Estimation of leaf area index using simulated UAV laser Scanning

Évaluation de l'indice de surface foliaire utilisant des ULS simulés

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1. For one aim: estimate leaf area from forest LiDAR data

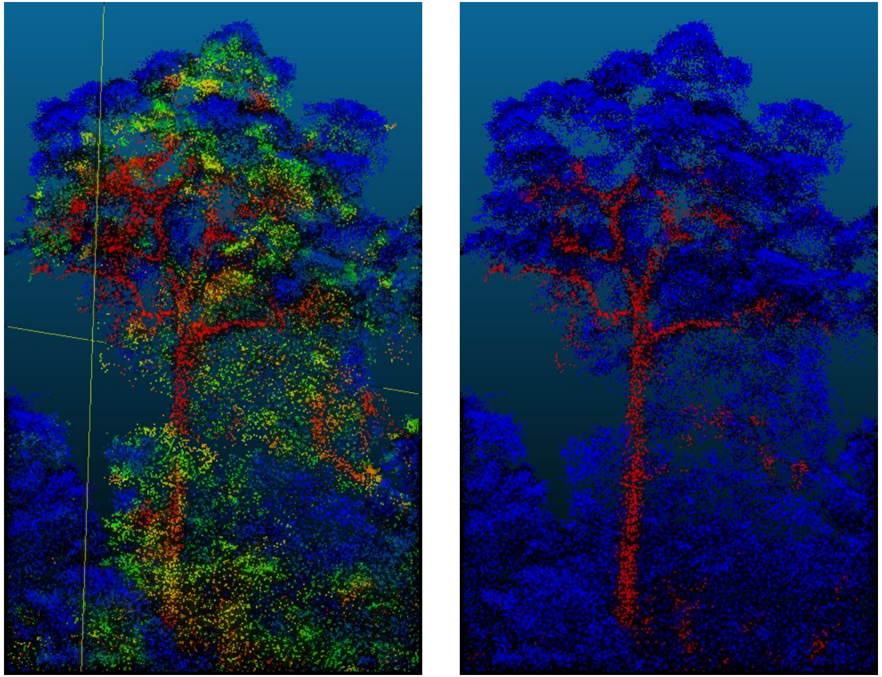
- **Leaf area index (LAI): half the total leaf area per unit horizontal ground surface area**
  - a key indicator for assessing plant growth and development, coupling vegetation to the climate system.
- **Accurately measuring LAI hinges on addressing three key challenges: *leaf/wood segmentation*, *leaf angle distribution*, *and* *leaf clumping***
  - for decades, forest canopy have been treated as a homogeneous, isotropic leaf layer in order to apply the Beer-Lambert law (it is still the mainstream method)
  - LiDAR technology now provides detailed 3D forest structure
- **First work focused on leaf/wood segmentation using UAV LiDAR**
  - SOUL, a deep learning model can process directly raw tropical data, use only point coordinates, end-to-end automatic approach, open-access
- **Second work focused on improving LAI estimation by minimizing woody contribution**
  - a simulation study, using DART model to simulate realistic forest LiDAR scenario
  - quantified the bias introduced by wood, leaf angle distribution and leaf clumping

2. Semantic segmentation On ULs (SOUL) model

- **SOUL** addresses the challenge of semantic segmentation on tropical forest ULS point clouds. Using only point coordinates as input.

- Geodesic Voxelization Decomposition (**GVD**) algorithme, regroups points within a regular 3D grid structure using a propagation criterion based on the geodesic distance

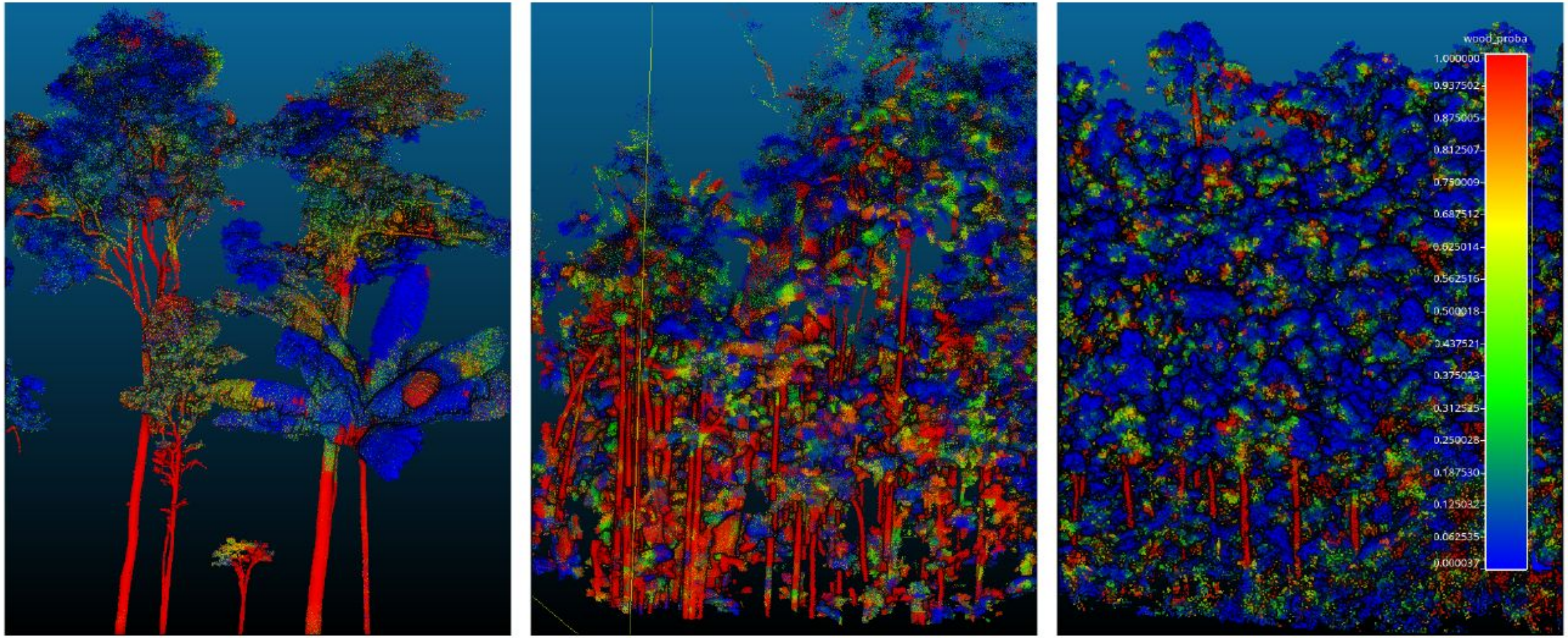
- **Rebalanced loss function**, a natural solution changes the ratio of the data participating in the training, addressing the class imbalance issue



SOUL True label

Fig.1 Qualitative results of SOUL on ULS test data

2.1 SOUL model on other datasets



(a) Paracou, French Guiana - TLS (b) NSW, Australia - MLS (c) Sandhausen, Germany - ULS

Figure 2. Qualitative results on various LiDAR data from different sites.

3. Improving the estimation of LAI

- A simulation study exposes ideas for improving the estimation of Leaf Area Index.
  - use simulation to study the deviation between the true LAD and estimated LAD
- **Multiple modification directly applied to forest mock-up Wytham woods in UK and Järvselja Birch Stand in Estonia**
  - adjust leaf angles to follow a specific distribution
  - shift leaf positions to eliminate clumping.
- **DART used to simulate LiDAR process**
  - DART is radiative transfer models, capability to model LiDAR waveforms and point clouds generated by Gaussian Decomposition
- **SOUL model used to segment leaf/wood**
  - Output used as wood mask
- **AMAPVox used to calculated LAI in voxel level (LAD)**
  - AMAPVox is a ray tracing R package, which calculates light attenuation
- **Propose SOUL + AMAPVox as a unique workflow to derive LAI from LiDAR data minimizing woody bias**

3.1 A simulation study

Fig 3.1 mock-up (obj file)

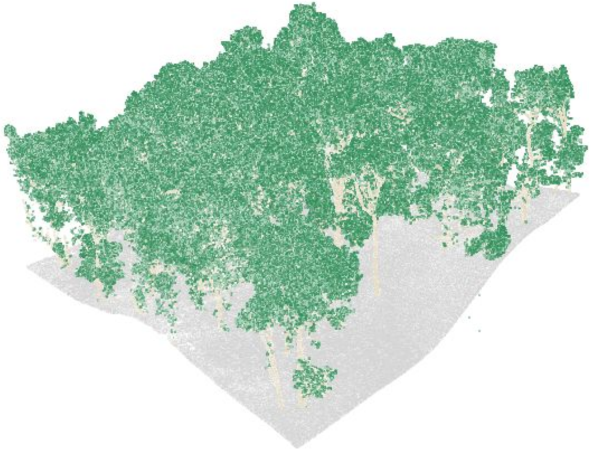


Fig 3.2 Point cloud (DART)

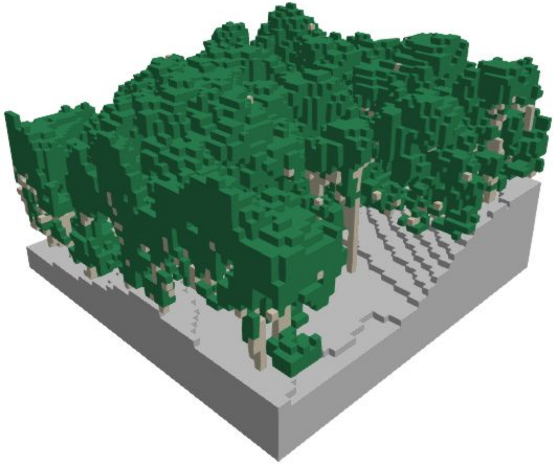


Fig 3.3 LAD* (AMAPVox)

* LAD, leaf area density. LAI is the integral of LAD in 3D space divided by surface.

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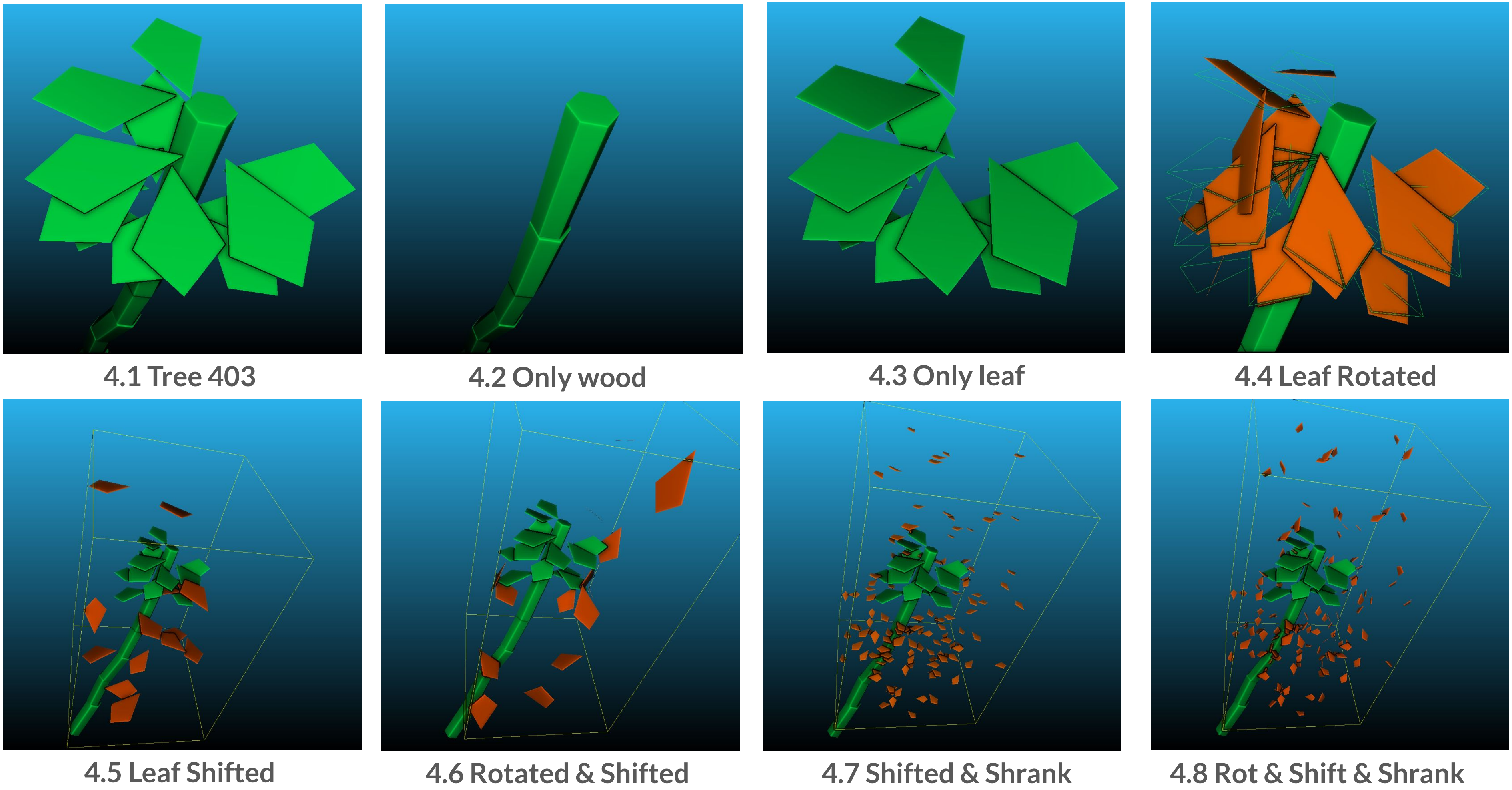

Fig.4 Modifications applied to mock-up : Tree 403 in Wytham woods

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3.3 DART used to simulate LiDAR process

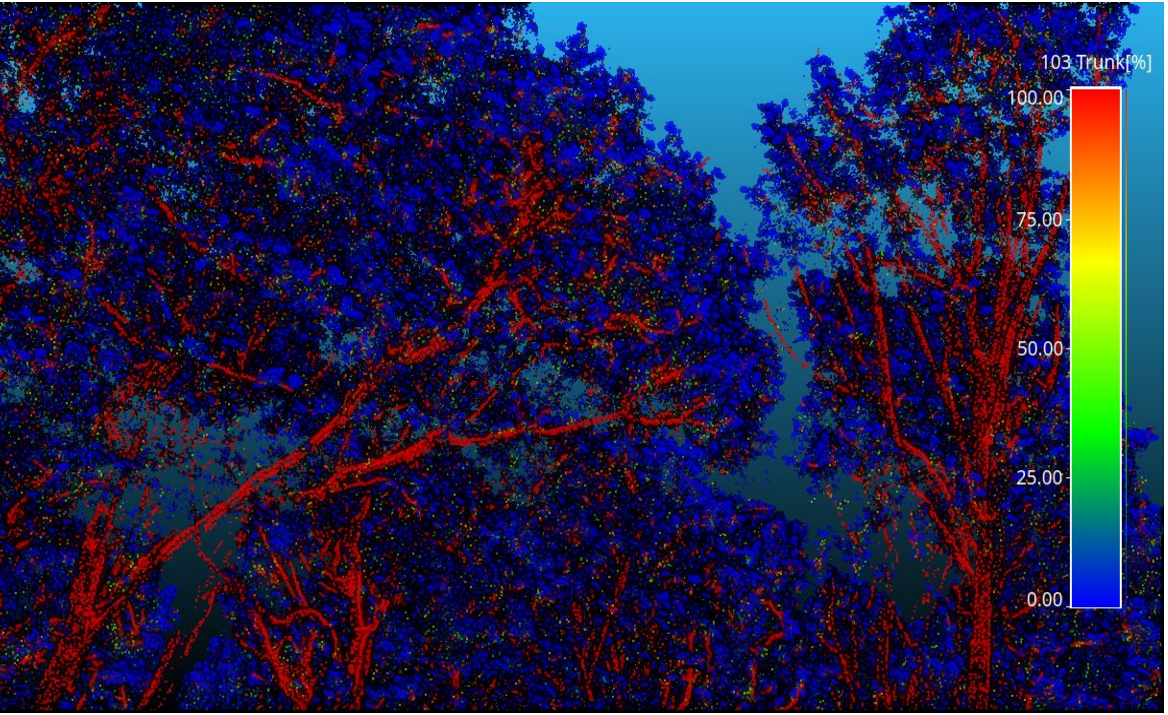

Fig 5.1 Wyham woods canopy (Woody ratio)

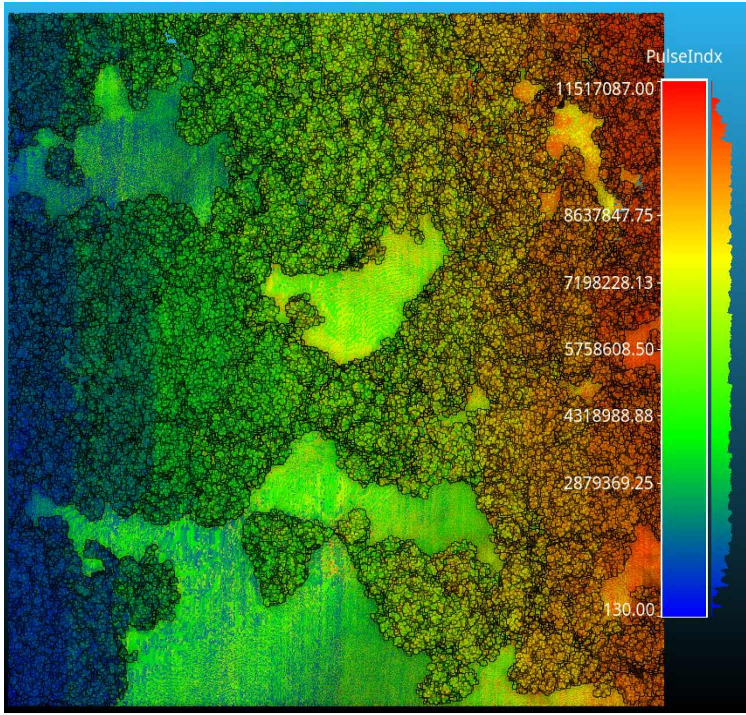

Fig 5.2 Top view

Fig.5 Simulated point clouds of Wytham Woods by DART, close view and top view.

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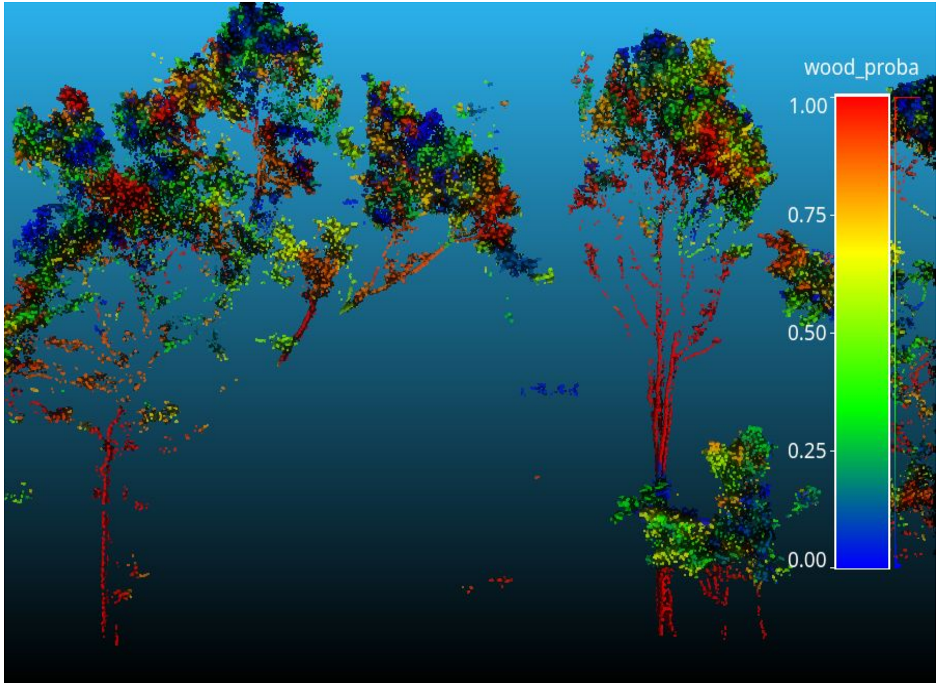

Fig 6.1 SOUL prediction

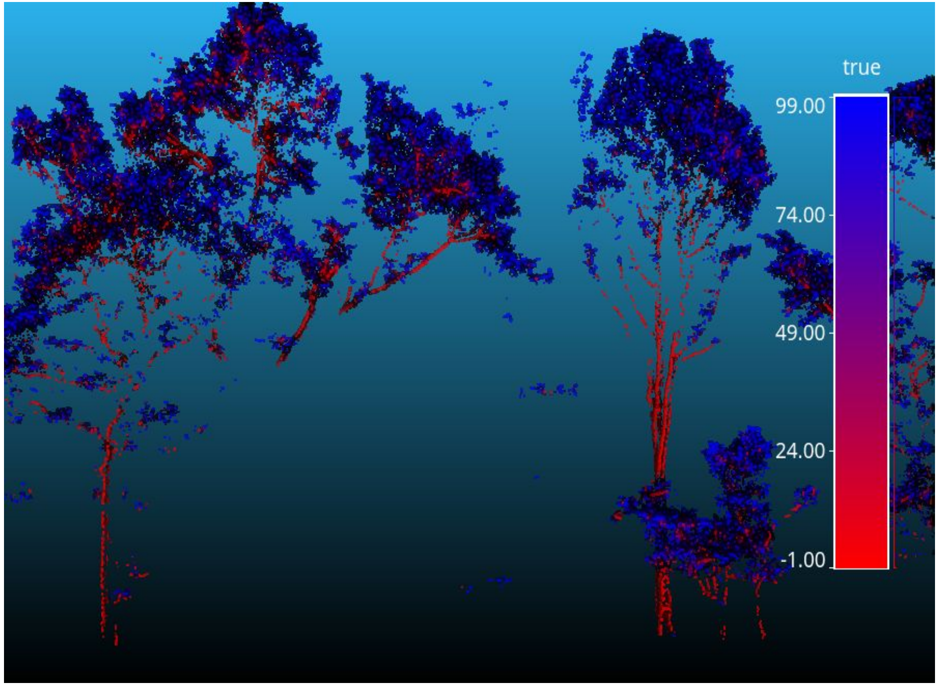

Fig 6.2 Ground truth

Fig.6 A cross-section of Wytham canopies, showing true and SOUL-predicted labels. The true label represents the woody component ratio provided by DART; and SOUL model weights are trained using real-world ULS data in Paracou.

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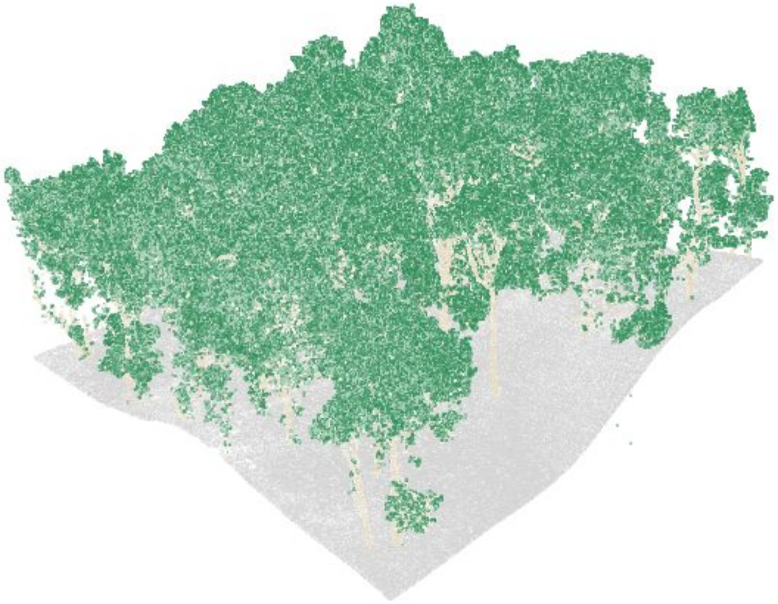

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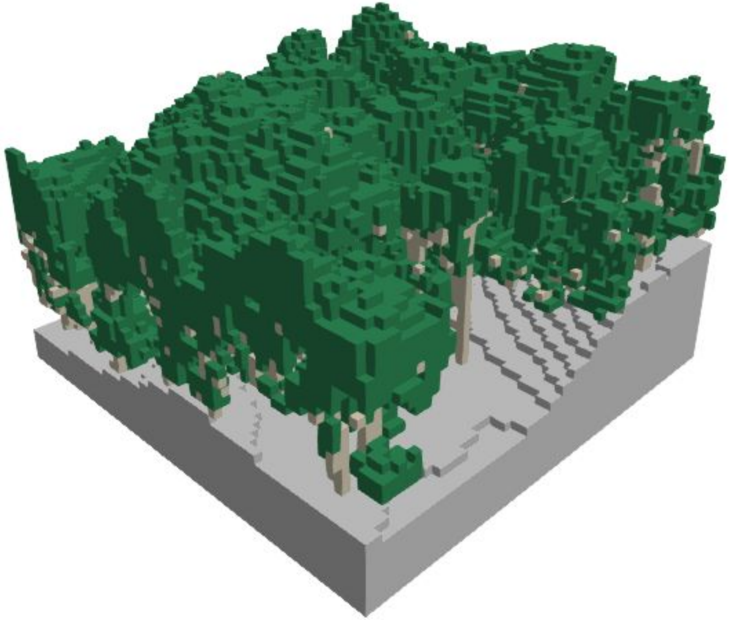

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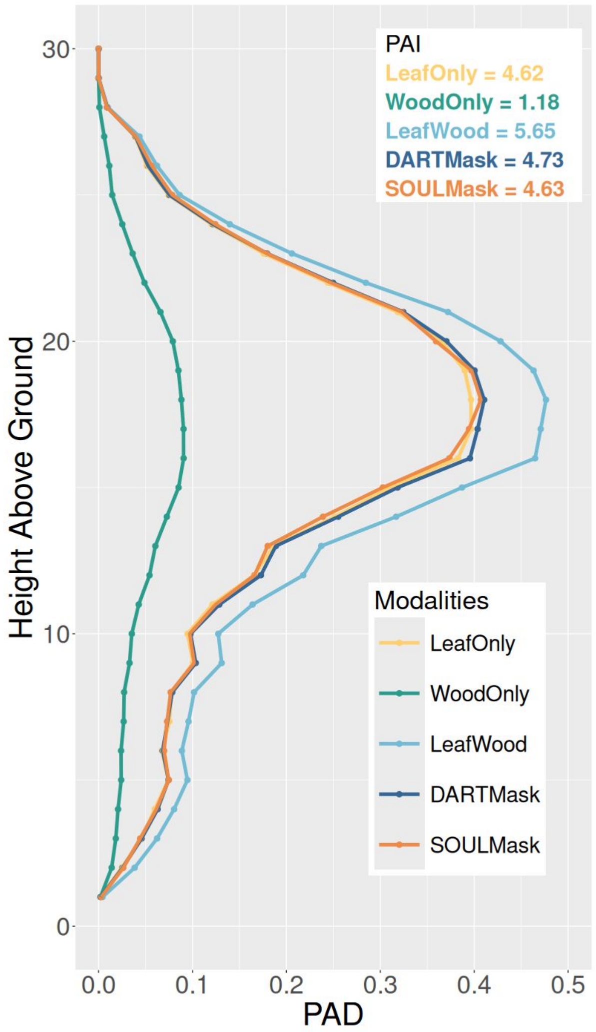


3.6 PAI to Apparent LAI

- Estimate LAI from LeafOnly give us Apparent LAI (LAI with bias introduced by leaf angle distribution and leaf clumping)
- Leaves and wood components are expected to exhibit distinct orientation distributions and clumping values, leaf/wood segmentation should be done before touching the other issues.
- Woody contribution to Apparent LAI exceed 20%, leading to an even bigger overestimation of the true leaf area.
- DARTMask, derived from the simulation process, can be considered an accurate wood mask; SOULMask achieves comparable accuracy to this DART mask.

Fig 7. PAD for LeafWood, WAD for WoodOnly, and LAD for LeafOnly of Wytham mock-up are displayed. SOUL and DART masks are employed to estimate apparent LAD for the LeafWood modality. Corresponding PAI/WAI/LAI are provided in the top right corner.

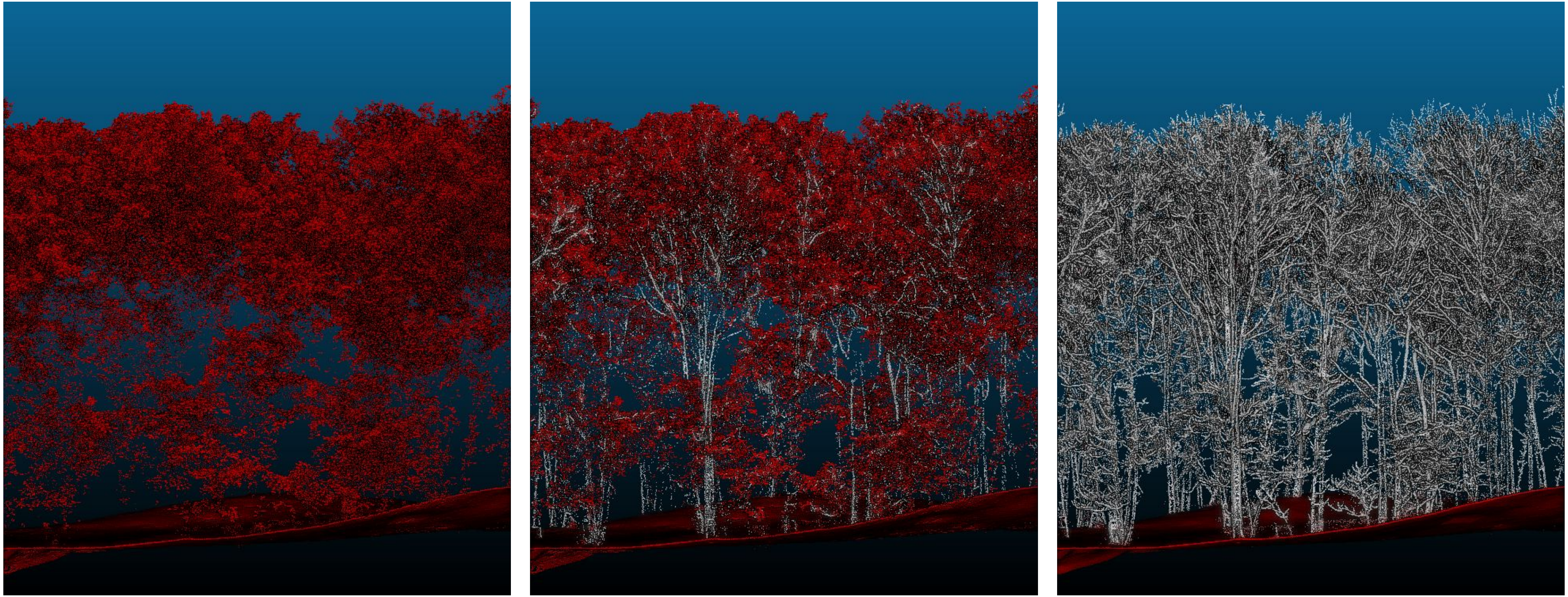
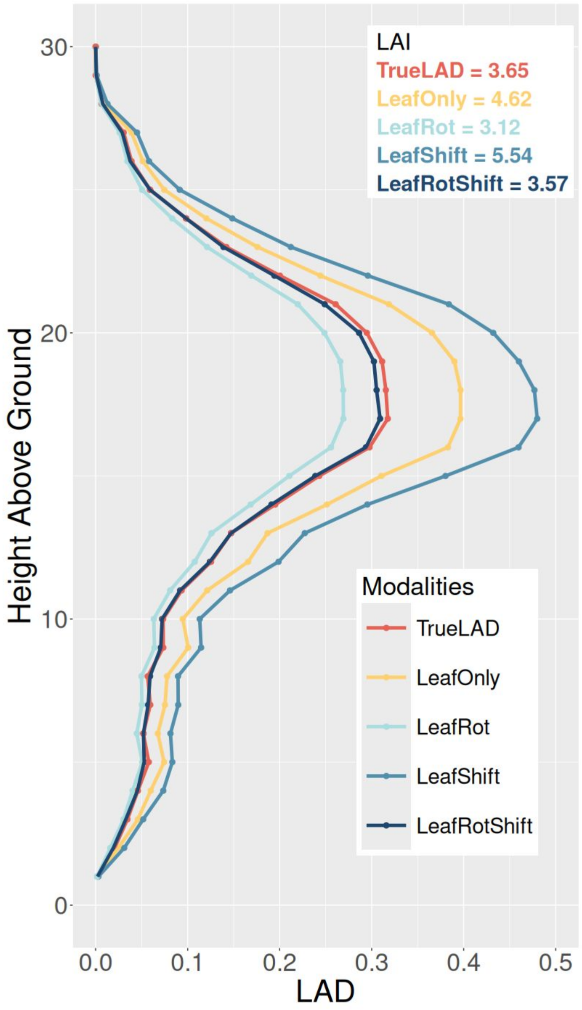


Fig 8.1 Only Leaf Fig 8.2 Leaf and wood Fig 8.3 Only wood

Fig.8 Point cloud simulation using DART : Wytham Woods



3.7 Apparent LAI to LAI

- LeafOnly Roted & Shifted scenario eliminates woody contribution, leaf angle distribution, and leaf clumping issues; our estimation result is very close to true LAI (3.65 ~ 3.57).
- Clumping refers to the non-homogeneous Poissonian distribution of leaves within a canopy; leaf angle affects the amount of light intercepted by leaves; both significantly influence LiDAR vegetation interaction, addressing these two issues independently may not be feasible.
- Forest mock-ups always represent particular cases, results found here such as the relative importance of different sources of bias may be not applicable to other situations.

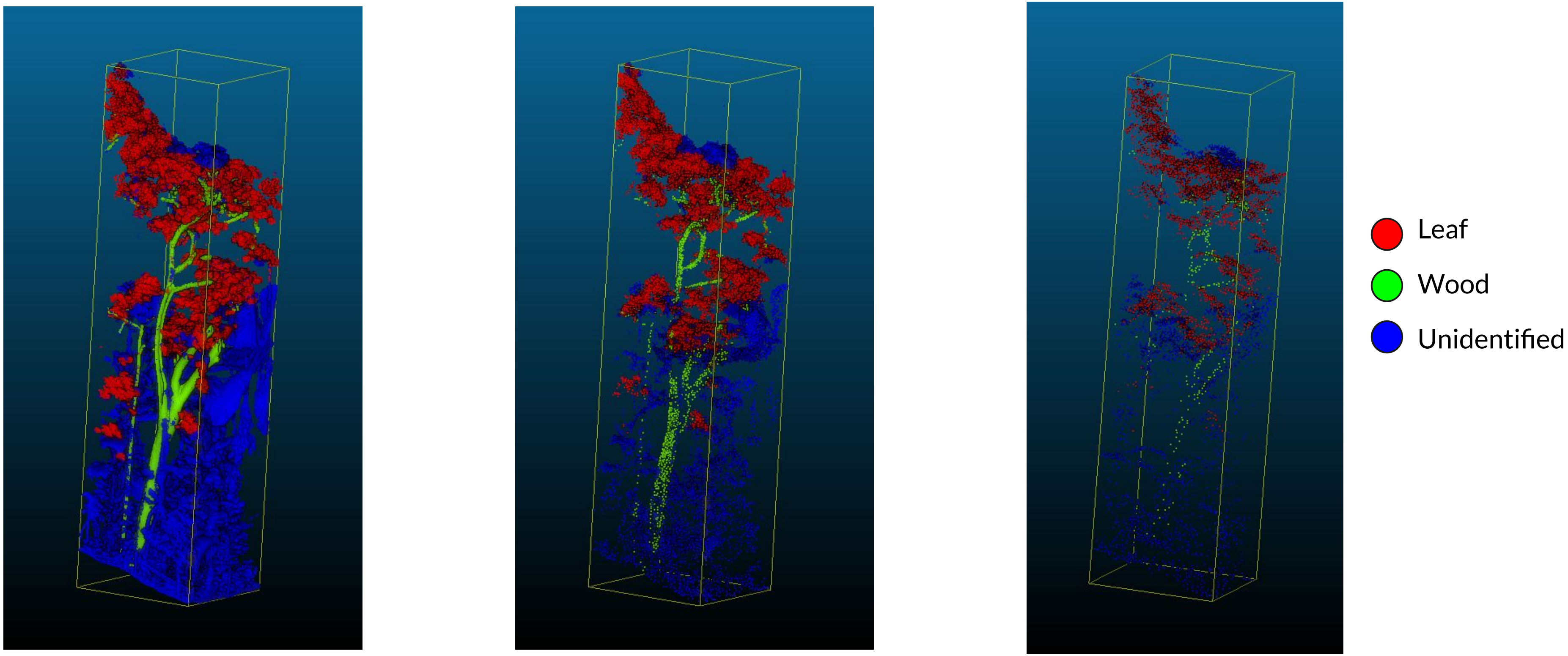
Fig 9. Vertical LAD profile for Wytham modalities, TrueLAD provided for comparison. In the absence of censoring, the LAI derived from the LeafRotShift scene is 2% lower than TrueLAI. Clumping bias effect is −25.21%, (LeafOnly - LeafShift)/TrueLAD, and leaf angle bias effect is 41.64%, (LeafOnly - LeafRot)/TrueLAD.

4. Perspectives for improving LAD estimation by ULS

- Develop local estimators (taking advantage of spatial dependence) of LAD that jointly estimate leaf orientation and the light extinction coefficient.
- Rely on the continuous improvement of the performance of drone lidars (divergence, penetration, calibrated intensity). The intensity measurements of the returns can indeed inform about the average orientation of the leaves.
- SOULv2: an unsupervised deep learning framework to adapt to the training needs of different types of forests, coming not soon!

Thank you!

(Looking for a Postdoc!)

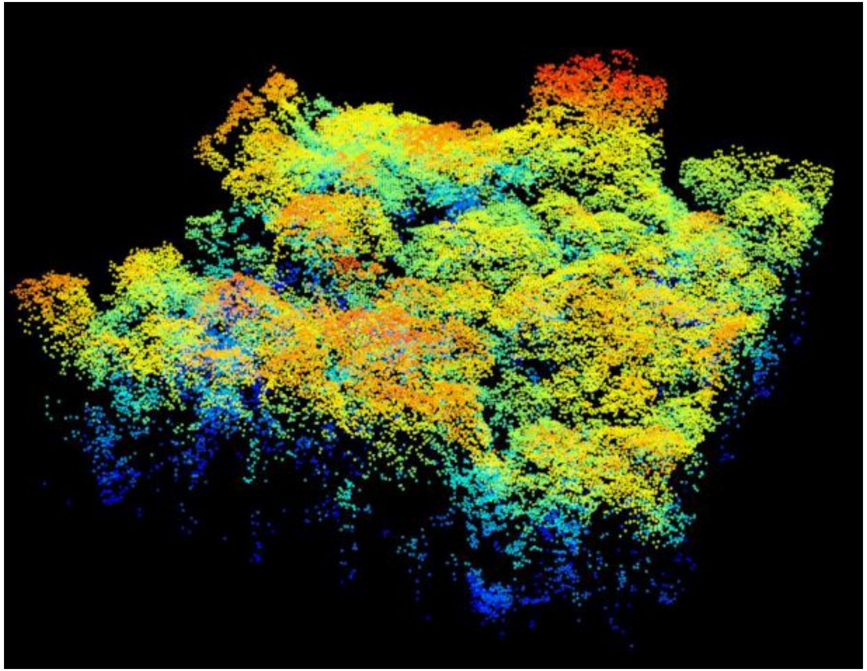


(a) Terrestrial Laser Scanning (TLS)

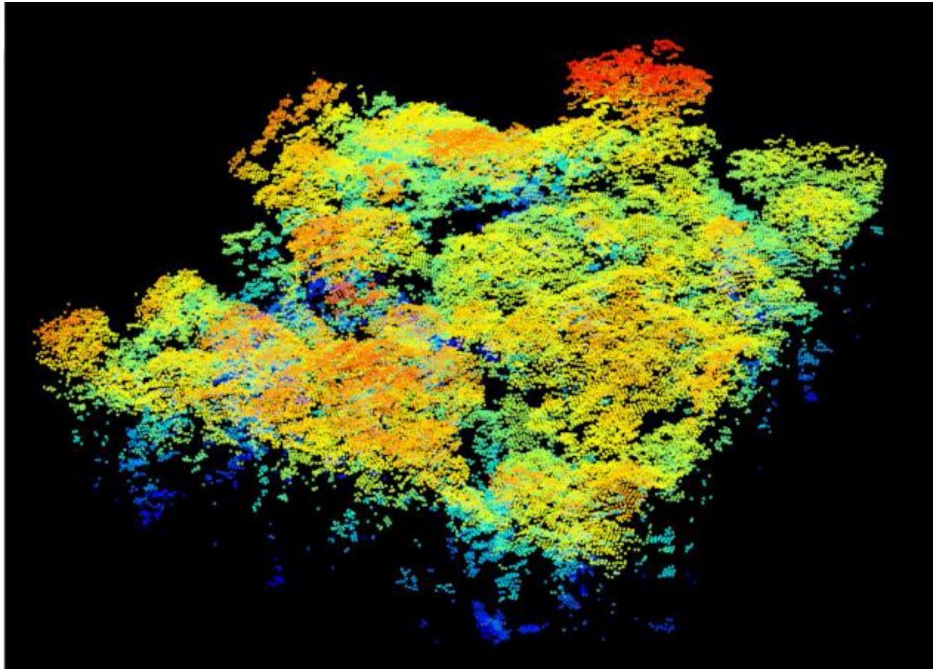
(b) Unmanned Aerial Vehicle (UAV) Laser Scanning (ULS)

(c) Aerial Laser Scanning (ALS)

Figure 2. LiDAR (Light Detection and Ranging) in a cuboid, 20 m x 20m x 50m,
"***More is different***" -- ***P. W. Anderson***



(a) Airborne Riegl LMS-Q780



(b) DART-RC (Ray-Carlo): simulated ALS data

Figure 3. DART simulation

DART has 3 major modes, we may use DART-RC which simulates LiDAR signals with a Ray-Carlo (RC) approach that combines ray tracking and forward Monte Carlo (MC) methods.

3. DART simulation

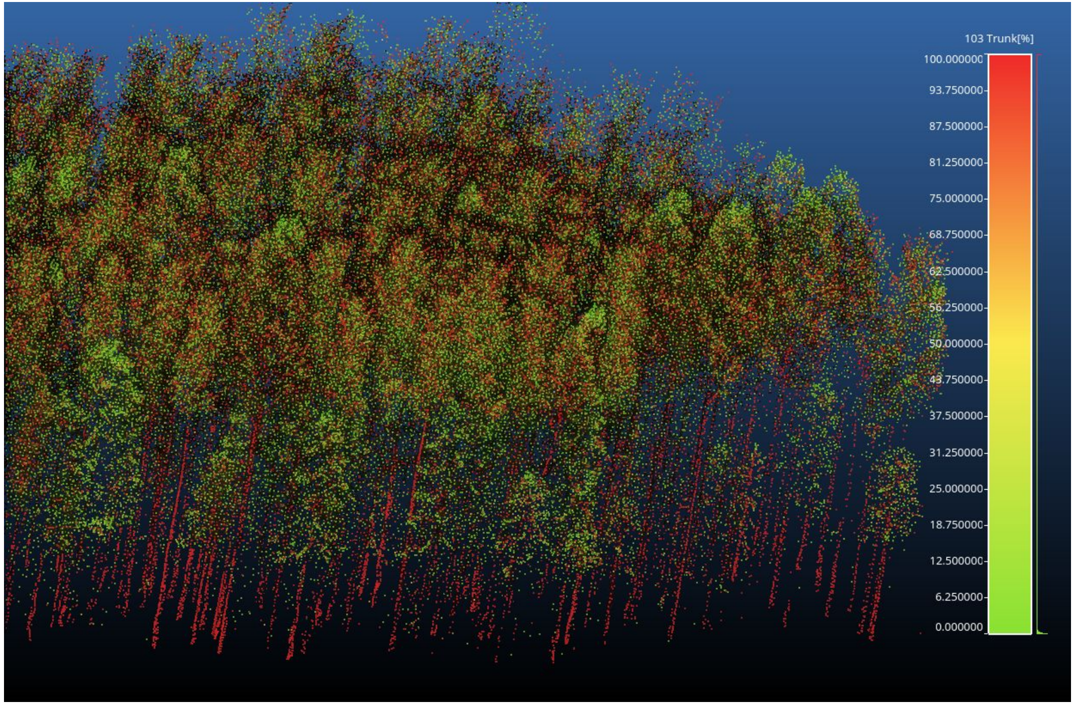


Figure 12. RAMI-V scene simulated by DART

Figure 13. wytham_woods_3d_model

Using a more realistic mock-up may help us address the problem.

Perspectives d’amélioration de l’estimation du LAD par ULS

Développer des estimateurs régionalisés (tirer partie de la dépendance spatiale) du LAD estimant de façon conjointe l'orientation foliaire et le coefficient d’extinction de la lumière

Compter sur l’amélioration continue des performances des lidar sur drone (divergence, penetration, intensité calibrée). Les mesures d’intensité des retours peuvent en effet informer sur l’orientation moyenne des feuilles.

Beer-Lambert Law in forest remote sensing

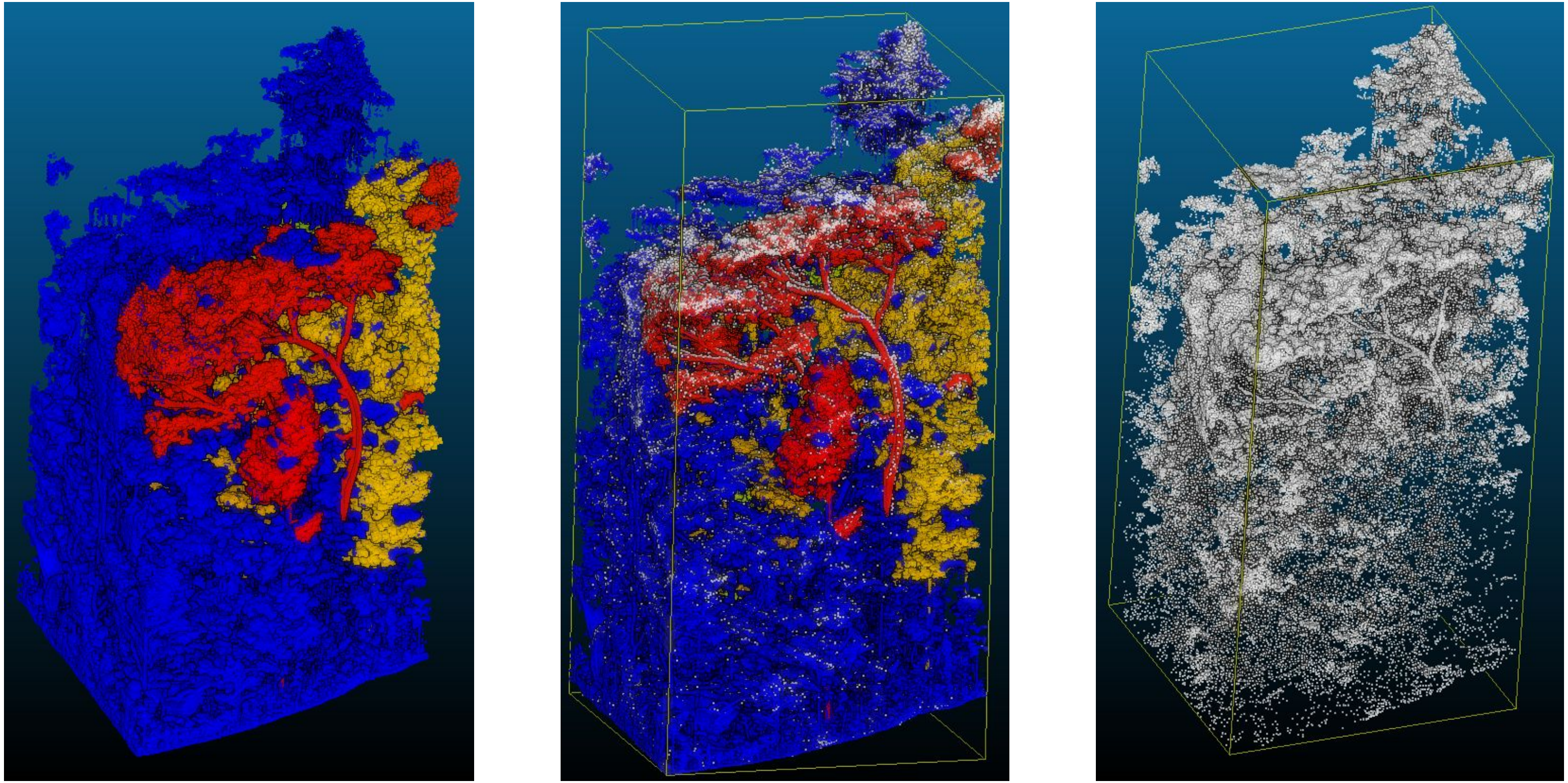
- The Beer-Lambert Law is a foundational principle in remote sensing methodology within atmospheric science (Monteith, 1965). This law posits an exponential relationship between light attenuation and the properties of the absorbing medium (Hu et al., 2014; Pimont et al., 2018). It asserts that the natural logarithm of light transmittance, λ, is proportional to the product of medium absorption coefficient, μ, density of absorbing particles, ρ, and path length of light travel through the medium (i.e. optical path length), l:

$$\lambda = \exp(-\mu\rho l)$$

- In adapting the Beer-Lambert Law to vegetation, the absorption coefficient, μ, is replaced by the leaf projection coefficient, G, which is no longer independent of light incident angle and, ρ, is substituted by the leaf area density, LAD. Both G and LAD are assumed to be uniform across the scene, and the path length, l, depends on the height of the foliage layer, h, and the zenith angle of incident pulse, θ:

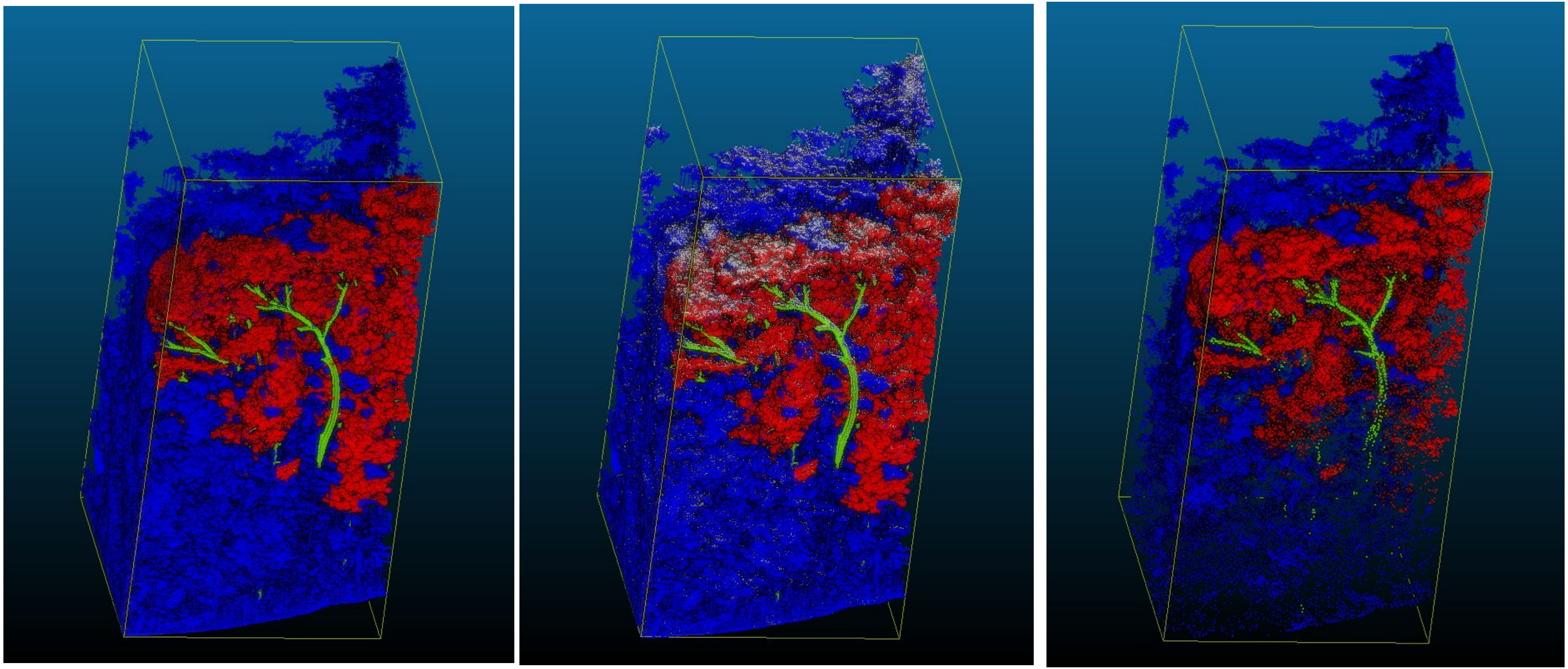
$$\rho = LAD = LAI/h, \quad l = h/\cos\theta$$

$$\lambda = \exp(-G \cdot LAI/\cos\theta)$$



(a) TLS (b) overlap (c) ULS

Figure 6. TLS and ULS co-registration



(a) TLS (b) overlap (c) ULS apres transfer label

Figure 7. TLS and ULS co-registration

5. Expectation

1. Good at method implementation, need comprehensive perspective on ecology problem
    a. I trust the Academic taste
    b. Always do Ordinary & sensible things, take some risk,

LAI Estimation Challenges

- LAI is a key indicator of vegetation health and productivity.
- Accurate LAI estimation is essential for effective forest management and conservation.
- Traditional LAI measurement methods are time-consuming, labor-intensive, and often inaccurate.
- LiDAR technology offers a promising solution for efficient and precise LAI estimation.