

# 3D and 4D forest models

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Finnish Centre of Excellence  
in Inverse Problems Research

# Change of (information) paradigm in forestry

- ◆ New demands for modern ecosystem services: biomass quantity and distribution, carbon cycle and footprint, timber quality and market, cultivation options, ecological and recreational functions, urban areas, ...
- ◆ Full forest information: “Google Nature” in your mobile phone
- ◆ 3D models, 4D time development
- ◆ Complete virtual environment: view from any location
- ◆ Quantitative: obtain any volumetric or geometric numerical results from any region
- ◆ Predictive: how will trees grow in different scenarios?

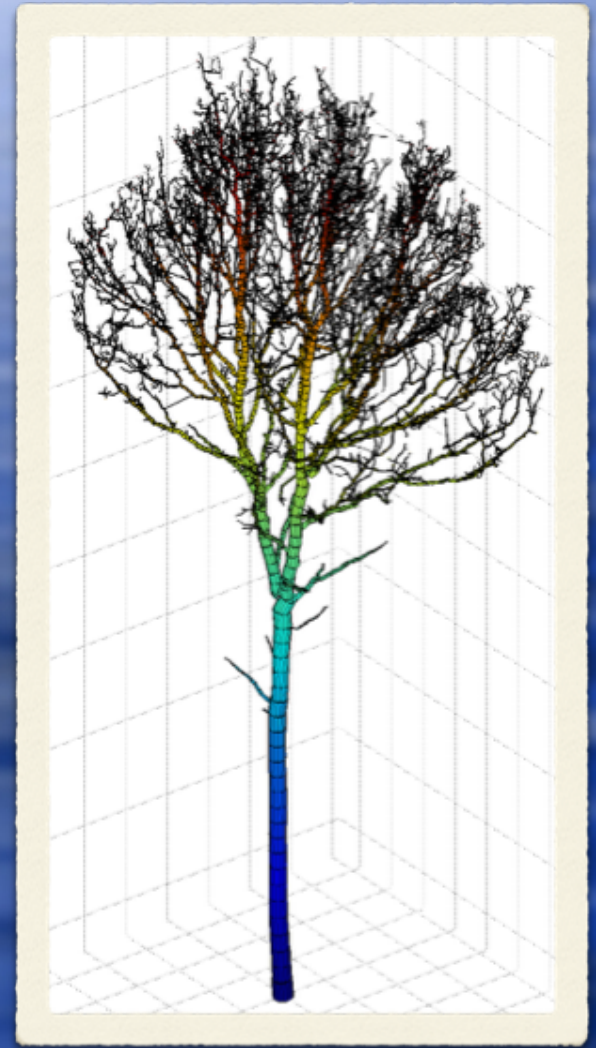


# Smart forest and infosphere

- ◆ See it, scan it, handle it with quantitative structure models (QSMs)
- ◆ Can do, will do: crowdsourcing – mobile lidar for everyone
- ◆ Upscaling: from terrestrial laser scanning (TLS) to satellite data – large comprehensively analyzed test plots for large-scale calibration
- ◆ Hyperspectral lidar information
- ◆ Represent leaves as “gas” or stochastic primitives around branches with matching leaf area density etc.

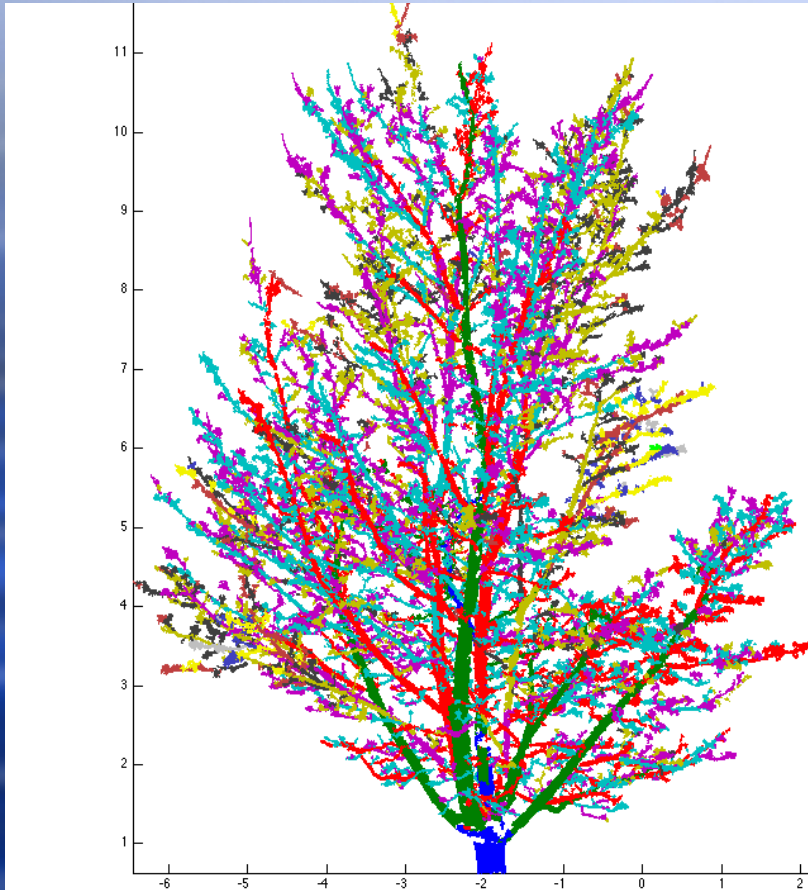
# QSM - Quantitative Structure Model

- \* Compact tree model containing essential topological and geometrical tree properties
  - Branching structure, branching order
  - Volumes, lengths, angles, taper, etc.
  - Rapid advances in laser scanning technology: lighter, cheaper, faster
  - => Ubiquitous laser scanning (cf. radars in cars)

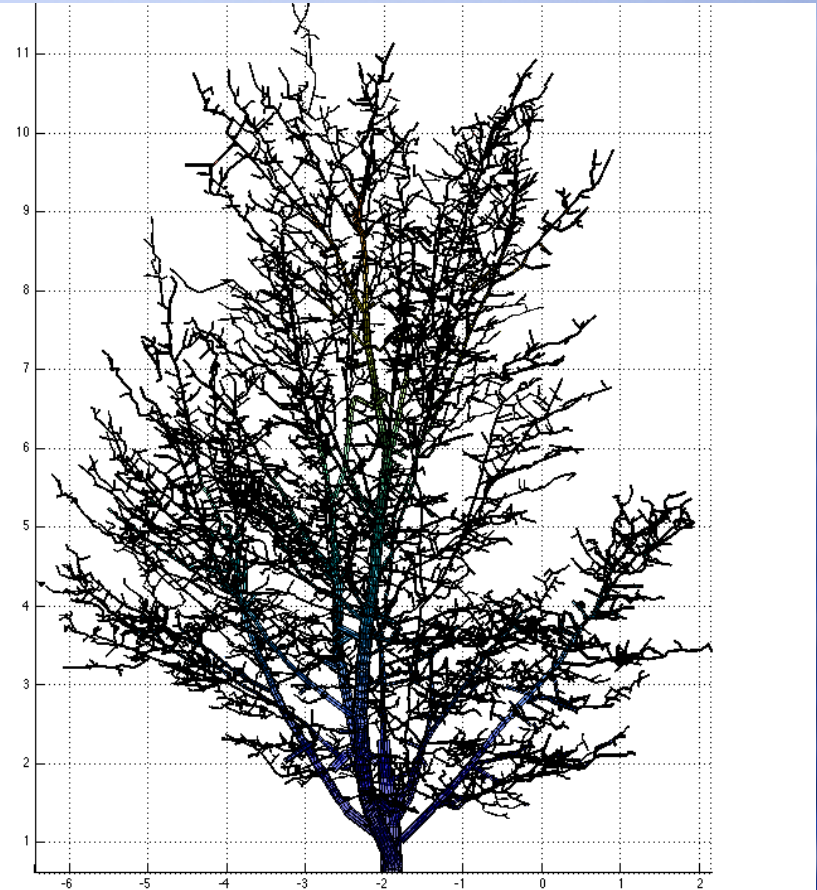




# Compact usable information



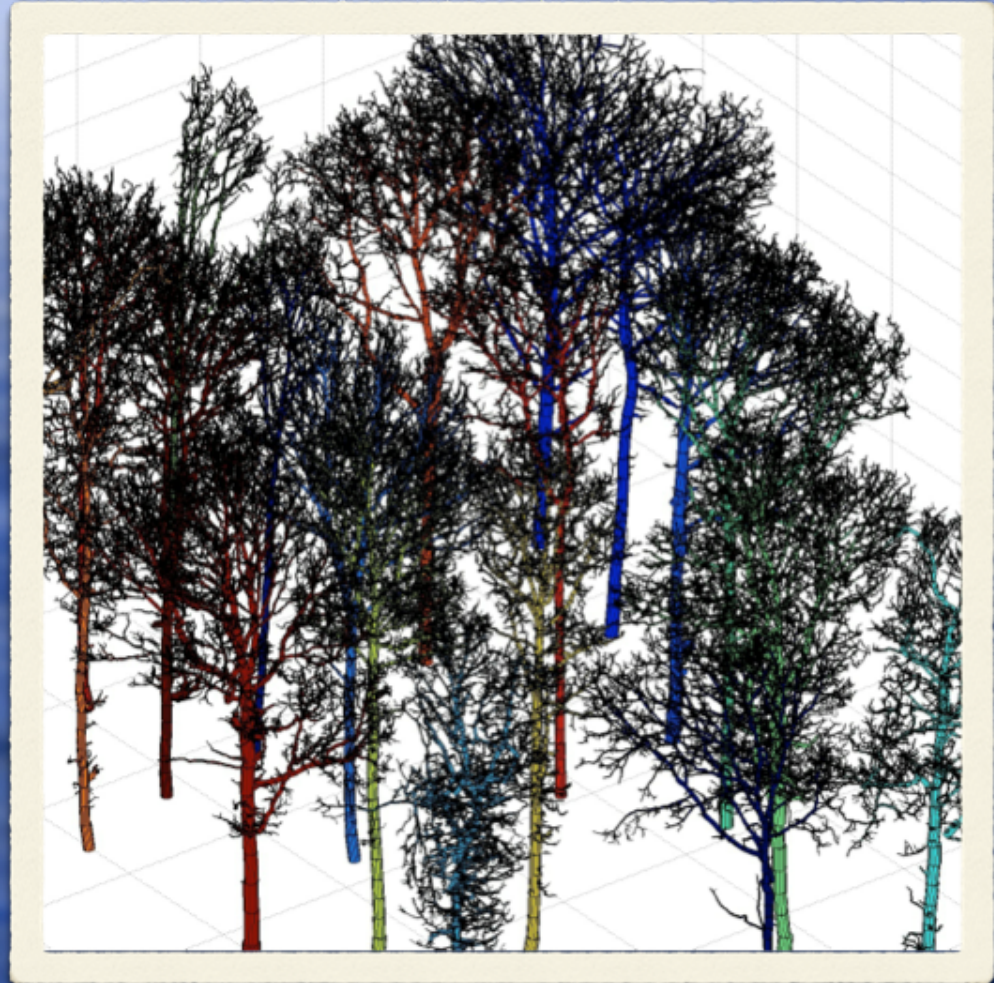
3 scan positions, high  
resolution (1,6M points)



Model (14 000 cylinders)

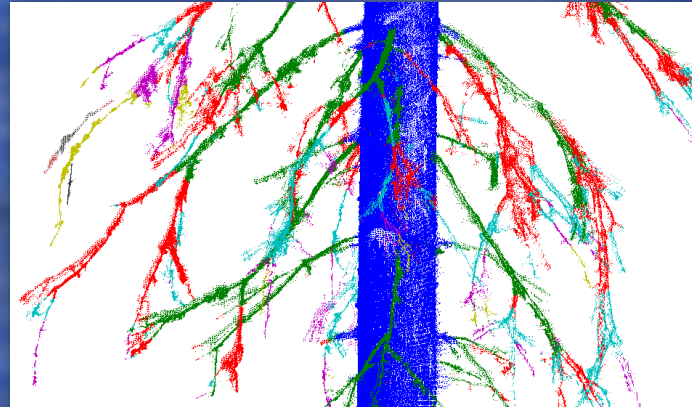
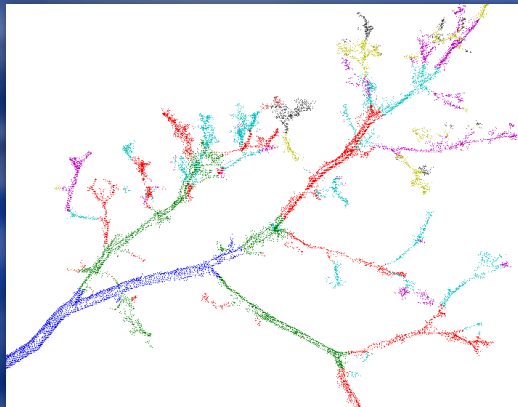
# Forest plot QSMs

- \* Fast modelling, tens of big trees in an hour
- \* Parallel computing allows hundreds of big trees in an hour
- \* Use the smallest required surface patch size instead of all points
- \* Robust cylinders as geometric primitives
- \* Surface continuity not required

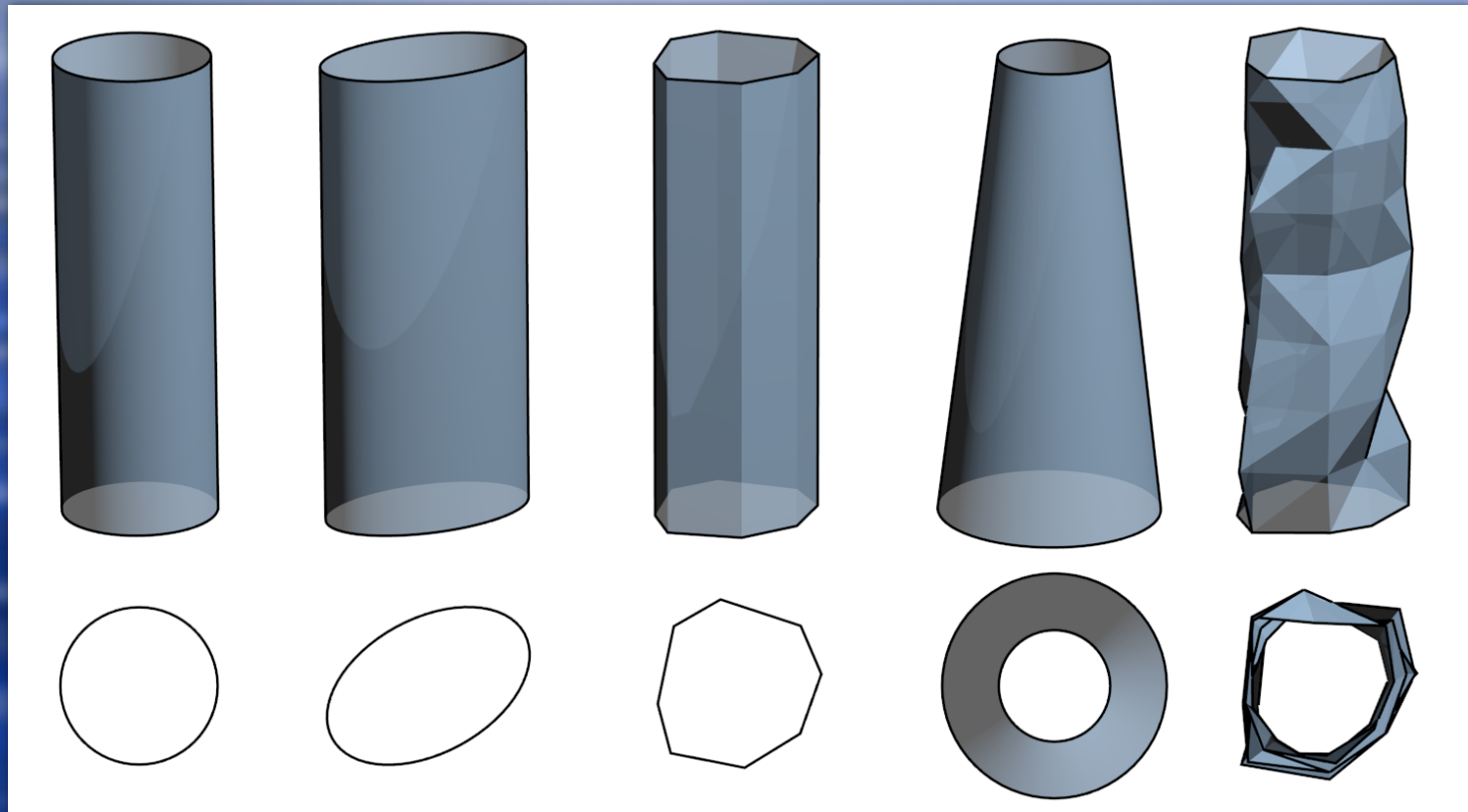




# Cover sets and segments

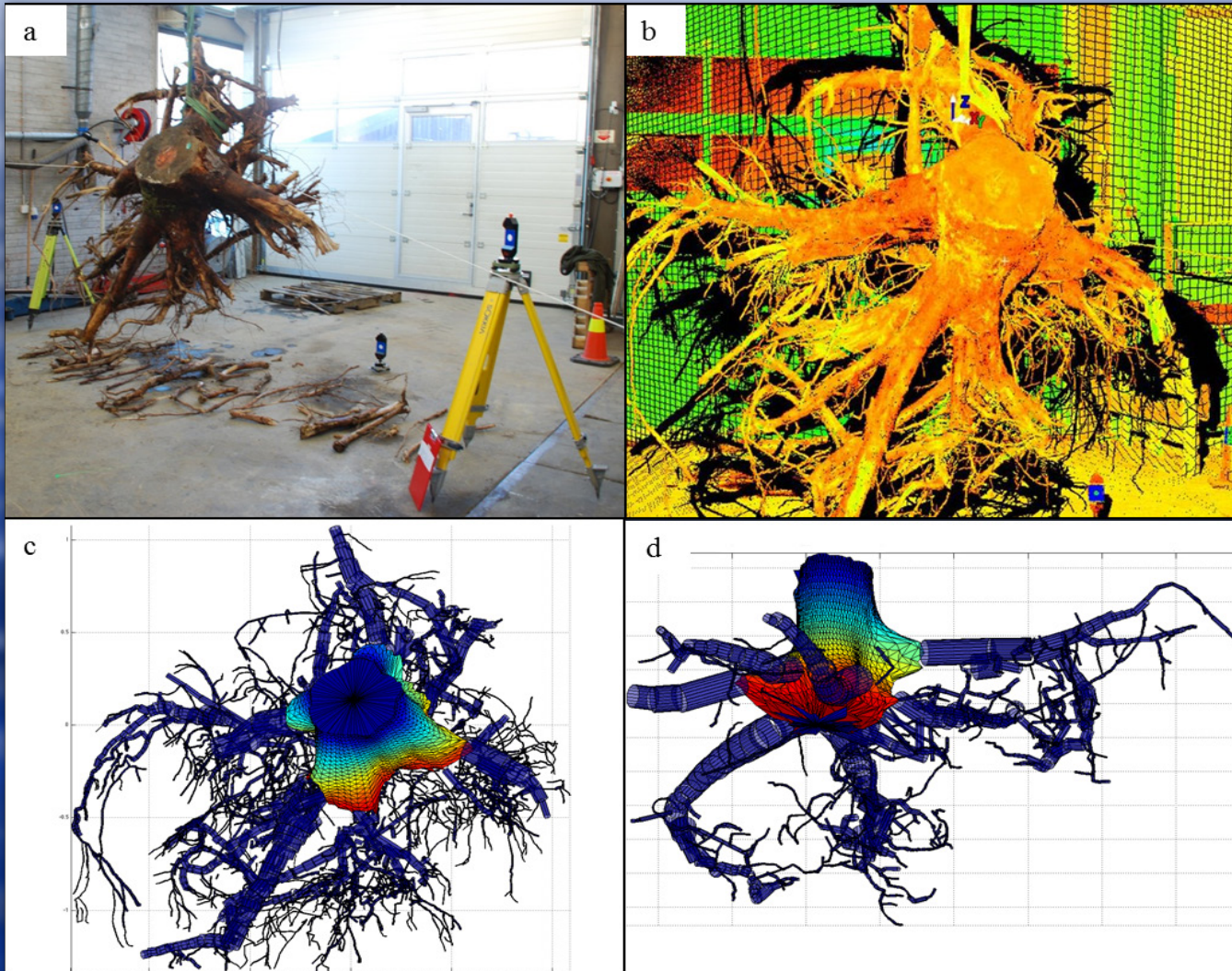


# Other geometric forms



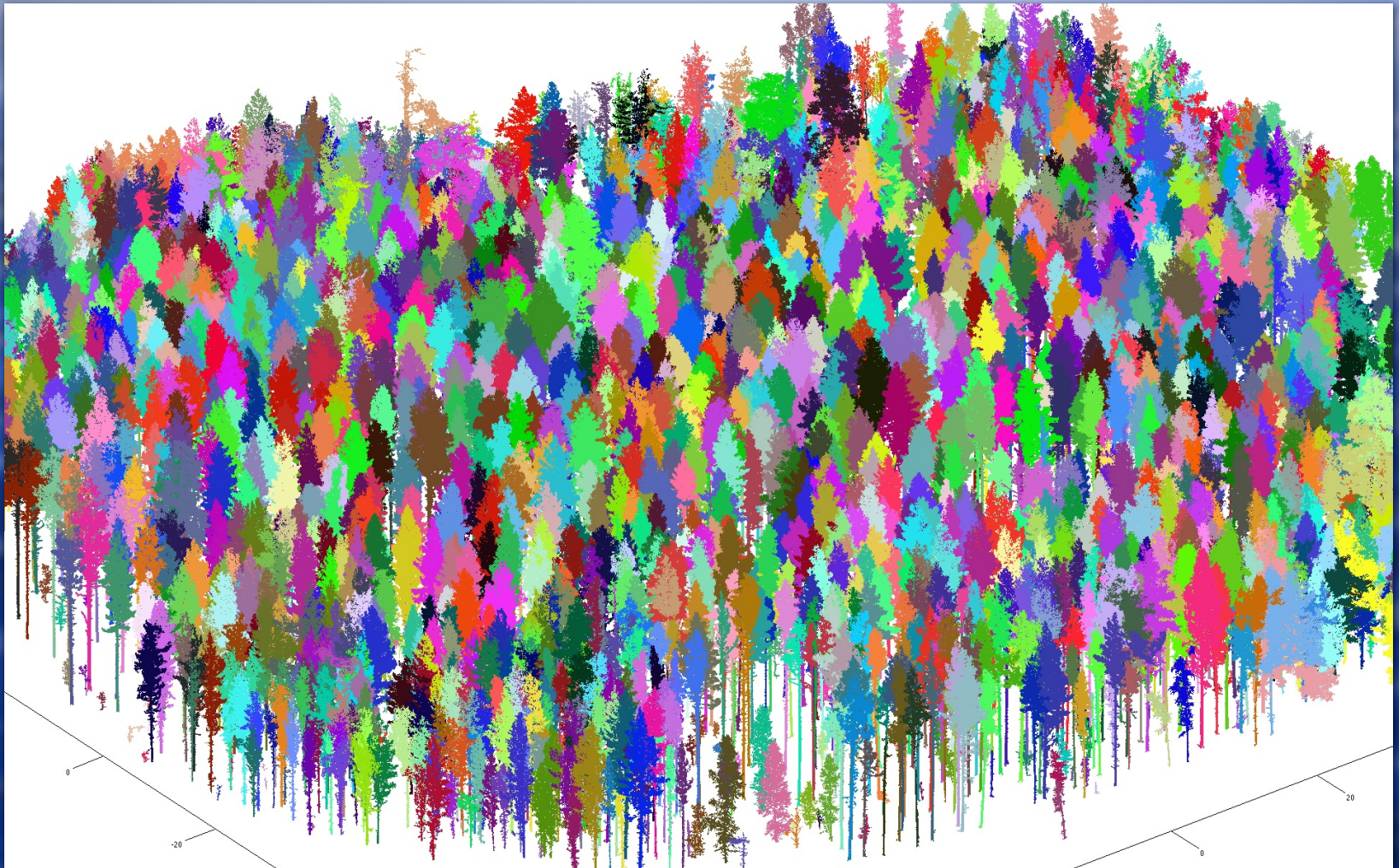


# Complex shapes possible



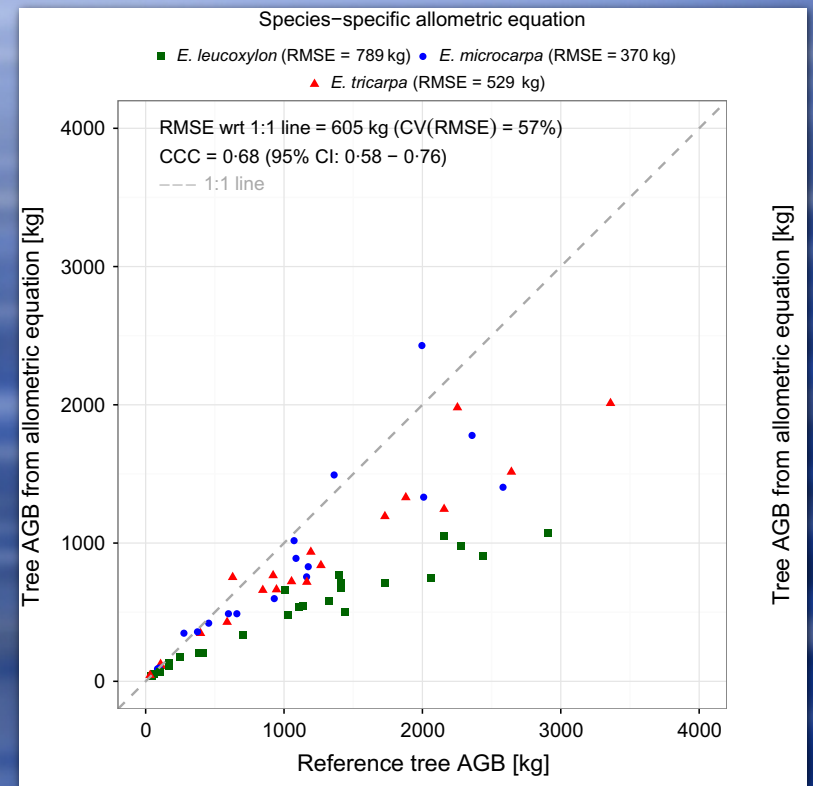
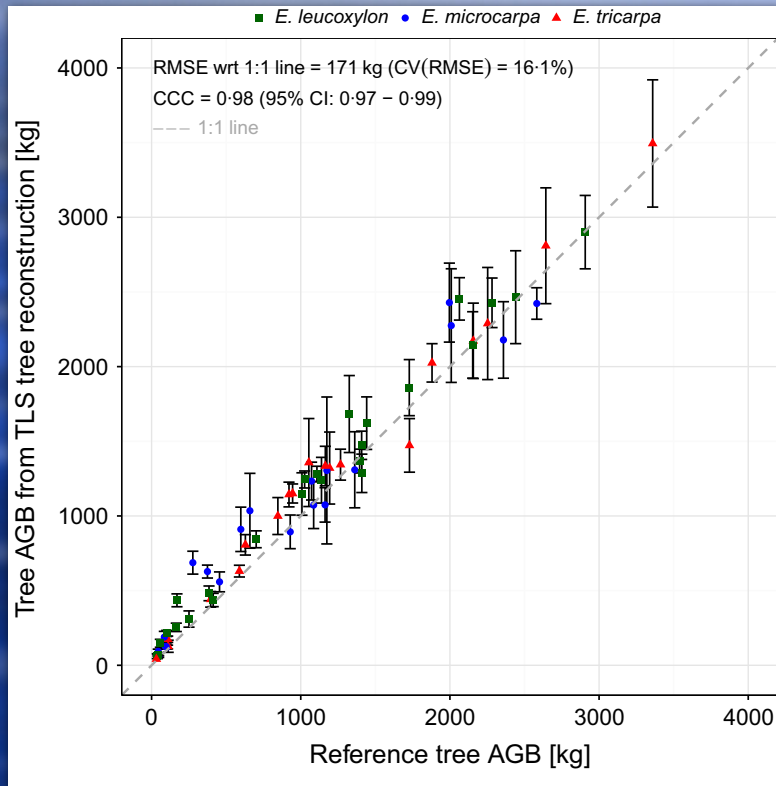


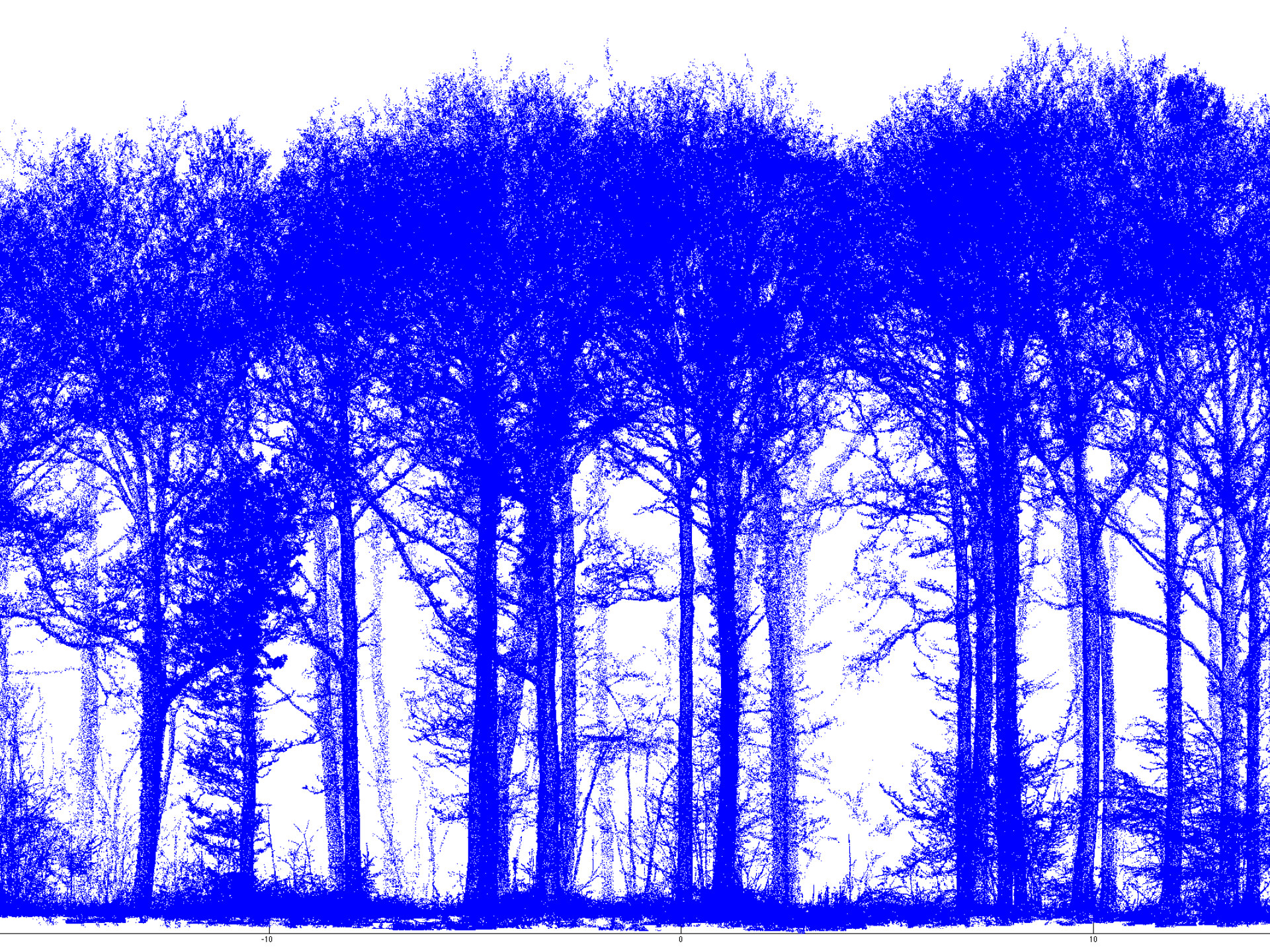
A day's work (scan from 10 spots, QSM on laptop)





# QSM vs. allometry: Australian Eucalypt plot (109 trees)



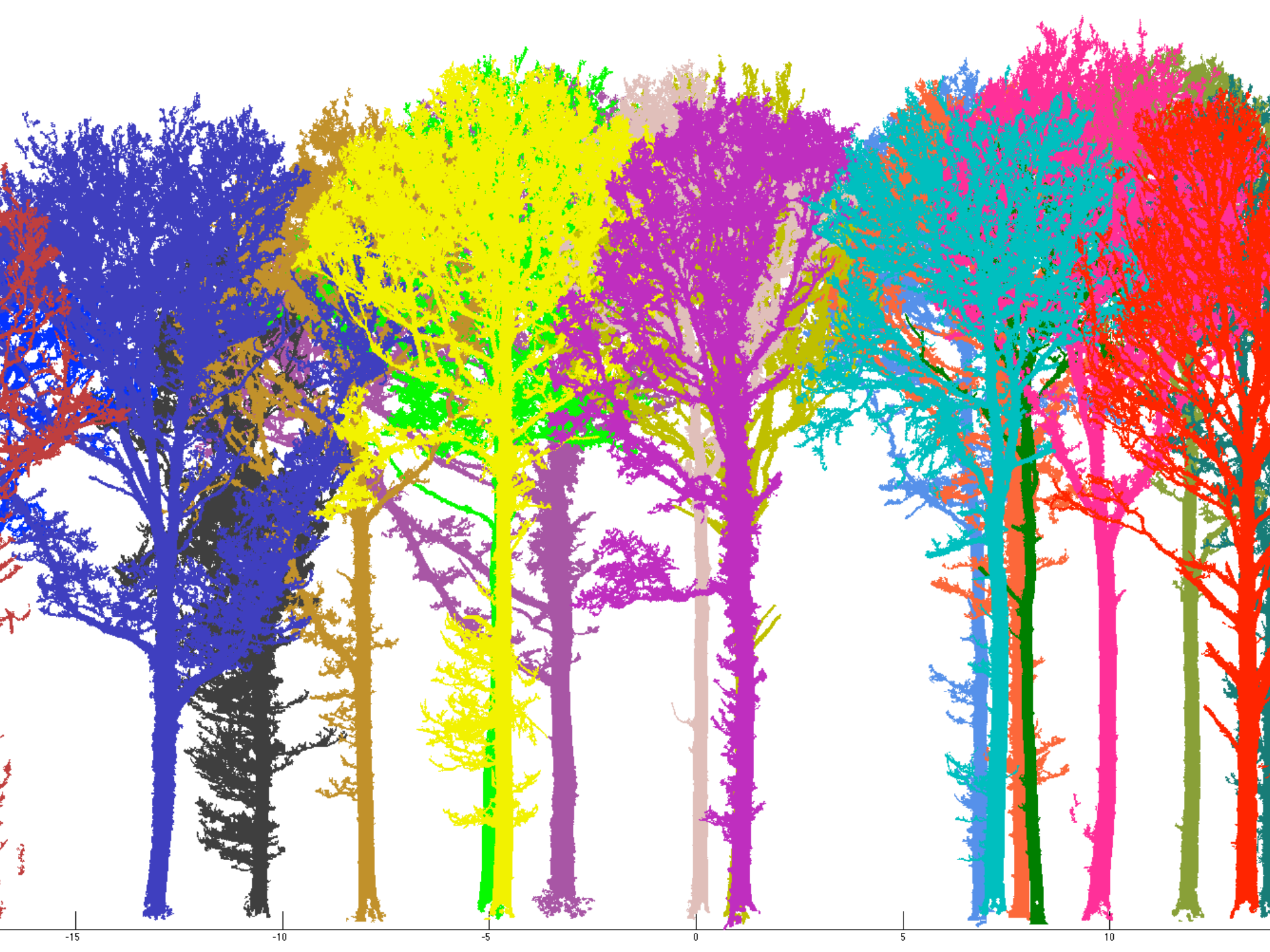


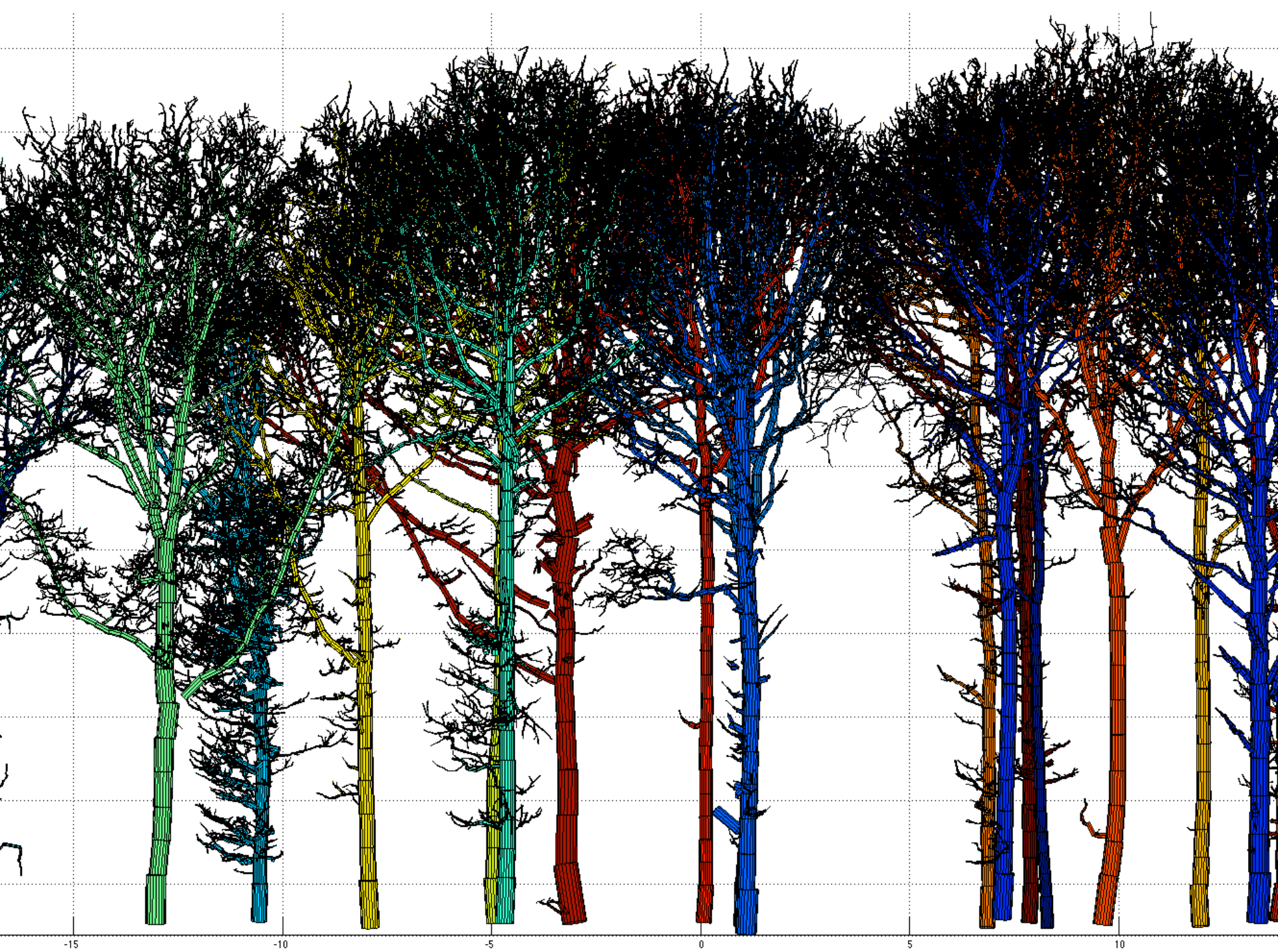
-10

0

10



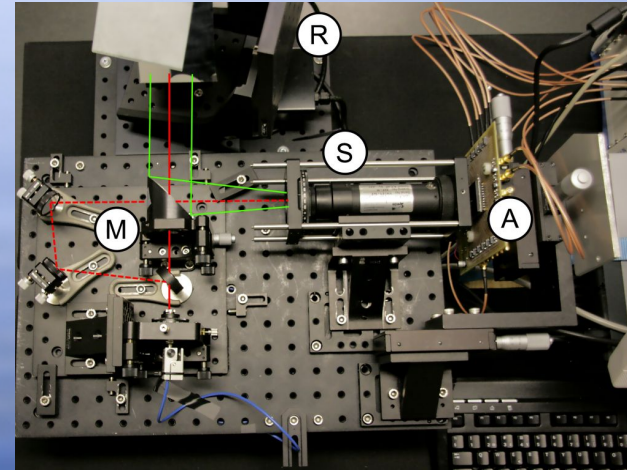






# The FGI hyperspectral lidar

- ◆ New concept & technology in laser scanning
- ◆ Active hyperspectral imaging simultaneously with topographic information
- ◆ Spectrum directly available for each point
- ◆ Based on supercontinuum laser technology





# Hyperspectral lidar (HSL)

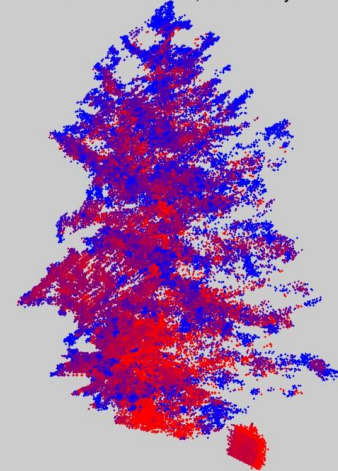
## Applications



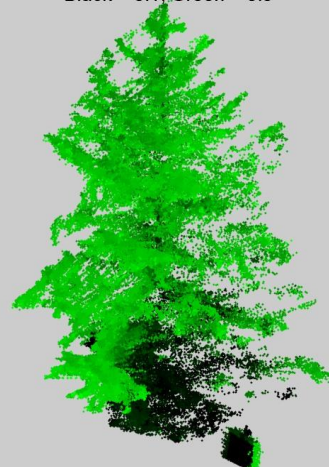
Backscattered Reflectance  
R=740nm, G=672nm, B=606nm



Water Index  
Blue = Moisture, Red = Dry



Normalized Difference Vegetation Index  
Black = 0.1, Green = 0.9



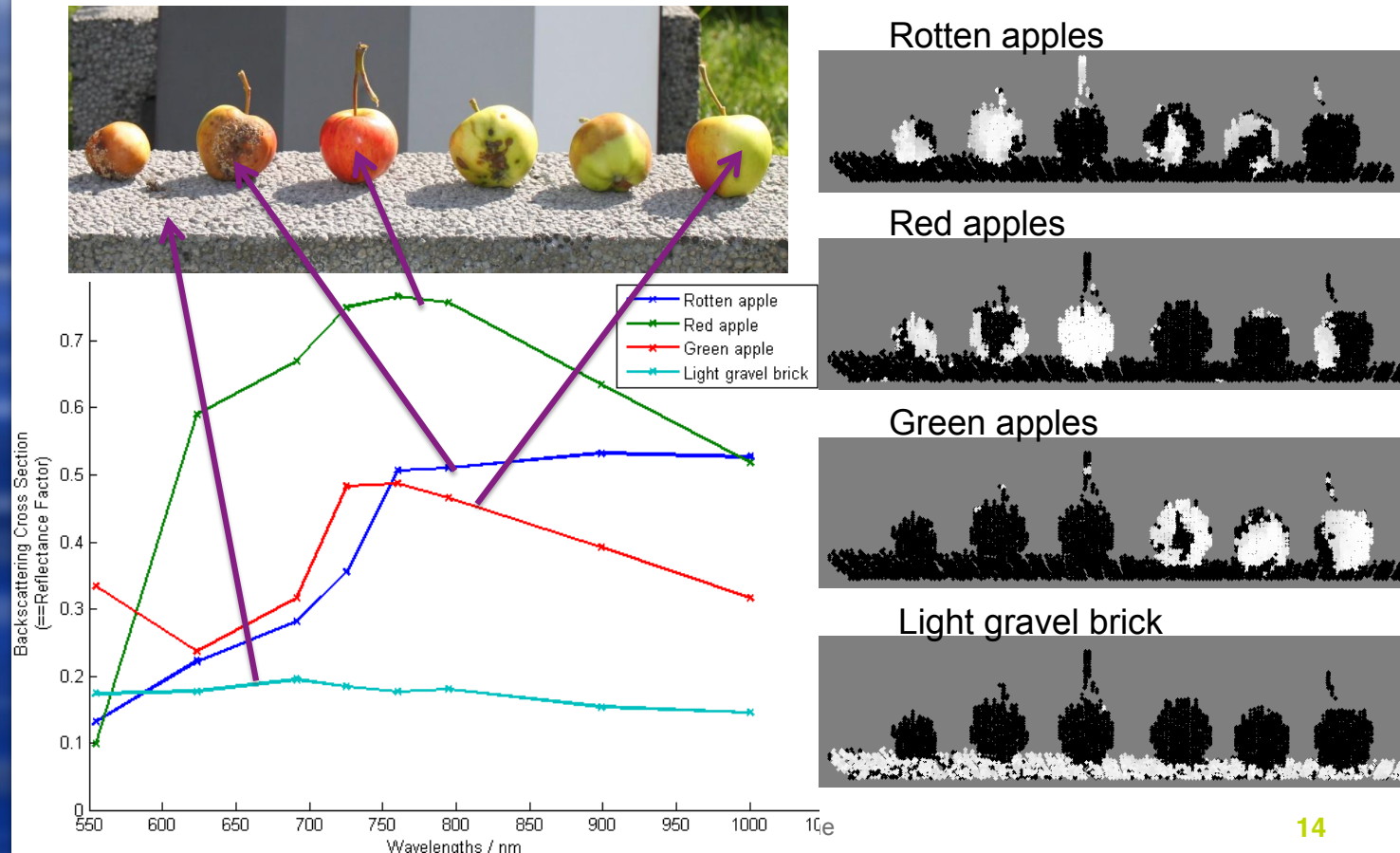
Modified Chlorophyll Absorption Ratio Index  
Black = -0.07, Yellow = 0.3





# HSL: target recognition

## Target classification example

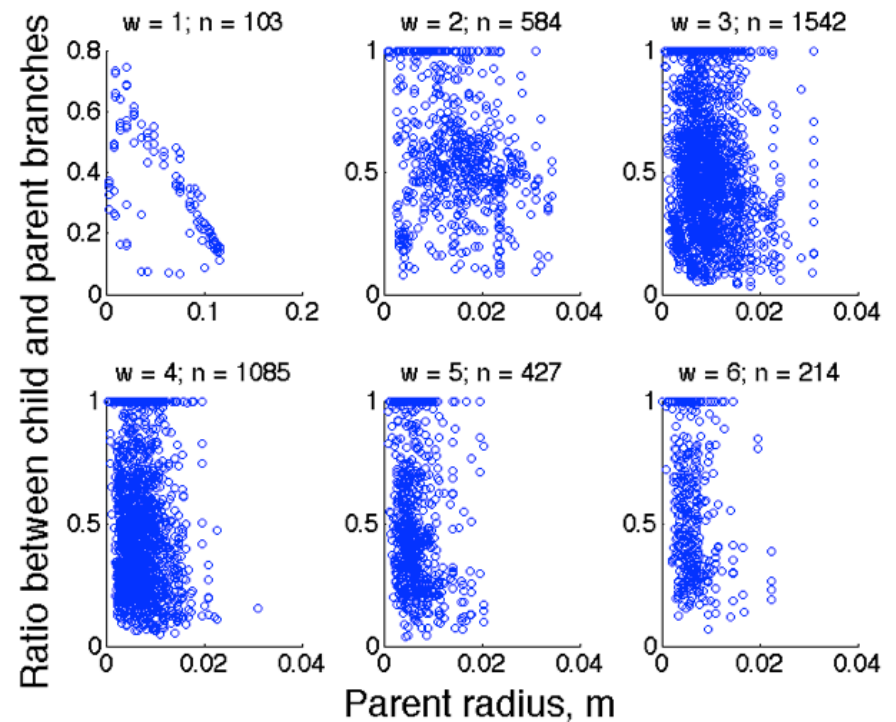
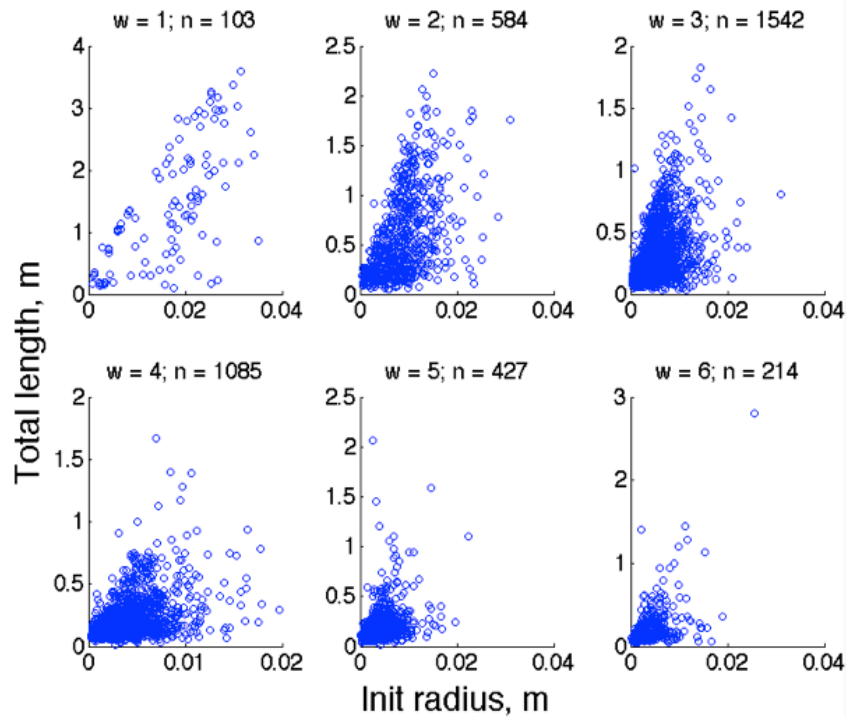


# Trees and forests as probabilistic concepts

- ◆ The growth of a tree (forest, organism, branching system) is a stochastic process -- not random, but unpredictable to some degree: genotype+environment
- ◆ A structure snapshot of the tree/forest (at any time) is the result of this process that contains deterministic, self-organizing and constraining elements (e.g., two branches cannot occupy the same volume; the competition for light and resources)
- ◆ The structure data are distribution functions  $p(u)$  in some measurement space spanned by  $u$
- ◆ The growth process rules  $q(s)$  of a tree model are also probability distributions (DFs): how likely is a tree to make a given choice (in some  $s$ -space) at a given time?

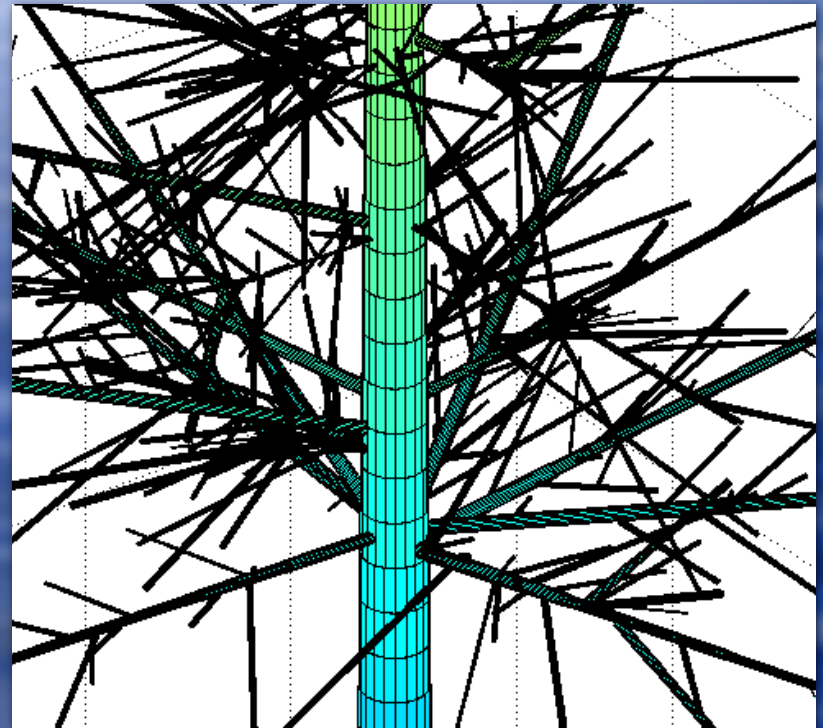


# Sample distributions $p(u)$



# 4D tree growth

- ◆ **HYPOTHESIS:** the genotype of a tree and environmental constraints can be represented by low-dim. stochastic DFs  $q(s)$
- ◆ This handles competition and other development effects in a consistent manner, and reduces the problem dimension
- ◆ 4D measurement data and fitting  $q(s) \rightarrow p(u)$  to 3D-data  $u$ -point distributions: likelihood-free inference
- ◆ Applicable to other organisms, societies, cities: find the growth rules





# FSPMs and synthetic trees

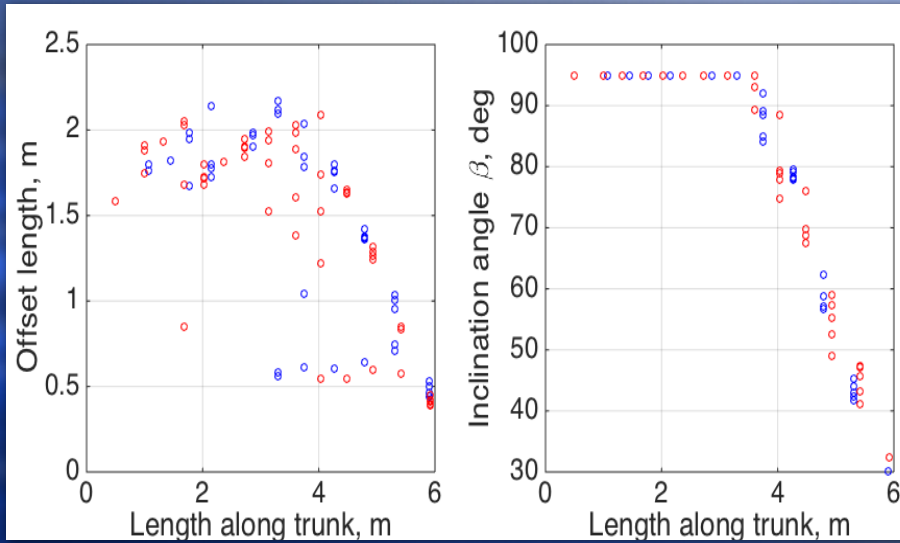
- ◆ We can use biology-based theoretical functional-structural plant models (FSPMs) such as Lignum, or
- ◆ More fully synthetic “4D-geometric” models that flexibly represent “typical” aspects of growth and structure without actual biological rules;
- ◆ Any practical model has elements of both; these are augmented with stochastic properties
- ◆ Deterministic parameters are turned into samples of DFs  $q(s)$ , and the parameters defining  $q$  are now our new model parameters
- ◆ With such a tuned model, we can create statistically similar trees that are not clones

# Structure distance measure

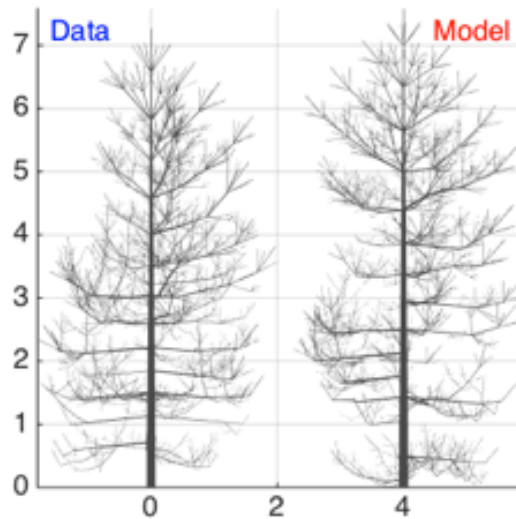
- ◆ Once we have a stochastic model with a parameter set, we create several sample trees from  $q(s)$  out of which we create QSMs and thus  $p(u)$  in selected spaces
- ◆ We define the structure distance measure; i.e., the difference  $D$  between two  $p(u)$  -- in principle zero for stat. similar trees of the same  $q(s)$
- ◆ Then we minimize  $D[p(u)_{\text{data}}, p(u)_{\text{model}}]$  iteratively (e.g., genetic algorithms) by tuning the parameters of  $q(s)$
- ◆ There is no unique choice for the model,  $D$ ,  $s$ , or  $u$ , or the parametrization of  $q$  and  $p$  (e.g., Gaussian)
- ◆ The choices probably depend on the species; we just have to experiment a lot
- ◆ Sometimes part of  $q$  and  $p$  may be essentially the same thing (e.g., distribution of branch tapering) so we get that part of  $q$  directly



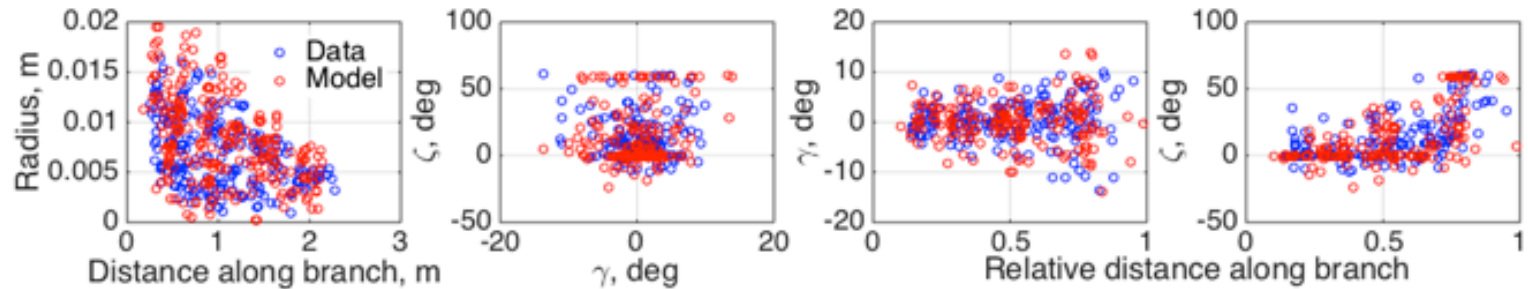
# Lignum simulation



# Lignum simulation

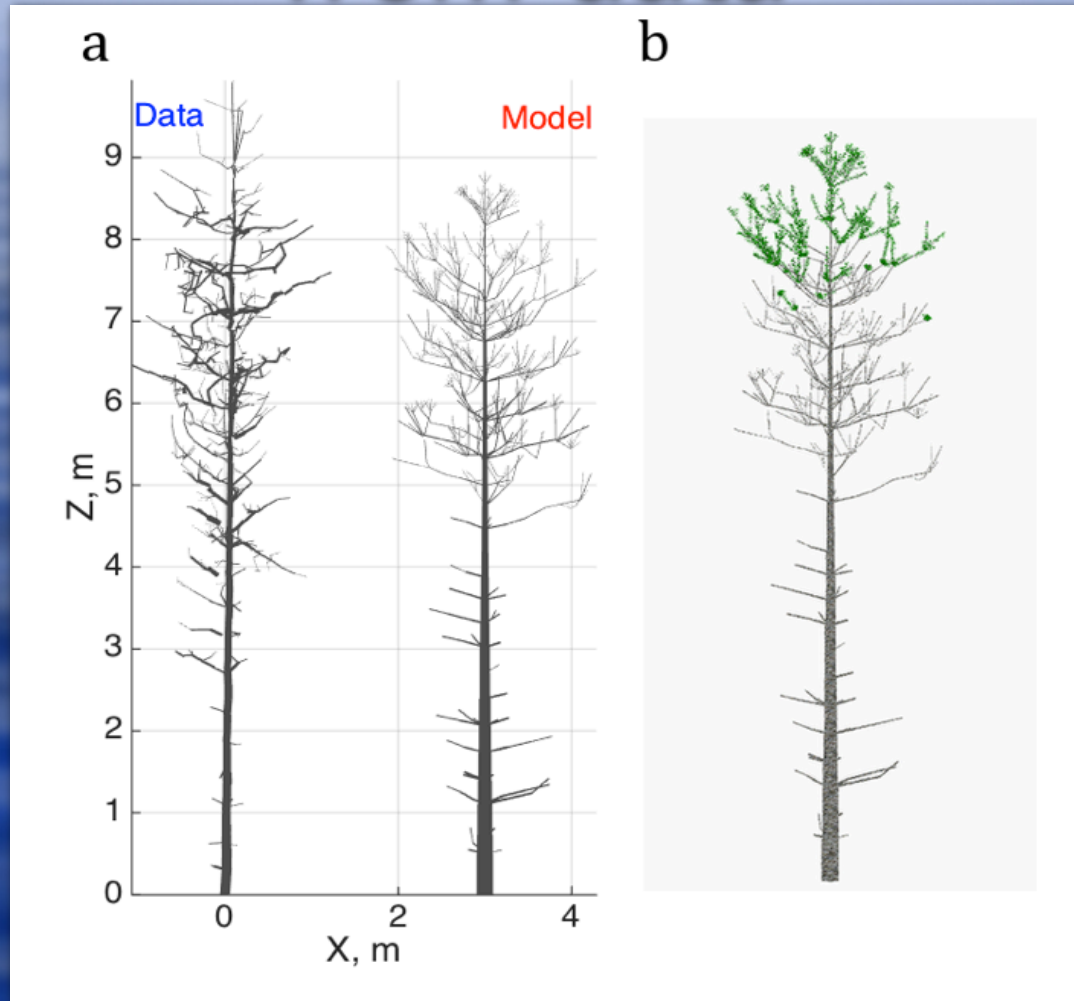


Parameter name	Data value	Model value (estimated)	Relative error, %
$L_R$ , mean	0.009	0.0094	4.65
$L_R$ , std	0.001	0.0009	6.95
$Q$ , mean	0.2	0.2058	2.88
$Q$ , std	0.03	0.0213	28.88
$T$	15	16	6.67
$\Delta\beta$	10.0	9.7665	2.33
$\Delta\zeta$	5.0	4.3708	12.58
$\beta_{init}$	35.0	40.4649	15.61





# Stochastic augmented Lignum from data



# Literature

- ◆ Raumonen & al. 2013, Rem. Sens. 5, 491
- ◆ Calders & al. 2015, Meth. Ecol. Evol. 6, 198
- ◆ Kaasalainen & al. 2014, Rem. Sens. 6, 3906
- ◆ *[math.tut.fi/inversegroup](http://math.tut.fi/inversegroup)*
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