A model-based approach for estimating the height distribution of eucalyptus plantations using low-density ALS data

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September 15, 2010

UNIVERSITY OF EASTERN FINLAND

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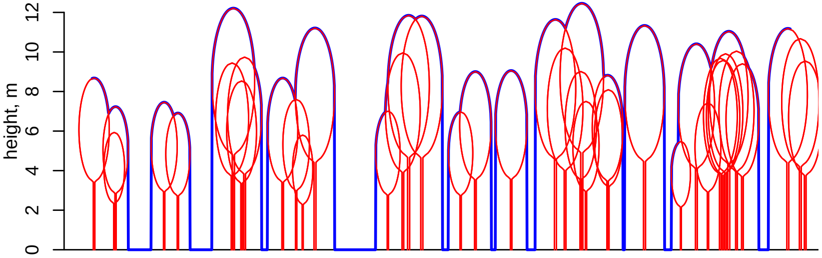
WoodWisdom-Net

WW-IRIS

Canopy surface



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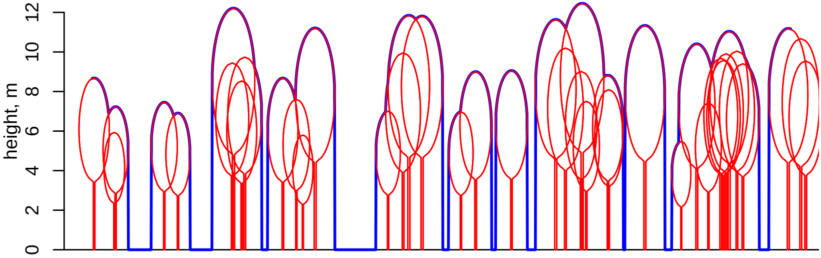

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- Individual trees generate the *canopy surface* (CS) of the stand

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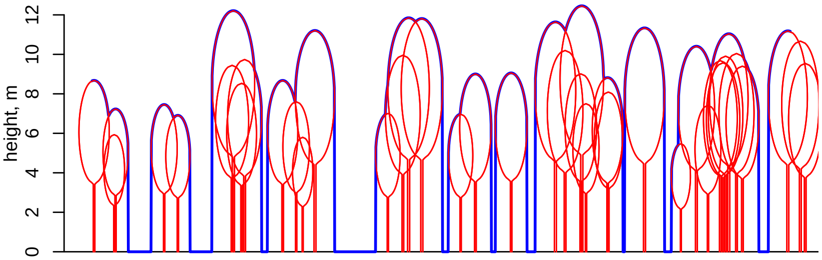
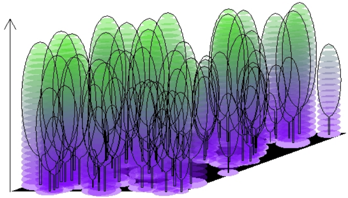
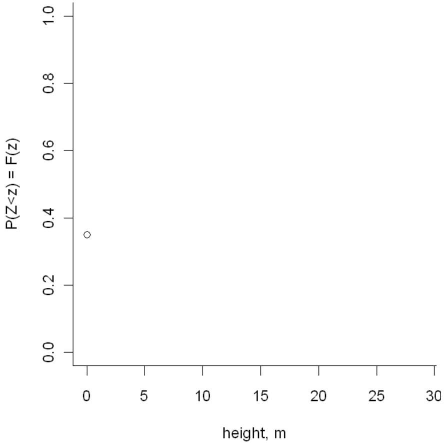


Under certain simplifying assumptions (e.g., a solid top surface of a tree), we can think that

- Individual trees generate the *canopy surface* (CS) of the stand
- ALS returns are (essentially) observations on that surface

Canopy surface (random spatial pattern)





The probability to have CS below a given height
= The probability that a random point does not hit the union of tree crowns

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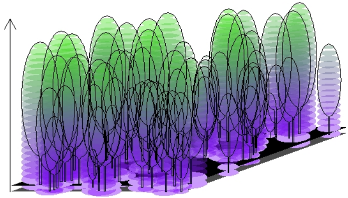

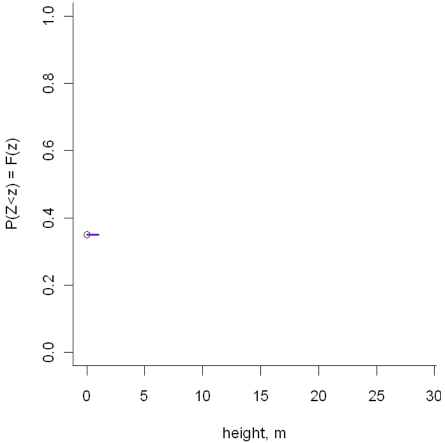

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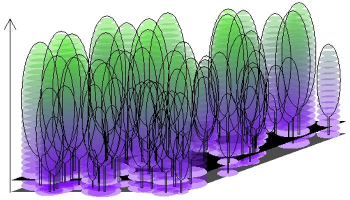

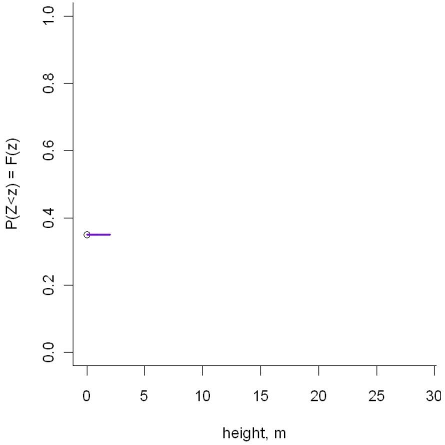

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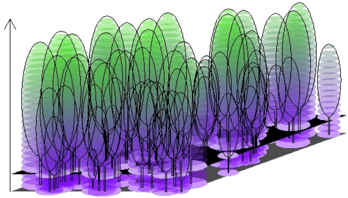

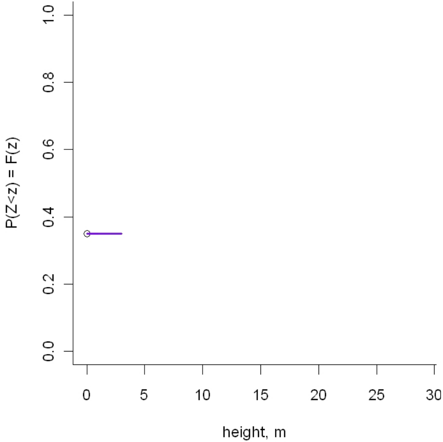

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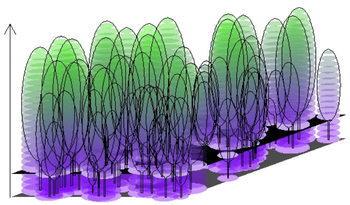

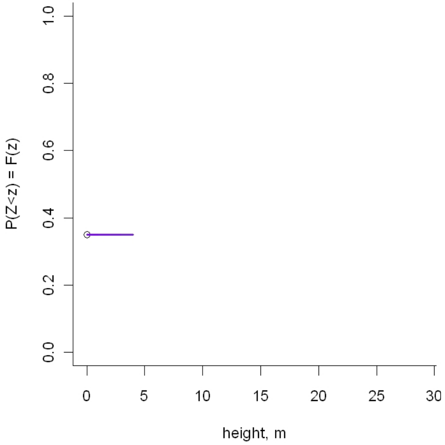

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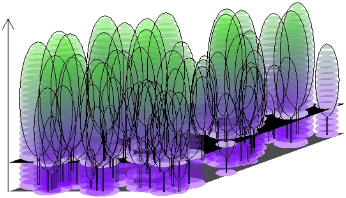

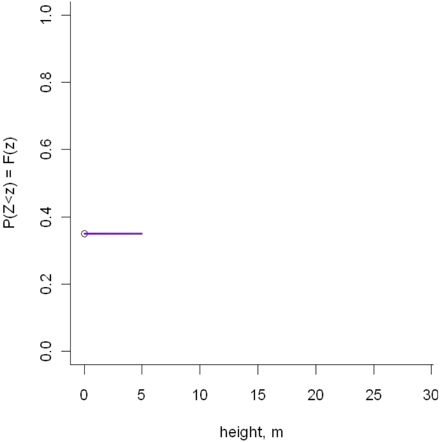

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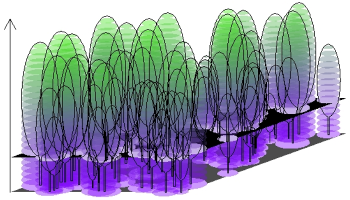

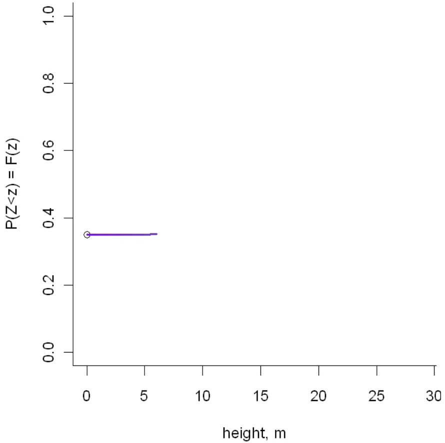

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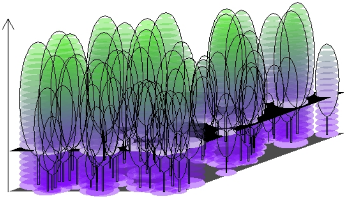

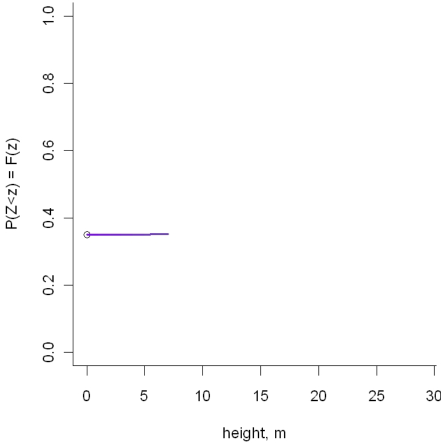

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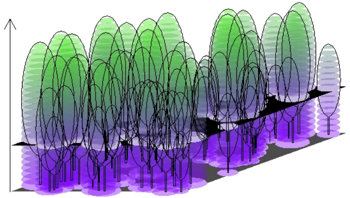

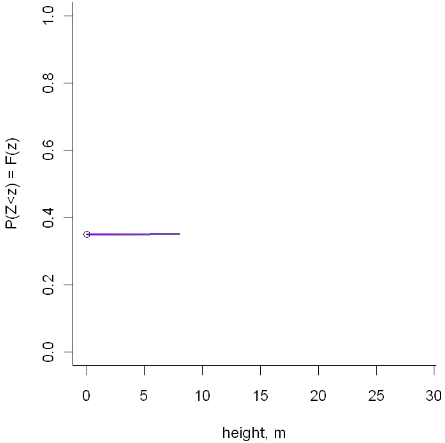

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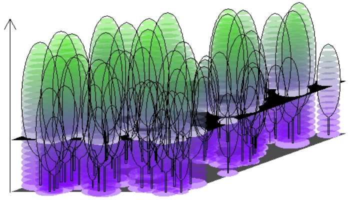

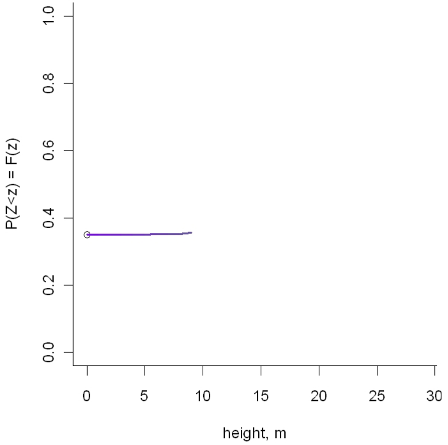

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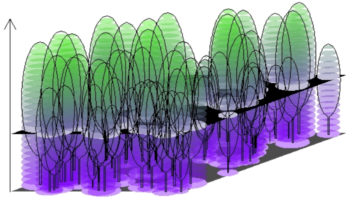

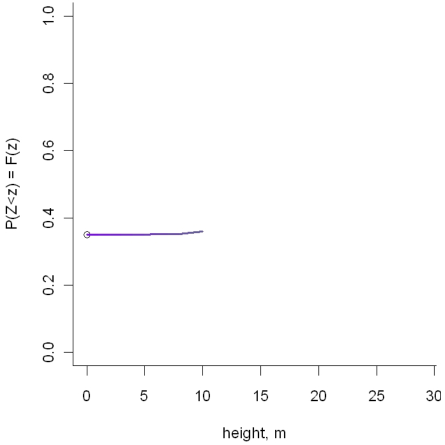

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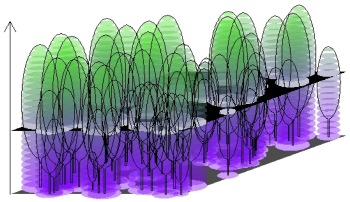

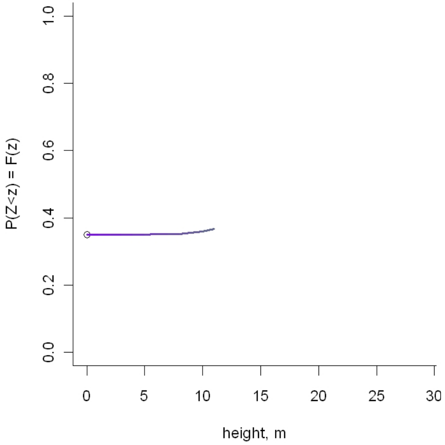

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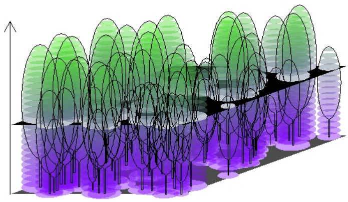

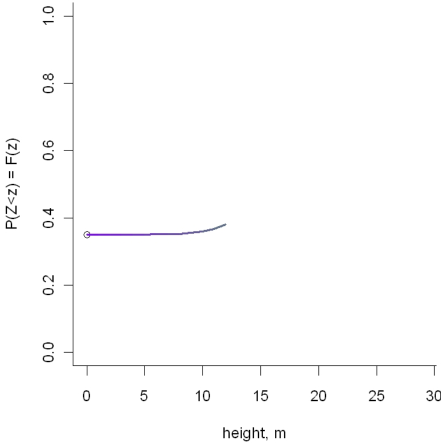

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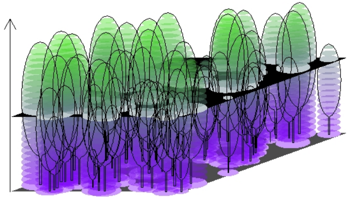

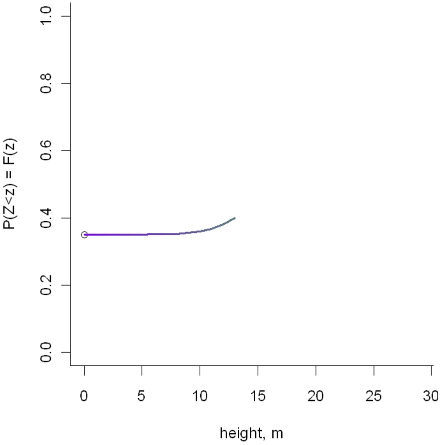

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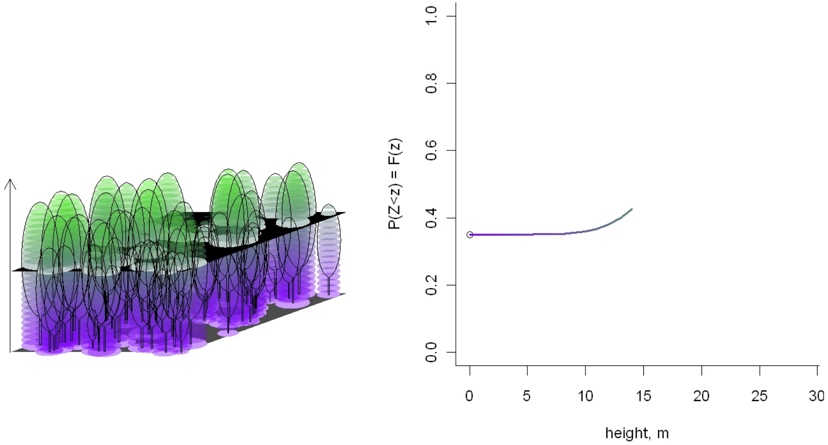

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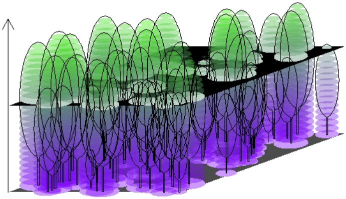

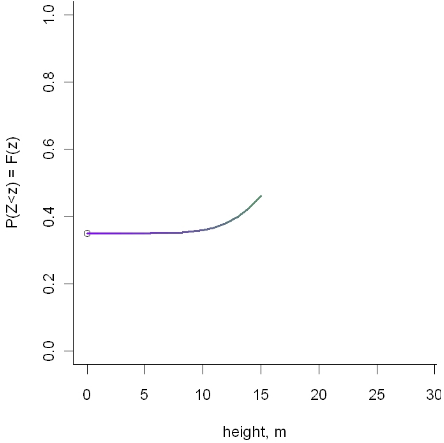

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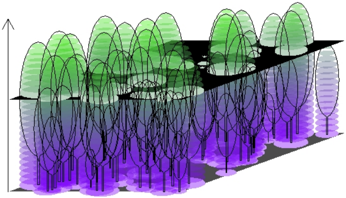

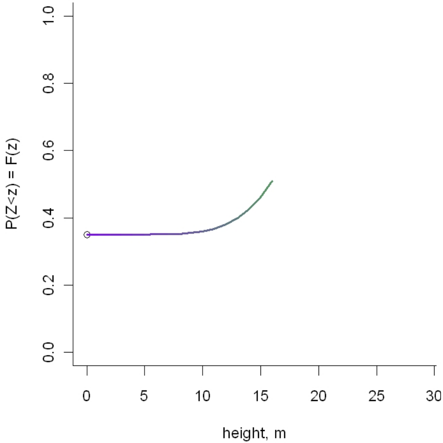

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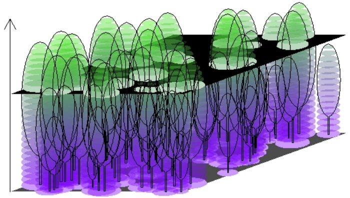

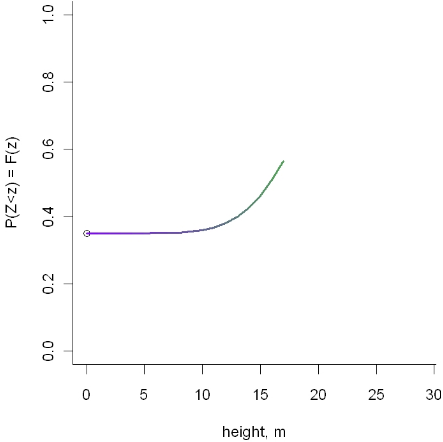

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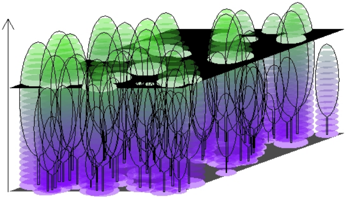

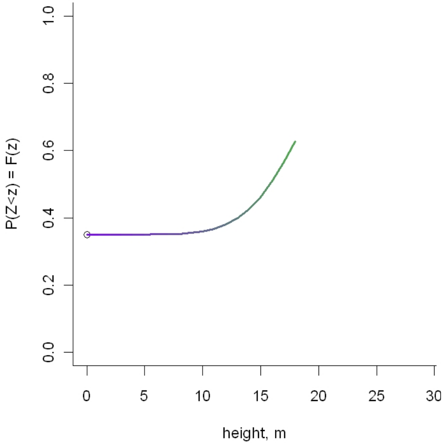

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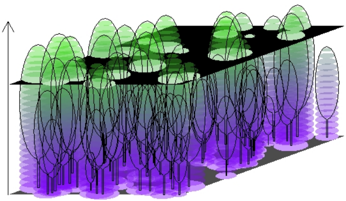

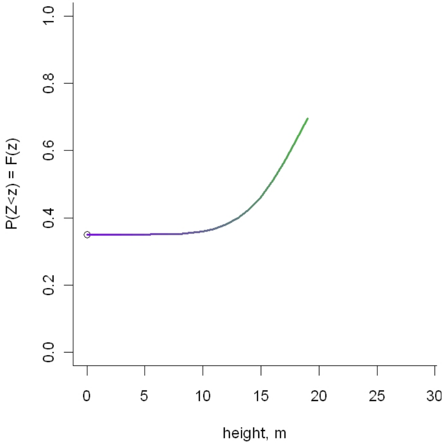

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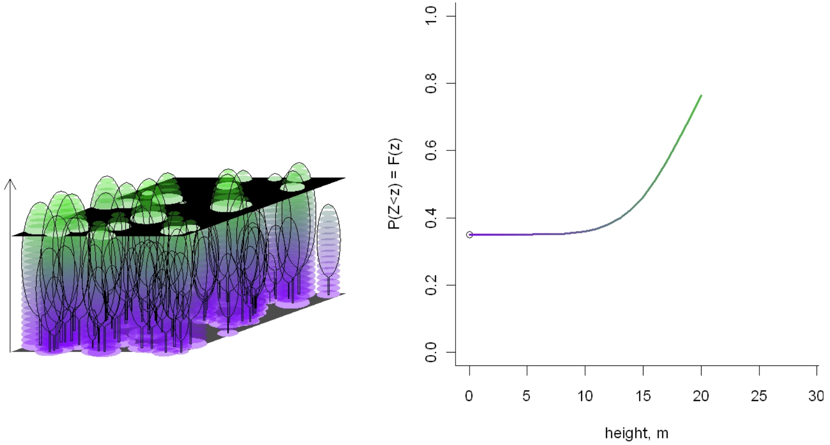

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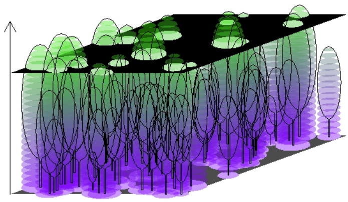

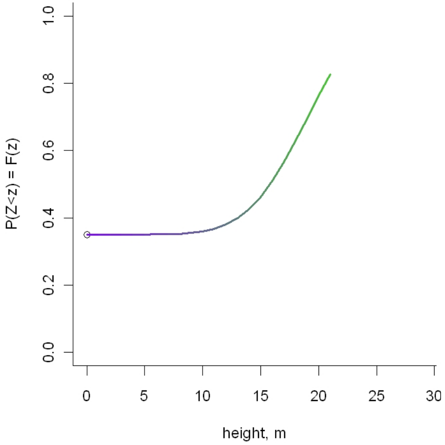

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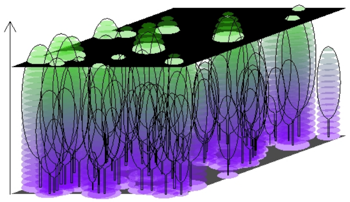

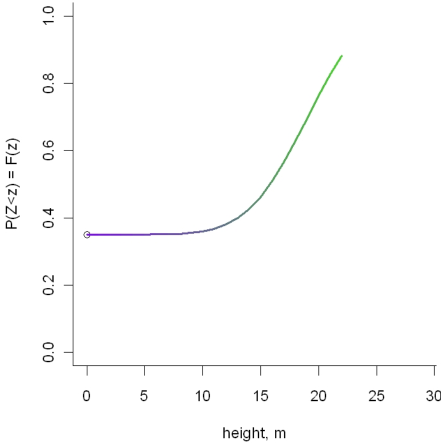

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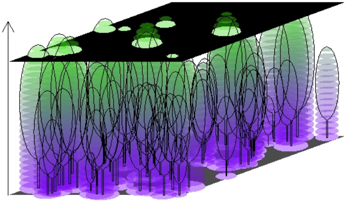

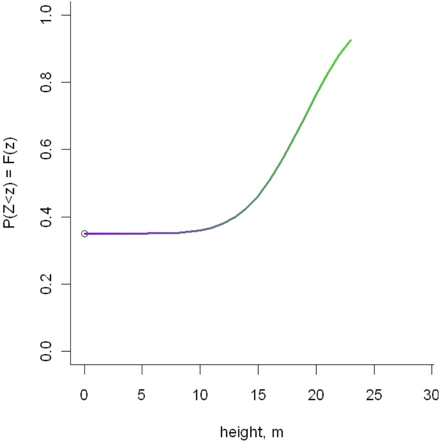

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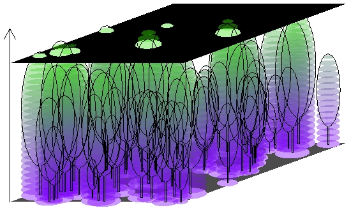

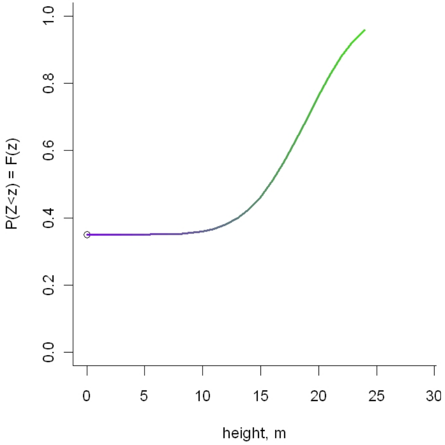

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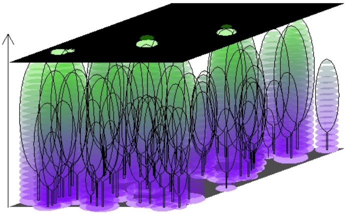

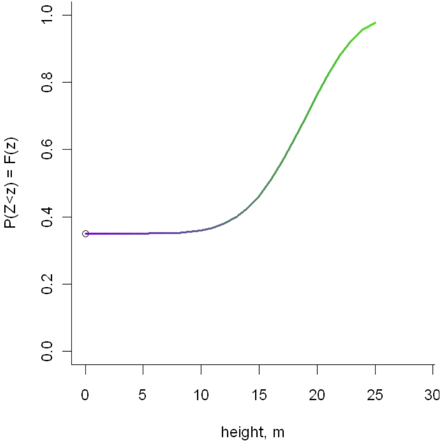

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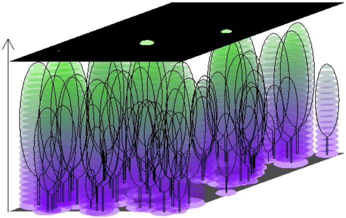

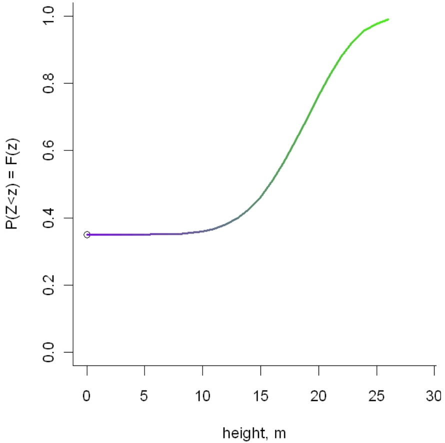

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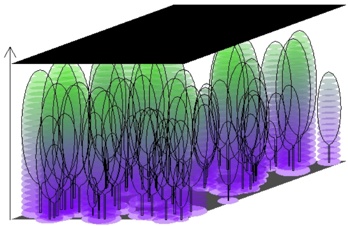
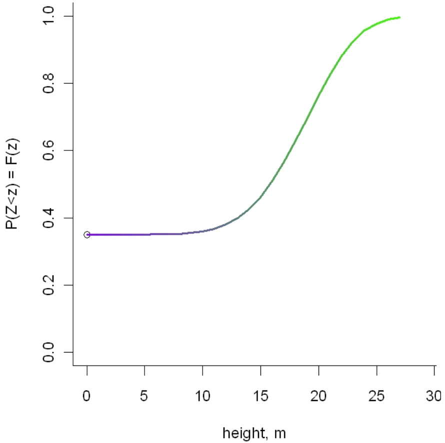




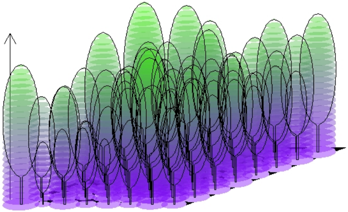
The probability to have CS below a given height
= The probability that a random point does not hit the union of tree crowns
≈ The c.d.f. of the random heights of pre-processed ALS returns, denoted by Z

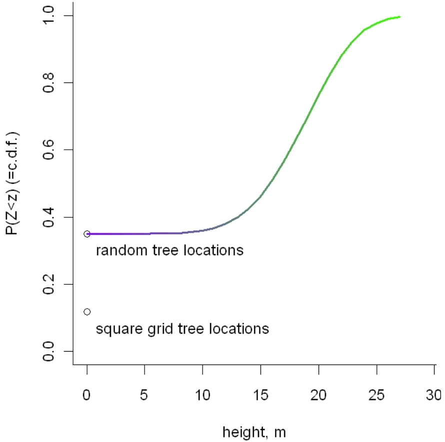
Canopy surface

The observed height of canopy surface, Z, is a random variable. The distribution depends on (Mehtätalo and Nyblom, 2009)

- The stand density (trees per ha)
- The stand-specific distribution of tree heights
- The crown shape of a tree with given total height
- The spatial pattern of tree locations

Canopy surface for square grid pattern





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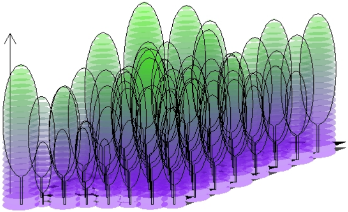

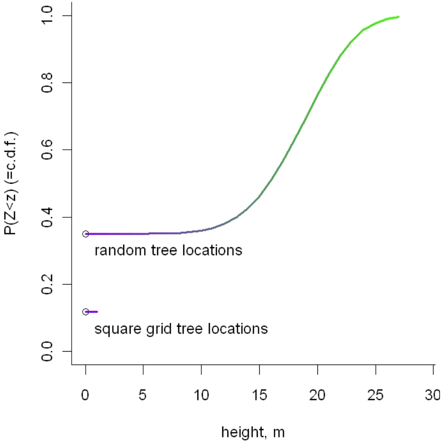

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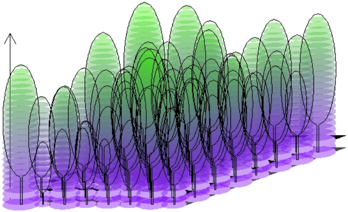

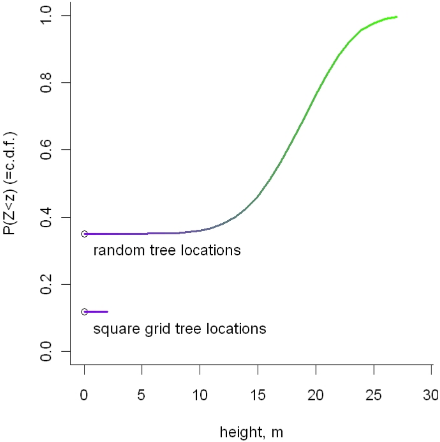

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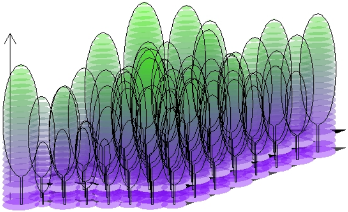

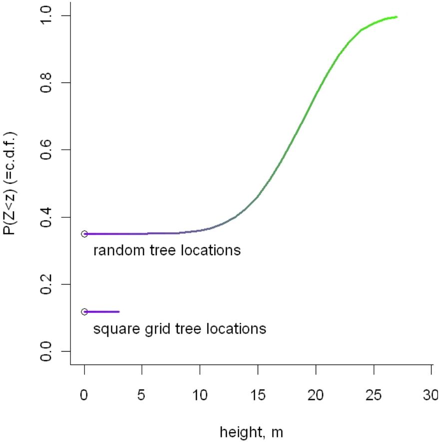

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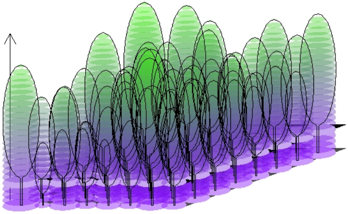

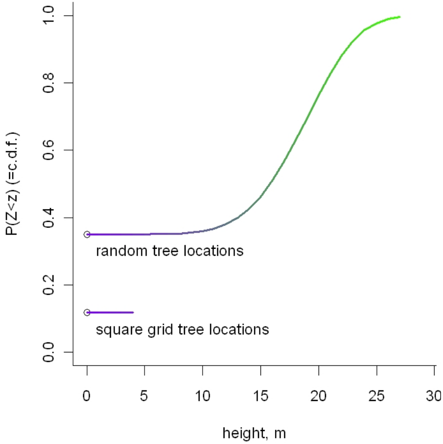

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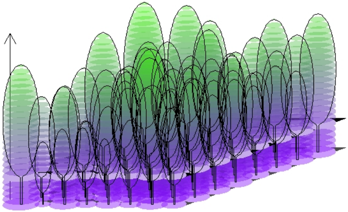

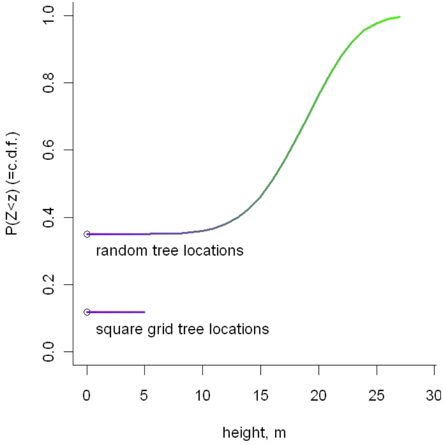

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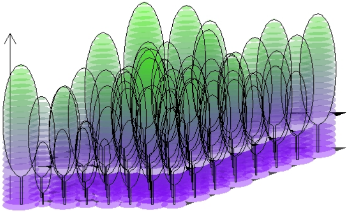

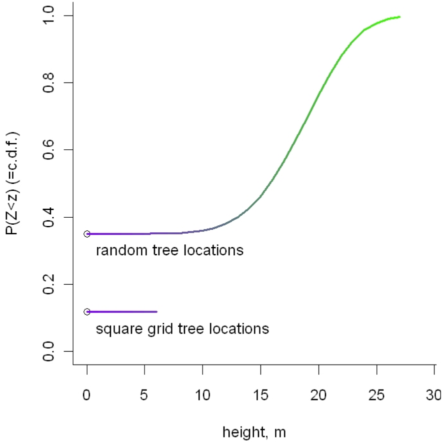

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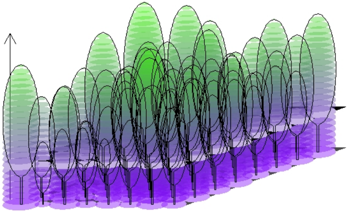

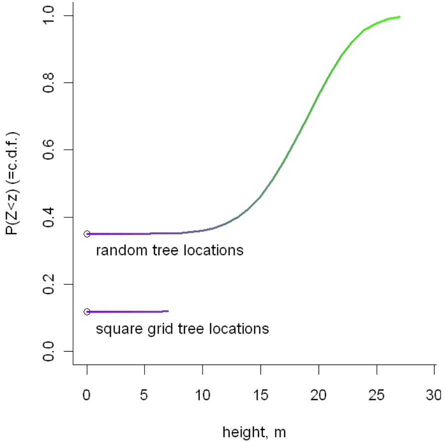

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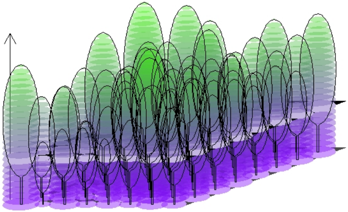

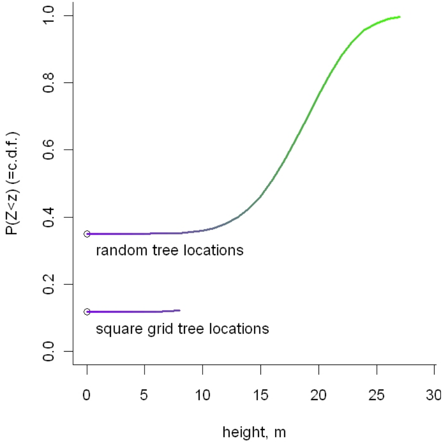

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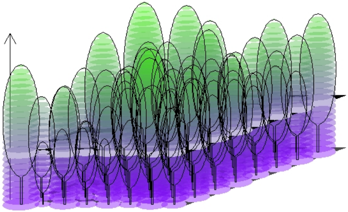

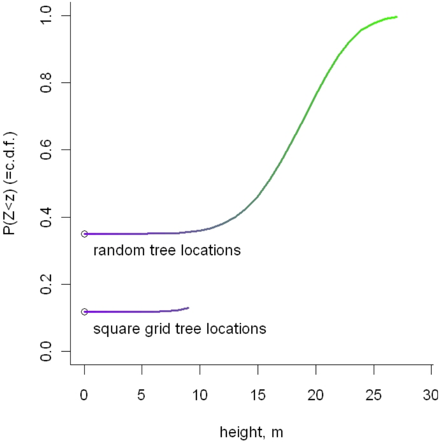

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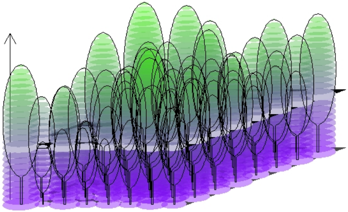

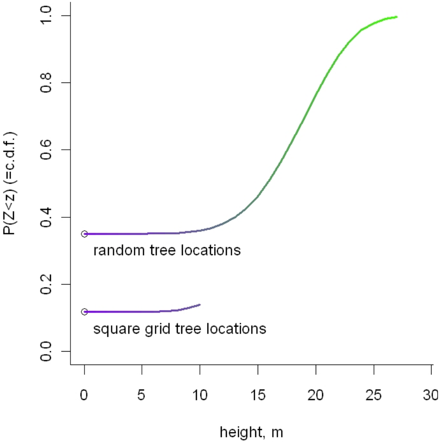

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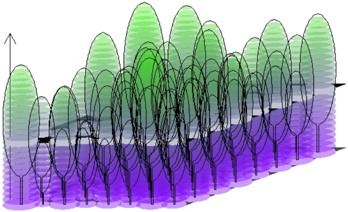

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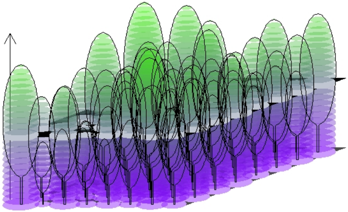

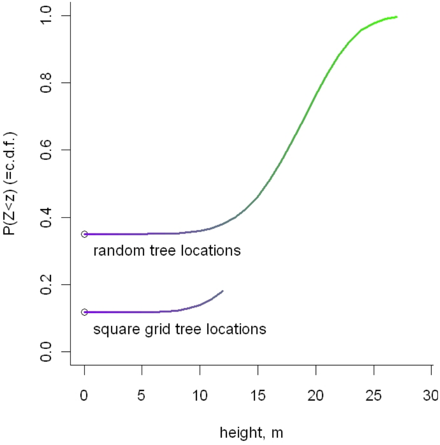

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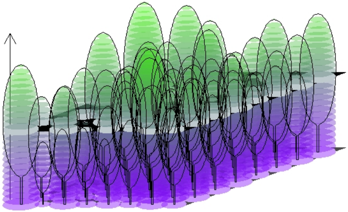

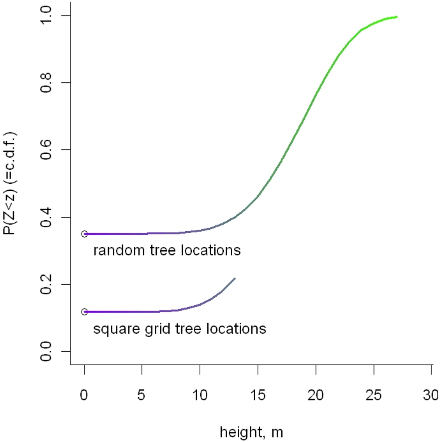

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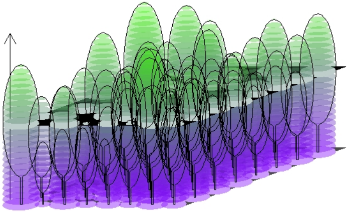

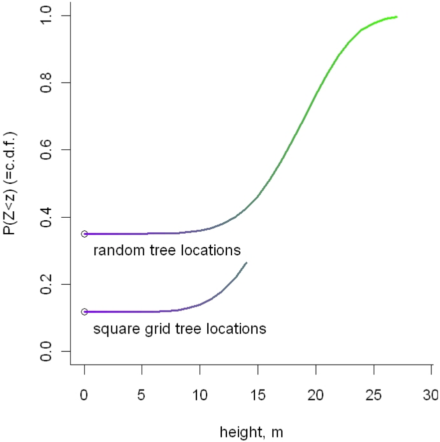

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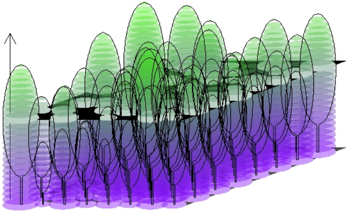

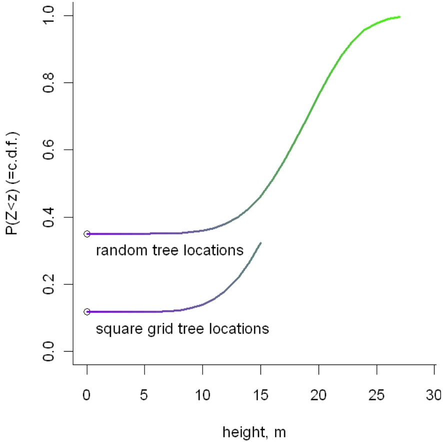

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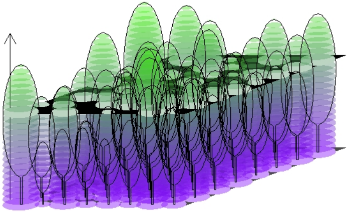

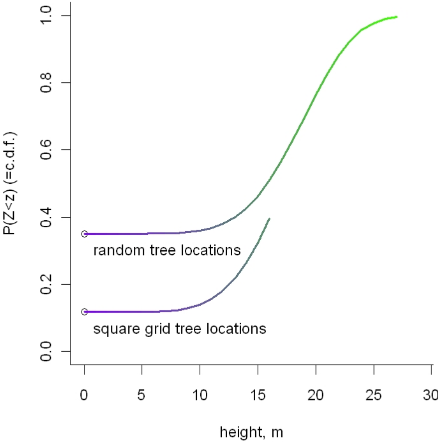

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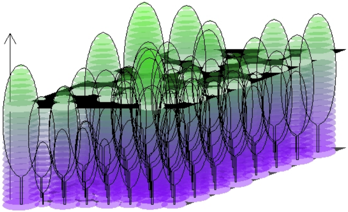

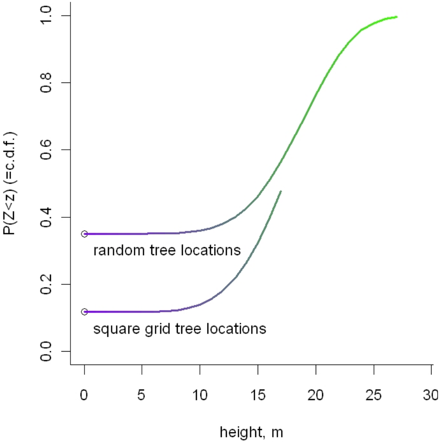

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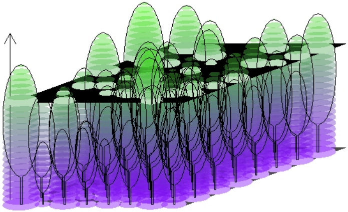

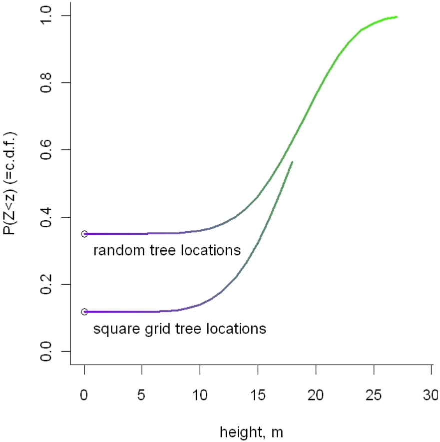

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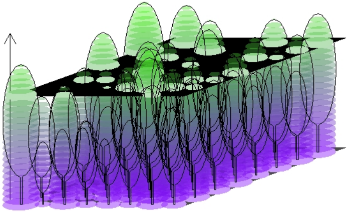

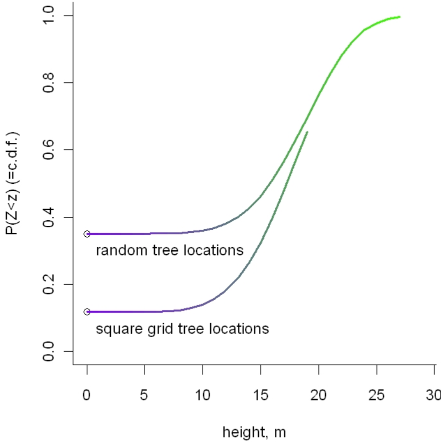

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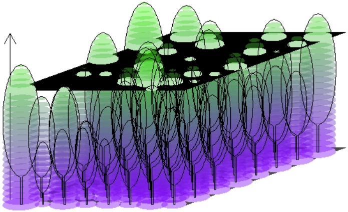

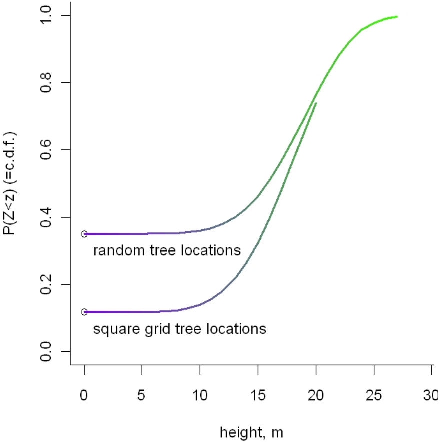

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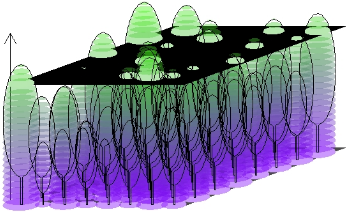

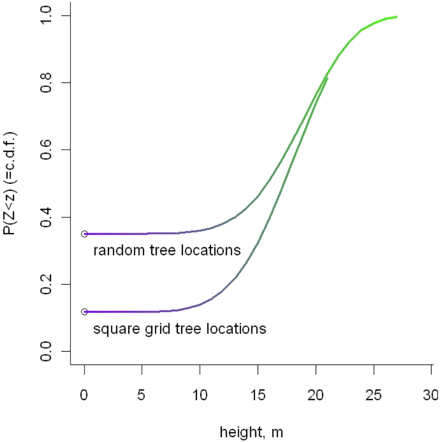

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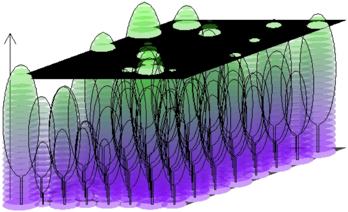

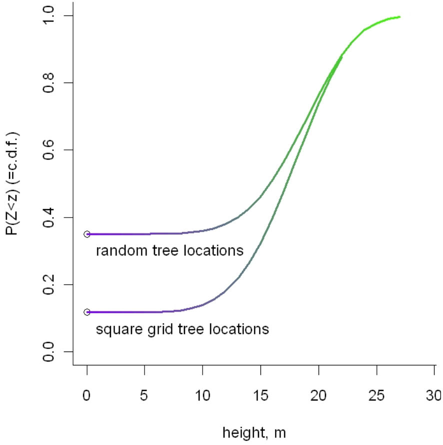

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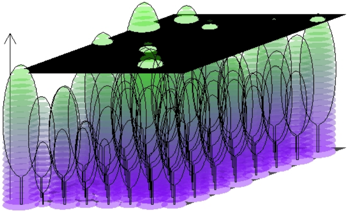

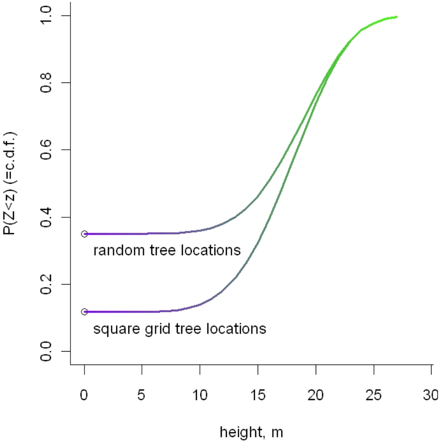

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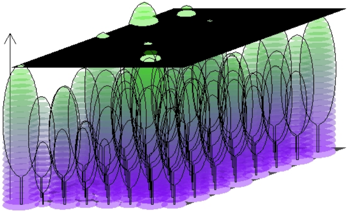

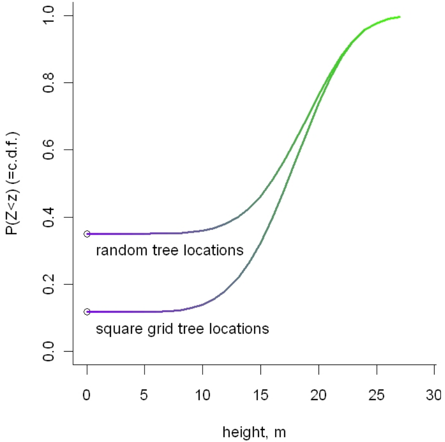

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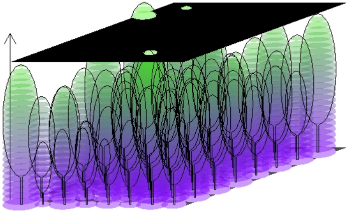

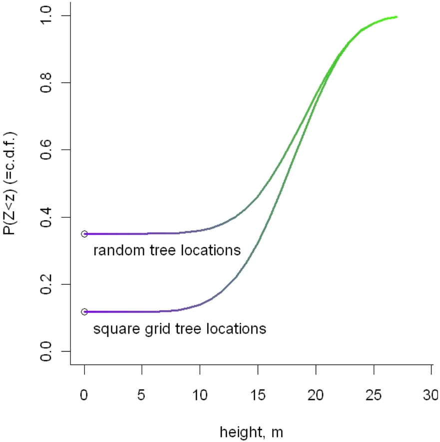

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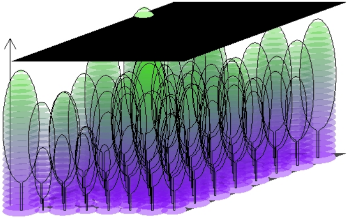

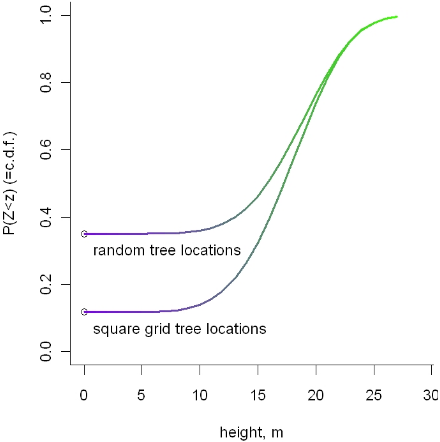

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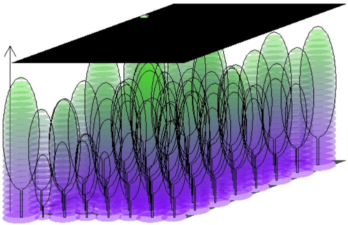

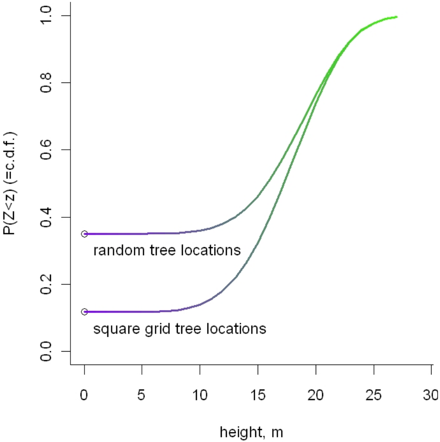

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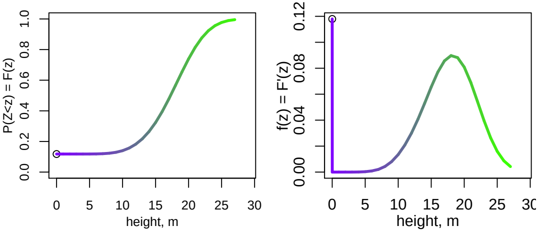
The probability density function (p.d.f.)

The p.d.f. is the first derivative of the c.d.f.



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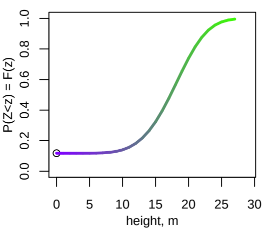

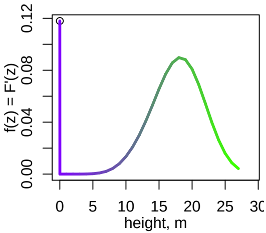

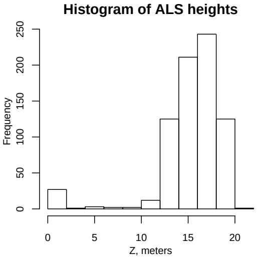

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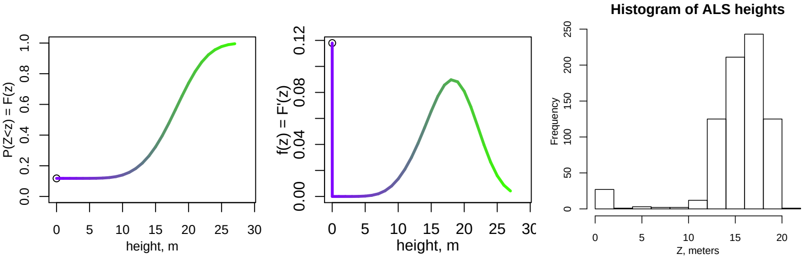

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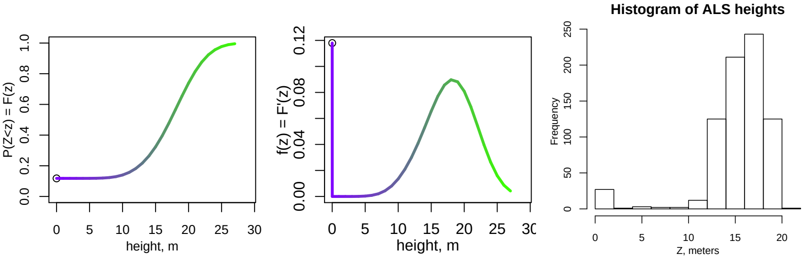

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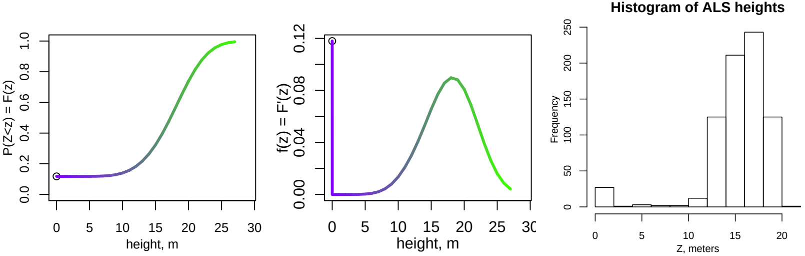

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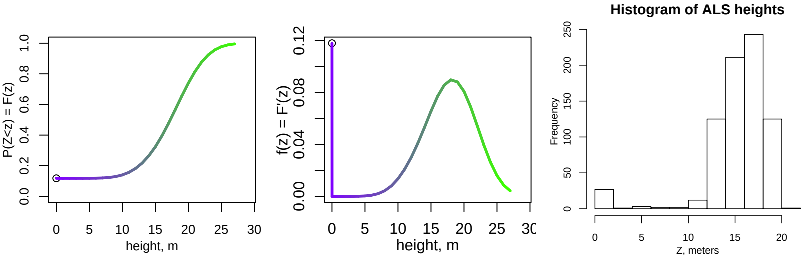

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- $\boldsymbol{\xi}$ includes the parameters of the stand-specific distribution of tree heights, e.g.,
  - the shape (α) and
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- λ is the stand density (trees per ha)

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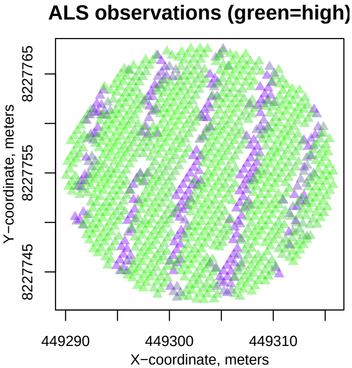
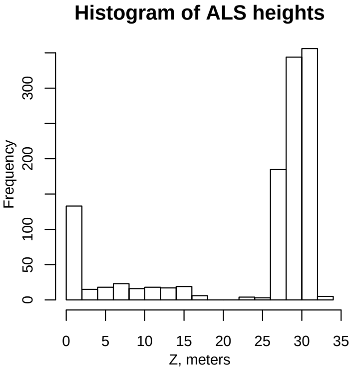
Study material

- 18 pairs of sample plots from the Veracel data (18 training and 18 evaluation plots).
- Distance between trees and stand density λ are known
- Three heights known for every 7th tree, and imputed for others using a stand-specific model
- ALS data were pre-processed and thinned to include $\approx$ 122 uniformly placed observations of canopy height (Z) for each plot (0.23 pulses/m^2)





Application to area-based inventory

1. Training stage using training sample plots

2. Prediction stage using evaluation plots

Application to area-based inventory

1. Training stage using training sample plots
    1. Estimate $\xi = (\alpha, \beta)'$ by fitting Weibull distribution to the measured tree heights
    2. Using the known $\boldsymbol{\xi}$ and stand density λ, fit the density function $f(z|\boldsymbol{\theta}, \boldsymbol{\xi}, \lambda)$ to the z-values to estimate the parameter $\boldsymbol{\theta} = (w, l, s)'$ for each plot.
    3. Model the plot-specific estimates of w, l, and s on mean of ALS observations $\bar{z}$
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   3. Model the plot-specific estimates of w, l, and s on mean of ALS observations $\bar{z}$
2. Prediction stage using evaluation plots
   1. Predict $\boldsymbol{\theta} = (w, l, s)'$ for the evaluation plots
   2. Using the predicted $\boldsymbol{\theta}$ and stand density λ, fit the density function $f(z|\boldsymbol{\theta}, \boldsymbol{\xi}, \lambda)$ to the z-values to estimate the distribution of tree heights (i.e parameter $\boldsymbol{\xi} = (\alpha, \beta)$) for each plot.
   3. Compute interesting stand characteristics, such as mean or dominant height and compare to the true known values.

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- In an alternative pairwise fitting approach, steps 1.3 and 2.1 were omitted. Instead, the estimates $\boldsymbol{\theta} = (w, l, s)'$ of the corresponding pair of the training dataset were used.

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   1. Predict $\boldsymbol{\theta} = (w, l, s)'$ for the evaluation plots
   2. Using the predicted $\boldsymbol{\theta}$ and stand density λ, fit the density function $f(z|\boldsymbol{\theta}, \boldsymbol{\xi}, \lambda)$ to the z-values to estimate the distribution of tree heights (i.e parameter $\boldsymbol{\xi} = (\alpha, \beta)$) for each plot.
   3. Compute interesting stand characteristics, such as mean or dominant height and compare to the true known values.

- In an alternative pairwise fitting approach, steps 1.3 and 2.1 were omitted. Instead, the estimates $\boldsymbol{\theta} = (w, l, s)'$ of the corresponding pair of the training dataset were used.
- If maximum likelihood is used in fitting, then asymptotic standard errros of estimates can be computed, too.

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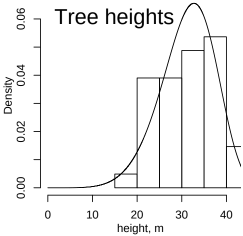
Example fit

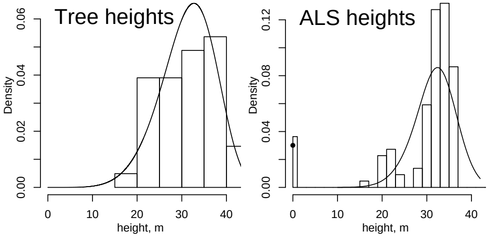
Training stage with teaching plot 11



Prediction stage with evaluation plot 11

Example fit

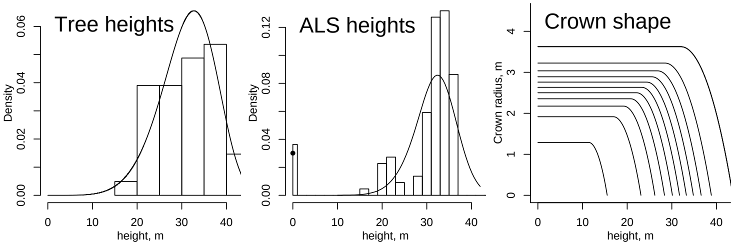
Training stage with teaching plot 11



Prediction stage with evaluation plot 11

Example fit

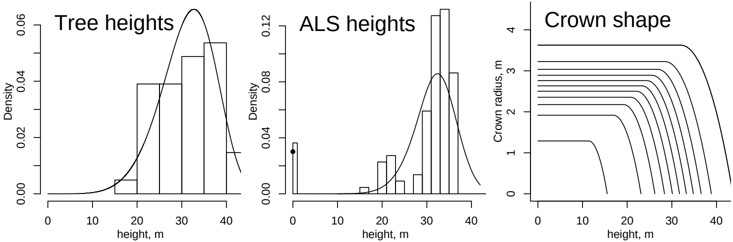
Training stage with teaching plot 11



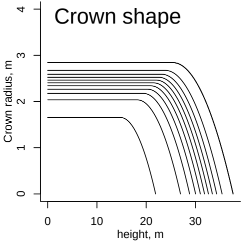
Prediction stage with evaluation plot 11

Example fit

Training stage with teaching plot 11

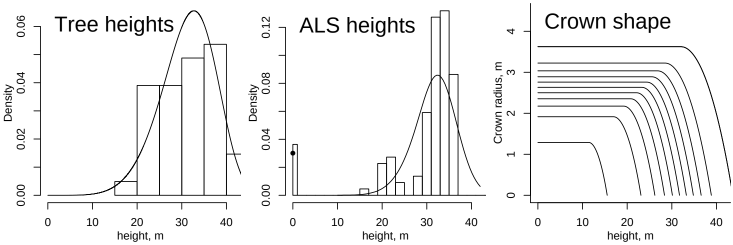


Prediction stage with evaluation plot 11

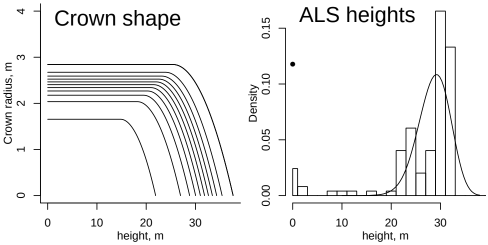


Example fit

Training stage with teaching plot 11

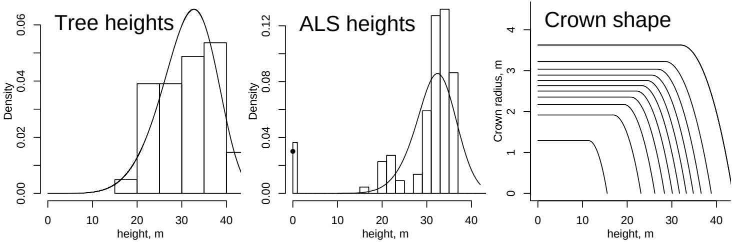


Prediction stage with evaluation plot 11

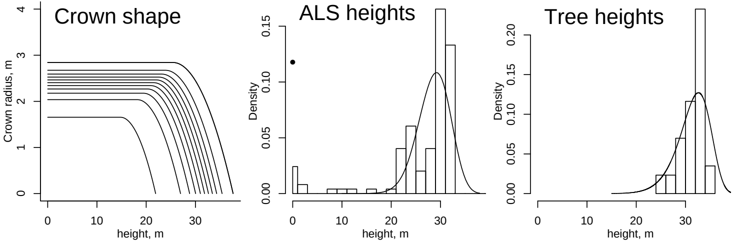


Example fit

Training stage with teaching plot 11



Prediction stage with evaluation plot 11



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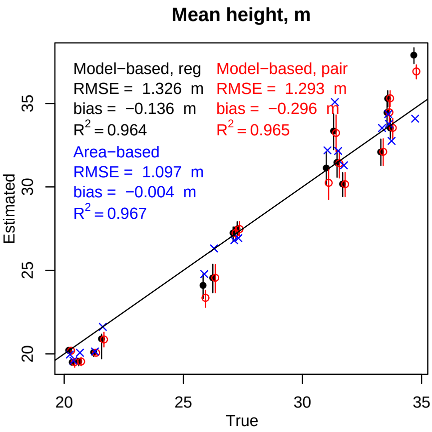
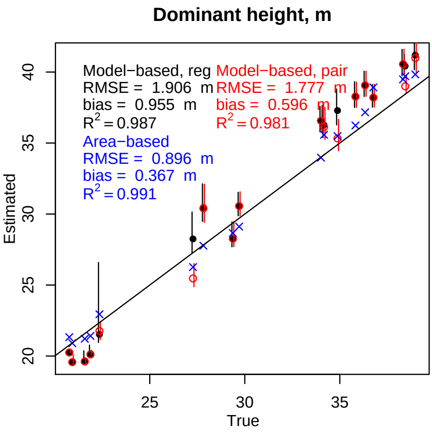
Results


Mean height, m
Model−based, reg
RMSE = 1.326 m
bias = −0.136 m
R2 = 0.964
Model−based, pair
RMSE = 1.293 m
bias = −0.296 m
R2 = 0.965
Area−based
RMSE = 1.097 m
bias = −0.004 m
R2 = 0.967
Estimated
True
20
25
30
35


Dominant height, m
Model−based, reg
RMSE = 1.906 m
bias = 0.955 m
R2 = 0.987
Model−based, pair
RMSE = 1.777 m
bias = 0.596 m
R2 = 0.981
Area−based
RMSE = 0.896 m
bias = 0.367 m
R2 = 0.991
Estimated
True
20
25
30
35
40

Discussion

- The developed model could provide a theoretical basis for the widely used area-based approach. This study reported the first empirical test of the approach.

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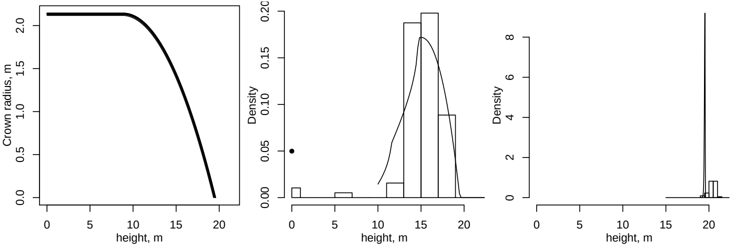

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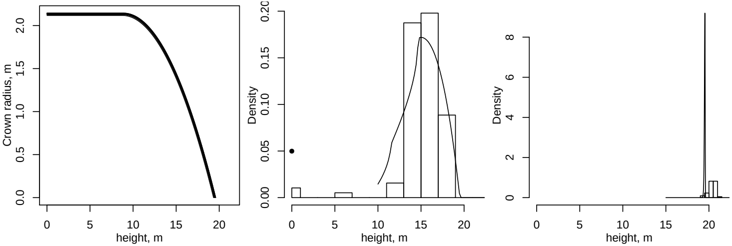
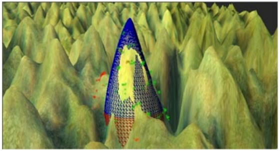


- Currently, heavy computations make estimation and model development slow. Efforts are underway to approximate the likelihood with less intensive functions. R and Matlab have been used for estimation.

Publications

- Mehtätalo, L. and Nyblom, J. 2009. Estimating forest attributes using observations of canopy height: A model-based approach. For. Sci. 55(5): 411-422.
- Mehtätalo, L. 2006. Eliminating the effect of overlapping crowns from aerial inventory estimates. Canadian Journal of Forest Research 36(7): 1649-1660.
- Mehtätalo, L. and Nyblom, J. A model-based approach for ALS inventory: Application to square grid spatial pattern. Revised MS.

Thank you for your interest



Silvilaser 2010
The 10th International Conference on LiDAR Applications for Assessing Forest Ecosystems
September 14th - 17th, 2010
Freiburg, Germany

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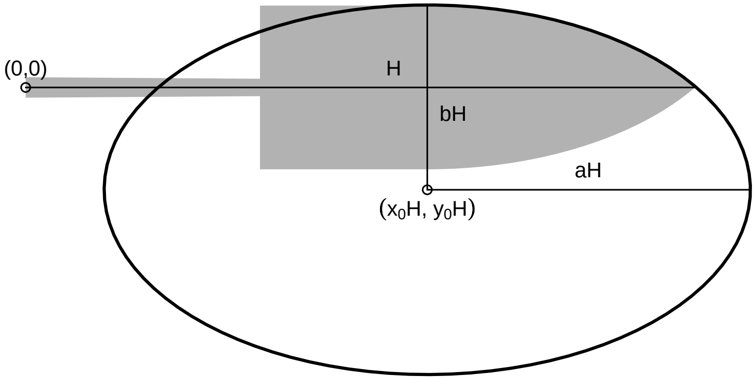
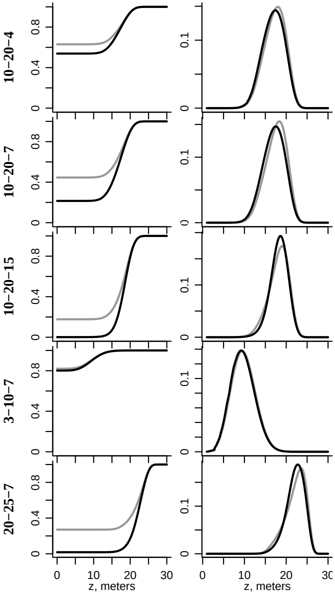
The applied model for crown shape



The effect of spatial pattern on the distribution



- The same values for stand density and Weibull parameters were used using
  - Square grid pattern (black), and
  - Random spatial pattern (gray)
- The graphs on the left show the c.d.f.'s of all observations
- The graphs on the right show the p.d.f.'s of canopy hits
- The values on the left show
  - shape (α) and
  - scale (β) parameters of the Weibull parameters, as well as
  - the stand density (λ, 100 trees per ha).
- The crown shape was ellipsoid with half axes $0.1H$ and $0.4H$.

An example with a Norway spruce plot