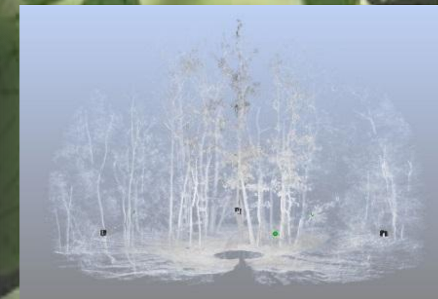
Estimation of Spatial Distribution of Leaf Area Density in Canopies from Terrestrial LiDAR Point Clouds

Maxime Soma, François Pimont, Sylvie Durrieu, Jean-Luc Dupuy





ESTIMATION OF SPATIAL DISTRIBUTION OF LEAF AREA DENSITY IN CANOPIES FROM TERRESTRIAL LiDAR POINT CLOUDS

SILVILASER, VIENNA, 28TH – 30TH SEPTEMBER 2021

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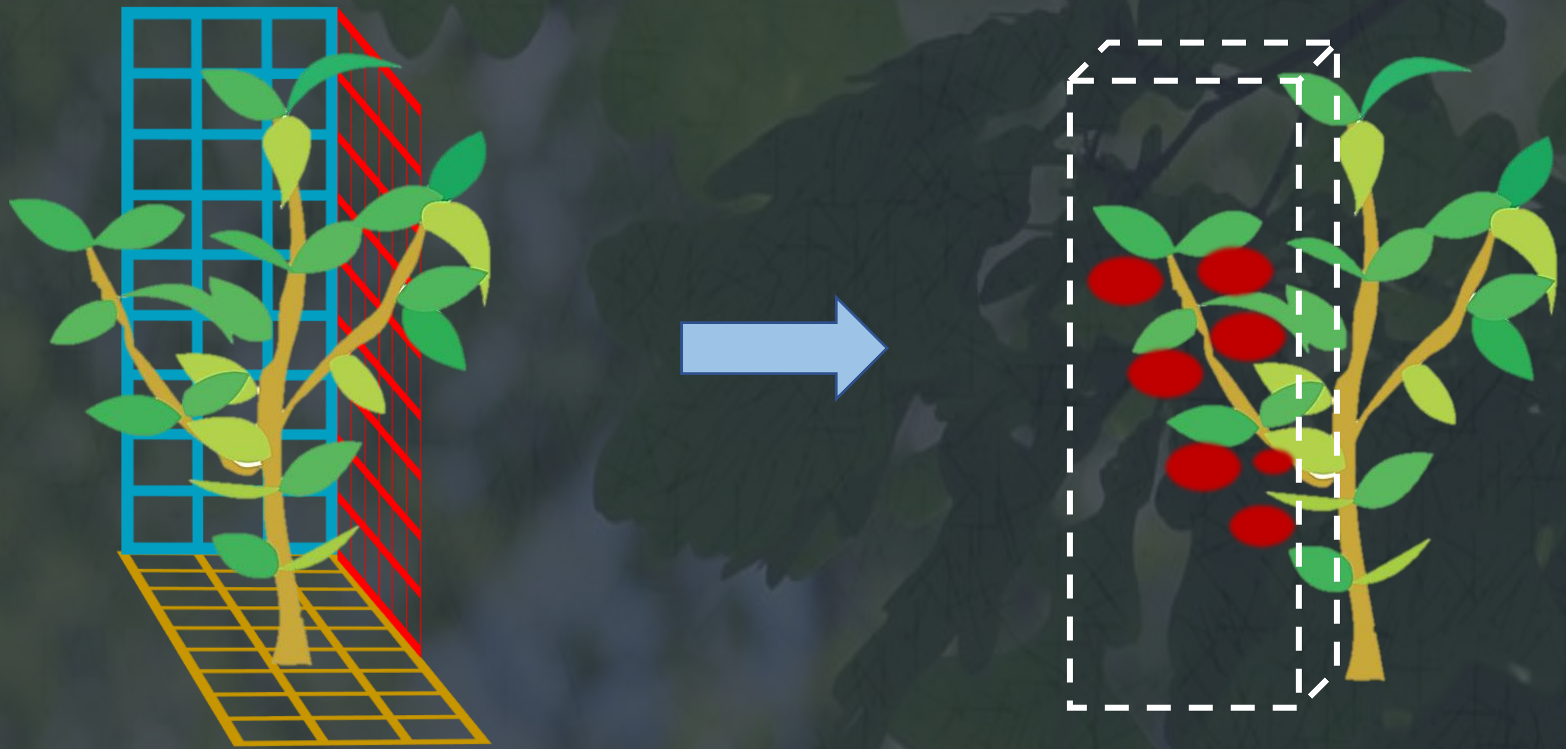
1. ÉCOLOGIE DES FORÊTS MÉDITERRANÉENNES (URFM) INRAe, AVIGNON
2. TERRITOIRES, ENVIRONNEMENT, TÉLÉDÉTECTION ET INFORMATION SPATIALE (TETIS), INRAe, MONTPELLIER

WHAT IS LEAF AREA DENSITY ?



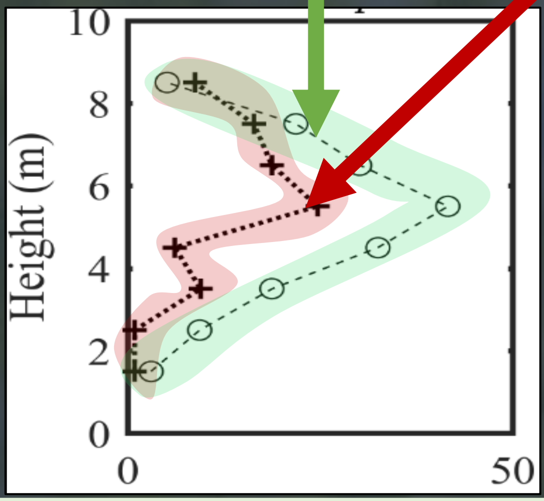
3D distribution of the one-sided leaves area ($m^2.m^{-3}$)

$$LAI(x,y) = \int_0^H LAD(x,y,z)dz$$

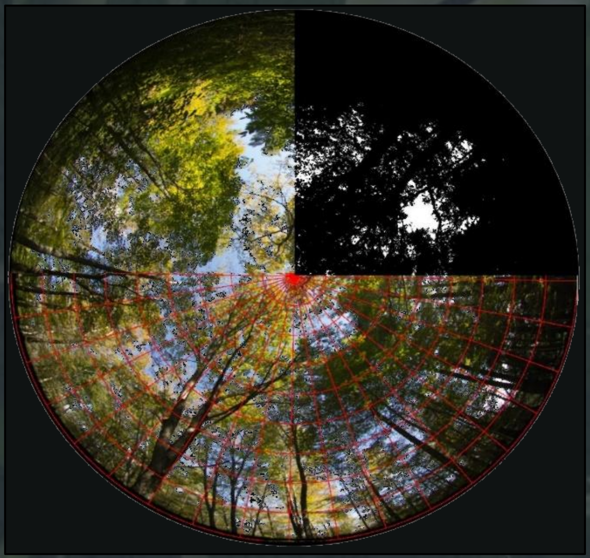
Leaf Area Index (LAI) ($m^2.m^{-2}$)

HOW TO MEASURE LEAF AREA ?

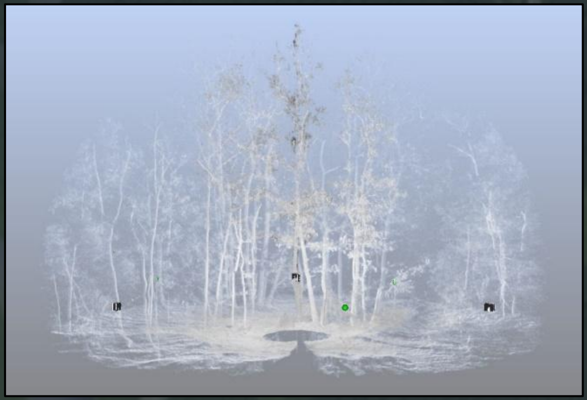
Destructively



Gap fraction theory (passive measurement - 2D)

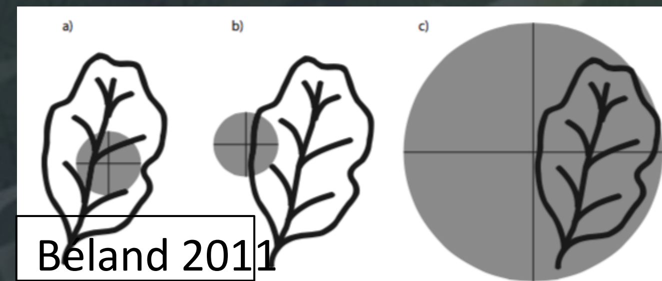


Full 3D description (active sensor) →Terrestrial LiDAR



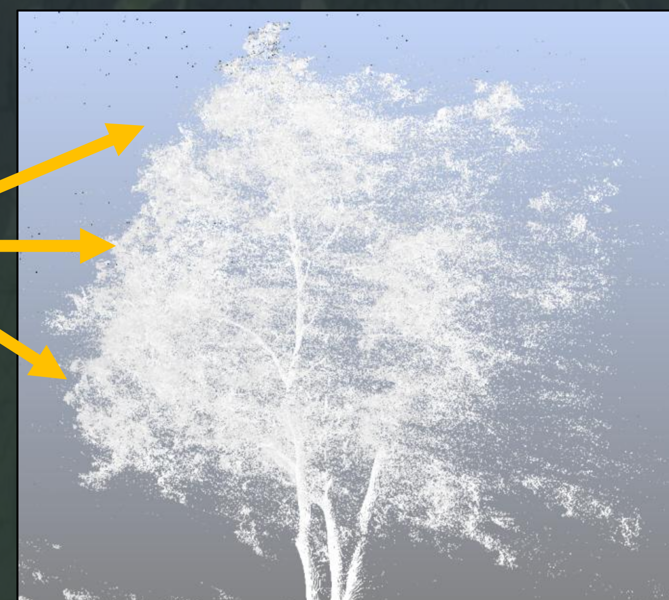
LIMITS OF TERRESTRIAL LiDAR DATA

LiDAR beams footprint is not infinetely thin and diverge with distance to targets



Heterogeneous sampling

Interactions with vegetation elements



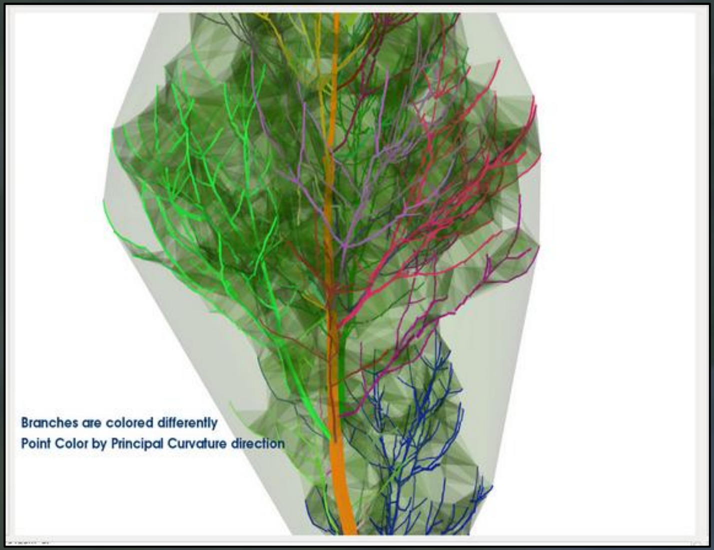
OBJECTIVE OF THE STUDY

How to relate a terrestrial LiDAR point cloud to Leaf Area Density with:

- **field vegetation elements (i.e. heterogenous)**
- **sampling limitations of instruments**
- **various scales of measures (branch, tree, stand)**

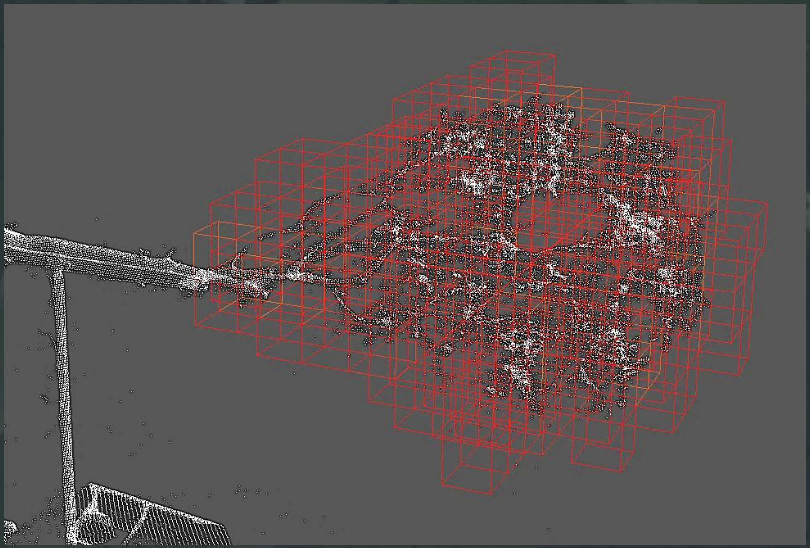
POINT CLOUDS ANALYSIS METHODS

Object-based / reconstruction



→ **Wood volume, branch levels etc.**

Statistics

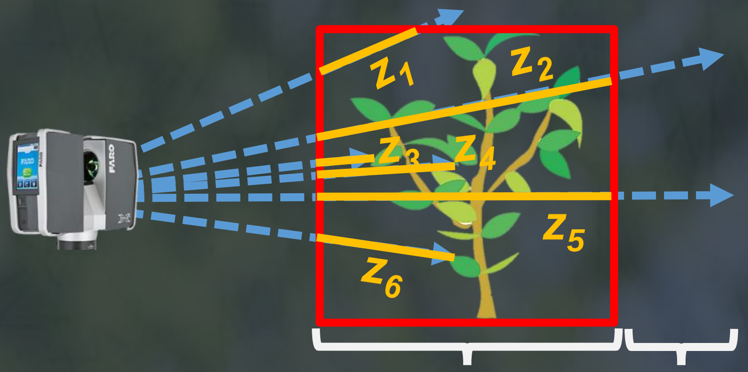


→ **Leaf area**

THEORETICAL RELATIONS BETWEEN POINTS AND LEAF AREA

Leaf fraction $LAD = F \frac{1}{G} \lambda$ Leaf projection factor

with λ the coefficient of attenuation



N = Ni + not intercepted

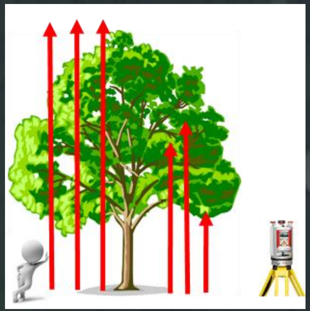
Beer-Lambert

$$Transmittance = e^{-\lambda\delta}$$

$$RDI = \frac{N_i}{N_i + N_g} = 1 - Transmittance$$

$$\hat{\lambda} = -\frac{ln(1 - RDI)}{\delta}$$

Contact frequency



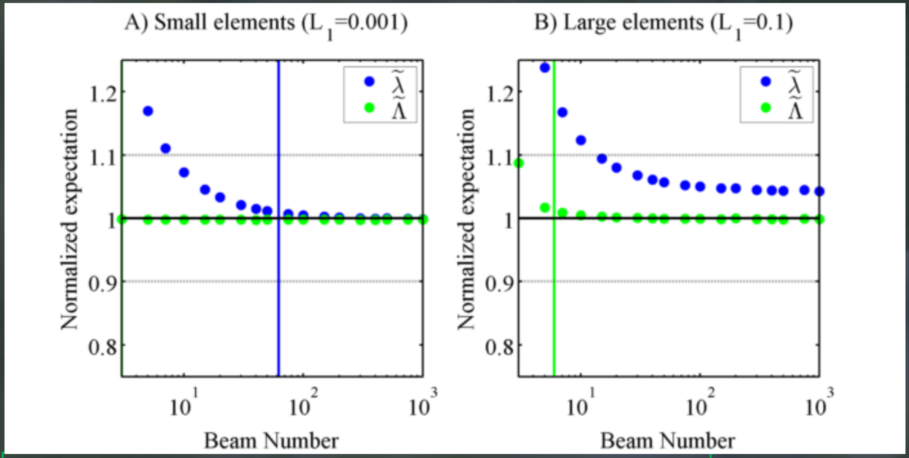
$$\tilde{\lambda} = \frac{RDI}{\bar{z}}$$

BUILDING UNBIASED ESTIMATORS USING NUMERICAL EXPERIMENT

Size of vegetation elements?

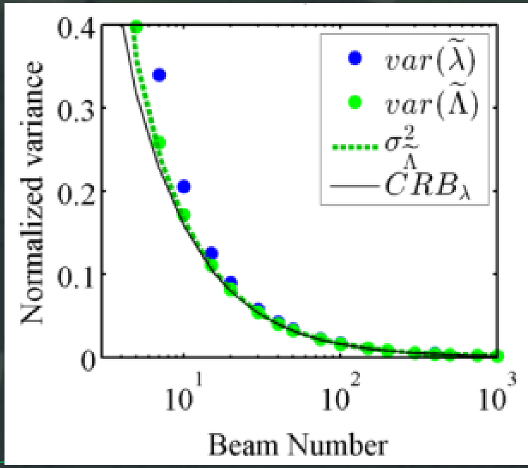
Low number of beams ?

Unequal beams path length ?



Validation of corrections

Bringing confidence intervals



CRB bound reached : there is no best unbiased estimator from this information

→ Selection of the corrected contact frequency estimator (Maximum Likelihood Estimator - MLE) for attenuation coefficient

$$\widetilde{LAD} = \frac{H}{G}\tilde{\Lambda} = \frac{H}{G\sum z_e}\left(\mathrm{Ni} - \frac{\sum_{hits} z_e}{\sum z_e}\right)$$

Pimont et al.

VALIDATION OF ESTIMATOR WITH ACTUAL VEGETATION AT LABORATORY

Indoor measurements at branch scale

Scans followed by destructive measurements of leaf areas

- Fully foliated
- Half-foliated
- Defoliated

at various distances:

2,5 m → 5 m → 10 m → 15 m → 20 m

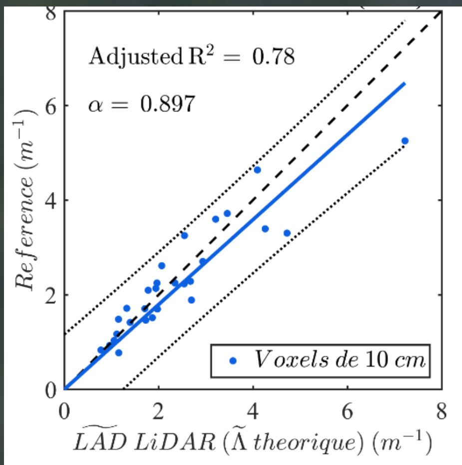
Quercus pubescens

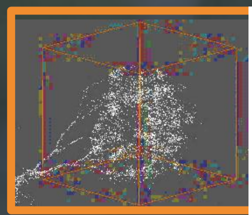
Quercus ilex

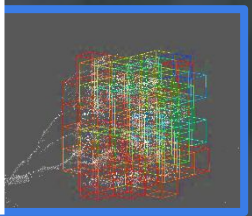
Pinus halepensis

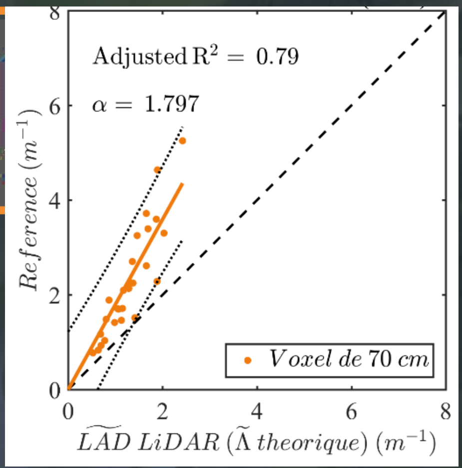
VALIDATION OF ESTIMATOR WITH ACTUAL VEGETATION AT LABORATORY

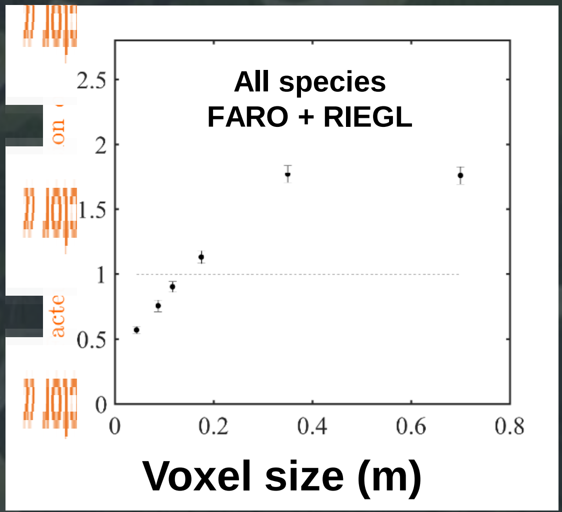
EFFECT OF VEGETATION HETEROGENEITY



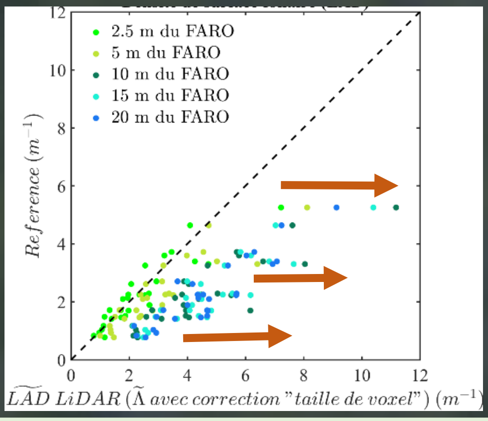


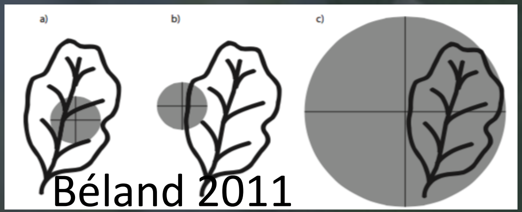


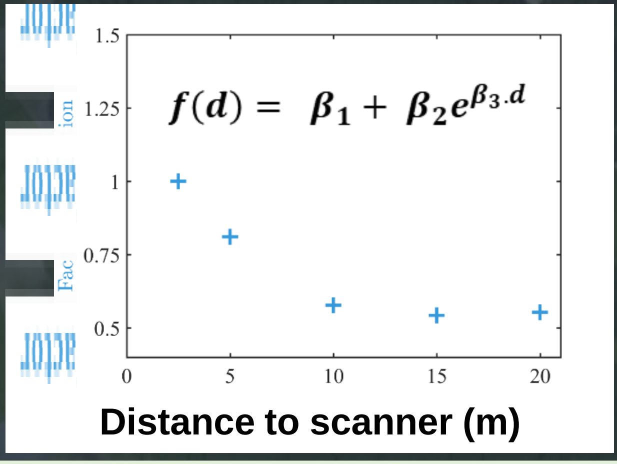




EFFECT OF DISTANCE TO FARO INSTRUMENT

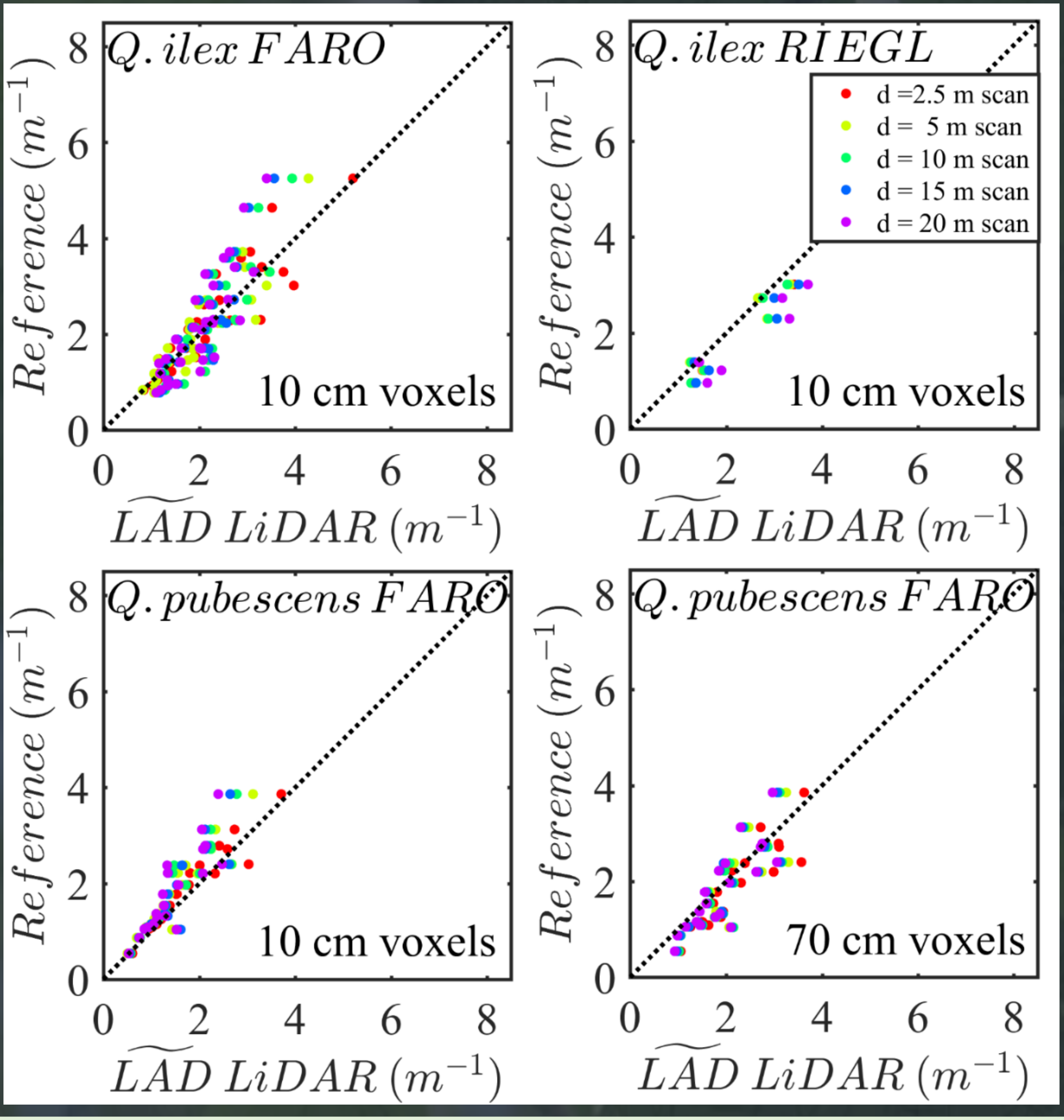






VALIDATION OF ESTIMATOR WITH ACTUAL VEGETATION AT LABORATORY

- unbiased
- 20% mean absolute error



Soma et al., 2018

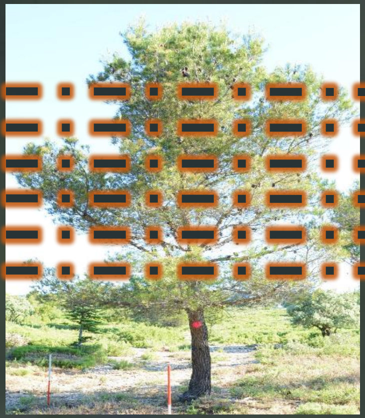
VALIDATION OF APPROACH AT TREE SCALE

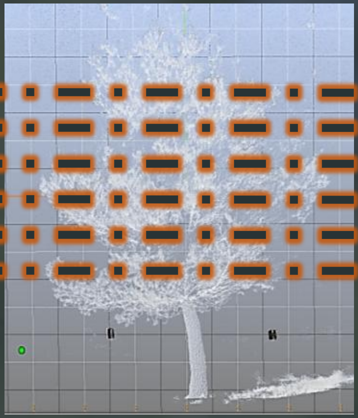
Degree of heterogeneity
LAD values

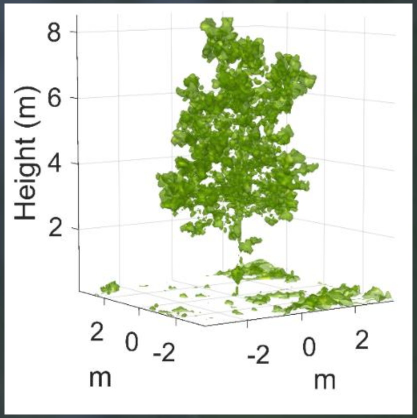
? ?

Variety of distances
Occlusion

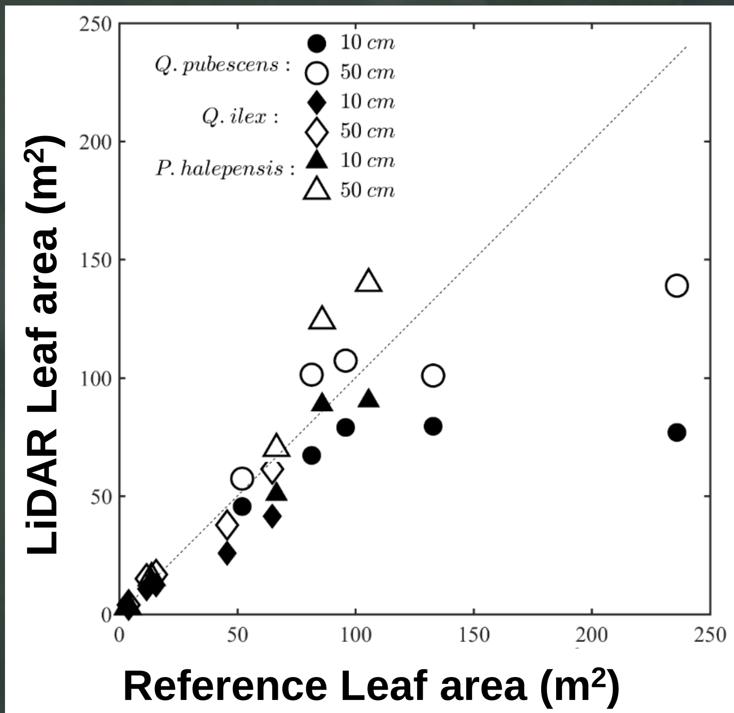
SCANS + DESTRUCTIVE VALIDATION ON 15 TREES

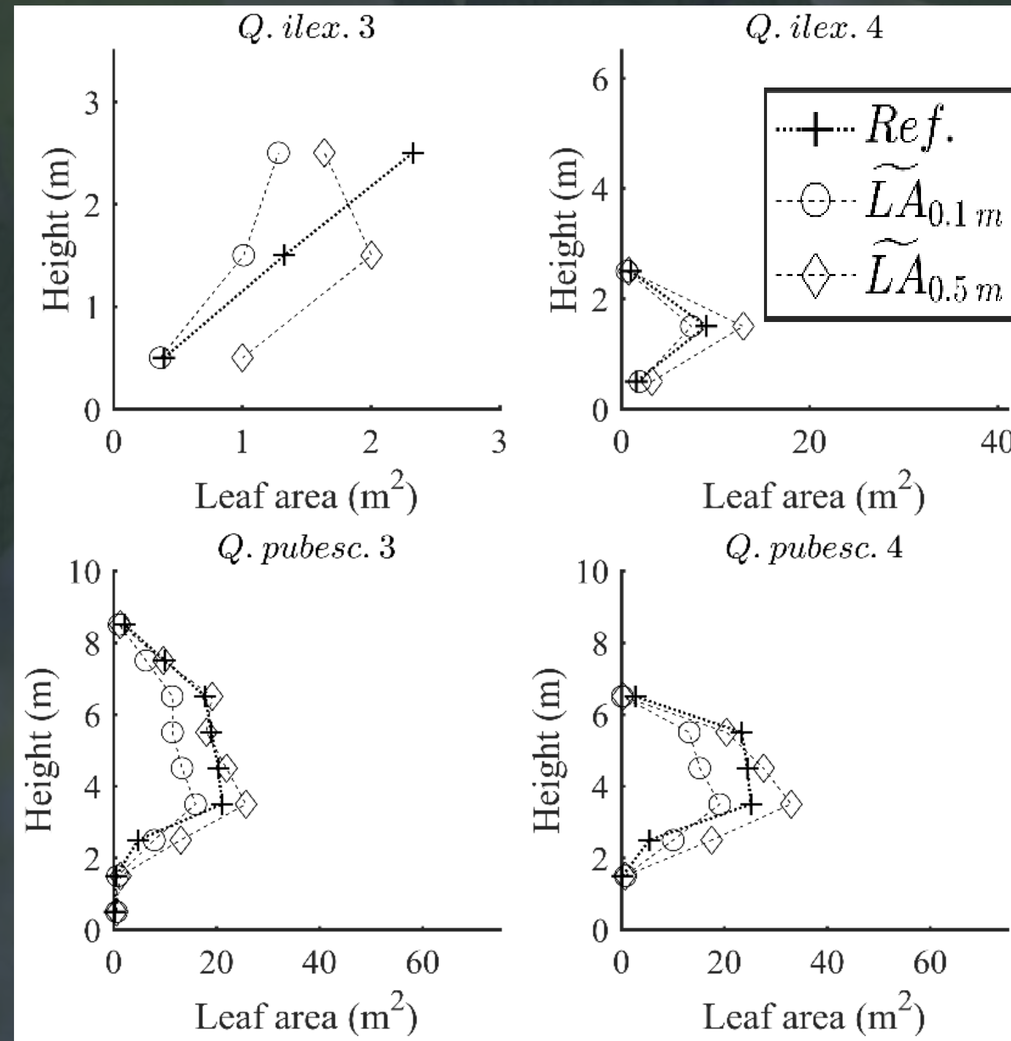






VALIDATION OF APPROACH AT TREE SCALE

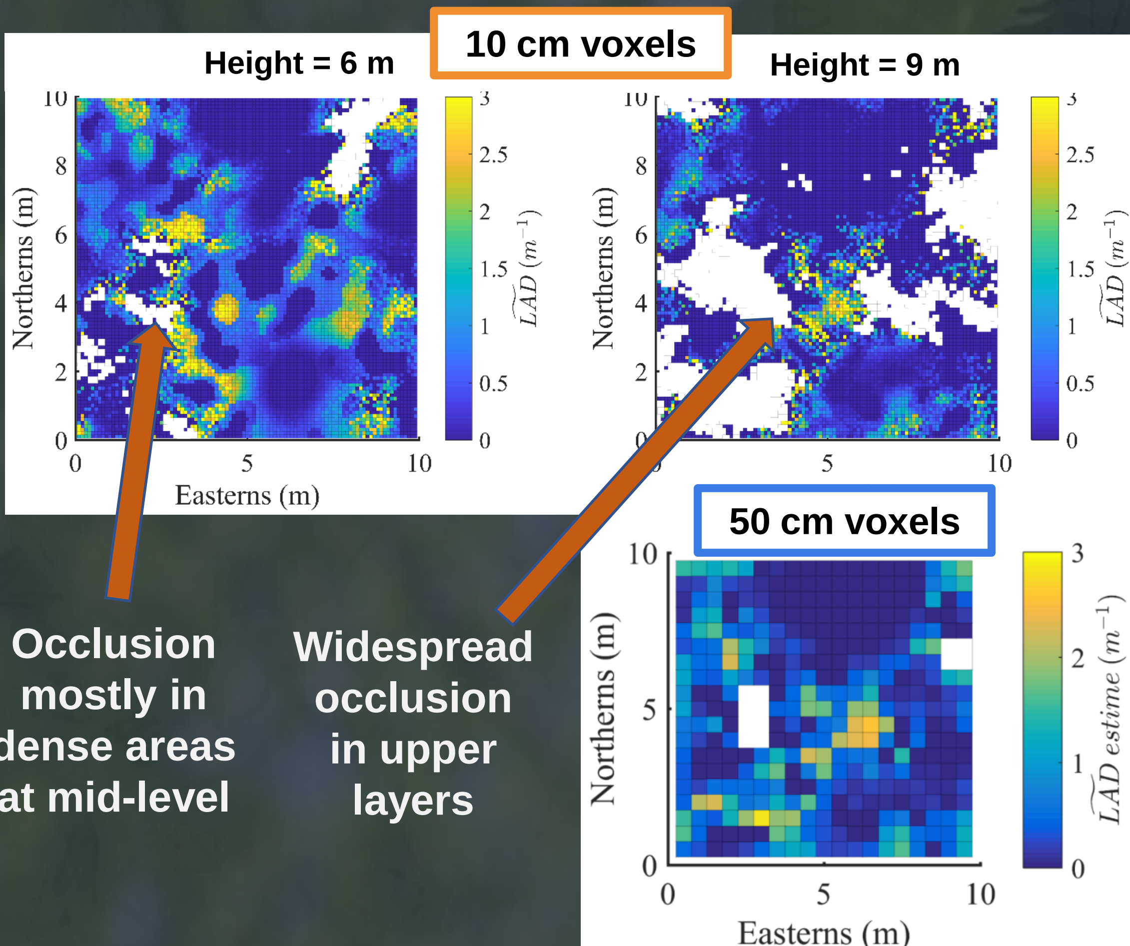




→ RMSE < 25% in most cases

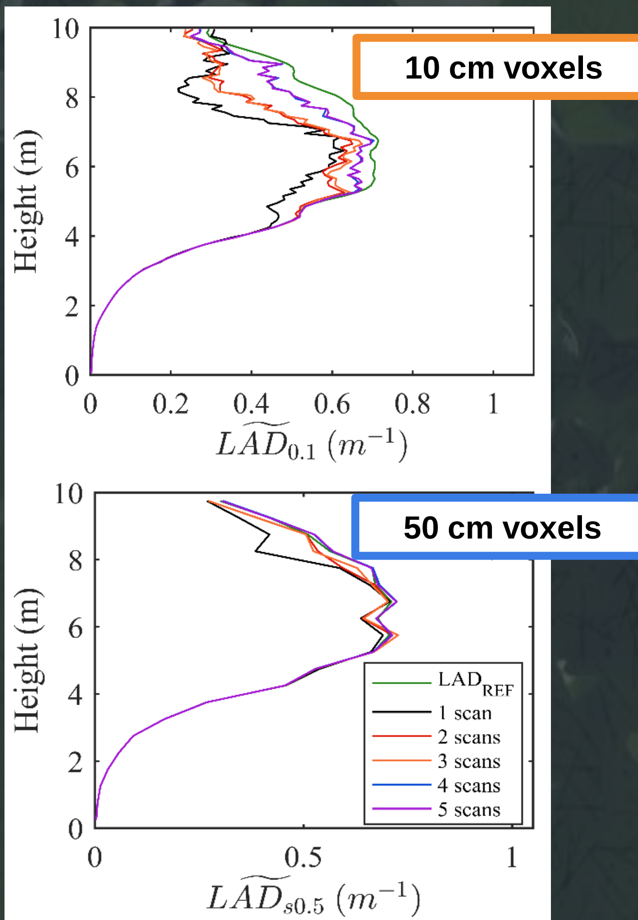
→ Larger errors with largest trees

INVESTIGATING INFLUENCE OF SAMPLING LIMITATIONS AT LARGER SCALE IN A VIRTUAL CANOPY



Occlusion mostly in dense areas at mid-level

Widespread occlusion in upper layers



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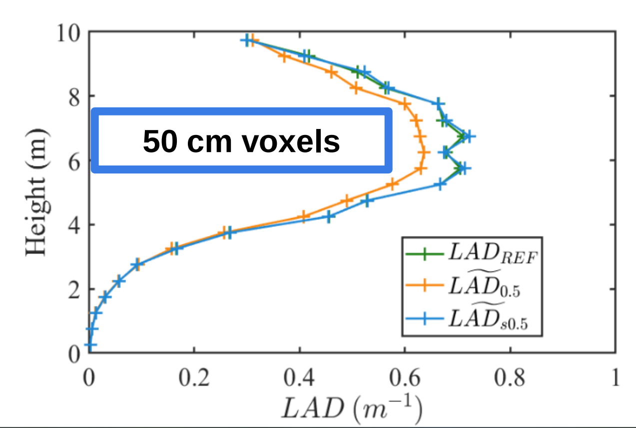
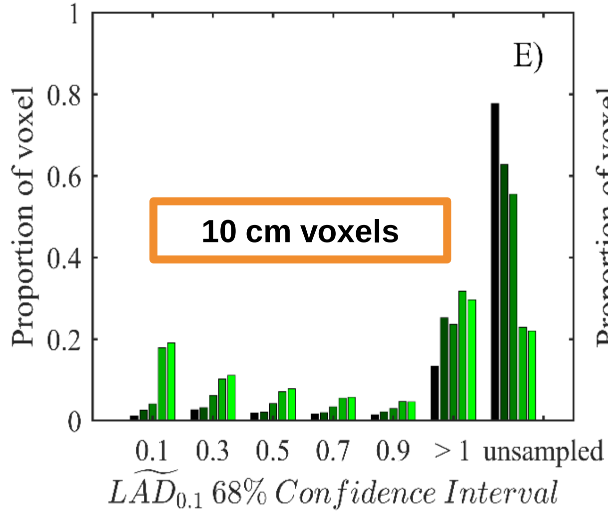
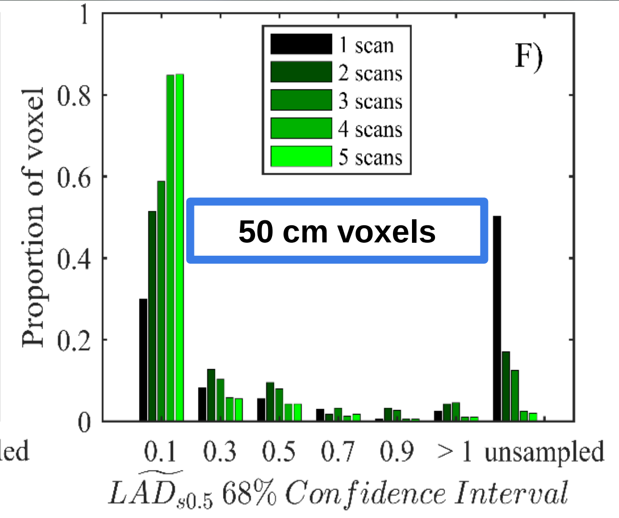


→ Correction for vegetation heterogeneity (i.e. voxel size) is necessary but spatially homogenous (calibration possible)

Soma et al., 2021



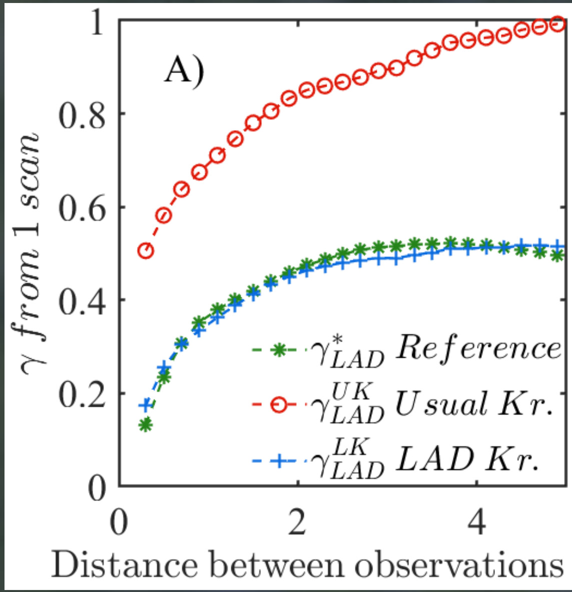


The main biais results from spatial correlation of occluded areas with dense LAD

Difficult to correct
→Best choice to limit occlusion and correct heterogeneity (0.5 voxels)

COMBINATION OF MLE ESTIMATOR AND VEGETATION STRUCTURE : A NEW KRIGING METHOD TO LIMIT BIAIS AND ERRORS IN LOW SAMPLING CONDITIONS

ENHANCING USUAL KRIGING WITH THE MLE ESTIMATOR



Usual estimator of variogram:

$$\sum_{\|x_k - x_l\| = h} \left(\widetilde{LAD}_k - \widetilde{LAD}_l\right)^2$$

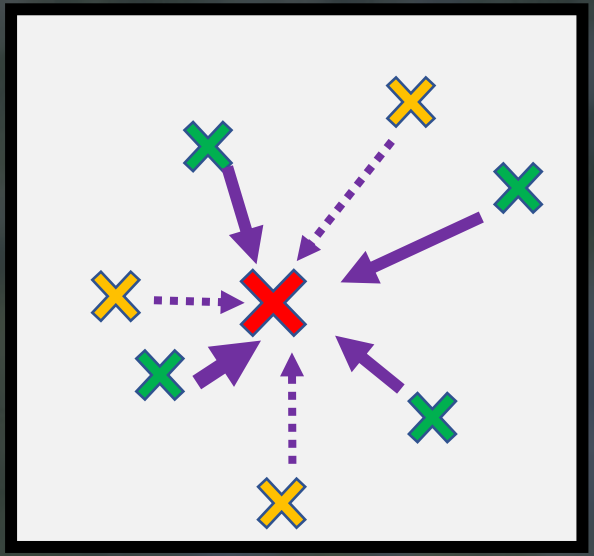
Estimator of variogram « LAD »:

$$\sum_{\|x_k - x_l\| = h} \left(\widetilde{LAD}_k - \widetilde{LAD}_l\right)^2 - \sigma_k^2 - \sigma_l^2$$

Level 1 : Correcting for noise through variances allows to retrieve the actual spatial correlation in vegetation

COMBINATION OF MLE ESTIMATOR AND VEGETATION STRUCTURE : A NEW KRIGING METHOD TO LIMIT BIAIS AND ERRORS IN LOW SAMPLING CONDITIONS

Level 2 : Integrating sampling criteria in kriging weights



Usual kriging:

$$LAD_x = \beta_1(d_{1,x})LAD_1 + \cdots + \beta_i(d_{i,x})LAD_i$$

Si $d_{1,x} \approx d_{i,x}$ alors, $\beta_1 = \beta_i$

« LAD » Kriging :

$$LAD_x = \beta_1(d_{1,x}, N_1)LAD_1 + \cdots + \beta_i(d_{i,x}, N_i)LAD_i$$

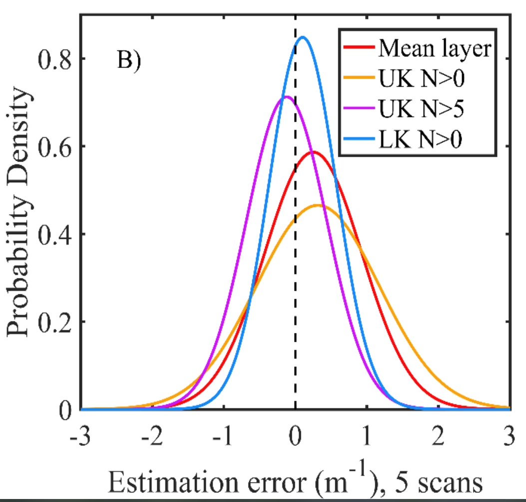
Si $d_{1,x} \approx d_{i,x}$ *et* $N_1 \ll N_i$,

alors, $\beta_1 \ll \beta_i$

N low *N* high

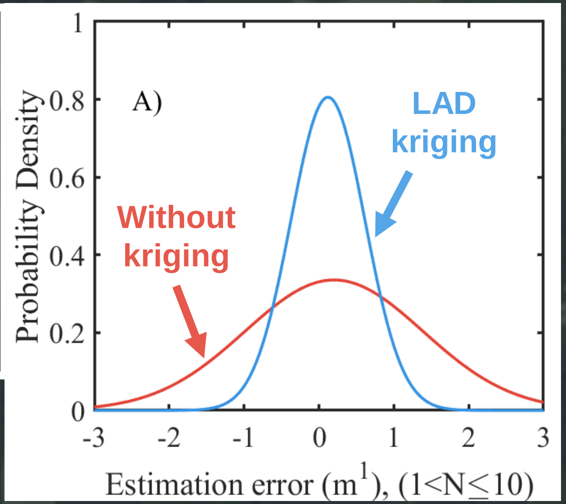
VALIDATION OF THE NEW KRIGING METHOD FOR LAD

VALIDATION OF THE METHOD ON A VIRTUAL REFERENCE CANOPY



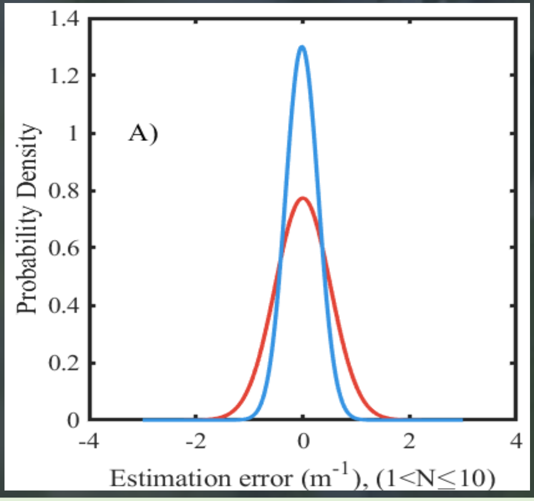
Lowest errors method in unexplored voxel

Potential to reduce errors in poorly sampled voxels



EXAMPLE APPLICATION TO FIELD DATA

Soma et al., 2020



- → Drop of RMSE from 0.72 m^{-1} to 0.48 m^{-1} in unexplored voxels
- → 0.92 m^{-1} to 0.42 m^{-1} in poorly explored voxels
- → No additional information or any threshold required

CONCLUSIONS OF THE STUDY AND PERSPECTIVES OF THE DEVELOPPED APPROACHES