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Non-parametric prediction and mapping of standing timber volume and biomass in a temperate forest

Workshop IBS-Dre AGs
Bayes Methodik, Räumliche Statistik,
Ökologie und Umwelt
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Overview

- Goal:
  - Spatial predictions of Forest Variables, standing timber volume and biomass by non-parametric regression models
  - Testing of various distance measures
  - Variable selection
- Data:
  - Forest Inventory data (design attributes)
  - Remote sensing data (predictor variables)
- Methods: Non-parametric regression models
- Results:
  - Performance (Bias, RMSE)
  - Variable Selection

Data
Forest Inventory

- Data from a forest inventory were collected on permanent circular sample plots in summer 2006
  - 100×200 m sample grid
  - The tree timber volume was calculated using the taper functions of Kublin (2003)
  - Tree biomass with Zell's (2008) parameters for the allometric equation

$$B = \beta_0 d^{\beta_1} h^{\beta_2} + \epsilon$$

d: diameter in breast height

h: tree height

$\beta_0, \beta_1, \beta_2$: tree specific function parameters

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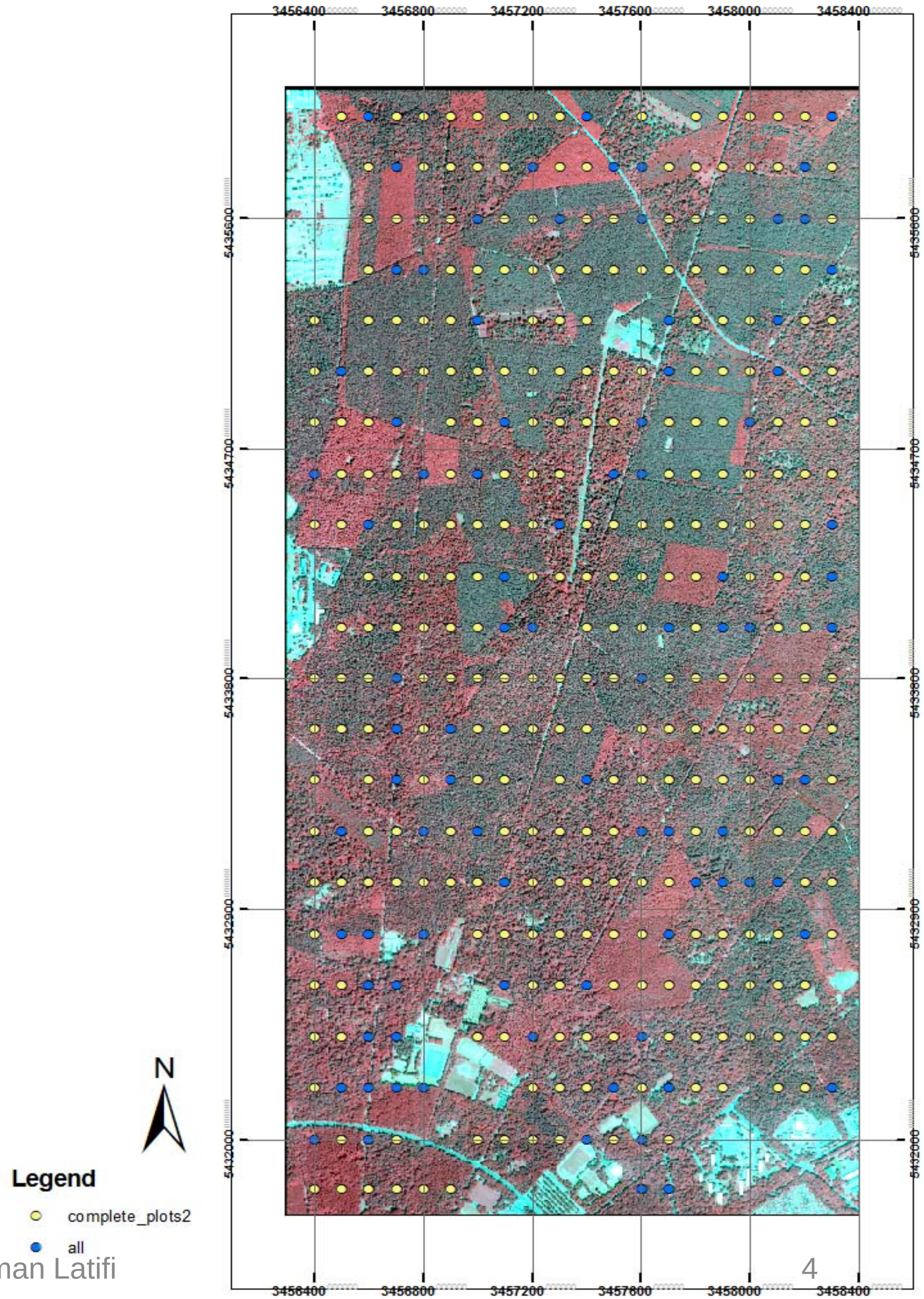
Data
Forest Inventory

- ➢Original 386 forest inventory sample plots
- ➢ 297 complete reference sample plots were used
- ➢ means from the two data sets were not significantly different (t-test)
- ➢ prediction at plot-scale



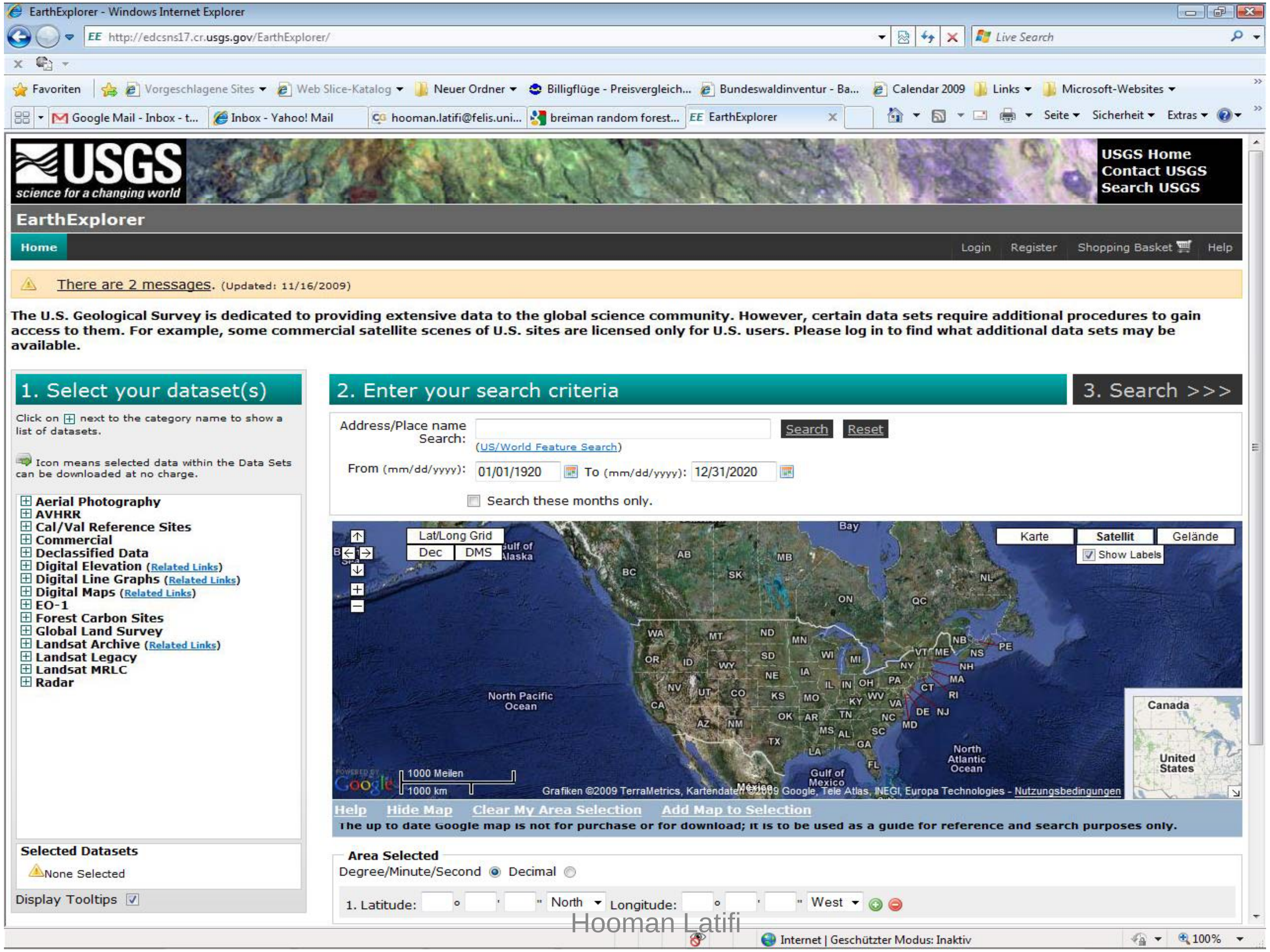
Data
Remote Sensing

- *The multispectral data*
  - Useful for the delineation of vegetation covers

- *The active remote sensing data (e.g. LiDAR altimetry)*
  - For characterization of highly variable forest canopy structures

(Koukoulas & Blackburg, 2005,IEEE Trans. Geo. Rem. Sens; Hudak et al., 2008,RSE).

Data
Remote Sensing



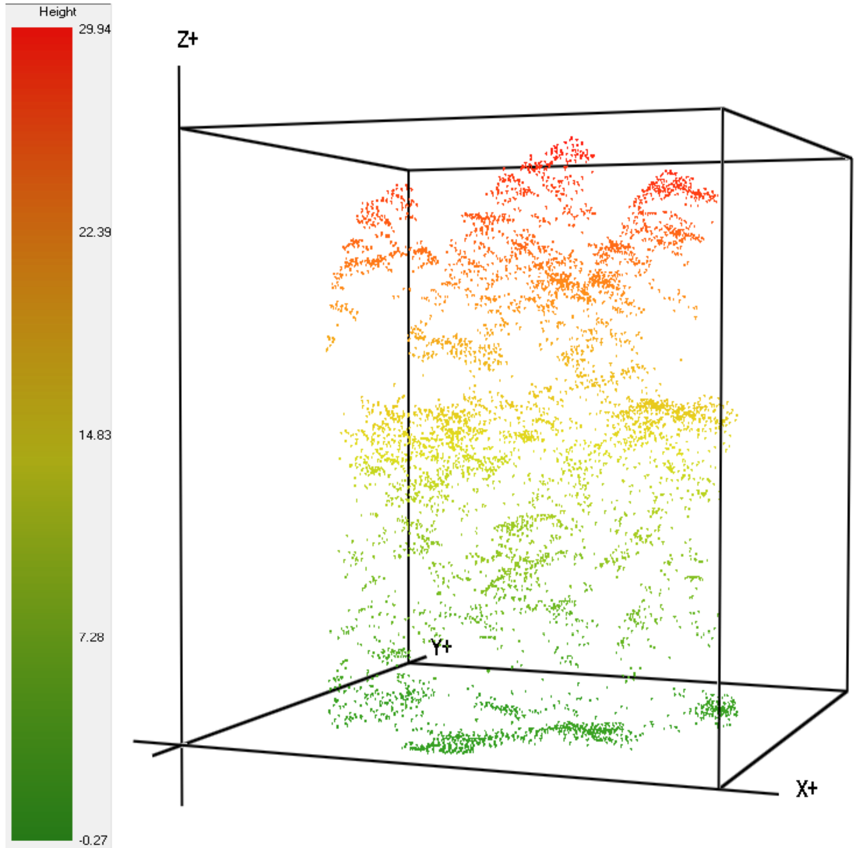
Data
Remote Sensing

- Optical data
  - CIR orthoimages
  - Thematic Mapper imagery

- small footprint LiDAR data
  (first-and-last pulses)
  - Height
  - intensity

Data
Remote sensing data
LiDAR (light detection and range)

Visualized first-pulse LiDAR point cloud at a sample plot level



Methods
Non-parametric regression

the non-parametric k-nearest neighbor estimator

$$\hat{y}_k(x) = \frac{1}{n}\sum_{i=1}^{n}\omega_{ki}(x)y_i$$ with weights $$\omega_{ki}(x) = \begin{cases} n/k & \text{if } i \in J_x, \\ 0 & \text{otherwise.} \end{cases}$$

denoted as Nadaraya-Watson-estimator:

$$\hat{y}_k(x) = \frac{\sum_{i=1}^{n} K_{d^{(k)}(x)}(d_i)y_i}{\sum_{i=1}^{n} K_{d^{(k)}(x)}(d_i)}$$

with uniform kernel estimator of variable bandwidth

$$K_{d^{(k)}}(u) = 1/2I\left(|u| \leq d^{(k)}\right)$$

and distance between the vector of *p* variables for the target unit and its *k*-th neighbor $d^{(k)} = d^{(k)}(x)$

Methods
Non-parametric regression

distance measure $$d_i = \sqrt{(x - x_i)^T \Omega (x - x_i)}$$

Euclidian distance $$\Omega = diag\{p\}$$

Mahalanobis distance $$\Omega = (Cov[X])^{-1}$$

Methods
Non-parametric regression

distance measure $$d_i = \sqrt{(x - x_i)^T \,\Omega\, (x - x_i)}$$

most similar neighbor
MSN distance

$$\underset{p \times p}{\Omega} = \underset{p \times s}{\Gamma} \quad \underset{s \times s}{\Lambda^2} \quad \underset{s \times p}{\Gamma^T}$$

canonical coefficients Γ

$$s = \min(p, t)$$

canonical correlation coefficients Λ

response variables $\underset{(n \times t)}{Y}$

regressor variables $\underset{(n \times p)}{X}$

$$u_1 = X\alpha_1 \;, \quad v_1 = Y\beta_1$$
$$\vdots \quad , \quad \vdots$$
$$u_s = X\alpha_s \;, \quad v_s = Y\beta_s$$

Methods
Non-parametric regression trees, Random Forests

❖ In **Random Forests** (Breiman, 2001), the NNs are obtained by numerous solutions (forests) of classification trees.

❖The distance is calculated as *one minus the proportion of terminal nodes from all regression trees* where the target observation is in the same terminal node as the specific reference unit

Methods
Variable selection

-The genetic algorithm (GA) applied for variable reduction is a search method that is based on the principle of evolution by natural selection.

[image removed]

(Trevino & Falciani, 2006)

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Results
I- variable selection

- GA search:
  - 11 variables for timber volume (7 from LiDAR
  - 21 predictors for biomass (15 from LiDAR)
    - mostly from FR height data

- Stepwise selection:
  - 5 predictors for timber volume (4 from LiDAR)
  - 4 predictors for biomass (3 from LiDAR)
    - All from FR height data

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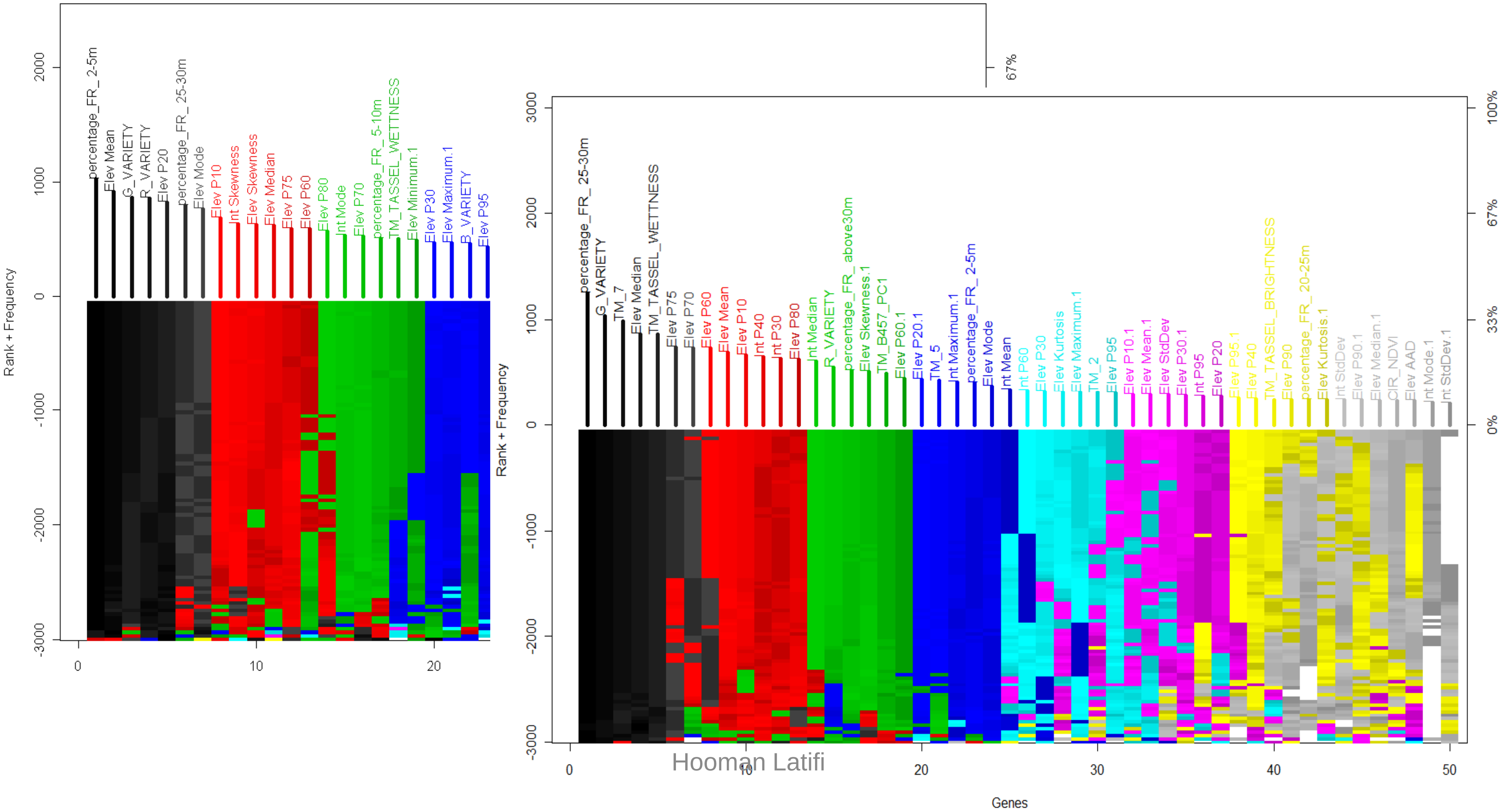
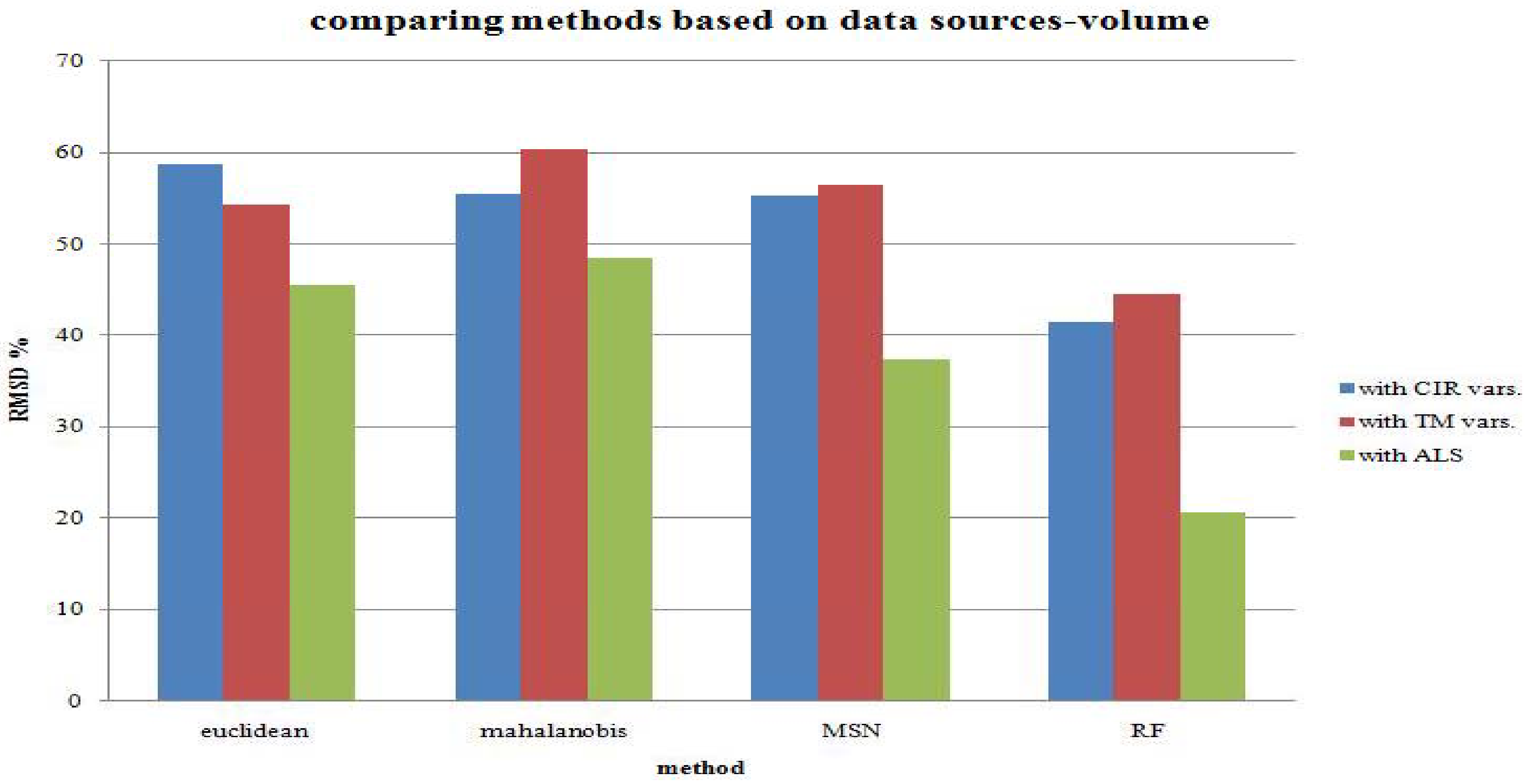
Results
I- variable selection

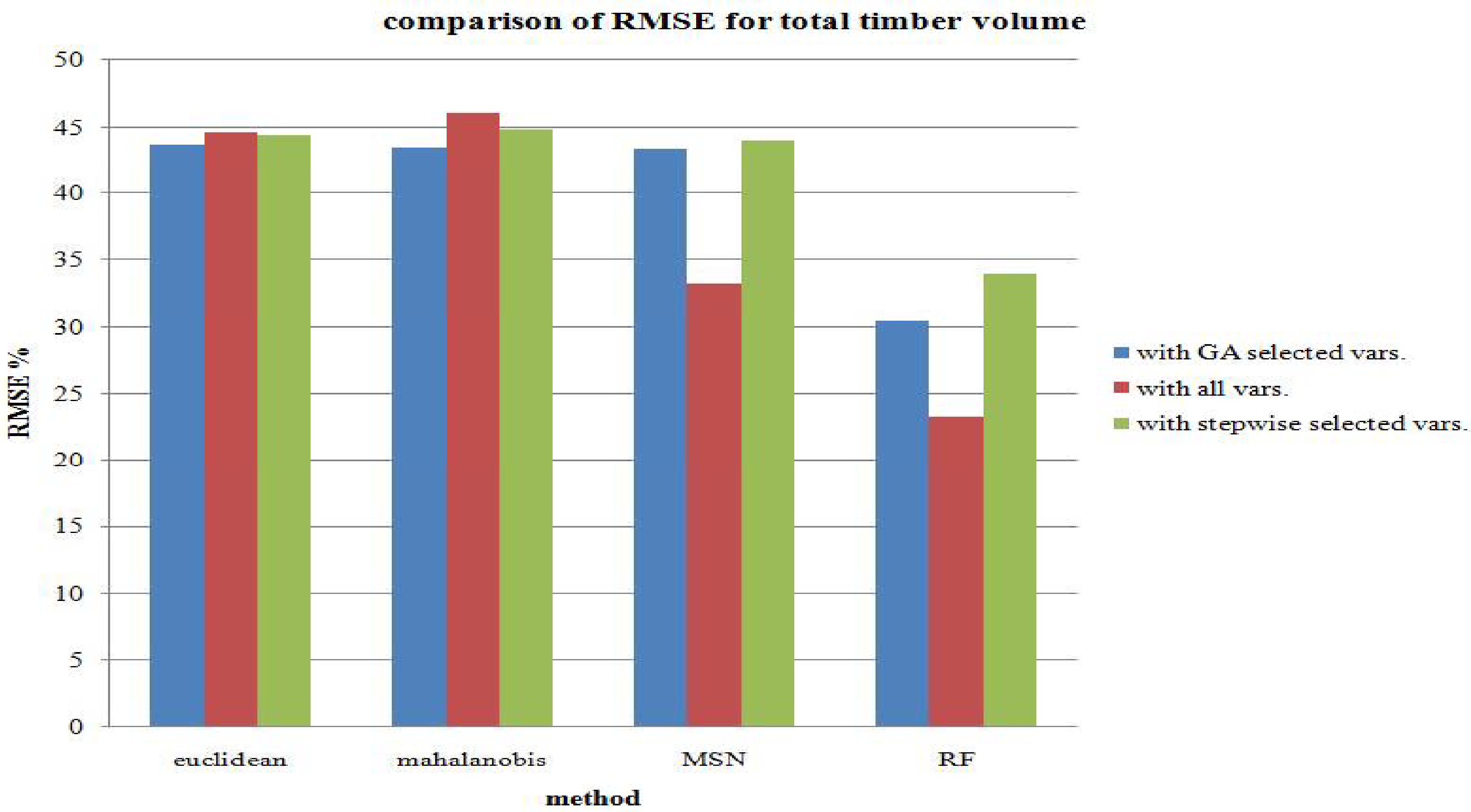


Hooman Latifi

Results
II- NN predictions



Results
II- NN predictions



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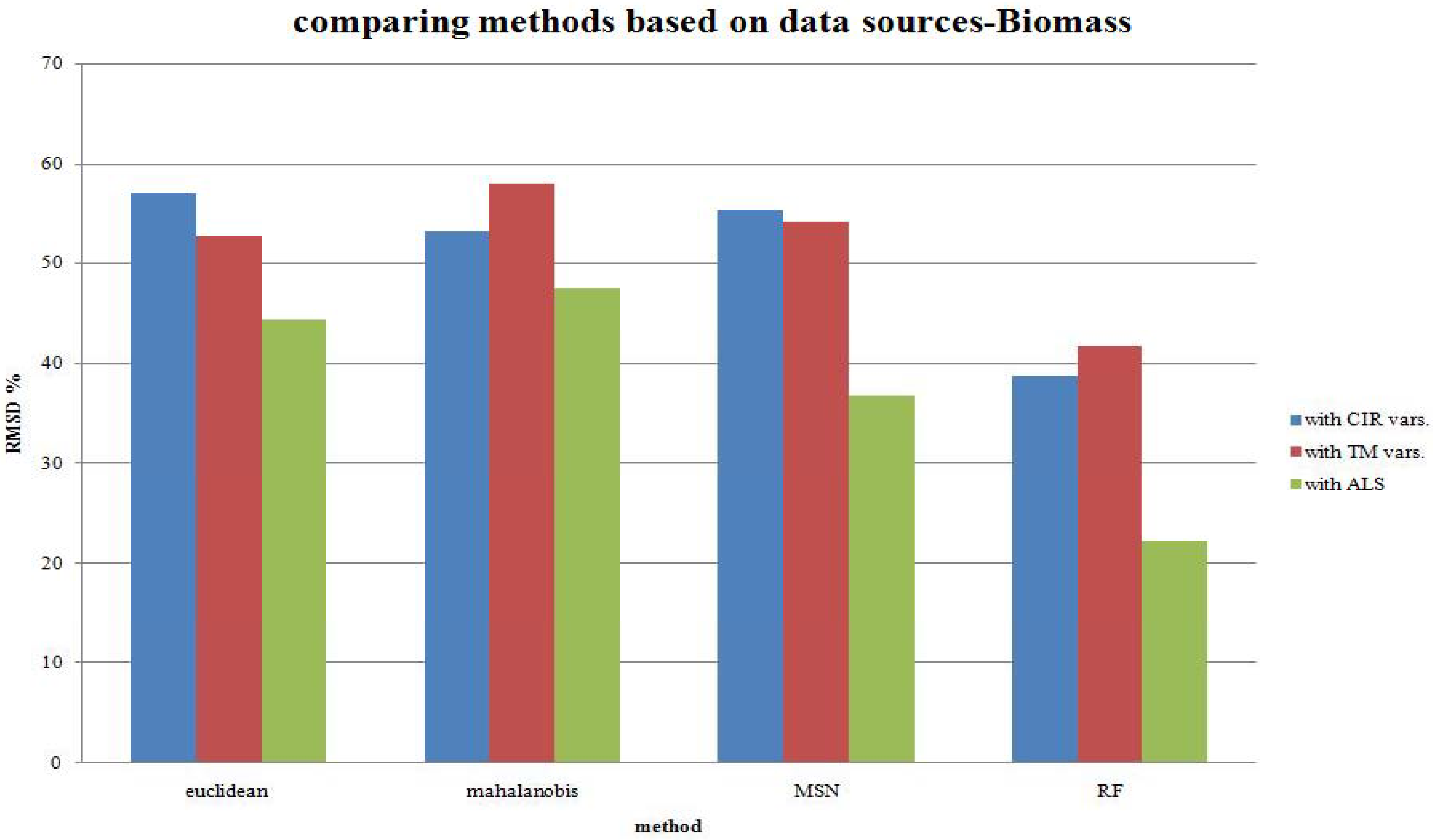
Results
II- NN predictions



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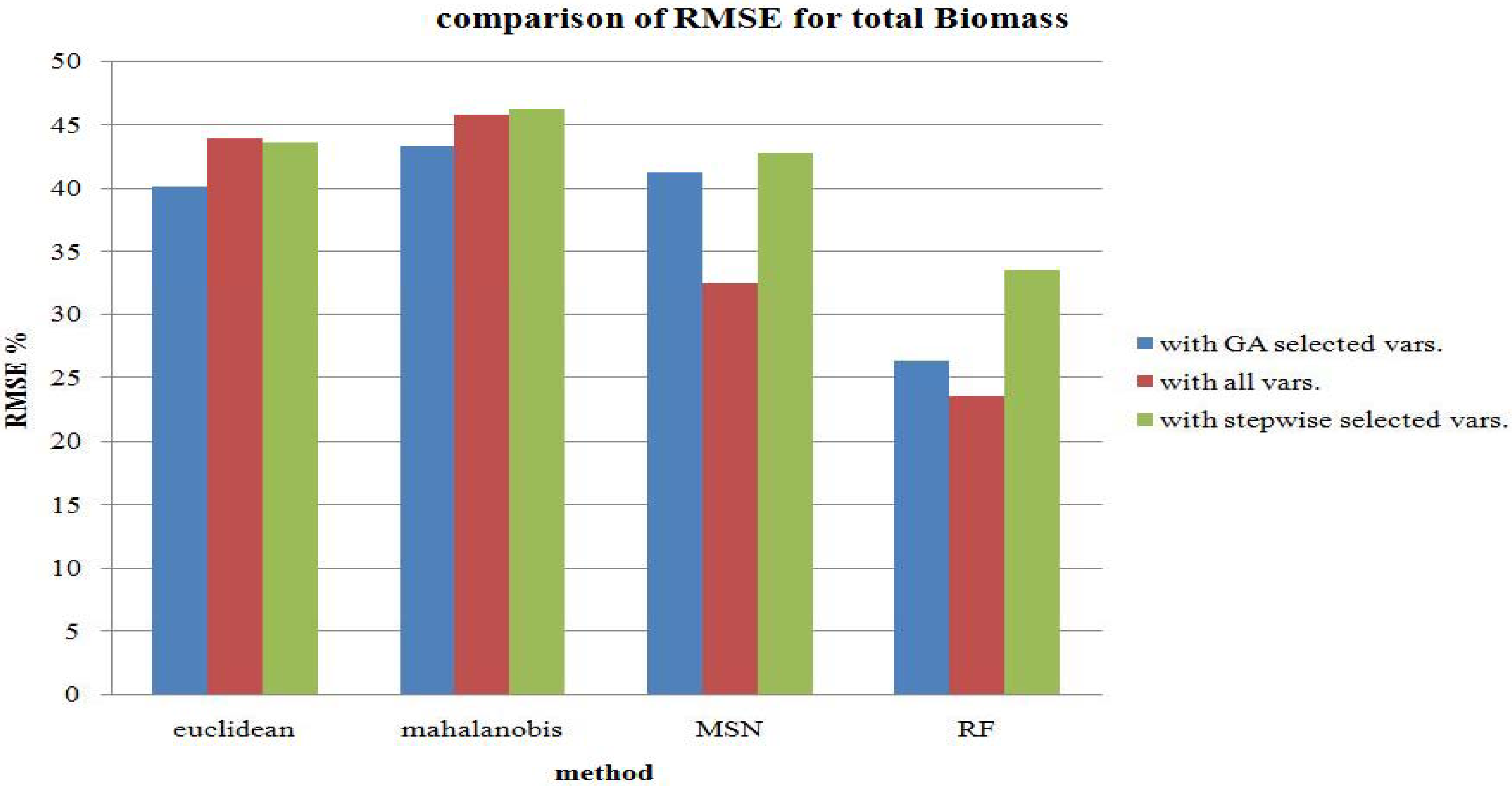
Results
II- NN predictions

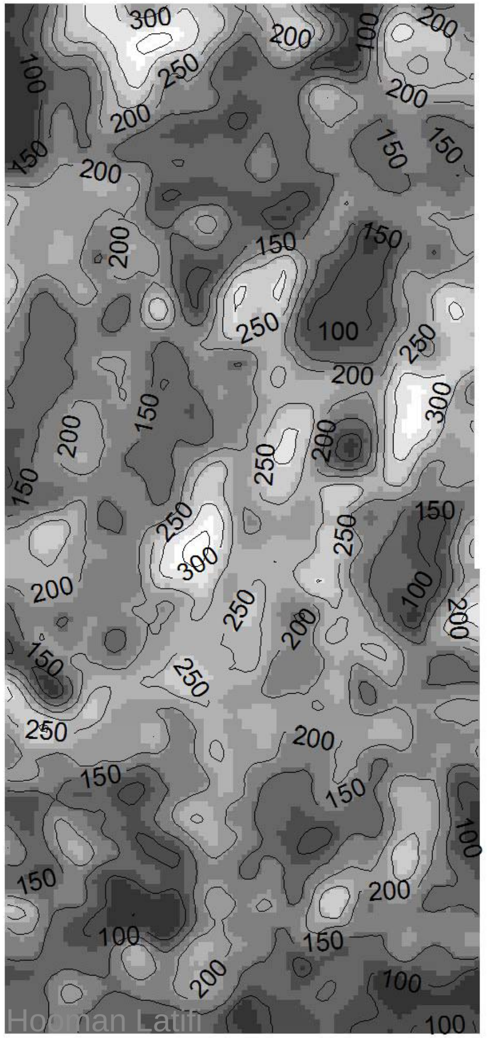


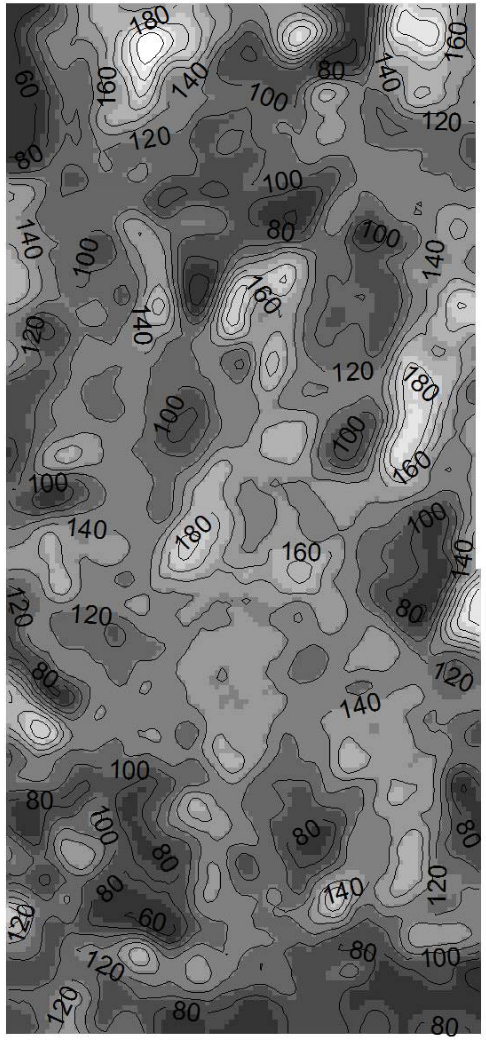
Results
III- spatial predictions over the whole area (gridding)

Predictions of timber volume (left) and total biomass (right) by

-RF method

- smoothed by An Epanechnikov-kernel with 100 m bandwidth





Discussion and Conclusion

- Variable selection based on GA search was superior to stepwise selections

- GA-selected variables (stabilized by a *high solution rate*) led to higher precision when applying Euclidean and Mahalanobis distances.

- MSN and Random Forests worked better with the full regressor variable set

- LiDAR-data were of major relevance

Discussion and Conclusion

- All the applied methods yielded approximately unbiased predictions (Bias% <2%)

- Some of the forest stands have a dense understory, mainly composed of deciduous species, which may be a potential source of error in height metrics estimation

- Further research:

  Could the height metrics extracted from rasterized LiDAR forms improve the results?!

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Thank you!

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