning data and field data from the Swedish national forest inventory. Forest Ecology and Management 547, 121395. https://doi.org/10.1016/j.foreco.2023.121395
Noordermeer, L., Gobakken, T., Næsset, E., Bollandsås, O.M., 2021. Economic utility of 3D remote sensing data for estimation of site index in Nordic commercial forest inventories: a comparison of airborne laser scanning, digital aerial photogrammetry and conventional practices. Scandinavian Journal of Forest Research 36, 55–67. https://doi.org/10.1080/02827581.2020.1854340

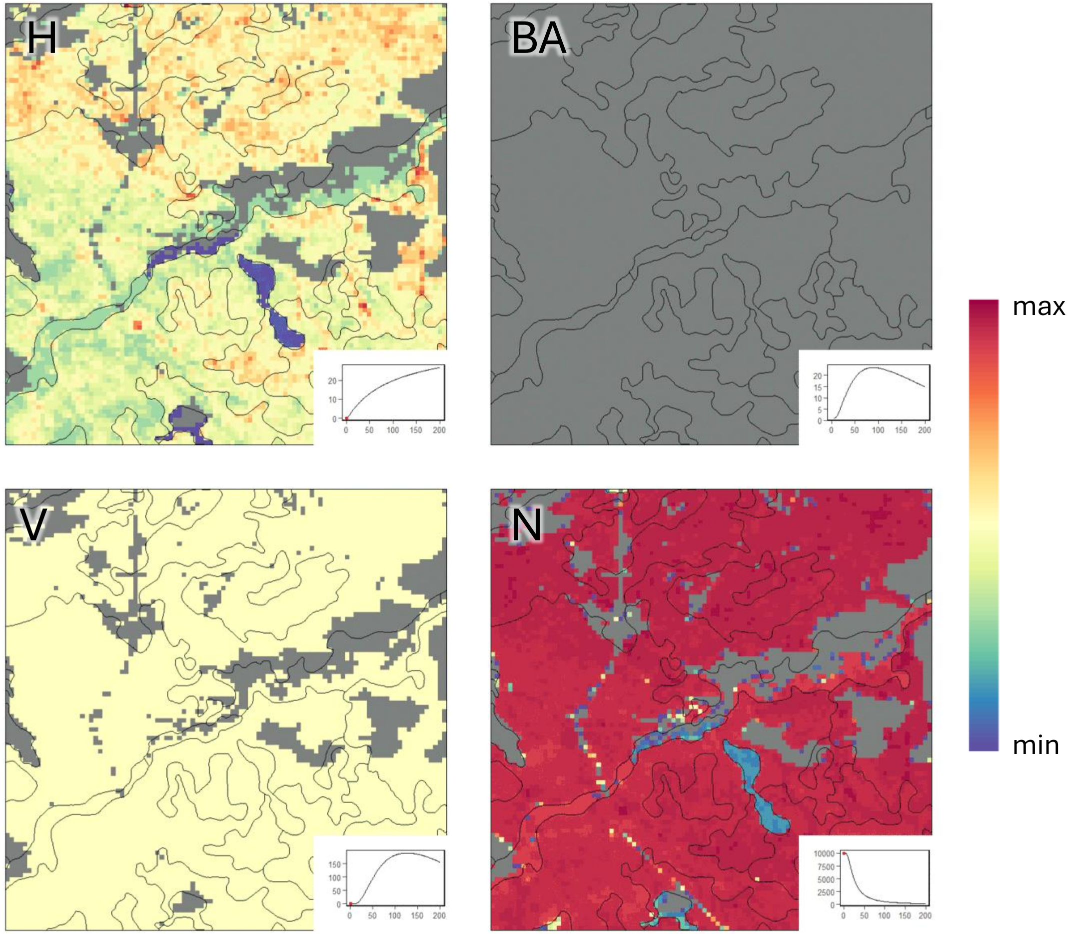
ALS + growth simulators



Tompalski, P., Coops, N.C., White, J.C., Goodbody, T.R.H., Hennigar, C.R., Wulder, M.A., Socha, J., Woods, M.E., 2021. Estimating Changes in Forest Attributes and Enhancing Growth Projections: a Review of Existing Approaches and Future Directions Using Airborne 3D Point Cloud Data. Current Forestry Reports. https://doi.org/10.1007/s40725-021-00135-w

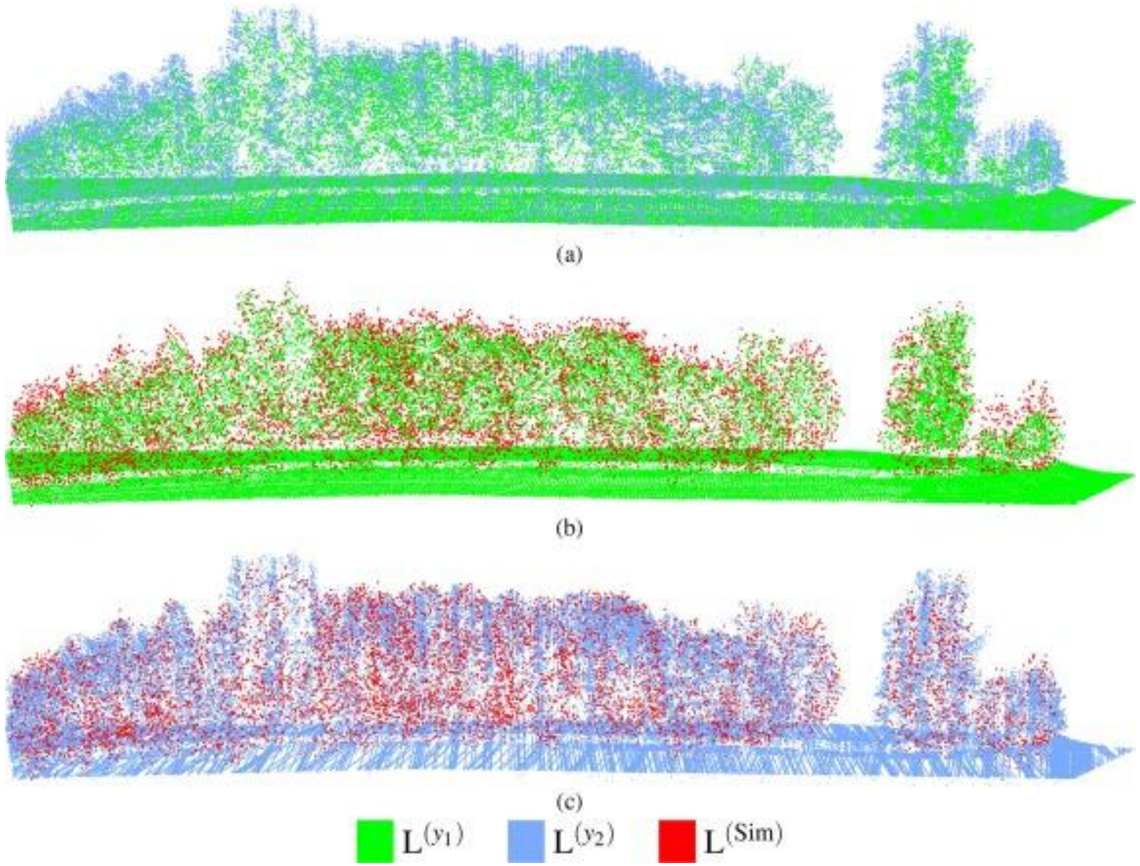
ALS + growth simulators

- Outcome:
  - Pixel-level trajectories of stand attributes
  - Attributes depend on the growth simulator



‘Growing’ the point cloud

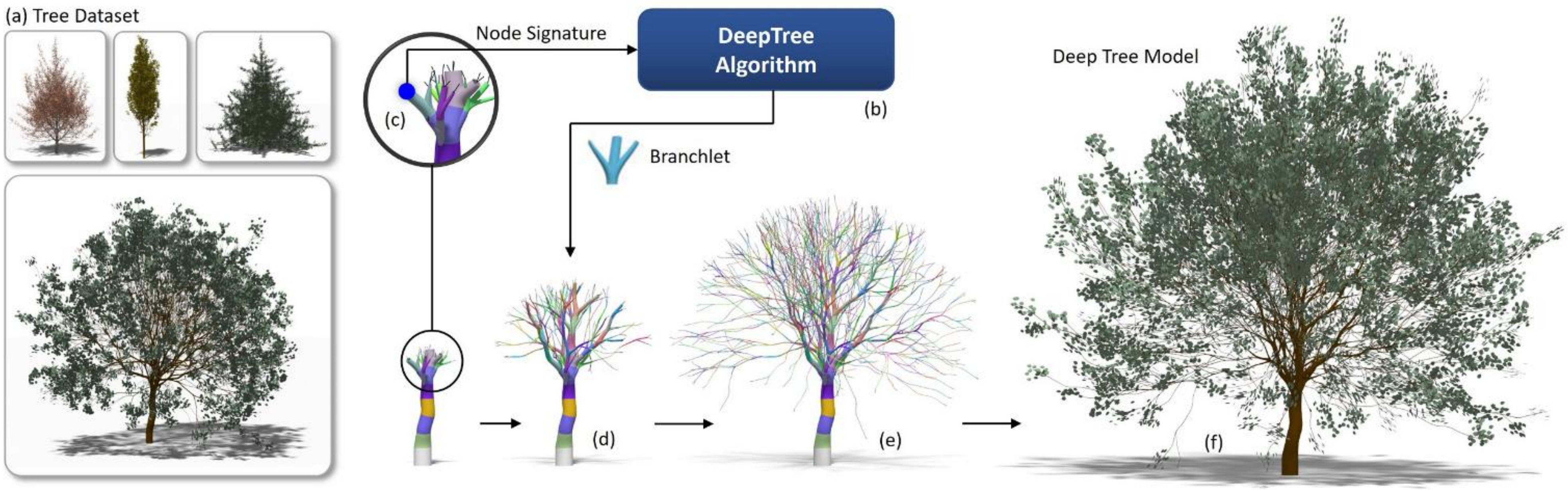
ALS → tree detection → shading-aware growth → asymmetric crown expansion → synthetic future point cloud



Kohek et al. 2022

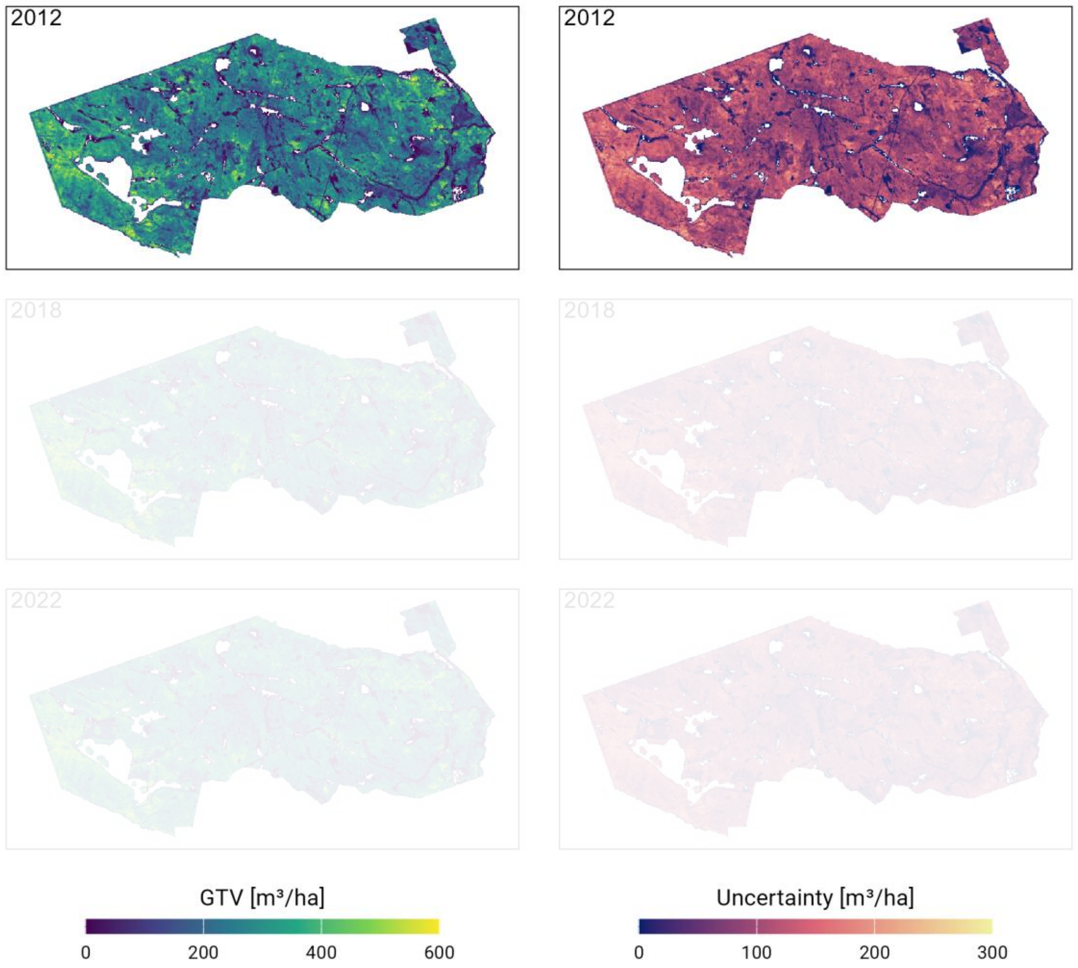
Kohek, Š., Žalik, B., Strnad, D., Kolmanič, S., Lukač, N., 2022. Simulation-driven 3D forest growth forecasting based on airborne topographic LiDAR data and shading. International Journal of Applied Earth Observation and Geoinformation 111, 102844. https://doi.org/10.1016/j.jag.2022.102844

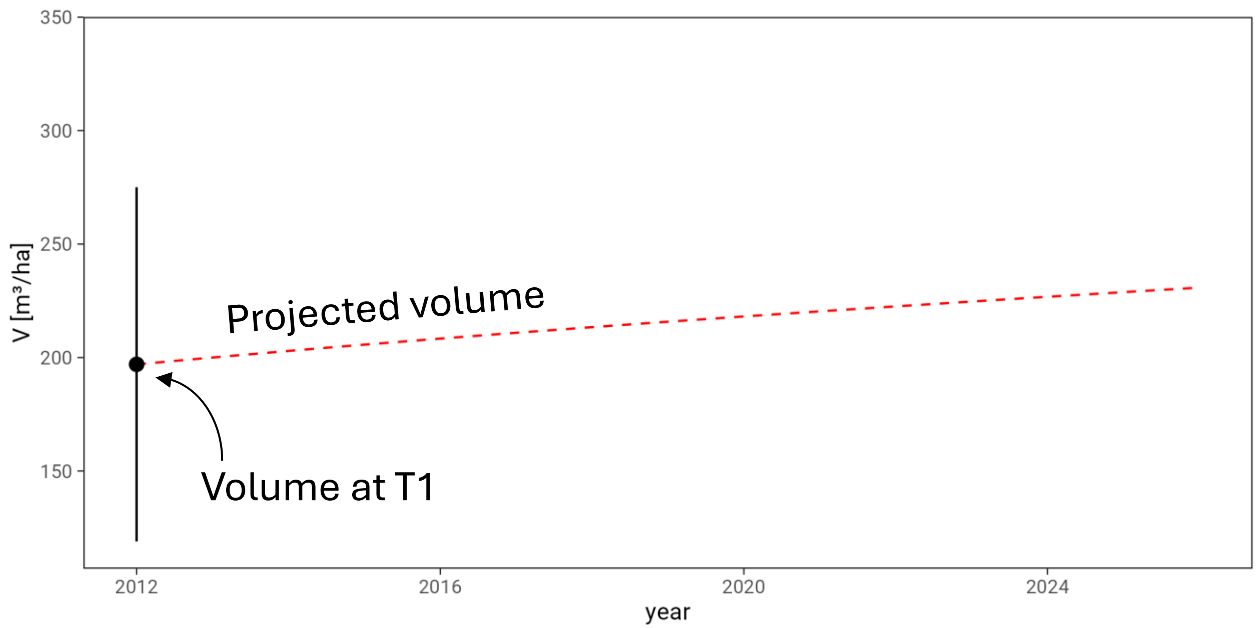
Generative modeling

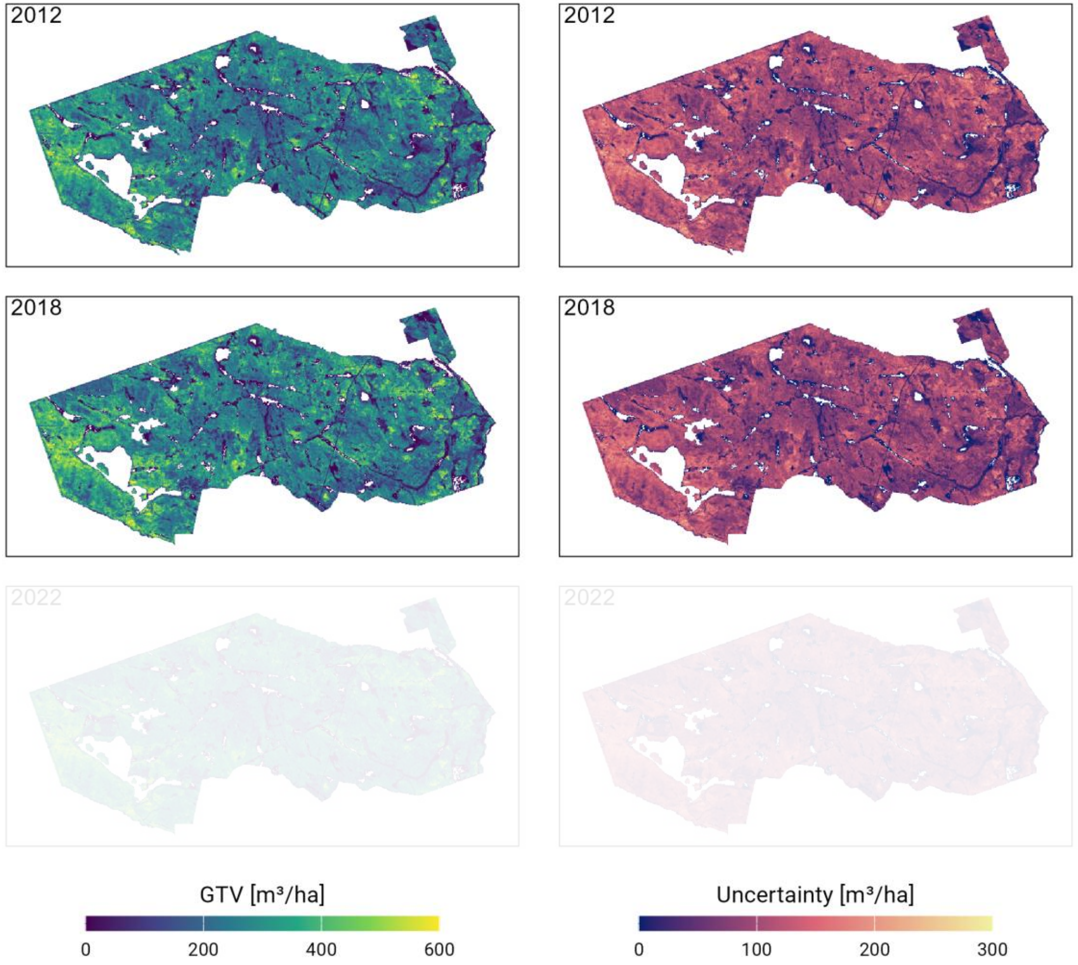


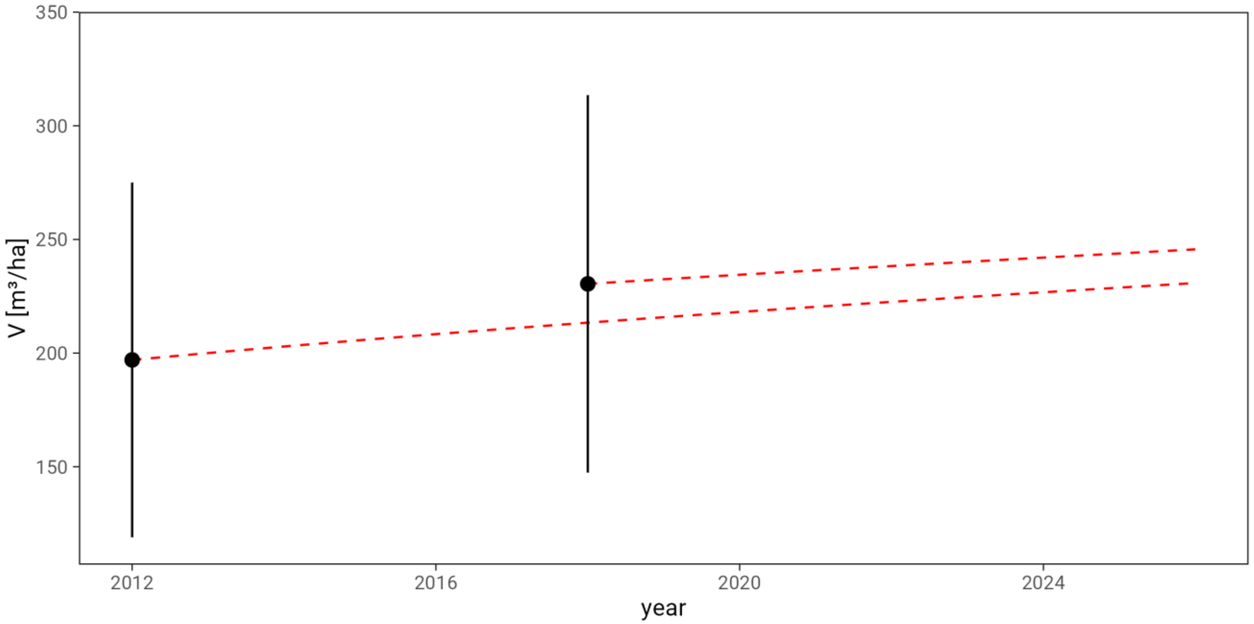
Zhou et al. 2024

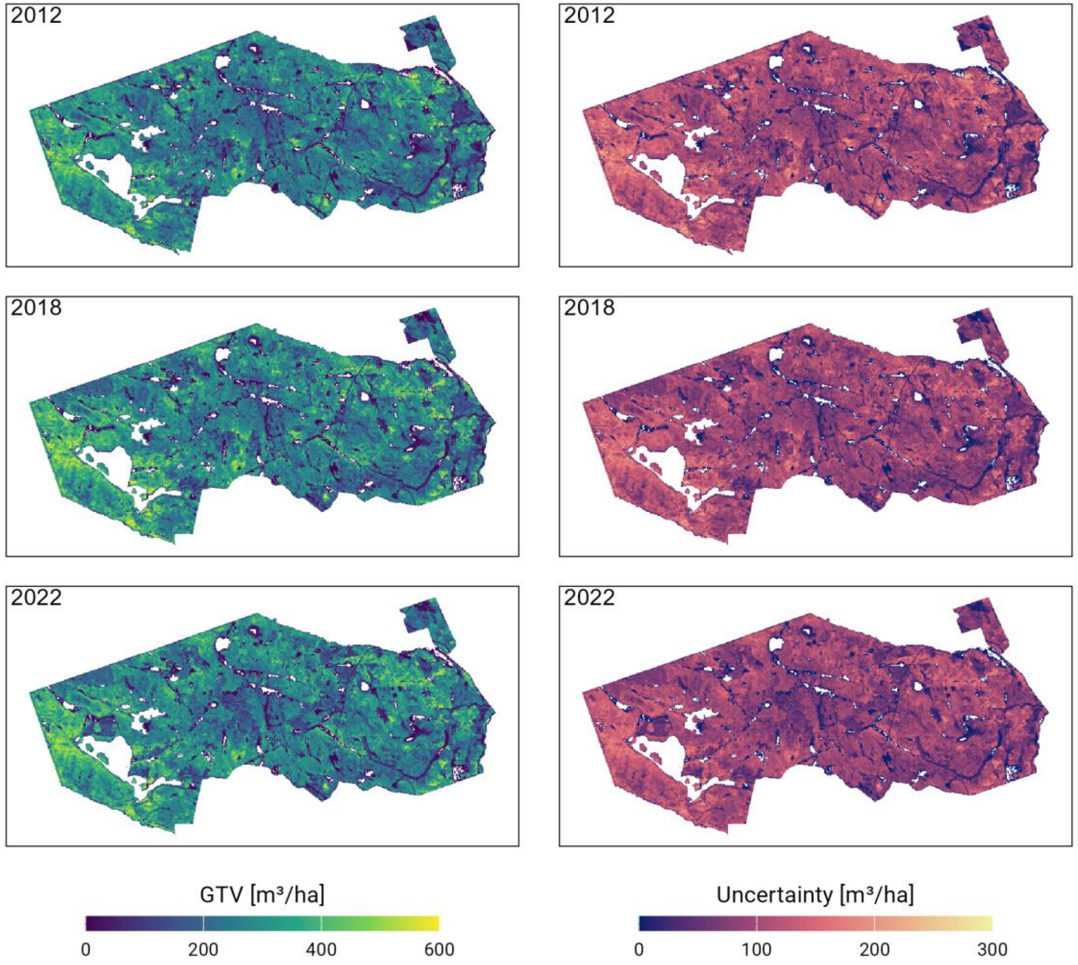
Zhou, X., Li, B., Benes, B., Fei, S., Pirk, S., 2024. DeepTree: Modeling Trees With Situated Latents. IEEE Transactions on Visualization and Computer Graphics 30, 5795–5809. https://doi.org/10.1109/TVCG.2023.3307887
Kulicki, M., Cabo, C., Trzciński, T., Będkowski, J., Stereńczak, K., 2024. Artificial Intelligence and Terrestrial Point Clouds for Forest Monitoring. Curr. For. Rep. 11, 5. https://doi.org/10.1007/s40725-024-00234-4

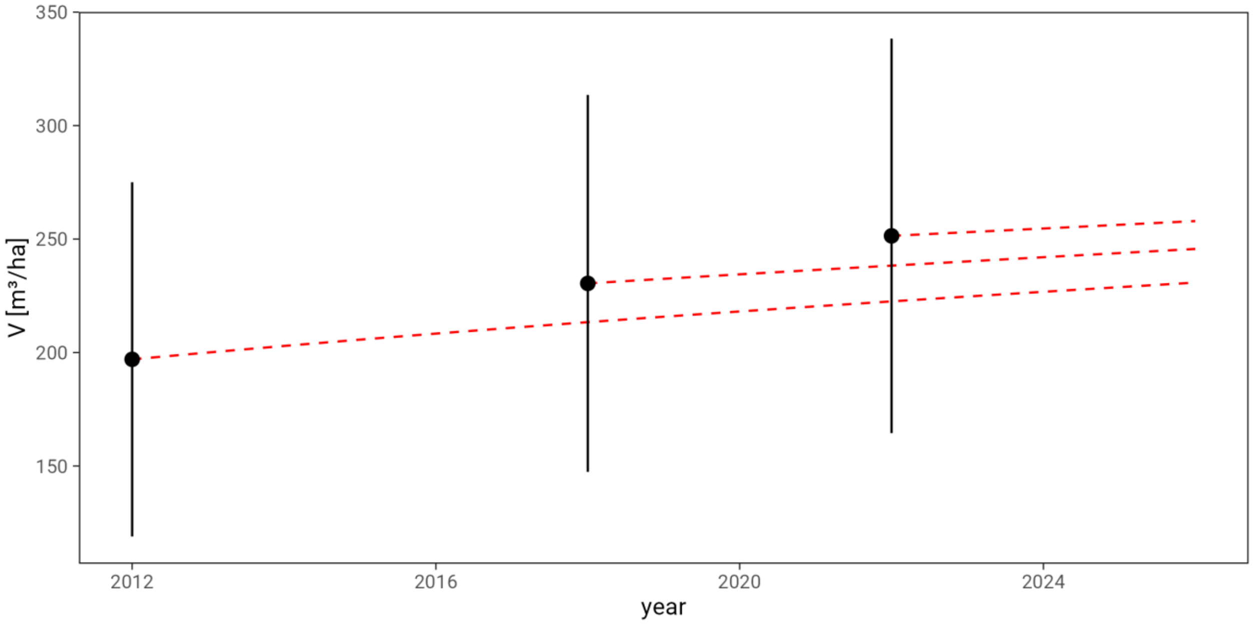

2012
2012
2018
2018
2022
2022
GTV [m³/ha]
0
200
400
600
Uncertainty [m³/ha]
0
100
200
300


350
300
250
200
150
V [m³/ha]
2012
2016
2020
2024
year
Projected volume
Volume at T1


2012
2012
2018
2018
2022
2022
GTV [m³/ha]
0
200
400
600
Uncertainty [m³/ha]
0
100
200
300

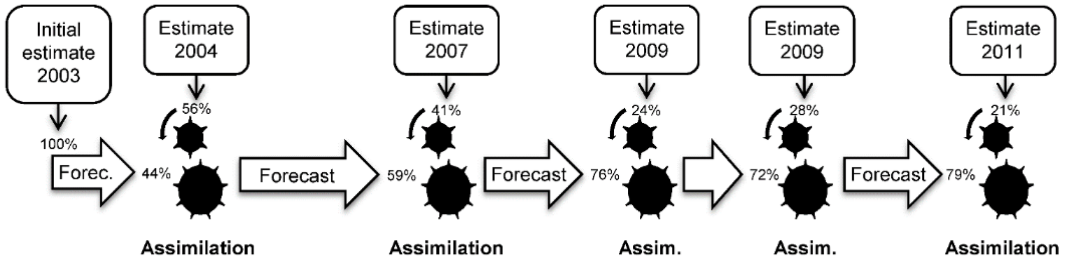

350
300
250
200
150
V [m³/ha]
2012
2016
2020
2024
year

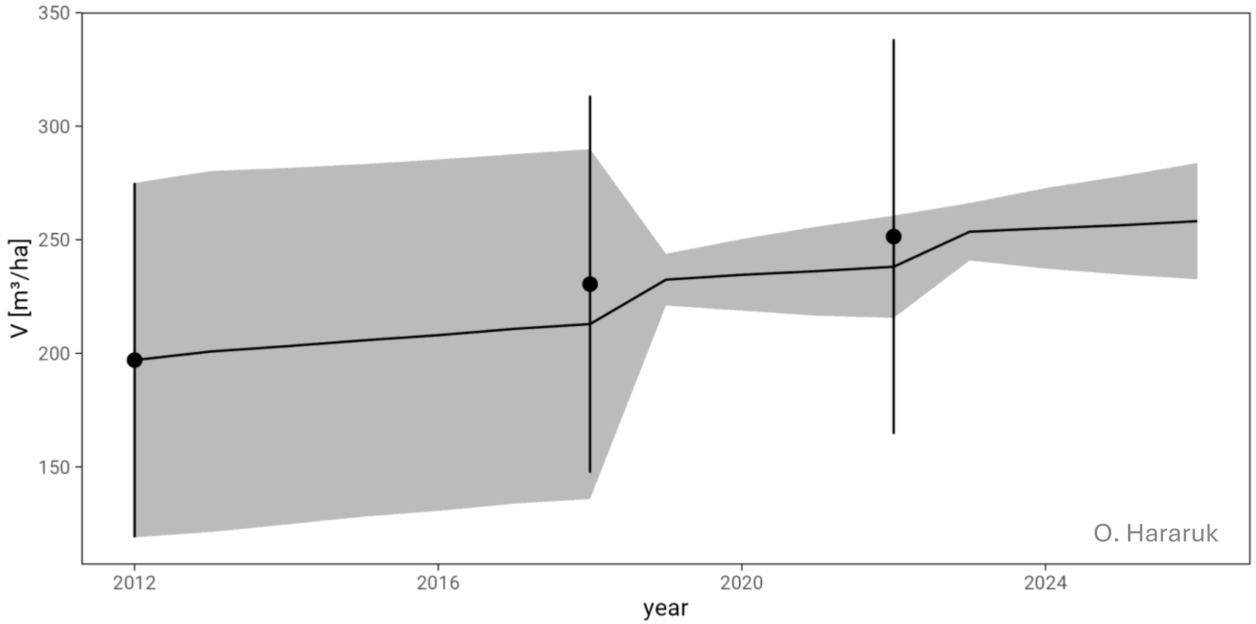

2012
2012
2018
2018
2022
2022
GTV [m³/ha]
0 200 400 600
Uncertainty [m³/ha]
0 100 200 300


350
300
250
200
150
V [m³/ha]
2012
2016
2020
2024
year

Data assimilation

- A mathematical procedure to update existing estimates with new observations
- Allows combining existing estimates of forest attributes, with new information derived based on new acquisitions

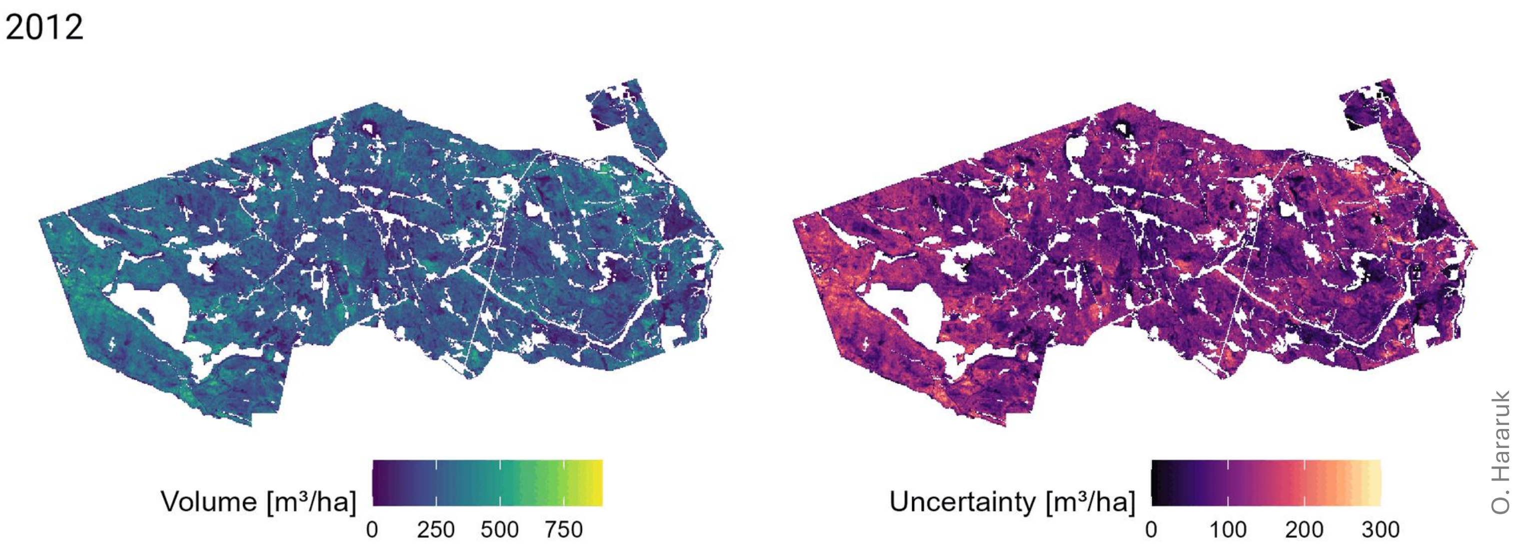




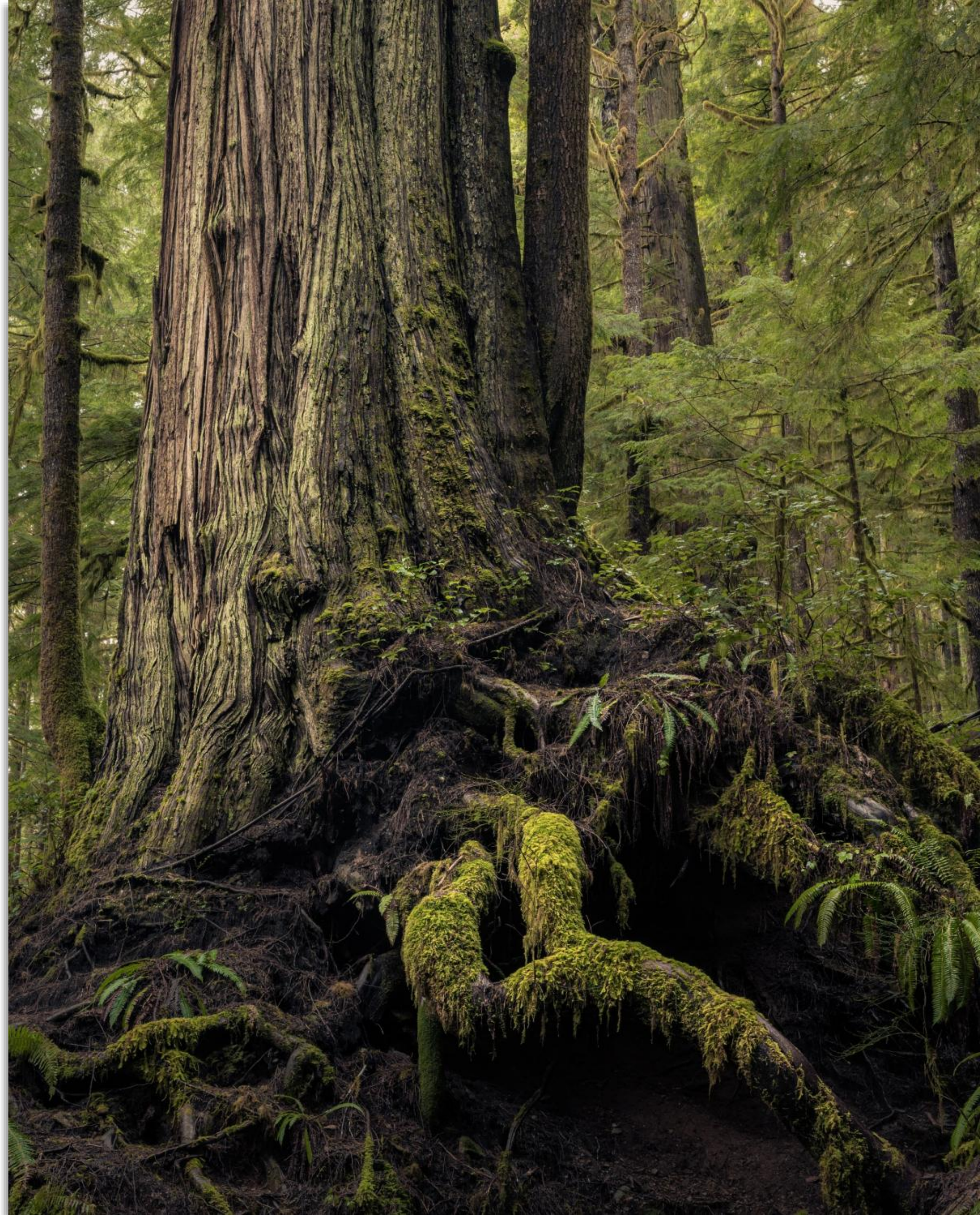
Hou, Zhengyang, Lauri Mehtätalo, Ronald E. McRoberts, Göran Ståhl, Timo Tokola, Parvez Rana, Jouni Siipilehto, and Qing Xu. "Remote Sensing-Assisted Data Assimilation and Simultaneous Inference for Forest Inventory." *Remote Sensing of Environment* 234, no. November (2019): 111431. https://doi.org/10.1016/j.rse.2019.111431.

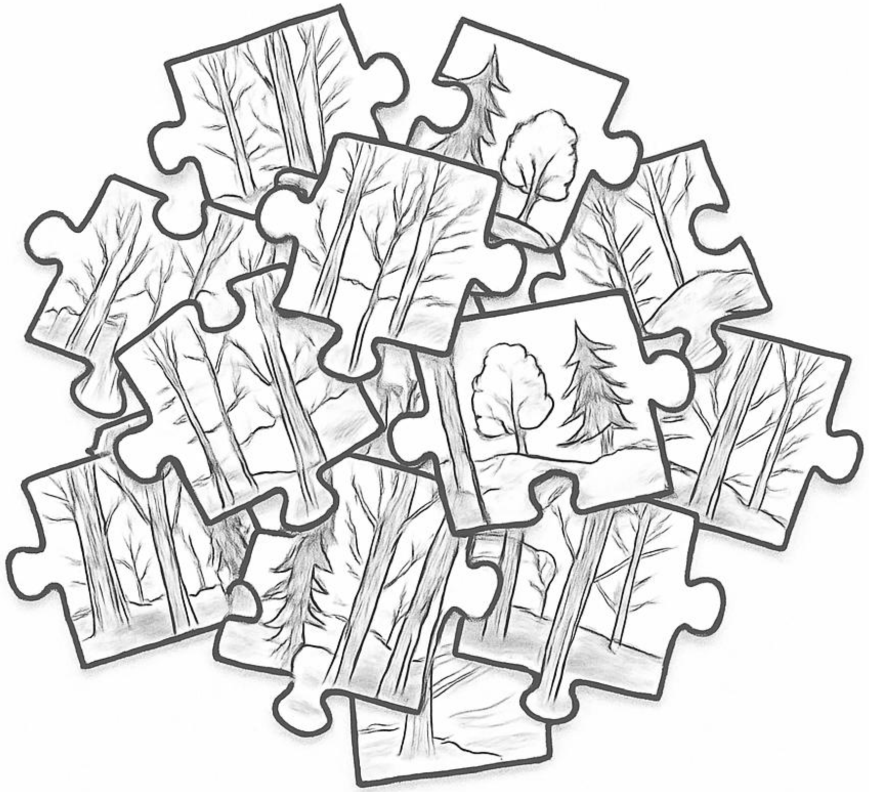
Nyström, Mattias, Nils Lindgren, Jörgen Wallerman, Anton Grafström, Anders Muszta, Kenneth Nyström, Jonas Bohlin, et al. "Data Assimilation in Forest Inventory: First Empirical Results." *Forests* 6, no. 12 (2015): 4540–57. https://doi.org/10.3390/f6124384.

Data assimilation

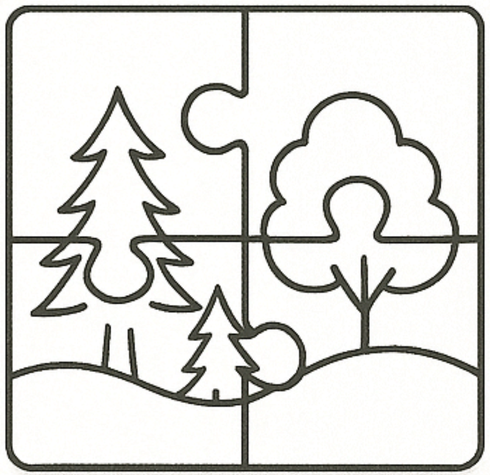


Lidar-based Growth Models?





Lidar-derived attributes



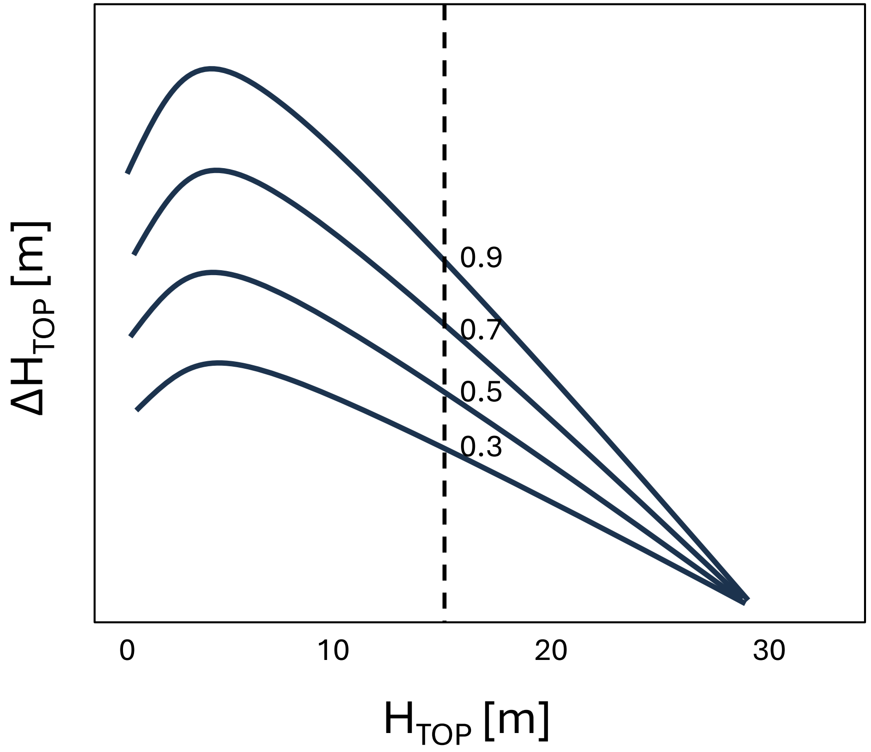
Traditional growth simulators

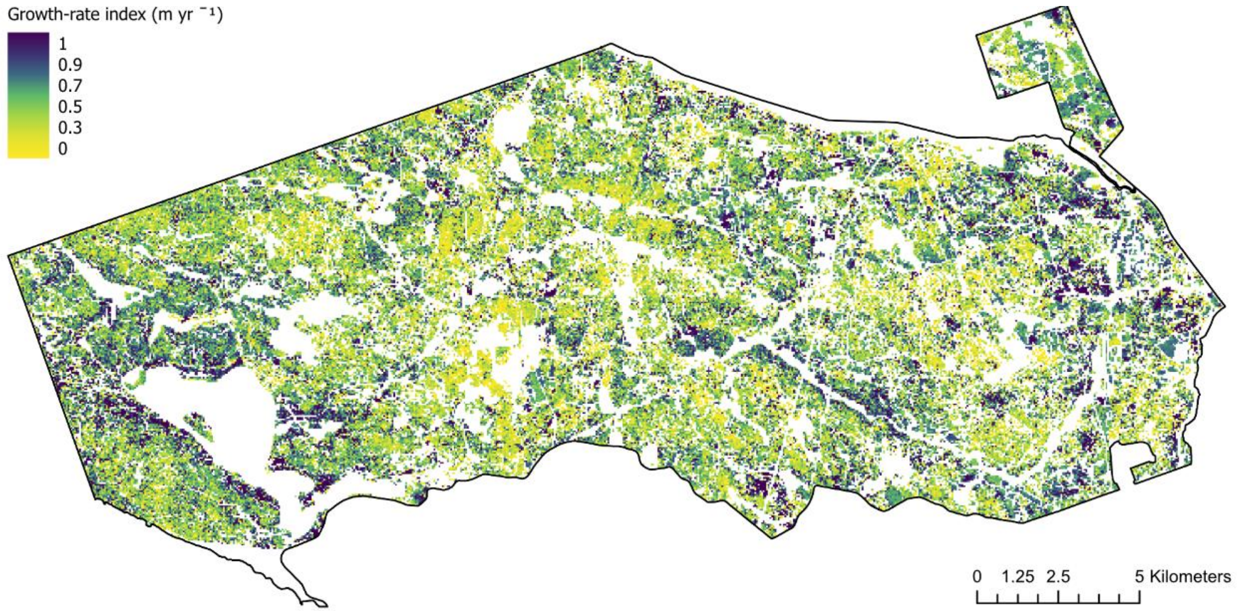
Growth Models Driven Entirely with Point Cloud Data Considering the cost associated with the development of growth simulators using traditional approaches, research should aim to continue to incorporate remote sensing-based products to improve estimates from growth and yield models.

Remote sensing-based growth functions do not necessarily need to mimic existing growth simulators that often contain complex modules to characterize mortality, ingrowth, competition, or account for various silviculture activities (e.g., thinning, fertilization) but rather utilize the advantages provided by point clouds and other remote sensing data.

Tompalski et al. 2021

Age-independent ‘site index’

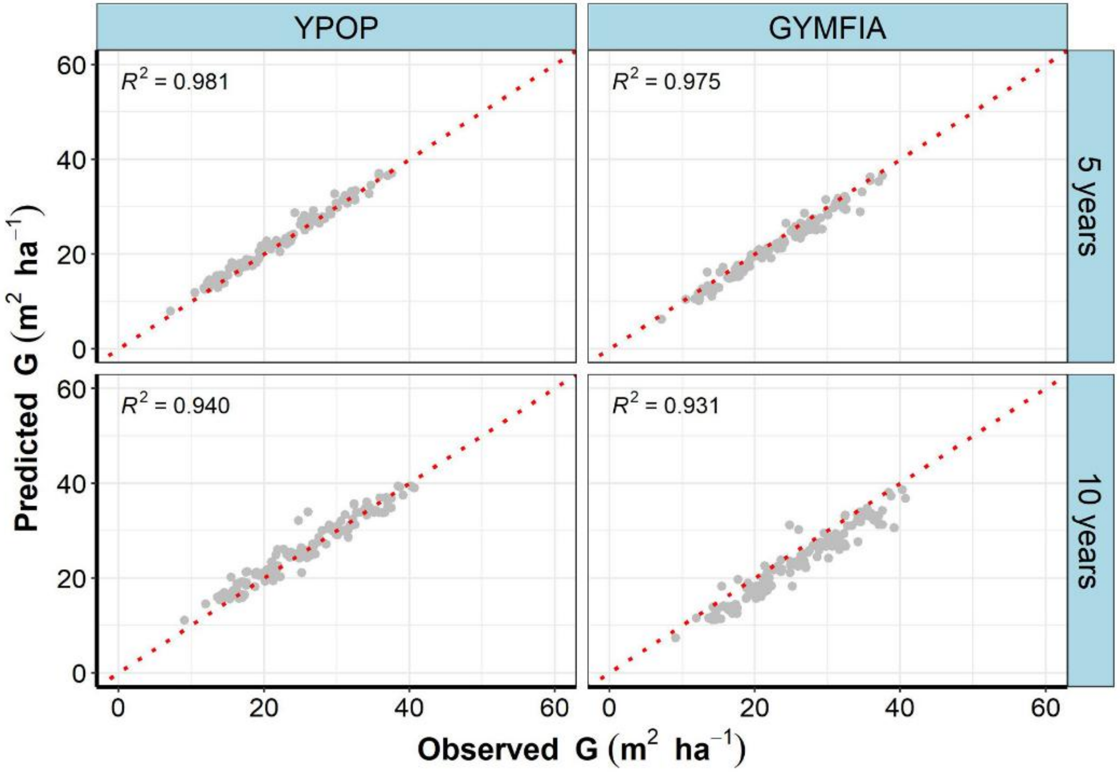




Riofrío, José, Joanne C. White, Piotr Tompalski, Nicholas C. Coops, and Michael A. Wulder. “Modelling Height Growth of Temperate Mixedwood Forests Using an Age-Independent Approach and Multi-Temporal Airborne Laser Scanning Data.” *Forest Ecology and Management* 543 (September 1, 2023): 121137. https://doi.org/10.1016/j.foreco.2023.121137.

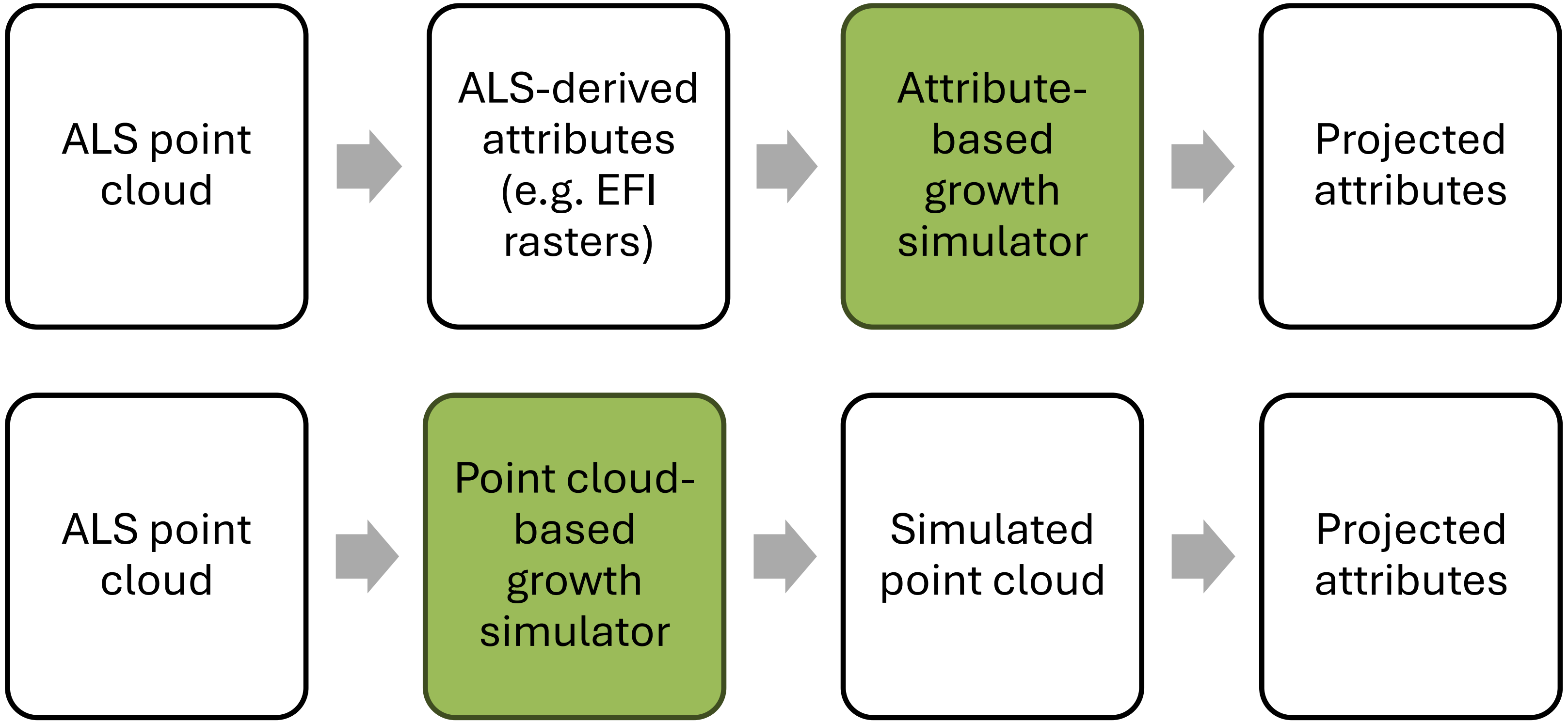
Age-independent growth & yield model

- Ogana et al. 2025
- System of differential equations to quantify the rate of forest growth based on previous conditions
- Inputs: N, BA, sum of DBH (optional)
- Modules for ingrowth, mortality, survival



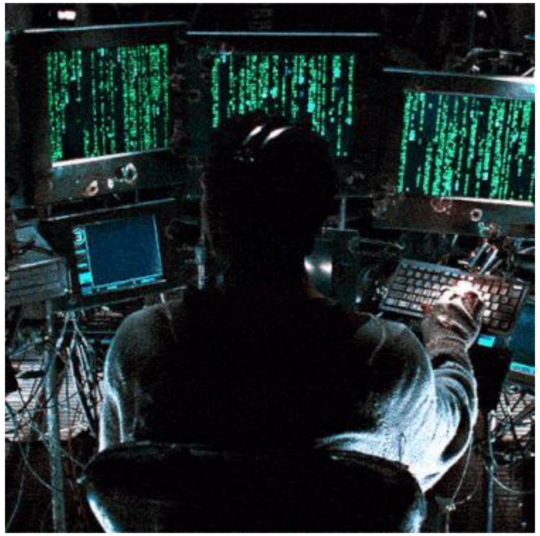
Ogana, F.N., Green, P.C., Radtke, P., 2025. Modeling the growth and yield of natural hardwood stands in the southern United States using the Forest Inventory and Analysis data. Forest Ecology and Management 586, 122722. https://doi.org/10.1016/j.foreco.2025.122722

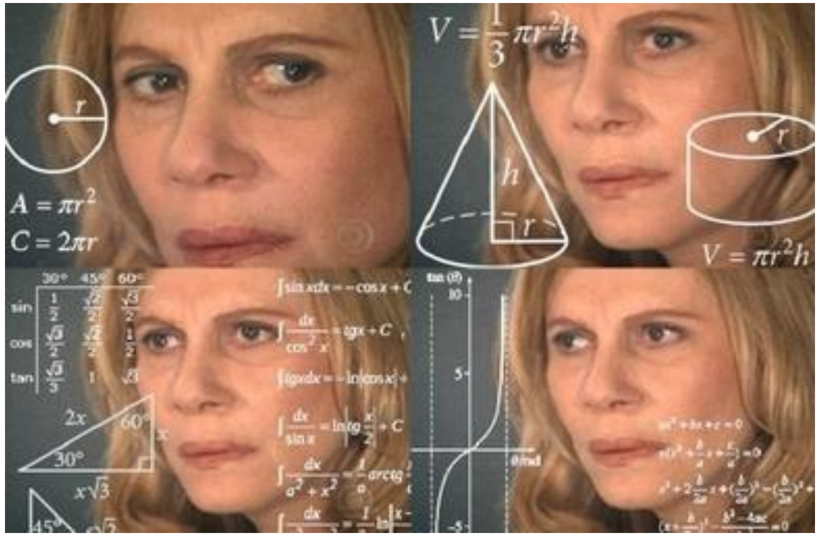
Idea of a lidar-based growth simulator



Idea of a lidar-based growth simulator

- Built with RS
  - Wall-to-wall calibration at pixel level – much larger sample size
  - LiDAR-first structure with coherent H-N-BA-V-AGB
  - Quantified uncertainty
- Used with RS
  - Data assimilation: reconcile attributes when new data is acquired
  - Disturbance & recovery dynamics
- Data from multiple sensors
- Independent validation





$$g^{(\Delta)}(t|\theta,\gamma,\tau) = \frac{1}{\Delta}\sum_{i=0}^{\Delta-1} g(t-i) + \gamma\,\frac{\Delta - \min(\Delta, t-\tau)}{\Delta}$$

$$\frac{dh}{dt} = \left(\frac{S}{h_r}\right) h\left[\left(\frac{\alpha}{h}\right)^{\gamma} - 1\right]\left[\left(\frac{\alpha}{h_r}\right)^{\gamma} - 1\right]^{-1}$$

$$f_T(x) = \left(\frac{\alpha_k}{\beta_k}\right)\left(\frac{x}{\beta_k}\right)^{\alpha_k - 1}\exp\left(\left(\frac{T}{\beta_k}\right)^{\alpha_k} - \left(\frac{x}{\beta_k}\right)^{\alpha_k}\right)$$

$$\widehat{\mathbb{V}}\left(\widehat{\tau}_{\mathcal{A}} - \tau_{\mathcal{A}}\right) = \mathbf{1}_{N_{\mathcal{A}}}^{\mathrm{T}}\begin{pmatrix} \mathbf{Z}_{\mathcal{A}}\widehat{\mathbb{V}}(\widehat{\boldsymbol{\alpha}})\mathbf{Z}_{\mathcal{A}}^{\mathrm{T}} - 2\widehat{\sigma^2}\mathbf{Z}_{\mathcal{A}}\left(\mathbf{Z}_{s_2}^{\mathrm{T}}\widehat{\boldsymbol{\Sigma}}_{s_2}^{-1}\mathbf{Z}_{s_2}\right)^{-1}\mathbf{Z}_{s_2}^{\mathrm{T}}\widehat{\boldsymbol{\Sigma}}_{s_2}^{-1}\widehat{\mathbf{C}}_{s_2,\mathcal{A}} \\ -2\widehat{\omega^2}\mathbf{Z}_{\mathcal{A}}\left(\mathbf{Z}_{s_2}^{\mathrm{T}}\widehat{\boldsymbol{\Sigma}}_{s_2}^{-1}\mathbf{Z}_{s_2}\right)^{-1}\mathbf{Z}_{s_2}^{\mathrm{T}}\widehat{\boldsymbol{\Sigma}}_{s_2}^{-1}\mathbf{X}_{s_2}\left(\mathbf{X}_{s_1}^{\mathrm{T}}\widehat{\boldsymbol{\Omega}}_{s_1}^{-1}\mathbf{X}_{s_1}\right)^{-1}\mathbf{X}_{s_1}^{\mathrm{T}}\widehat{\boldsymbol{\Omega}}_{s_1}^{-1}\widehat{\mathbf{D}}_{s_1,\mathcal{A}} \\ +\widehat{\omega^2}\widehat{\boldsymbol{\Omega}}_{\mathcal{A}} + \widehat{\sigma^2}\widehat{\boldsymbol{\Sigma}}_{\mathcal{A}} \end{pmatrix}\mathbf{1}_{N_{\mathcal{A}}}$$

Key takeaways

- We need accurate information on growth – important economic decisions depend on it
- People who understand lidar are not the people who understand growth
- Existing models are not taking full advantage of what lidar can offer. We need approaches that integrate it directly.