# Apprentissage par transfert pour discriminer le bois/feuille des Unmanned aerial vehicle Laser Scanning (ULS)

PhD student:
Yuchen BAI

*Supervisor:*
Jean-Baptiste DURAND
Grégoire VINCENT
Florence FORBES

## Outline

- ❏ Introduction
- ❏ Three identified questions
- ❏ Prototype model
- ❏ Perspectives

## Introduction

- Airborne Laser Scanning (ALS) :
  - RIEGL LMSQ780
  - point density : ~70/m$^2$ , pulse density : ~40/m$^2$
- Terrestrial Laser Scanning (TLS):
  - RIEGL VZ-400
  - point density : >200,000/m$^2$ , pulse density : >200,000/m$^2$
- Unmanned aerial vehicle (UAV) Laser Scanning (ULS):
  - RIEGL miniVUX-1UAV
  - point density : >750/m$^2$ , pulse density : >500/m$^2$

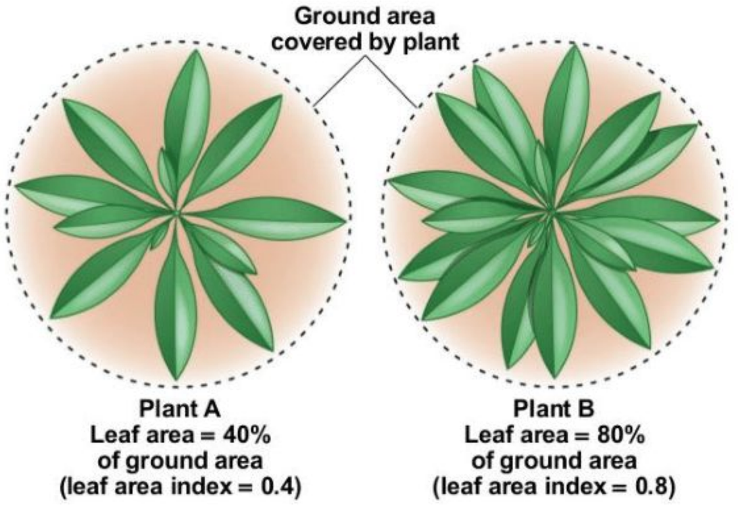
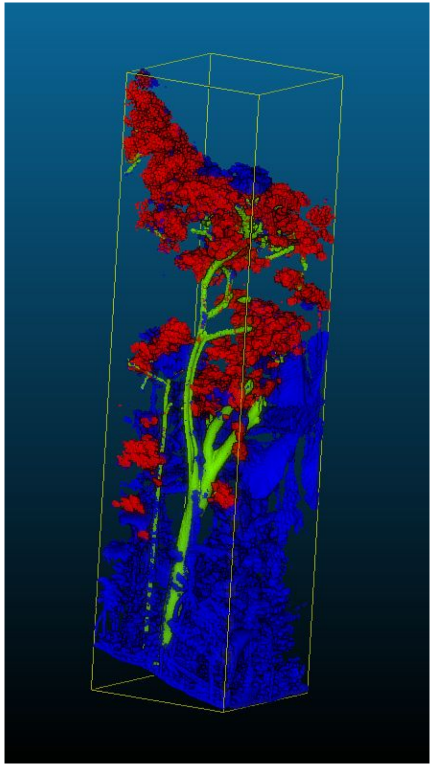
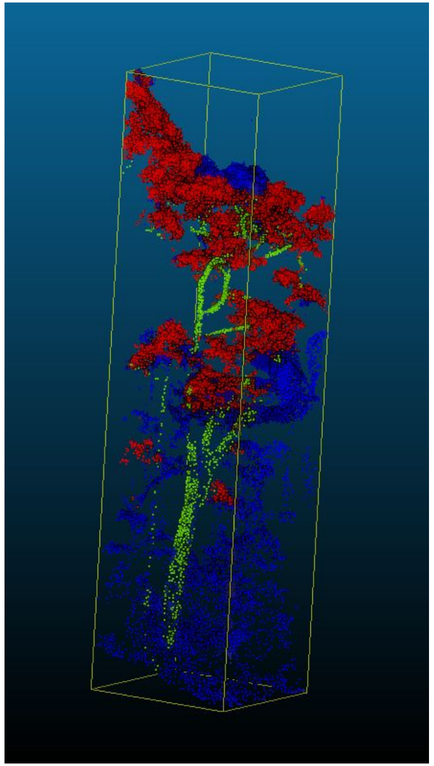

Ground area covered by plant
Plant A
Leaf area = 40% of ground area (leaf area index = 0.4)
Plant B
Leaf area = 80% of ground area (leaf area index = 0.8)

Figure 1. Leaf Area Index (LAI)

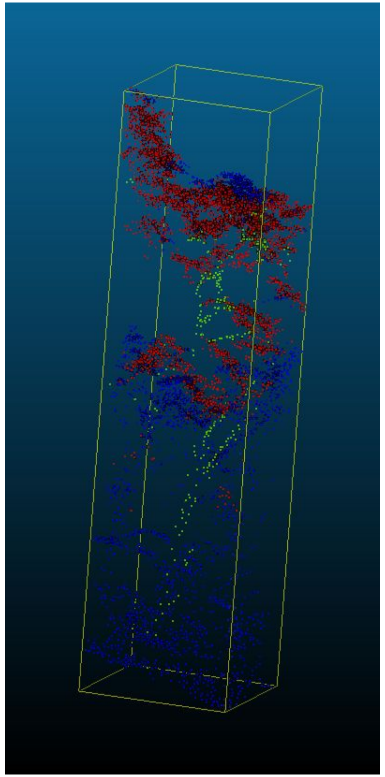
The leaf area density (**LAD**) is defined as the total one-sided leaf area of photosynthetic tissue per unit canopy volume. The Leaf area index (**LAI)** is then derived by integrating the leaf area density over the canopy height. It corresponds to the one sided leaf area per unit horizontal ground surface area.



(a) Terrestrial Laser Scanning (TLS)



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



(c) Aerial Laser Scanning (ALS)

🔴 Leaf

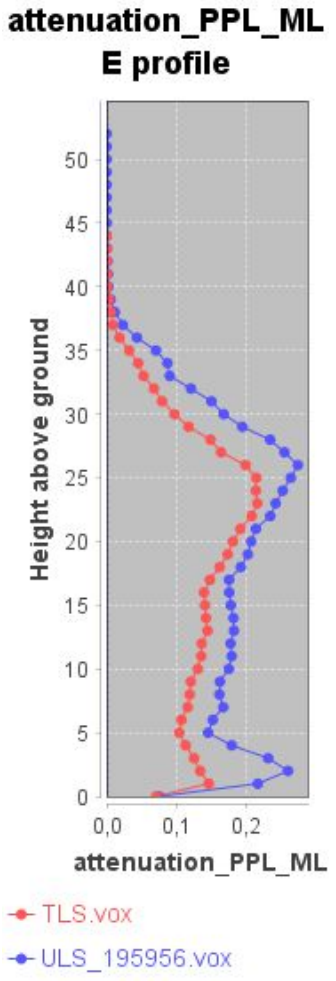
🟢 Wood

🔵 Unidentified

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

## Three identified questions

- How to do semantic segmentation (wood-leaf discrimination) on ULS data?
  - TLS -> dense, small footprint and fewer mixed points
  - no good approach for drone data (Unmanned aerial vehicle Laser Scanning (ULS))
- How to get a more accurate and unbiased point estimator of vegetation density?
  - clumping (aggregate distribution of leaves),
  - occlusion (limited penetration and incomplete exploration of voxels)
  - develop estimates which are less biased and have lower variance
- How to correct the censorship bias of undetected targets?
  - undetected hits bias the calculated signal attenuation and the estimated leaf areas.
  - model the effect of this censorship and correct this bias
  - in dense canopies, systematic overestimation of Leaf Area Index (LAI) 10~30% in magnitude
  - simulation!



## State of the Arts methods

- ❑ Methods based on geometric and spatial properties
  - ❑ Treeseg[1], LeWos[2], Quantitative Structure Models (QSMs) based[3], Superpoint based[4], Itakura et al. [10]
- ❑ Methods based on Random forest :
  - ❑ 'Deep Points Consolidation algorithm'[5]
- ❑ Methods based on Deep Learning :
  - ❑ Point-wise methods : FSCT[6], Deep-RBN[7], Morel et al.'s method [8]
  - ❑ Voxel-wise methods : Windrim et al.'s method[9], Yang et al. [11]

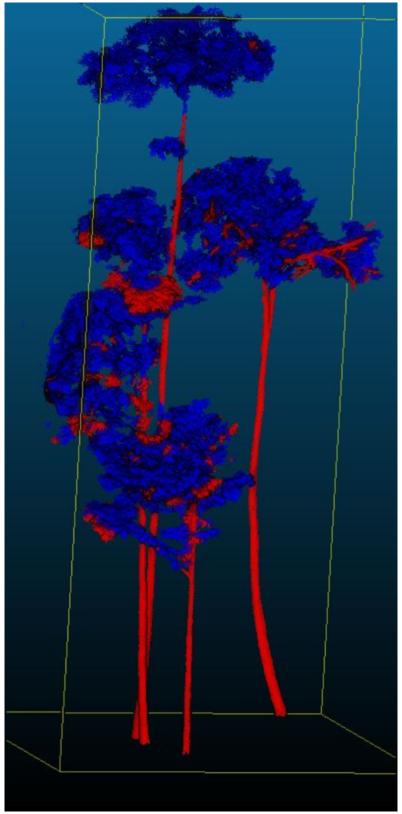


Fig 3. Lewos on TLS data

## Prototype model : Point-Voxel based neural network

Semantic segmentation on ULS dataset

How to get training data?

- ❑ **label transfer from TLS to ULS data**
- ❑ training with TLS and fine-tuning with ULS
- ❑ downsample the TLS data

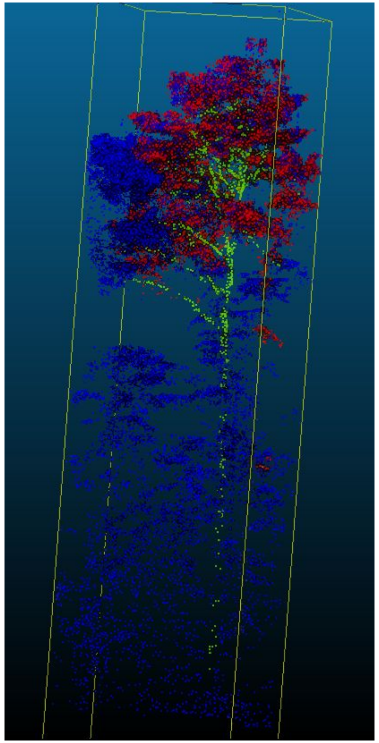


Fig 4. ULS-like data

## Use Canopy Height Model (CHM) to qualify co-registration quality

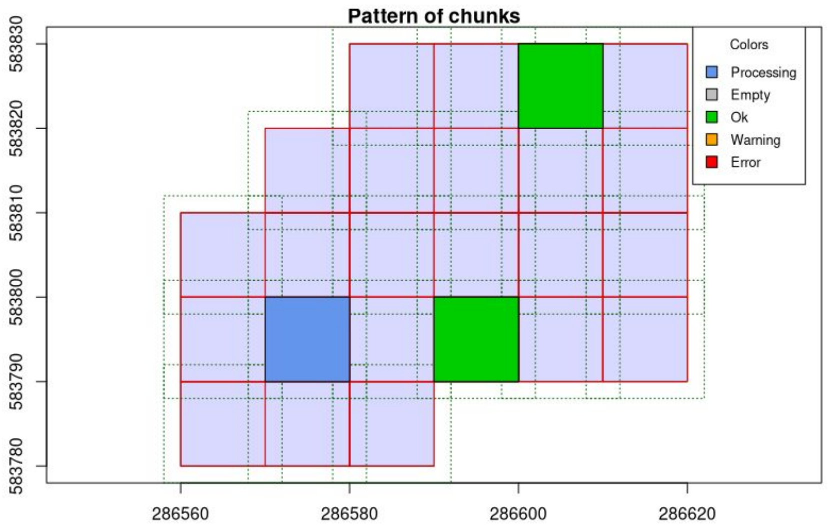
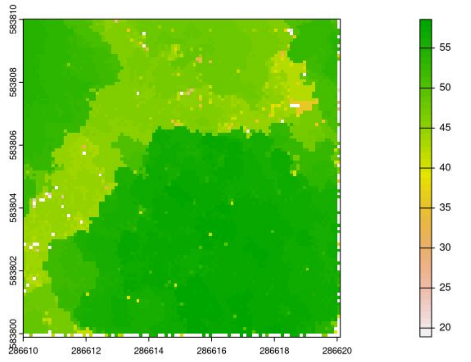
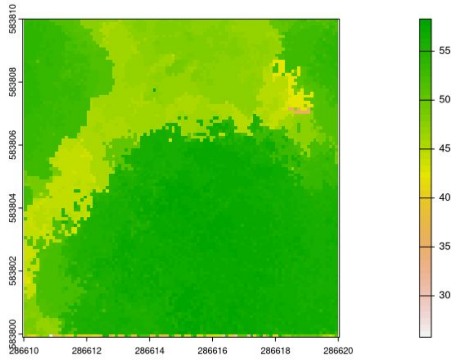
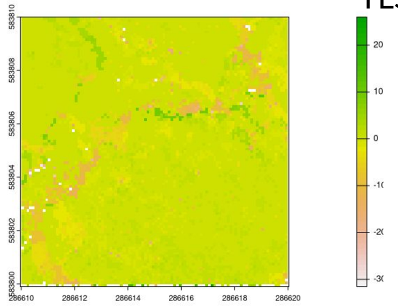


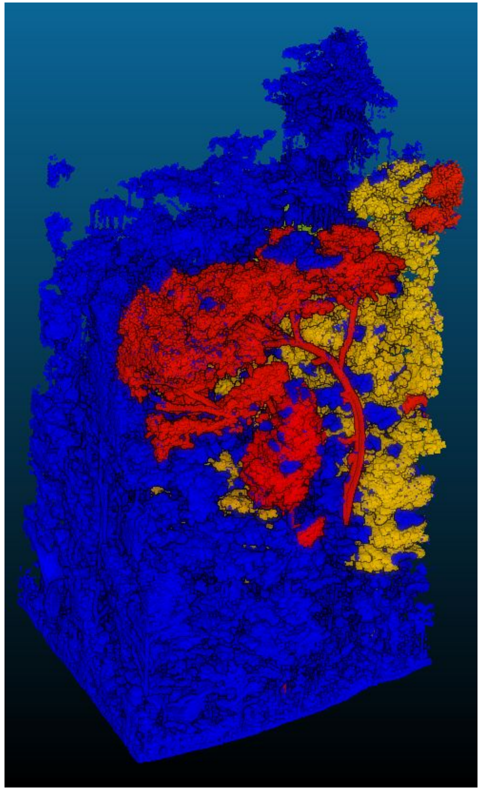
Figure 5.  CHM comparaison

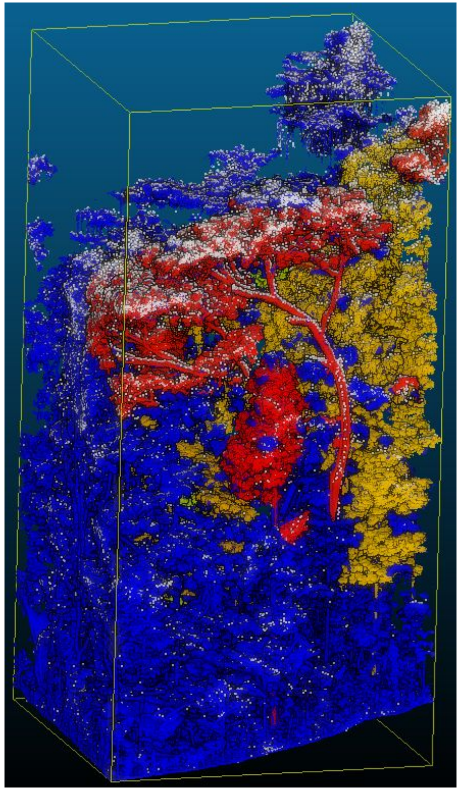

ULS CHM


TLS CHM



Diff CHM = ULS CHM - TLS CHM


(a) TLS


(b) overlap

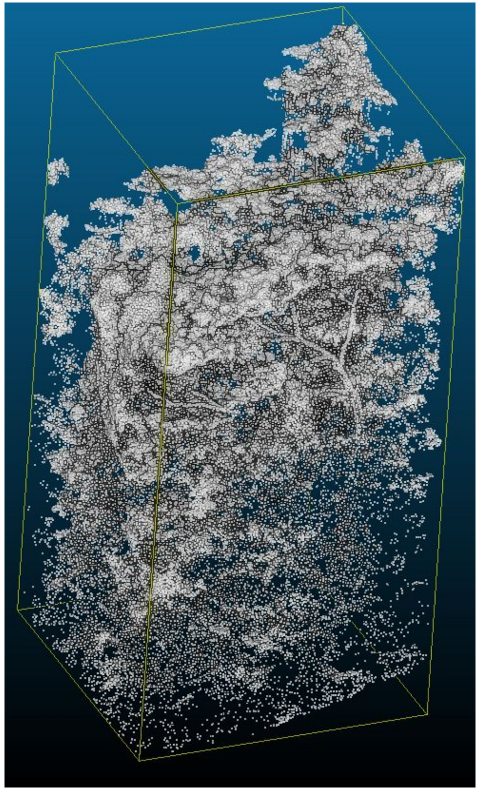
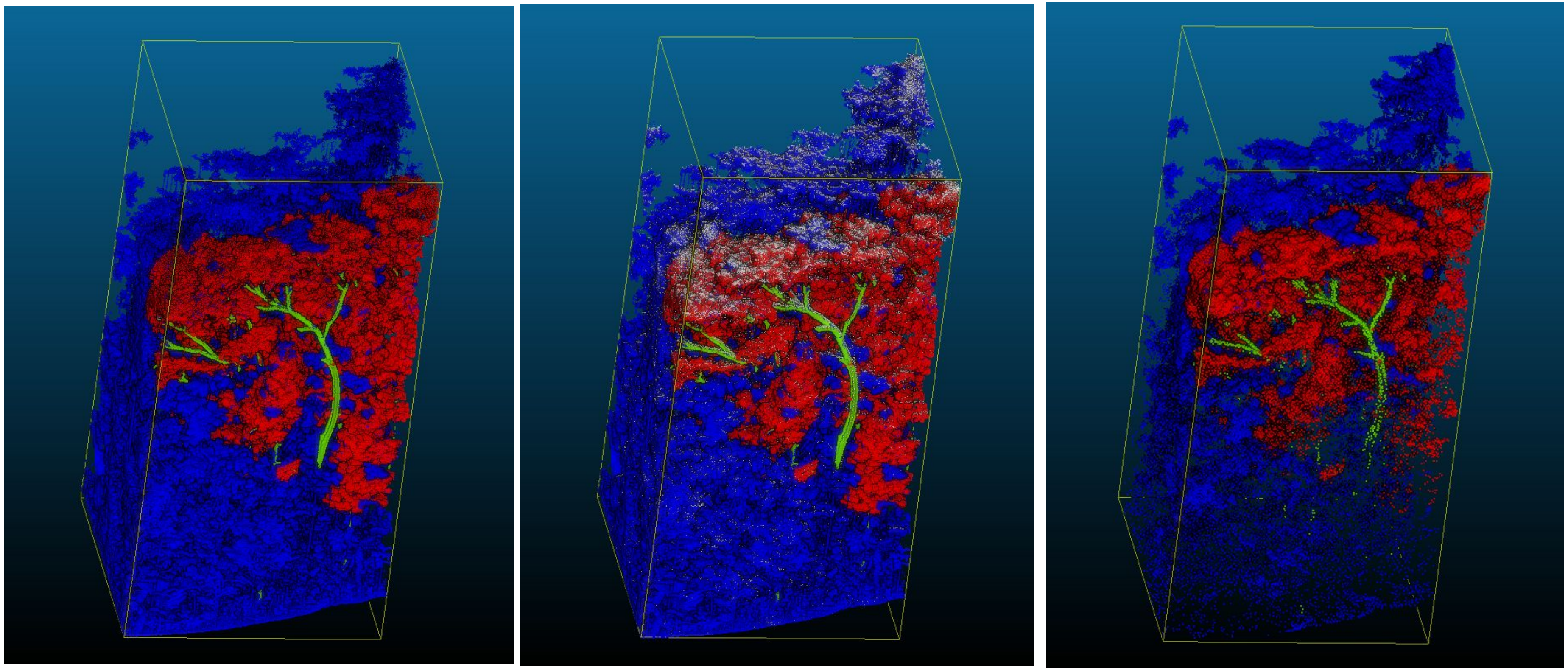

(c) ULS

Figure 6. TLS and ULS co-registration



(a) TLS

(b) overlap

(c) ULS apres transfer label

Figure 7. TLS and ULS co-registration

## The architecture of Prototype Model

### Input

- voxelized cuboid (e.g. point density)
- 5000 points (x, y , z)
- scalar (intensity, return number,  etc.)
- roughness, illuminance, verticality, etc.

[x,y,z, ((intensity * number of return) / return number), scan angle, , $f_1, f_2, \ldots, f_{321}$, $f_1, f_2, \ldots, f_n$, $f_1, f_2, \ldots, f_n$]

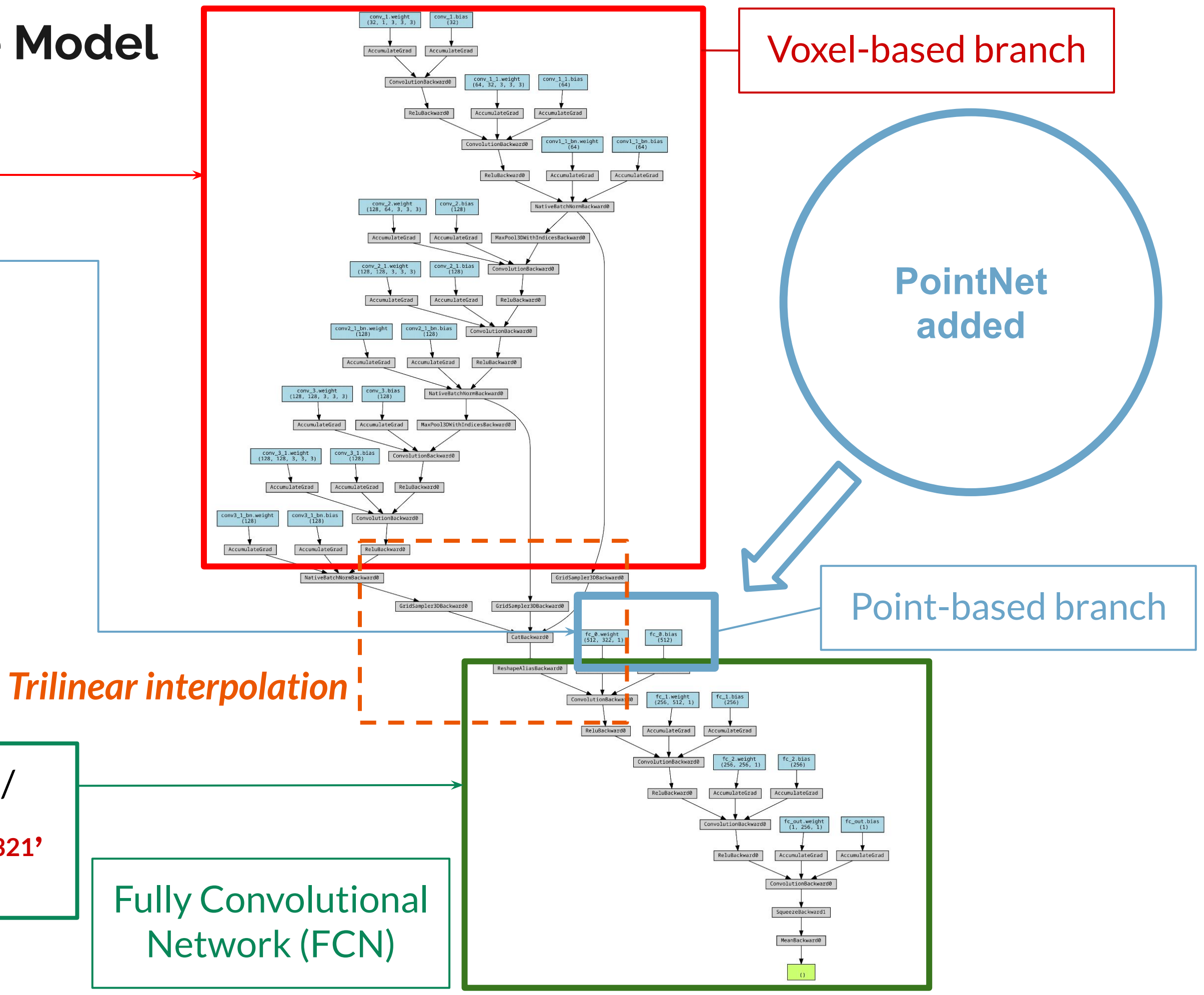
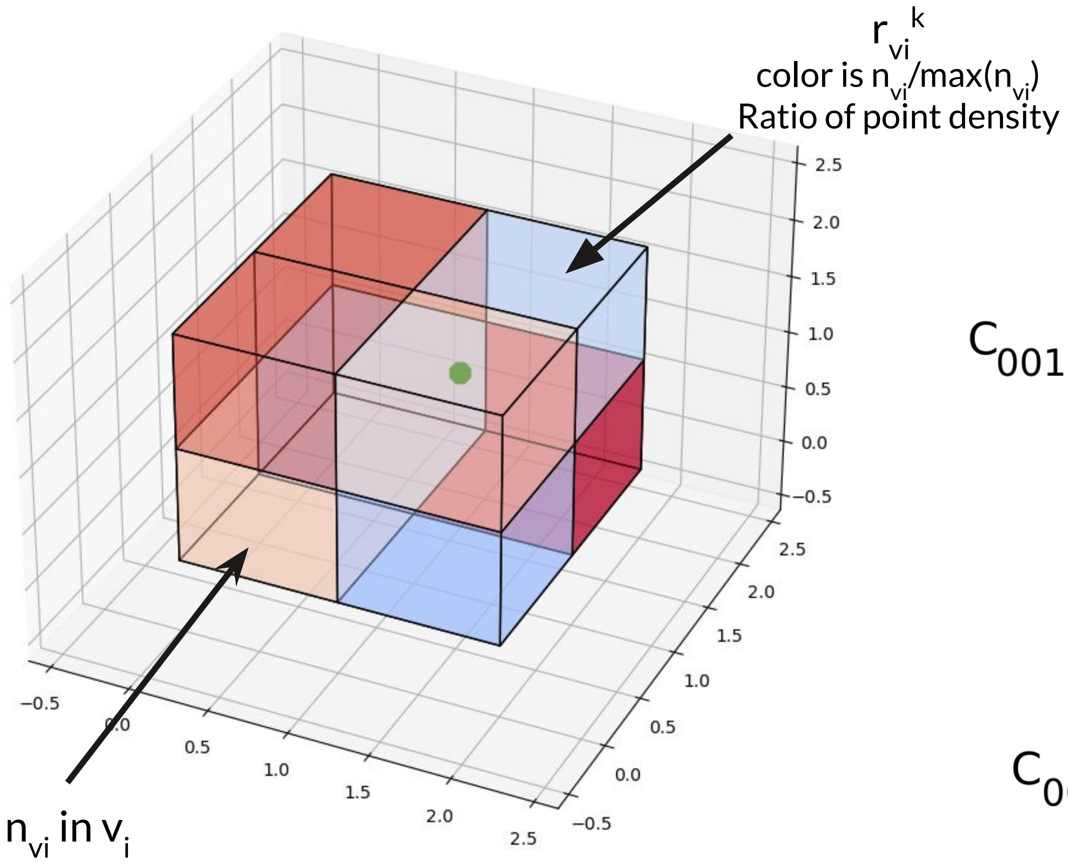


Figure 8. The architecture of the prototype model



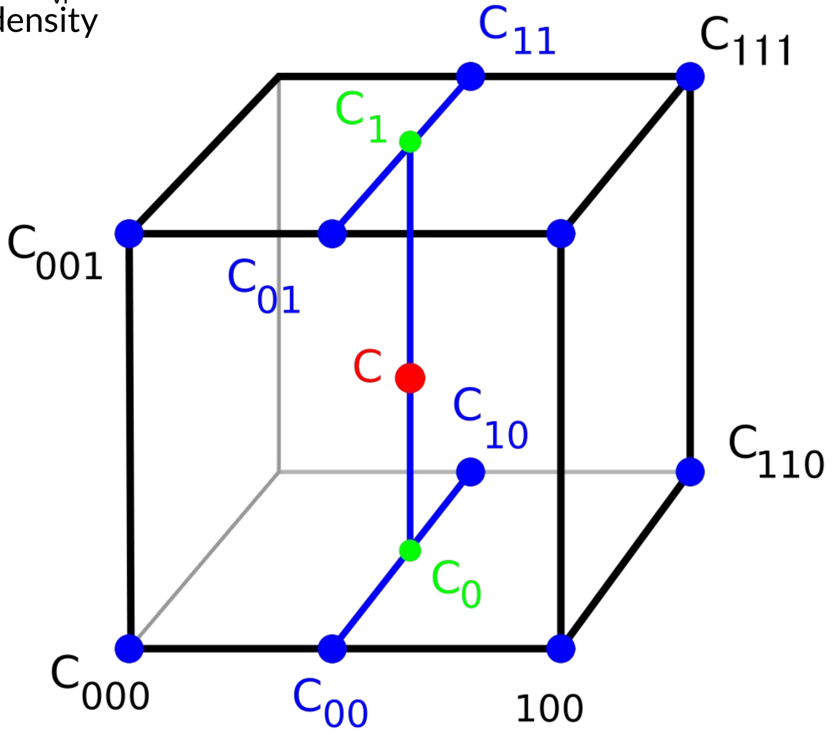
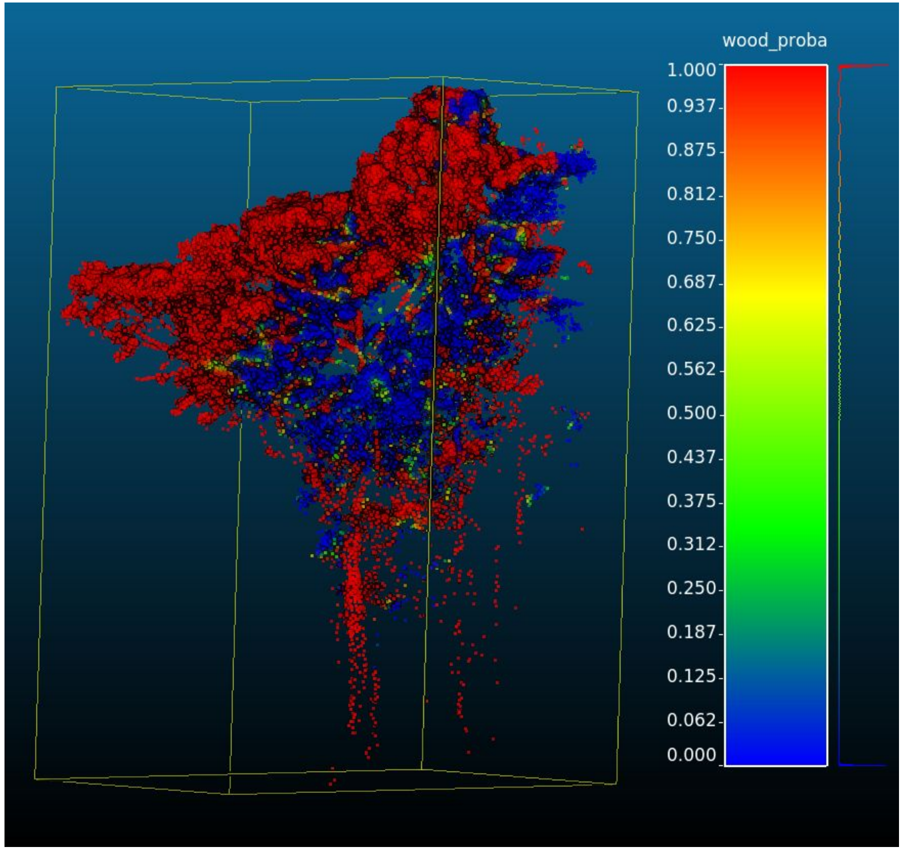
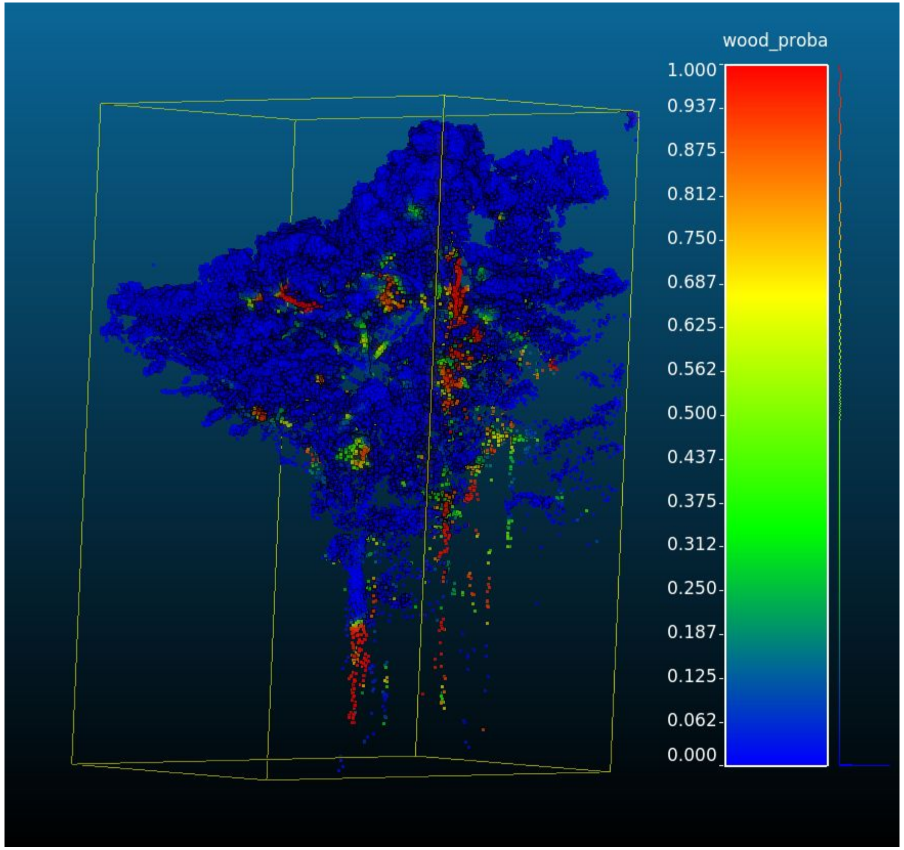


Figure 9. Trilinear interpolation

It approximates the value of a function at an intermediate point *(x,y,z)* within the local axial rectangular prism linearly, using function data on the lattice points. Find 8 nearest voxels in the space.



(a) overpredict wood



(b) overpredict leaf

Figure 10. Preliminary results : overprediction!

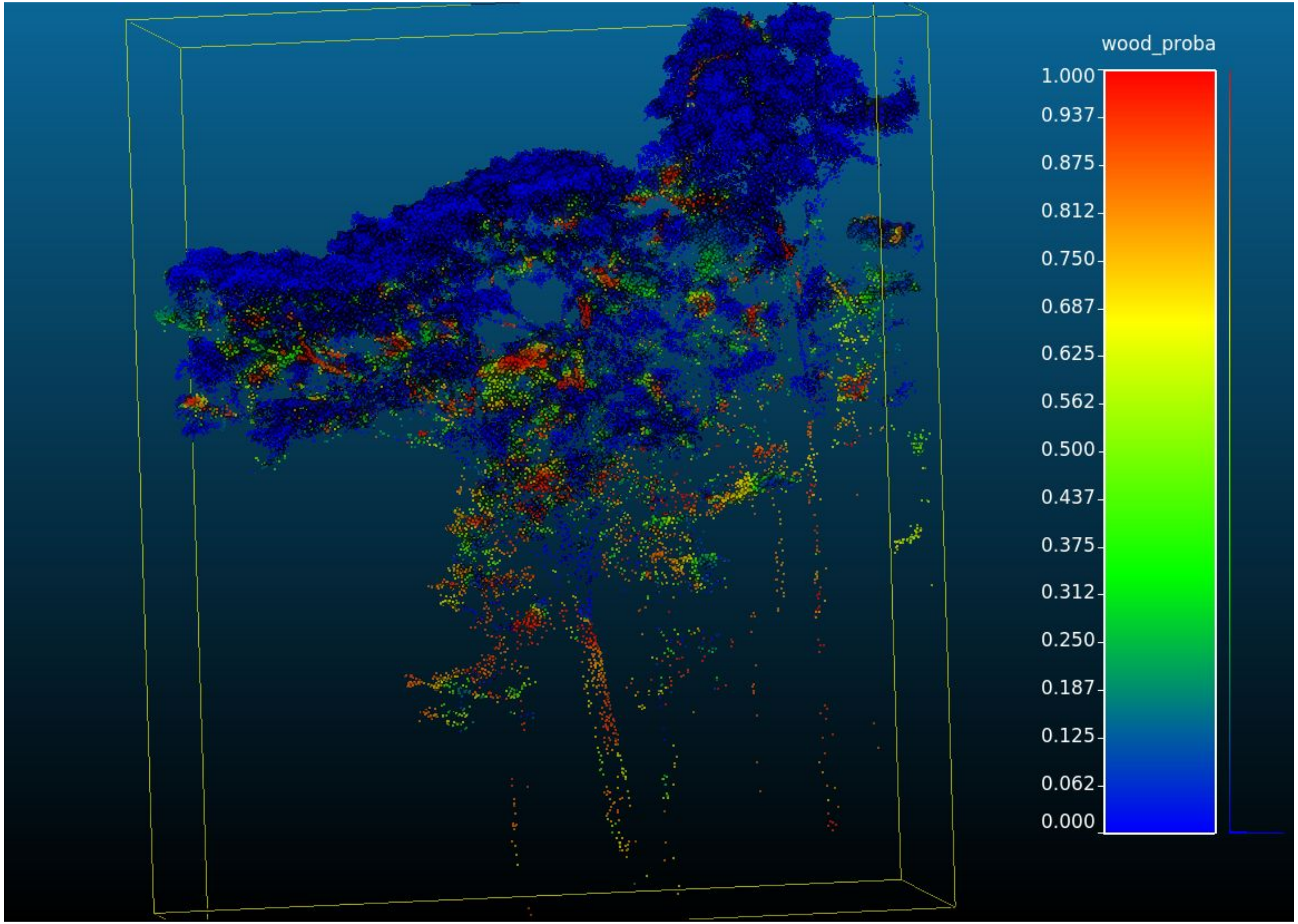


Figure 11. Failure prediction for some parts, need to improve

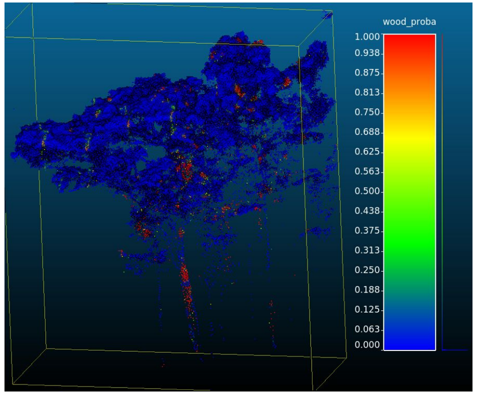


Fig 12-1. Training on tls, p@intensity, v@ratio point density, 0.2m, acc<50%

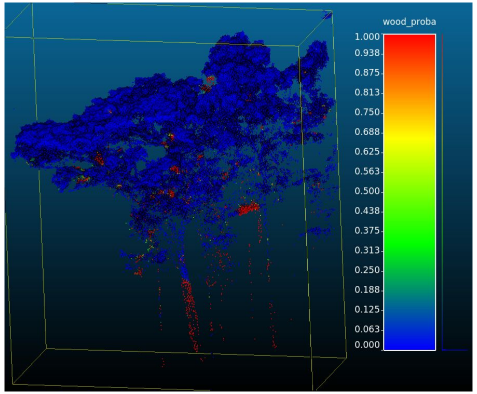


Fig 12-2. p@elevation, v@ratio point density, 0.2m, acc<50%

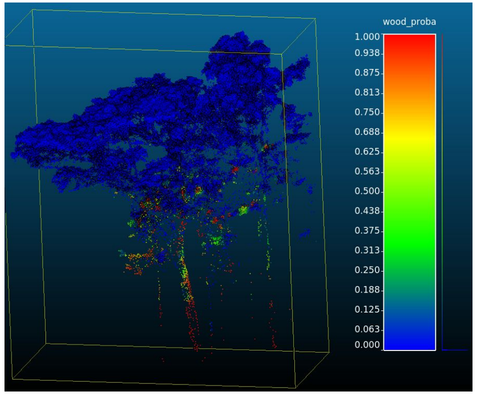


Fig 12-3. p@intensity, v@ratio point density, 0.1m, acc<50%

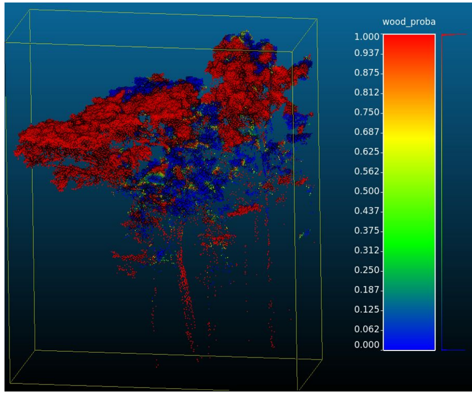


Fig 12-4. p@intensity, v@ratio point density, 0.1m, without rescaling, acc<70%

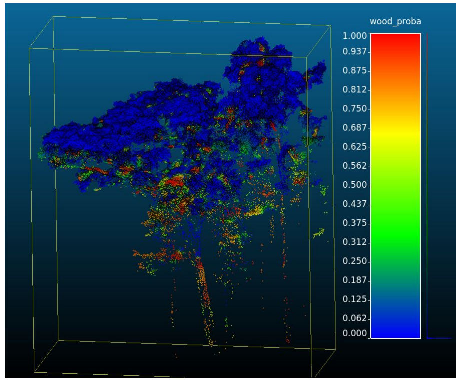


Fig 12-5. p@intensity, v@ratio point density, 0.1m, rescaling, acc=85%

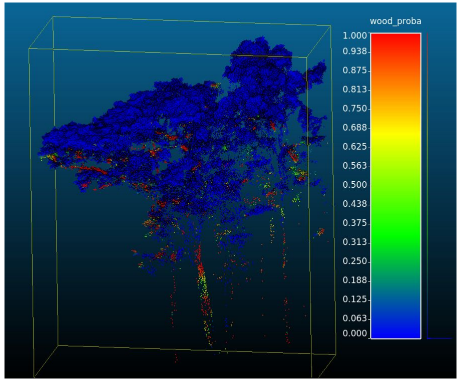


Fig 12-6. p@intensity, v@ratio point density, 0.1m, rescaling, acc=80%

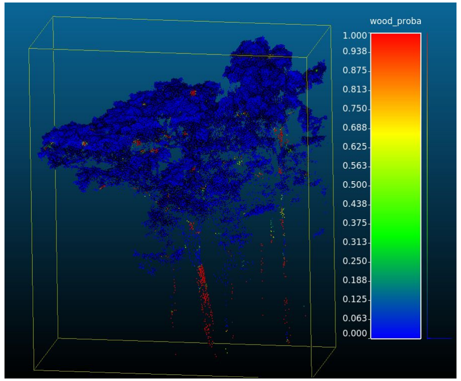


Fig 12-7. p@intensity, v@ratio return number, 0.1m, rescaling, acc <50%

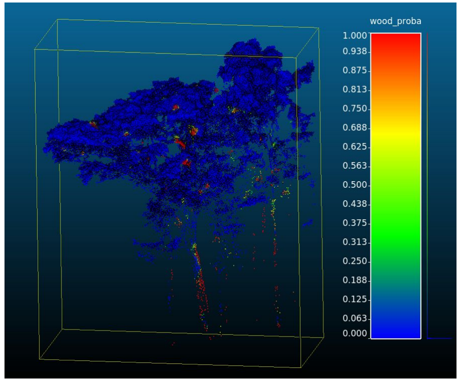


Fig 12-8. p@intensity, v@std intensity, 0.1m, rescaling, acc<50%

Fig 12: Still no desired result

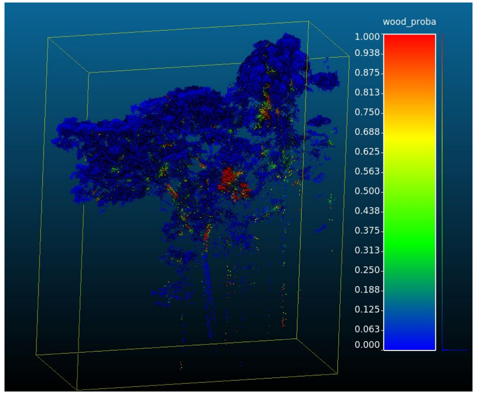


Fig 12-9. p@intensity, v@occupacy 1 or 0, 0.1m, acc<50%

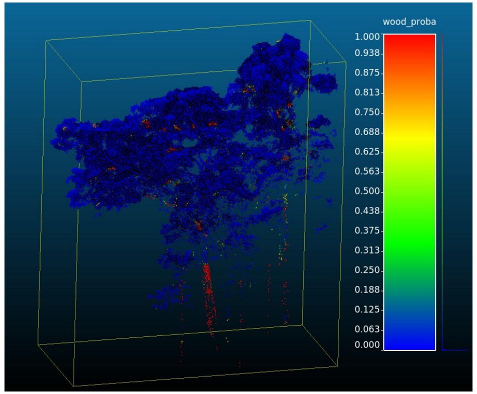


Fig 12-10. p@intensity, v@intensity moyen, 0.1m, acc<50%

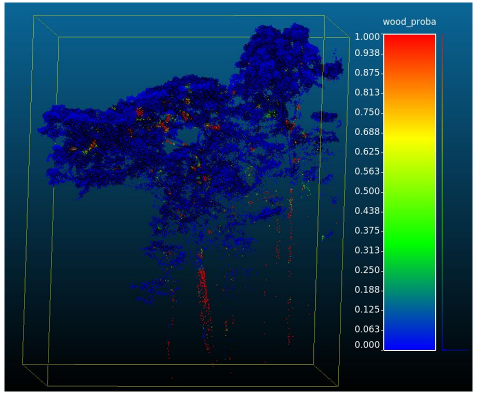


Fig 12-11. p@intensity + elevation, v@ratio point number, 0.1m, acc<50%

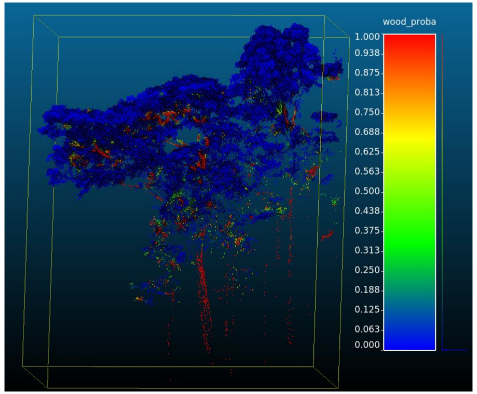


Fig 12-12. p@intensity + elevation, v@ratio point number, 0.1m, pointnet, acc=90%

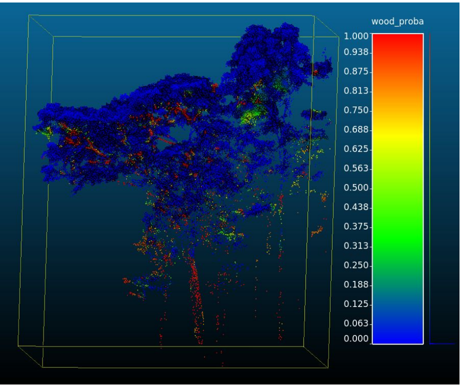


Fig 12-13. p@intensity + elevation, v@ratio point number, 0.1m, pointnet, acc=92.061%

Fig 12-14. p@intensity, v@ratio point number, 0.1m, pointnet, class weights added

Fig 12-15. p@intensity, v@ratio point number, 0.1m, pointnet, ensure the proportion of wood points when sampling

Fig 12: Result on test data, improvement needed

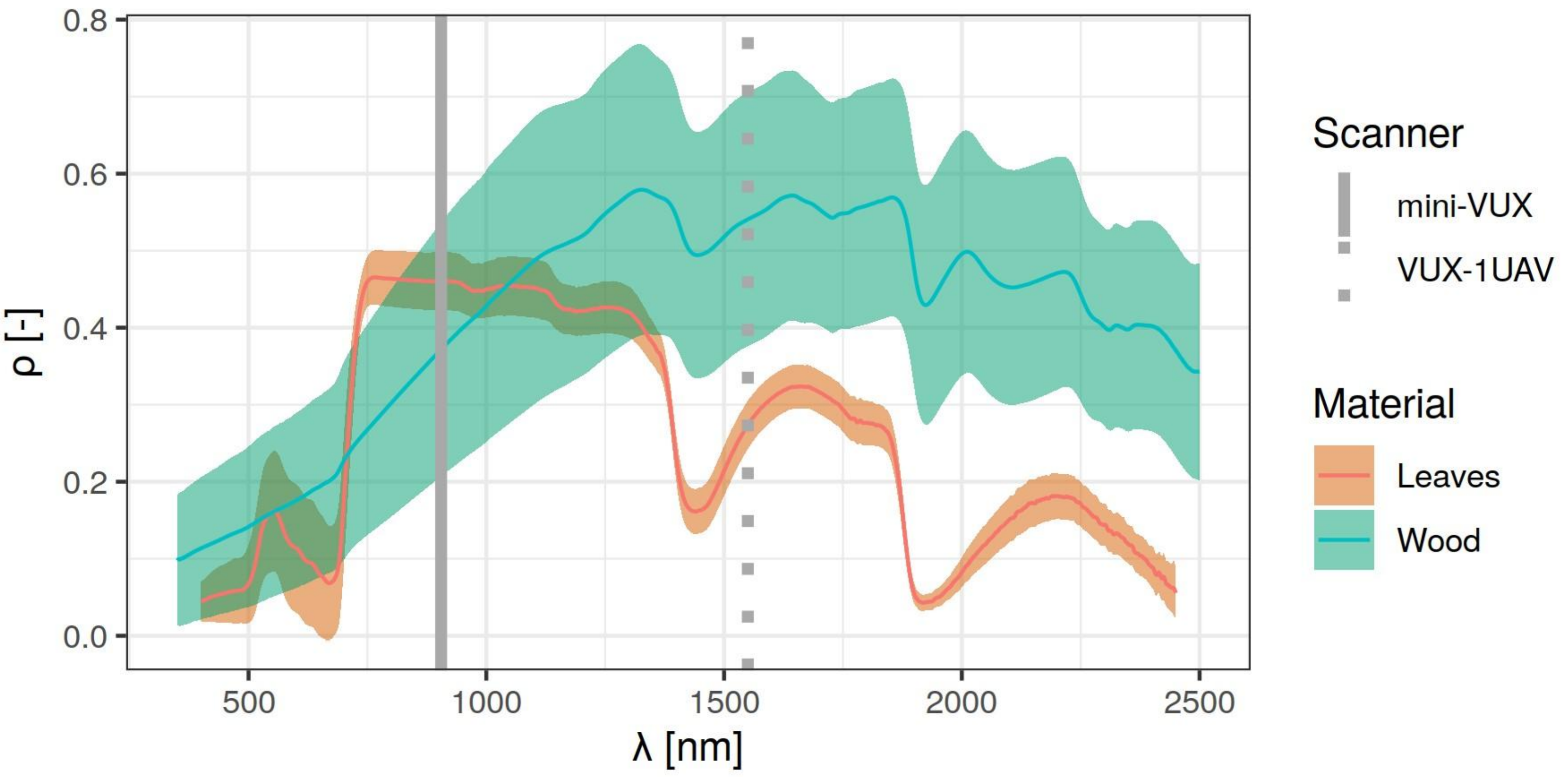
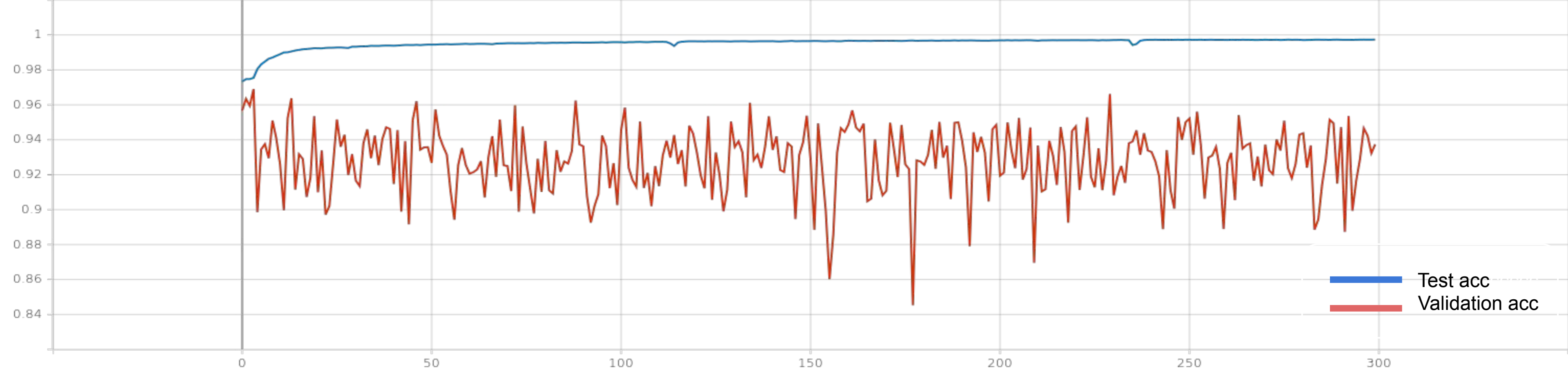
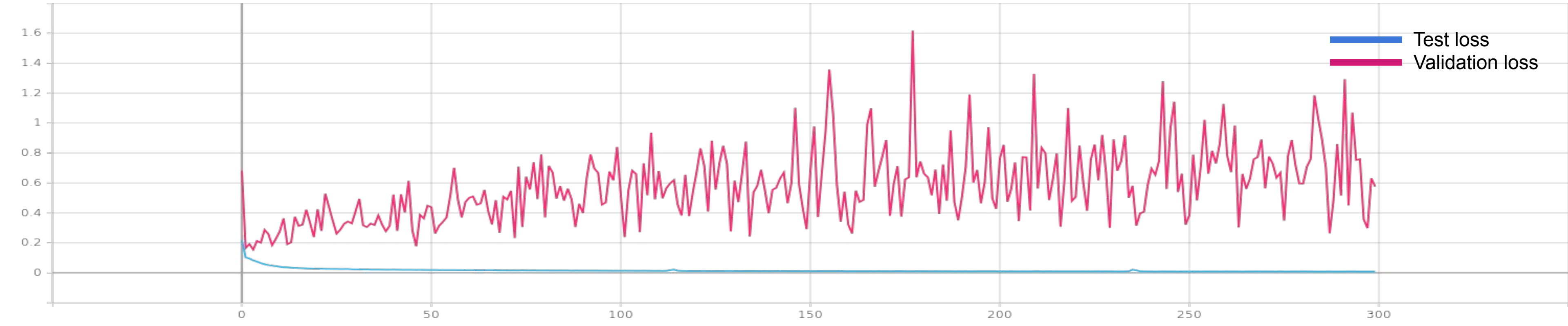


Figure 13. reflectance ratio (intensity), ULS (905 nm) vs TLS (1550 nm), ***Greg Vincent***



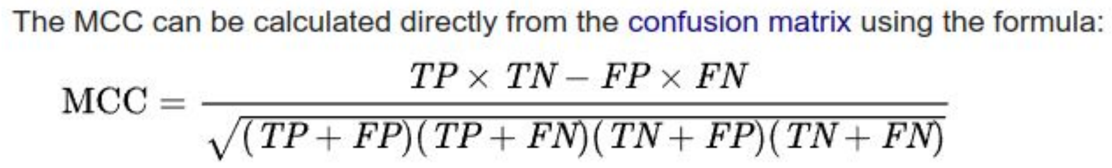
(a) accuracy , 300 epochs



(b) loss, 300 epochs

Figure 14. Plot loss and accuracy for training 300 epochs

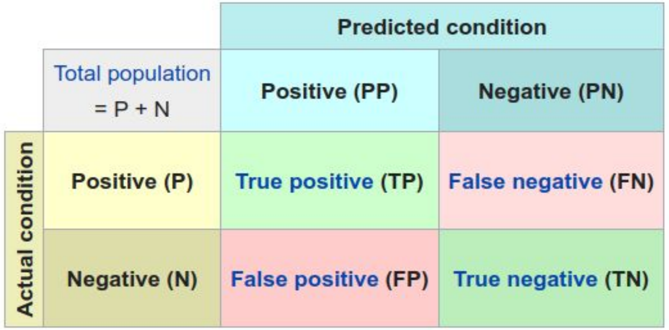
## 2.4 Matthew Coefficient Correlation (MCC)



The MCC can be calculated directly from the confusion matrix using the formula:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Fig 13. Matthew Coefficient Correlation / Phi coefficient



| | | Predicted condition | |
|---|---|---|---|
| | Total population = P + N | Positive (PP) | Negative (PN) |
| Actual condition | Positive (P) | True positive (TP) | False negative (FN) |
| | Negative (N) | False positive (FP) | True negative (TN) |

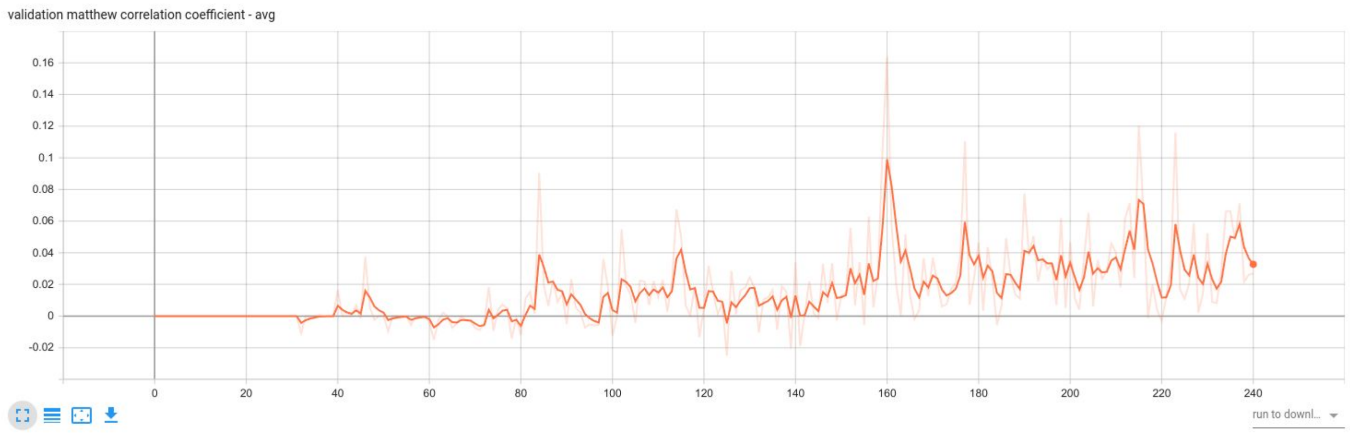


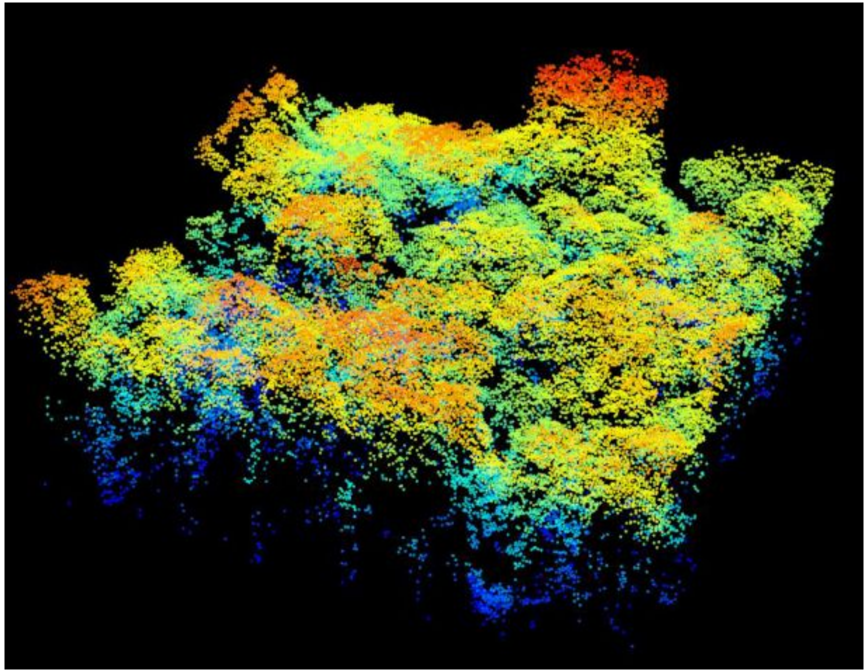
Fig 15. MCC is a good metric for class imbalance case

|  |  | Prediction |  |
|---|---|---|---|
|  | Total test point = 100000 | Wood | Leaf |
| True situation | Wood | 328 | 3182 |
|  | Leaf | 4325 | 92165 |

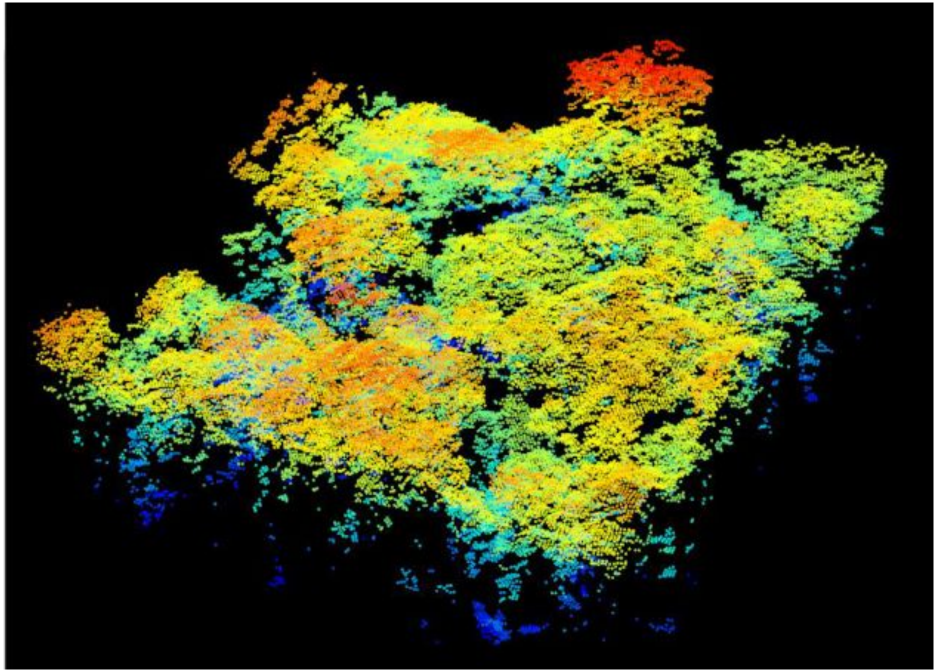
Figure 13. Confusion Matrix for the best result so far (sample size=5000 point, epoch = 546)

## Perspectives

- Improving existing DL prototype model
- Limits of current estimators of vegetation density
  - estimation of clumping parameter required
  - study spatial dependencies by using hierarchical Bayesian models.
- The censorship bias of undetected interceptions
  - undetected interceptions biases the calculated signal attenuation and the estimated leaf areas
  - model the effect and correct this bias



(a) Airborne Riegl LMS-Q780



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

Figure 16. 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.

# Reference

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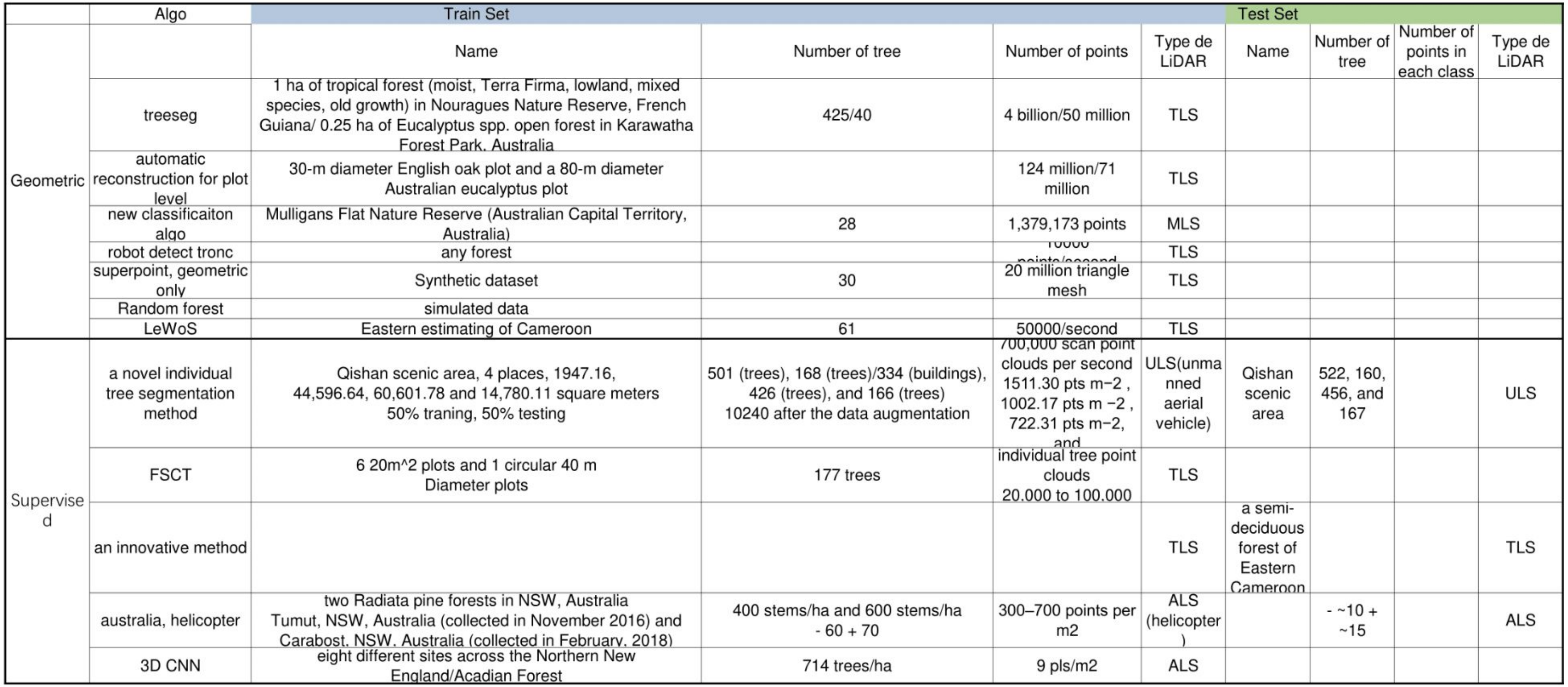
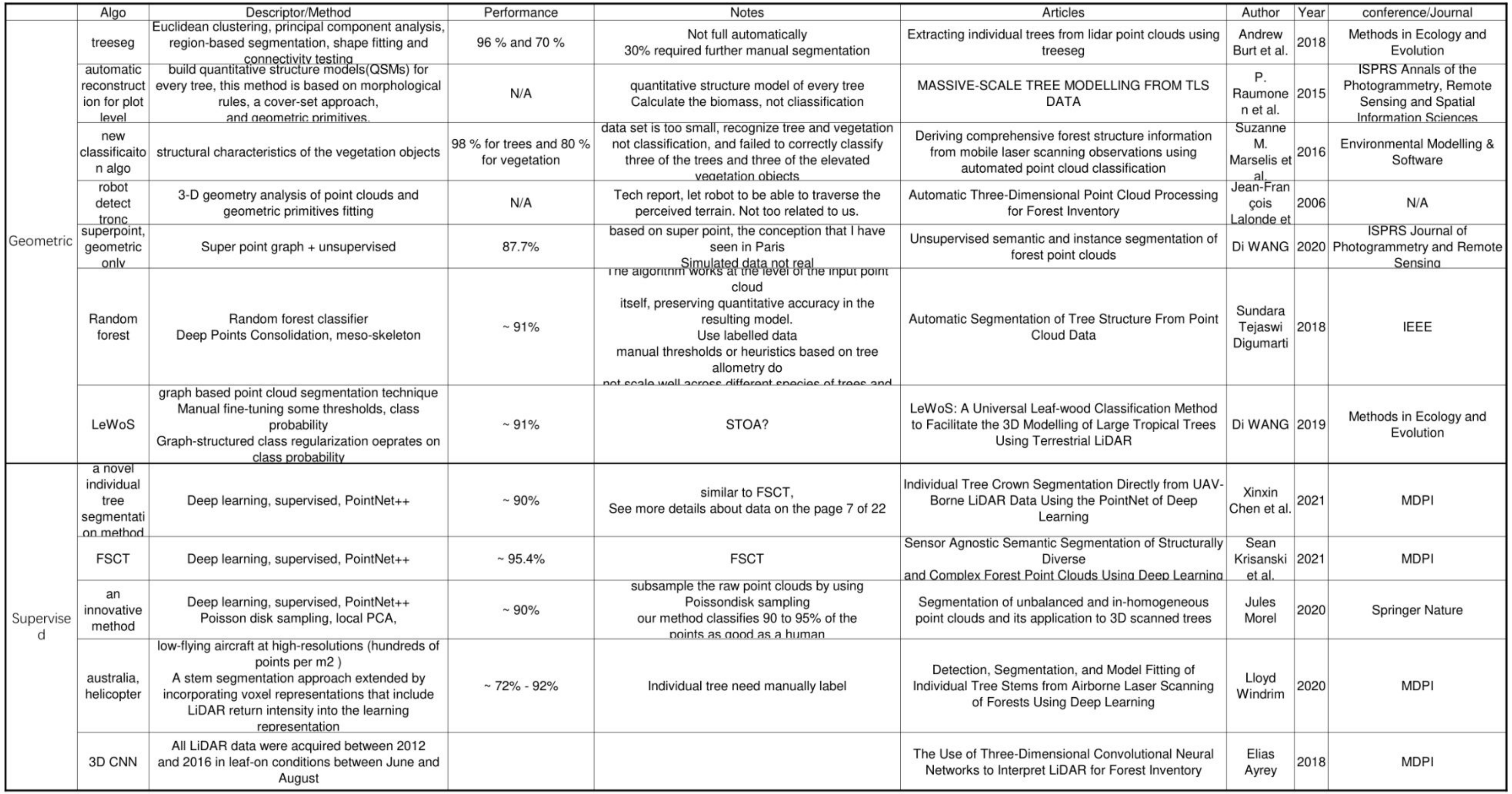
# Annexe A. Compare 12 different methods



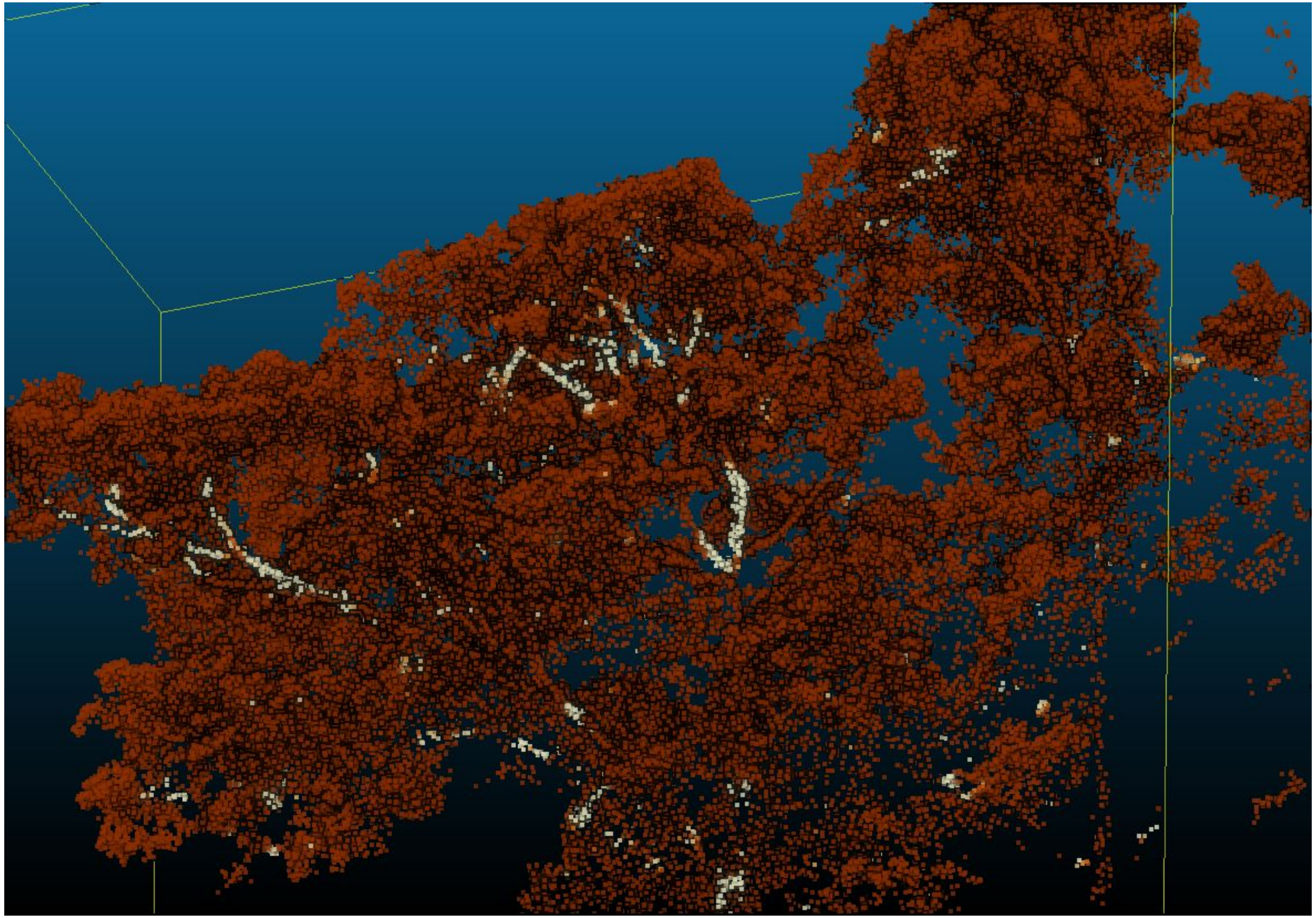
| | Algo | Train Set | | | | Test Set | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Name | Number of tree | Number of points | Type de LiDAR | Name | Number of tree | Number of points in each class | Type de LiDAR |
| Geometric | treeseg | 1 ha of tropical forest (moist, Terra Firma, lowland, mixed species, old growth) in Nouragues Nature Reserve, French Guiana/ 0.25 ha of Eucalyptus spp. open forest in Karawatha Forest Park, Australia | 425/40 | 4 billion/50 million | TLS | | | | |
| | automatic reconstruction for plot level | 30-m diameter English oak plot and a 80-m diameter Australian eucalyptus plot | | 124 million/71 million | TLS | | | | |
| | new classificaiton algo | Mulligans Flat Nature Reserve (Australian Capital Territory, Australia) | 28 | 1,379,173 points | MLS | | | | |
| | robot detect tronc | any forest | | 10000 points/second | TLS | | | | |
| | superpoint, geometric only | Synthetic dataset | 30 | 20 million triangle mesh | TLS | | | | |
| | Random forest | simulated data | | | | | | | |
| | LeWoS | Eastern estimating of Cameroon | 61 | 50000/second | TLS | | | | |
| Supervised | a novel individual tree segmentation method | Qishan scenic area, 4 places, 1947.16, 44,596.64, 60,601.78 and 14,780.11 square meters 50% traning, 50% testing | 501 (trees), 168 (trees)/334 (buildings), 426 (trees), and 166 (trees) 10240 after the data augmentation | 700,000 scan point clouds per second 1511.30 pts m−2 , 1002.17 pts m −2 , 722.31 pts m−2, and | ULS(unmanned aerial vehicle) | Qishan scenic area | 522, 160, 456, and 167 | | ULS |
| | FSCT | 6 20m^2 plots and 1 circular 40 m Diameter plots | 177 trees | individual tree point clouds 20.000 to 100.000 | TLS | | | | |
| | an innovative method | | | | TLS | a semi-deciduous forest of Eastern Cameroon | | | TLS |
| | australia, helicopter | two Radiata pine forests in NSW, Australia Tumut, NSW, Australia (collected in November 2016) and Carabost, NSW, Australia (collected in February, 2018) | 400 stems/ha and 600 stems/ha - 60 + 70 | 300–700 points per m2 | ALS (helicopter) | | - ~10 + ~15 | | ALS |
| | 3D CNN | eight different sites across the Northern New England/Acadian Forest | 714 trees/ha | 9 pls/m2 | ALS | | | | |

# Annexe A-bis. Compare 12 different methods



| | Algo | Descriptor/Method | Performance | Notes | Articles | Author | Year | conference/Journal |
|---|---|---|---|---|---|---|---|---|
| | treeseg | Euclidean clustering, principal component analysis, region-based segmentation, shape fitting and connectivity testing | 96 % and 70 % | Not full automatically<br>30% required further manual segmentation | Extracting individual trees from lidar point clouds using treeseg | Andrew Burt et al. | 2018 | Methods in Ecology and Evolution |
| | automatic reconstruction for plot level | build quantitative structure models(QSMs) for every tree, this method is based on morphological rules, a cover-set approach, and geometric primitives. | N/A | quantitative structure model of every tree<br>Calculate the biomass, not cliassification | MASSIVE-SCALE TREE MODELLING FROM TLS DATA | P. Raumonen et al. | 2015 | ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences |
| | new classificaiton algo | structural characteristics of the vegetation objects | 98 % for trees and 80 % for vegetation | data set is too small, recognize tree and vegetation not classification, and failed to correctly classify three of the trees and three of the elevated vegetation objects | Deriving comprehensive forest structure information from mobile laser scanning observations using automated point cloud classification | Suzanne M. Marselis et al. | 2016 | Environmental Modelling & Software |
| | robot detect tronc | 3-D geometry analysis of point clouds and geometric primitives fitting | N/A | Tech report, let robot to be able to traverse the perceived terrain. Not too related to us. | Automatic Three-Dimensional Point Cloud Processing for Forest Inventory | Jean-François Lalonde et | 2006 | N/A |
| Geometric | superpoint, geometric only | Super point graph + unsupervised | 87.7% | based on super point, the conception that I have seen in Paris<br>Simulated data not real | Unsupervised semantic and instance segmentation of forest point clouds | Di WANG | 2020 | ISPRS Journal of Photogrammetry and Remote Sensing |
| | Random forest | Random forest classifier<br>Deep Points Consolidation, meso-skeleton | ~ 91% | The algorithm works at the level of the input point cloud<br>itself, preserving quantitative accuracy in the resulting model.<br>Use labelled data<br>manual thresholds or heuristics based on tree allometry do<br>not scale well across different species of trees and | Automatic Segmentation of Tree Structure From Point Cloud Data | Sundara Tejaswi Digumarti | 2018 | IEEE |
| | LeWoS | graph based point cloud segmentation technique<br>Manual fine-tuning some thresholds, class probability<br>Graph-structured class regularization oeprates on class probability | ~ 91% | STOA? | LeWoS: A Universal Leaf-wood Classification Method to Facilitate the 3D Modelling of Large Tropical Trees Using Terrestrial LiDAR | Di WANG | 2019 | Methods in Ecology and Evolution |
| | a novel individual tree segmentation method | Deep learning, supervised, PointNet++ | ~ 90% | similar to FSCT,<br>See more details about data on the page 7 of 22 | Individual Tree Crown Segmentation Directly from UAV-Borne LiDAR Data Using the PointNet of Deep Learning | Xinxin Chen et al. | 2021 | MDPI |
| | FSCT | Deep learning, supervised, PointNet++ | ~ 95.4% | FSCT | Sensor Agnostic Semantic Segmentation of Structurally Diverse<br>and Complex Forest Point Clouds Using Deep Learning | Sean Krisanski et al. | 2021 | MDPI |
| Supervised | an innovative method | Deep learning, supervised, PointNet++<br>Poisson disk sampling, local PCA, | ~ 90% | subsample the raw point clouds by using Poissondisk sampling<br>our method classifies 90 to 95% of the points as good as a human | Segmentation of unbalanced and in-homogeneous point clouds and its application to 3D scanned trees | Jules Morel | 2020 | Springer Nature |
| | australia, helicopter | low-flying aircraft at high-resolutions (hundreds of points per m2 )<br>A stem segmentation approach extended by incorporating voxel representations that include LiDAR return intensity into the learning representation | ~ 72% - 92% | Individual tree need manually label | Detection, Segmentation, and Model Fitting of Individual Tree Stems from Airborne Laser Scanning of Forests Using Deep Learning | Lloyd Windrim | 2020 | MDPI |
| | 3D CNN | All LiDAR data were acquired between 2012 and 2016 in leaf-on conditions between June and August | | | The Use of Three-Dimensional Convolutional Neural Networks to Interpret LiDAR for Forest Inventory | Elias Ayrey | 2018 | MDPI |

## Annexe B. Small branches can also be detected



# Annexe C. merged TLS data

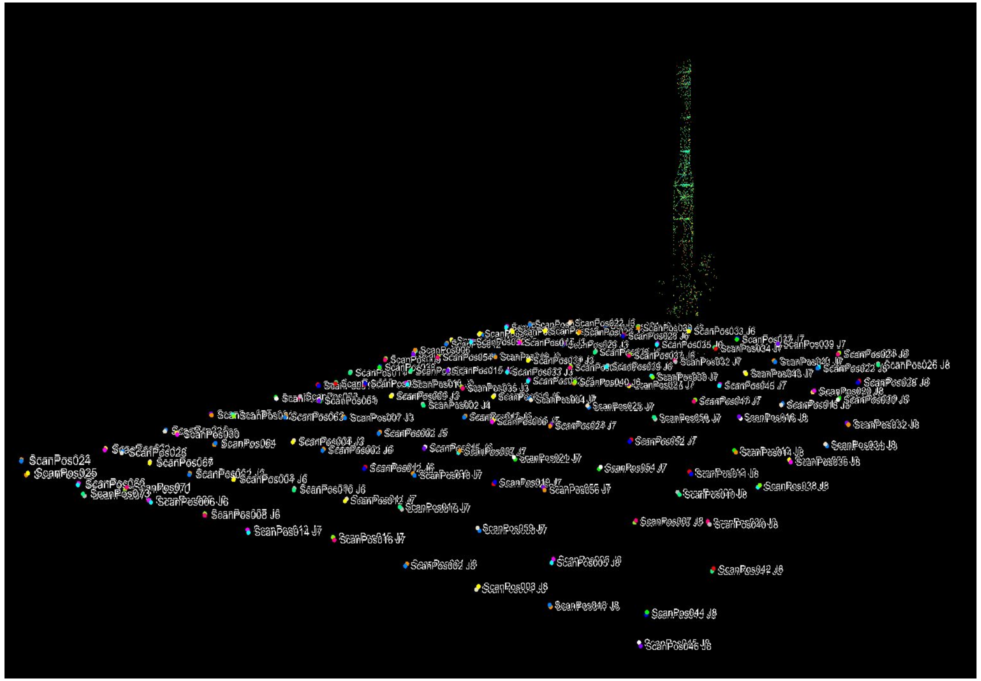


Figure 2. Different scanning position under tower

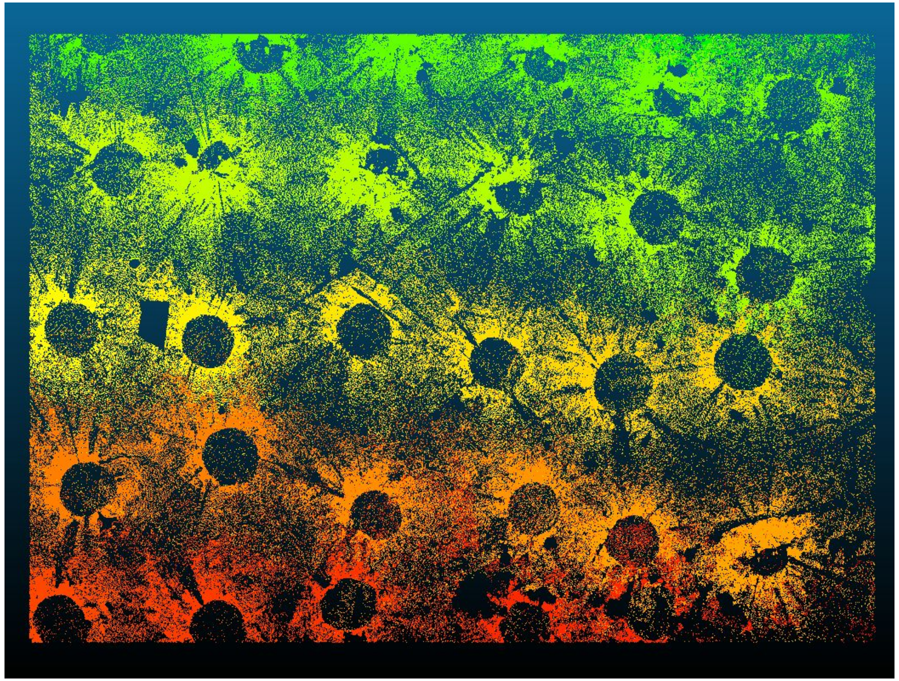
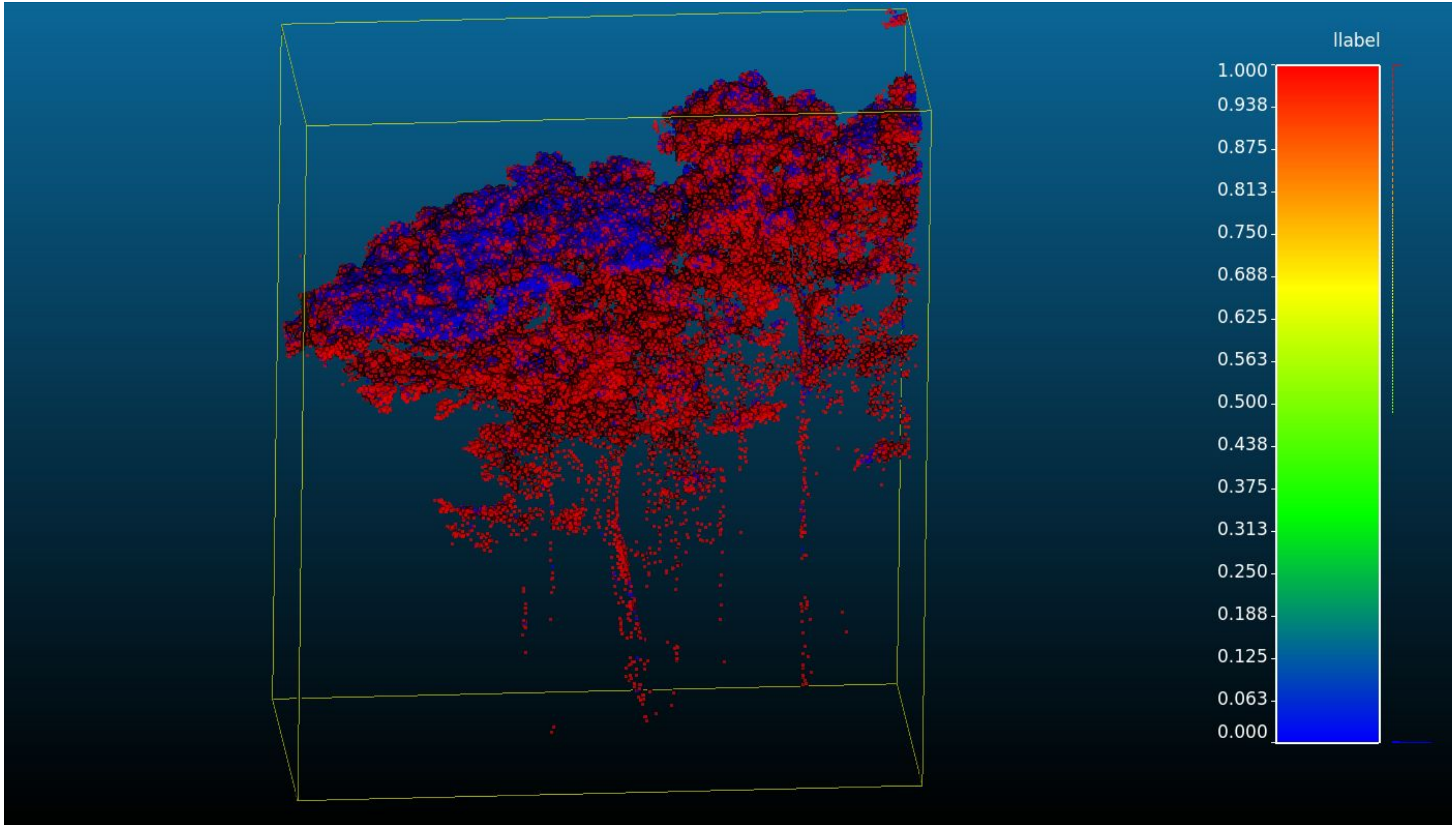


Figure 3. A part of TLS Digital Terrain Model (DTM)

## Annexe D. Training on TLS predict on ULS



## Prototype model : Point-Voxel based neural network

Semantic segmentation on ULS data

- ❏ label transfer from TLS to ULS data
- ❏ training with TLS and fine-tuning with ULS
- ❏ **Subsample ULS-like data from the TLS data**

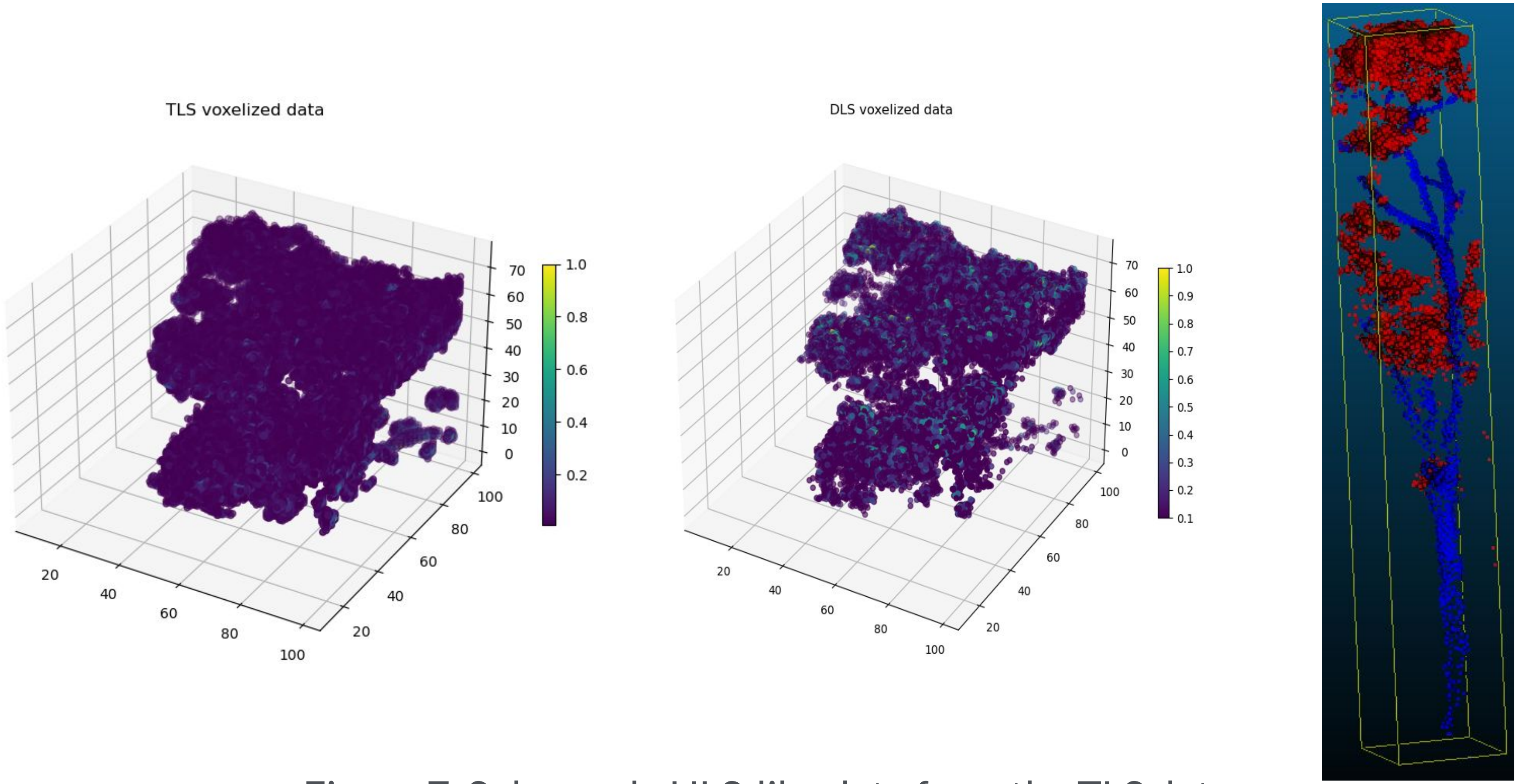


Figure 7. Subsample ULS-like data from the TLS data

## 1.3 Subsample ULS-like data from the TLS data

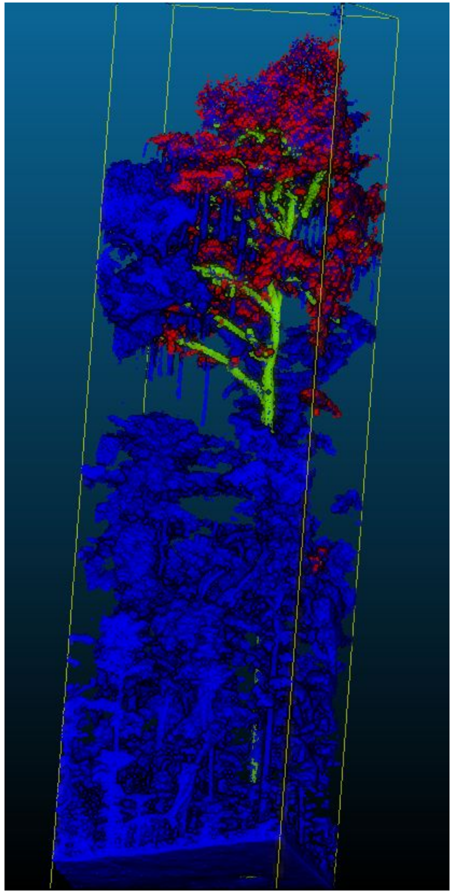


Fig 4: TLS 36.laz

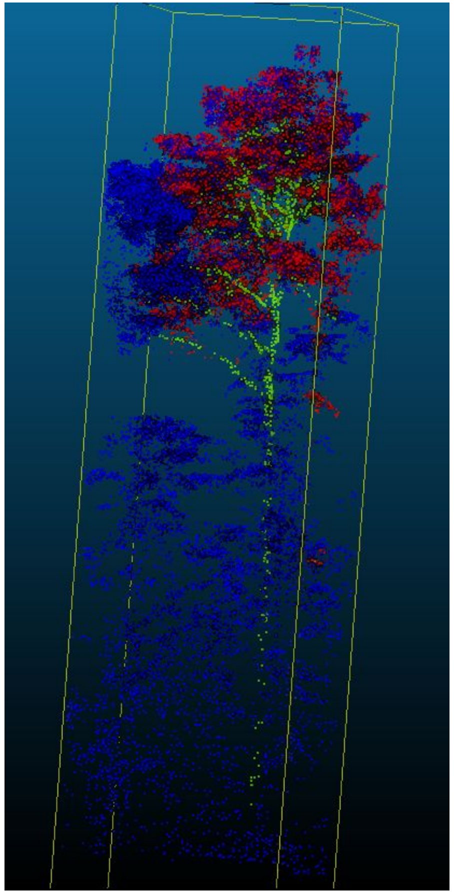
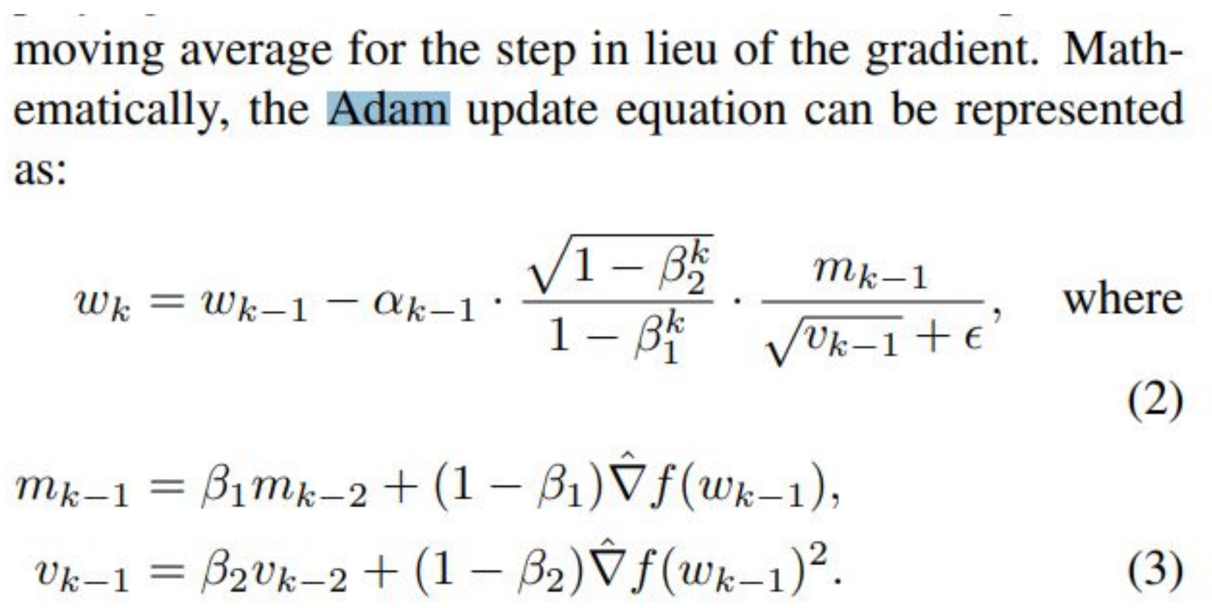


Fig 5: ULS-like data from TLS 36.laz

## 2.3 Adam or SGD + Nestrov momentum?



moving average for the step in lieu of the gradient. Mathematically, the Adam update equation can be represented as:

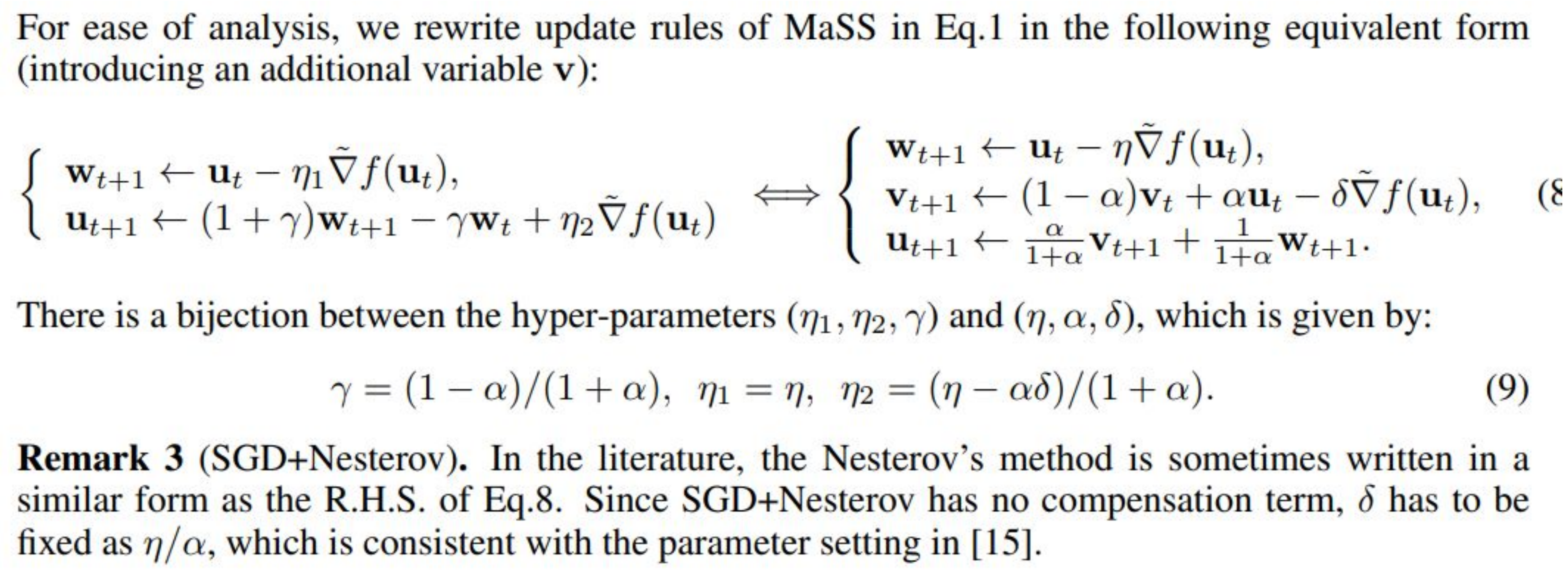
$$w_k = w_{k-1} - \alpha_{k-1} \cdot \frac{\sqrt{1-\beta_2^k}}{1-\beta_1^k} \cdot \frac{m_{k-1}}{\sqrt{v_{k-1}}+\epsilon}, \quad \text{where} \tag{2}$$

$$m_{k-1} = \beta_1 m_{k-2} + (1-\beta_1)\hat{\nabla} f(w_{k-1}),$$
$$v_{k-1} = \beta_2 v_{k-2} + (1-\beta_2)\hat{\nabla} f(w_{k-1})^2. \tag{3}$$

Fig 9. Adam update equation

[*] Nitish Shirish Keskar, Richard Socher, “Improving Generalization Performance by Switching from Adam to SGD”

## 2.3 Adam or SGD + Nestrov momentum?



For ease of analysis, we rewrite update rules of MaSS in Eq.1 in the following equivalent form (introducing an additional variable $\mathbf{v}$):

$$\begin{cases} \mathbf{w}_{t+1} \leftarrow \mathbf{u}_t - \eta_1 \tilde{\nabla} f(\mathbf{u}_t), \\ \mathbf{u}_{t+1} \leftarrow (1+\gamma)\mathbf{w}_{t+1} - \gamma \mathbf{w}_t + \eta_2 \tilde{\nabla} f(\mathbf{u}_t) \end{cases} \Longleftrightarrow \begin{cases} \mathbf{w}_{t+1} \leftarrow \mathbf{u}_t - \eta \tilde{\nabla} f(\mathbf{u}_t), \\ \mathbf{v}_{t+1} \leftarrow (1-\alpha)\mathbf{v}_t + \alpha \mathbf{u}_t - \delta \tilde{\nabla} f(\mathbf{u}_t), \\ \mathbf{u}_{t+1} \leftarrow \frac{\alpha}{1+\alpha}\mathbf{v}_{t+1} + \frac{1}{1+\alpha}\mathbf{w}_{t+1}. \end{cases} \quad (8$$

There is a bijection between the hyper-parameters $(\eta_1, \eta_2, \gamma)$ and $(\eta, \alpha, \delta)$, which is given by:

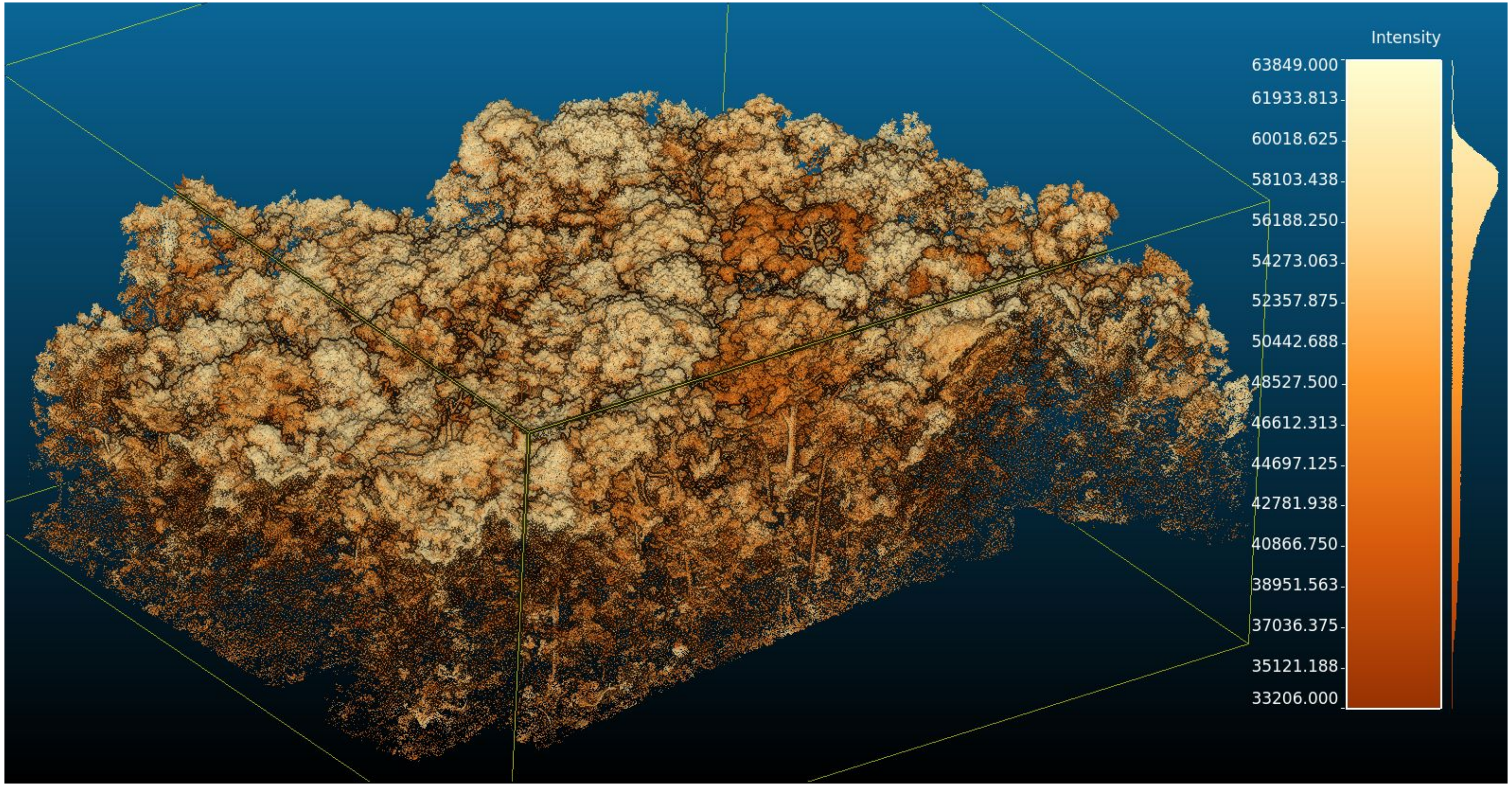
$$\gamma = (1-\alpha)/(1+\alpha), \;\; \eta_1 = \eta, \;\; \eta_2 = (\eta - \alpha\delta)/(1+\alpha). \qquad (9)$$

**Remark 3** (SGD+Nesterov)**.** In the literature, the Nesterov's method is sometimes written in a similar form as the R.H.S. of Eq.8. Since SGD+Nesterov has no compensation term, $\delta$ has to be fixed as $\eta/\alpha$, which is consistent with the parameter setting in [15].

Fig 10. Nestrove SGD update equation

[*] Chaoyue Liu, Mikhail Belkin, "Accelerating SGD with momentum for over-parameterized learning"

# Annexe 2. ULS merged data (intensity)



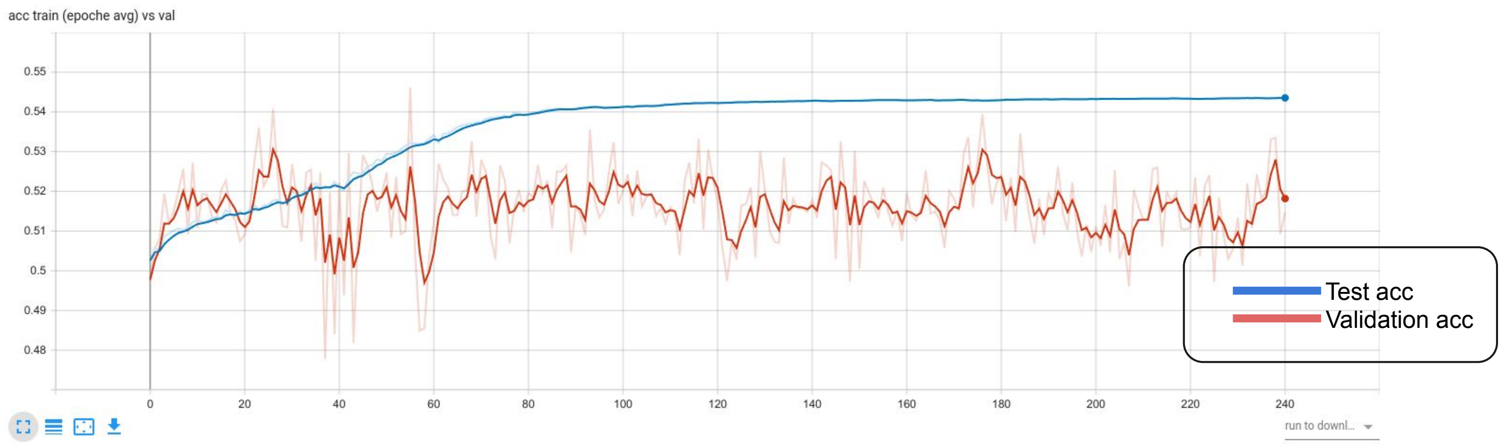


Fig 11. Accuracy of 300 epochs on new dataset, SGD + Nestrov, class weights

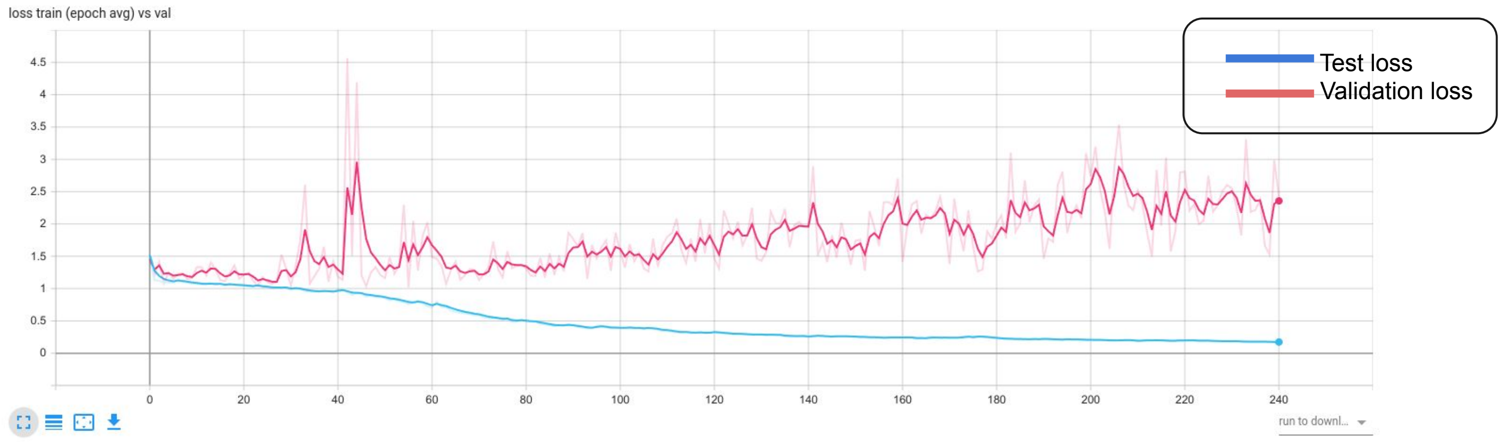
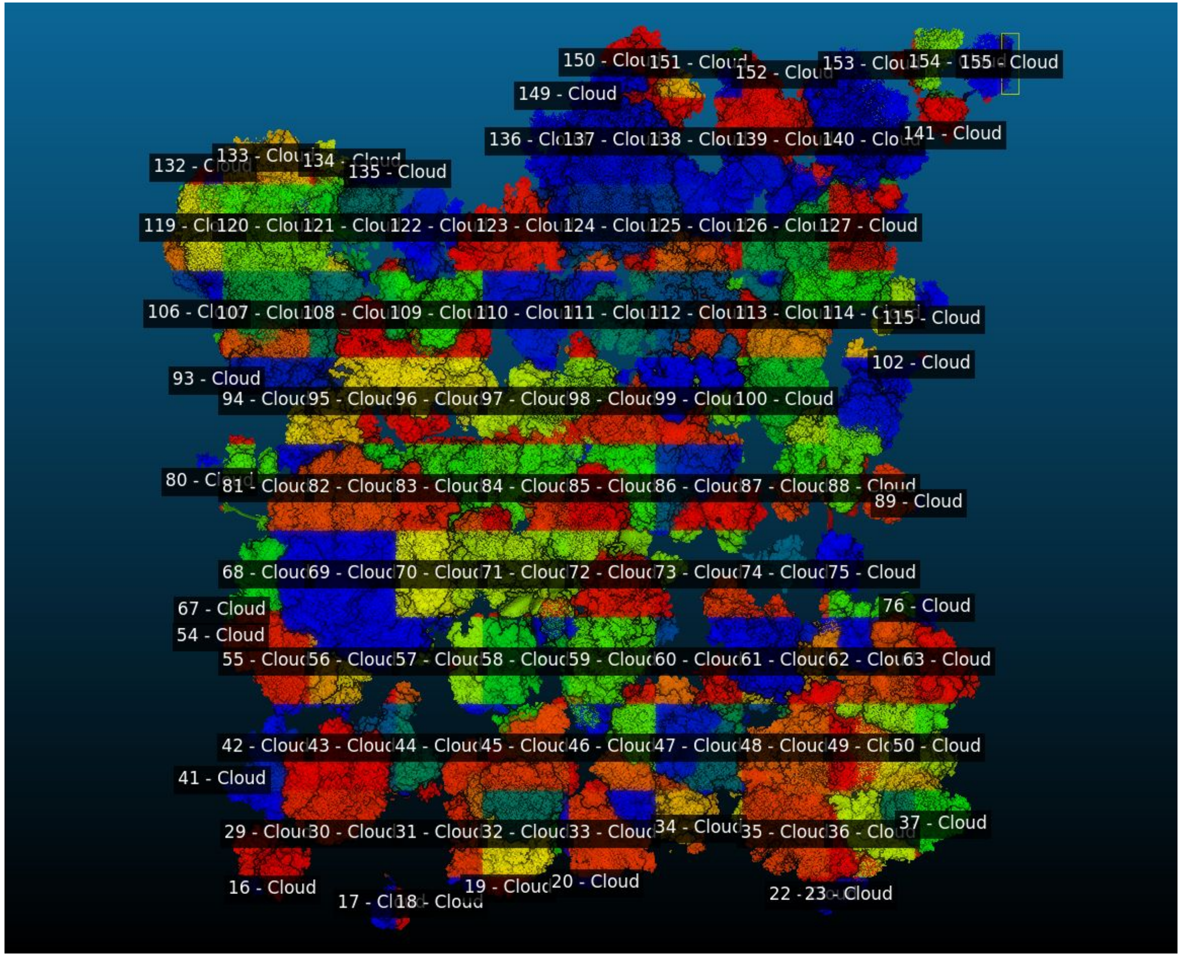
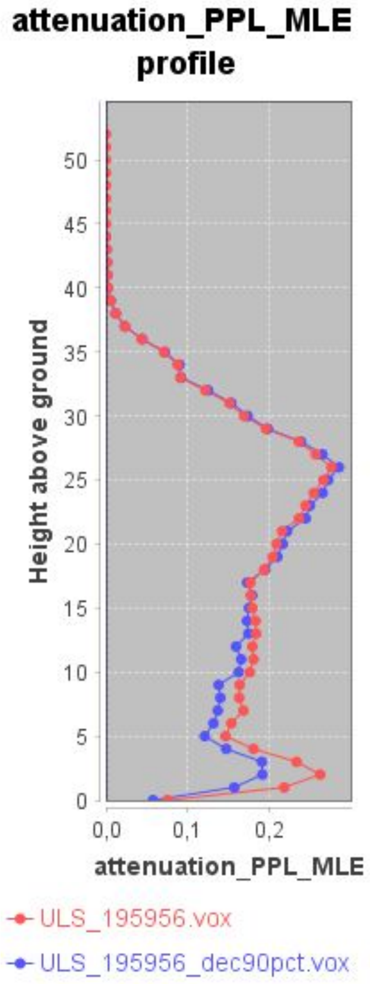


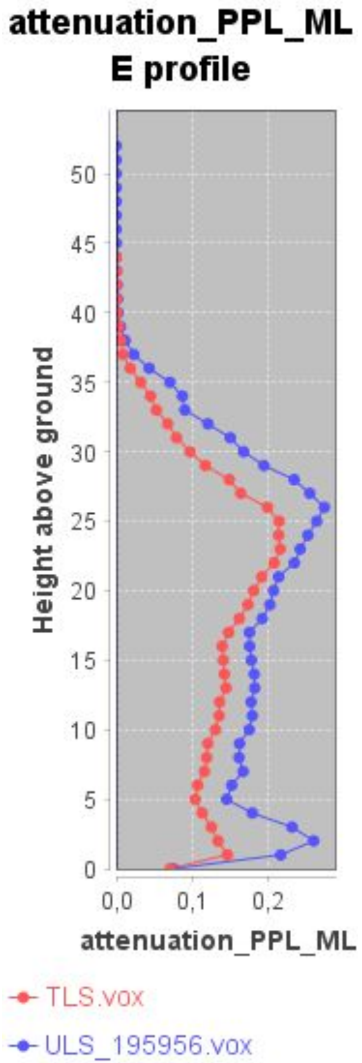
Fig 12. Loss of 300 epochs on new dataset, SGD + Nestrov, class weights

# Annexe 3. Tls parcels with labels



# Attenuation





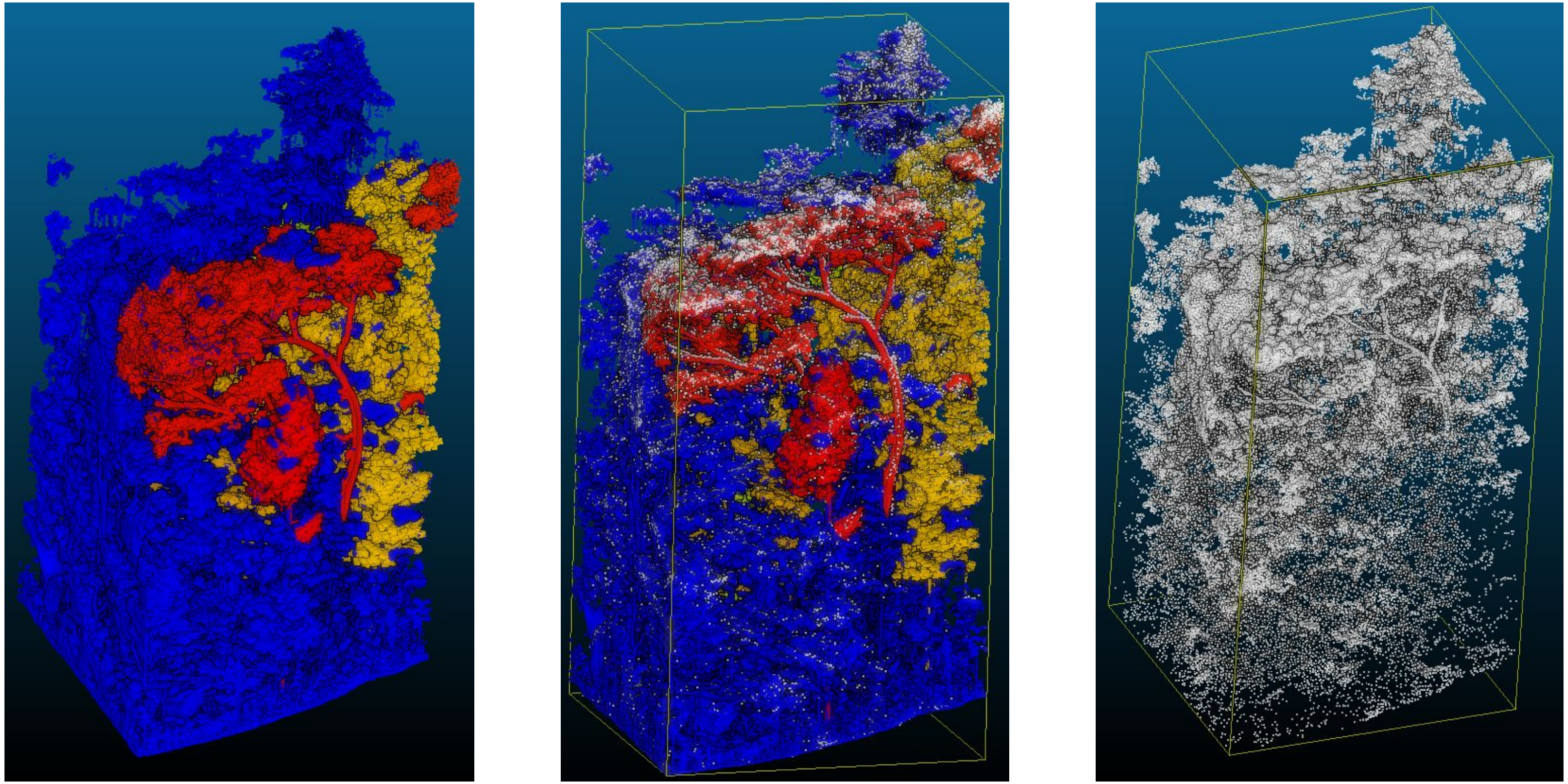

(a) TLS (b) overlap (c) ULS

Figure 4. TLS and ULS co-registration

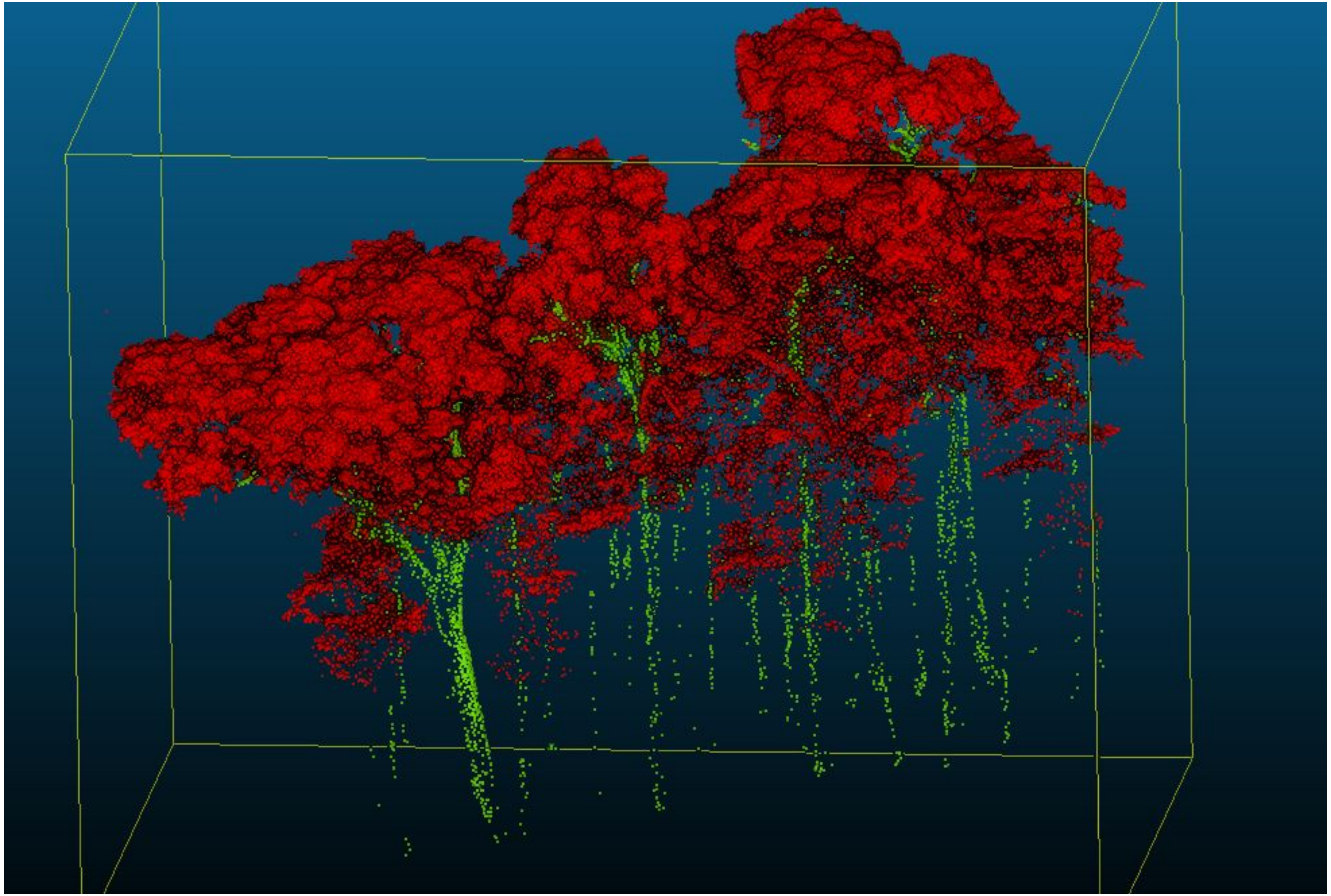


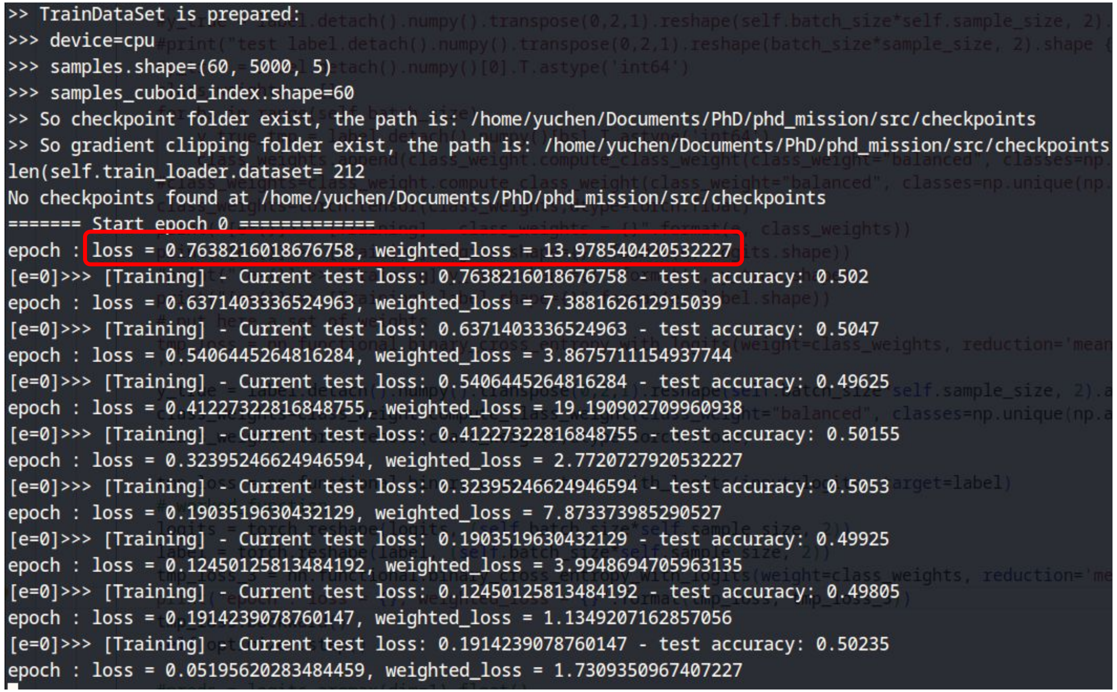
Figure 6. label transfer from TLS to ULS data

# NEURAL NETWORKS FOR LEAF/WOOD DISCRIMINATION IN LIDAR FOR LEAF AREA DENSITY ESTIMATION

PhD student:
Yuchen BAI

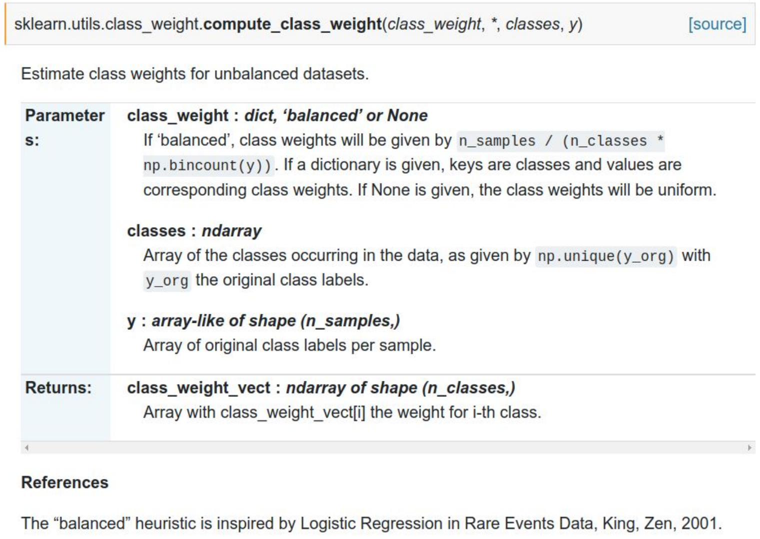
*Supervisor:*
Jean-Baptiste DURAND
Grégoire VINCENT
Florence FORBES

## 2.2 Weighted loss/class weights for wood&leaf



```
>> TrainDataSet is prepared:
>>> device=cpu
>>> samples.shape=(60, 5000, 5)
>>> samples_cuboid_index.shape=60
>> So checkpoint folder exist, the path is: /home/yuchen/Documents/PhD/phd_mission/src/checkpoints
>> So gradient clipping folder exist, the path is: /home/yuchen/Documents/PhD/phd_mission/src/checkpoints
len(self.train_loader.dataset= 212
No checkpoints found at /home/yuchen/Documents/PhD/phd_mission/src/checkpoints
======= Start epoch 0 =============
epoch : loss = 0.7638216018676758, weighted_loss = 13.978540420532227
[e=0]>>> [Training] - Current test loss: 0.7638216018676758 - test accuracy: 0.502
epoch : loss = 0.6371403336524963, weighted_loss = 7.388162612915039
[e=0]>>> [Training] - Current test loss: 0.6371403336524963 - test accuracy: 0.5047
epoch : loss = 0.5406445264816284, weighted_loss = 3.8675711154937744
[e=0]>>> [Training] - Current test loss: 0.5406445264816284 - test accuracy: 0.49625
epoch : loss = 0.41227322816848755, weighted_loss = 19.190902709960938
[e=0]>>> [Training] - Current test loss: 0.41227322816848755 - test accuracy: 0.50155
epoch : loss = 0.32395246624946594, weighted_loss = 2.7720727920532227
[e=0]>>> [Training] - Current test loss: 0.32395246624946594 - test accuracy: 0.5053
epoch : loss = 0.1903519630432129, weighted_loss = 7.873373985290527
[e=0]>>> [Training] - Current test loss: 0.1903519630432129 - test accuracy: 0.49925
epoch : loss = 0.12450125813484192, weighted_loss = 3.9948694705963135
[e=0]>>> [Training] - Current test loss: 0.12450125813484192 - test accuracy: 0.49805
epoch : loss = 0.1914239078760147, weighted_loss = 1.1349207162857056
[e=0]>>> [Training] - Current test loss: 0.1914239078760147 - test accuracy: 0.50235
epoch : loss = 0.05195620283484459, weighted_loss = 1.7309350967407227
```

Fig 7: wood point predictions are dominant



sklearn.utils.class_weight.**compute_class_weight**(*class_weight*, *, *classes*, *y*) [source]

Estimate class weights for unbalanced datasets.

**Parameters:**

**class_weight : *dict, 'balanced' or None***
If 'balanced', class weights will be given by `n_samples / (n_classes * np.bincount(y))`. If a dictionary is given, keys are classes and values are corresponding class weights. If None is given, the class weights will be uniform.

**classes : *ndarray***
Array of the classes occurring in the data, as given by `np.unique(y_org)` with `y_org` the original class labels.

**y : *array-like of shape (n_samples,)***
Array of original class labels per sample.

**Returns:**

**class_weight_vect : *ndarray of shape (n_classes,)***
Array with class_weight_vect[i] the weight for i-th class.

**References**

The "balanced" heuristic is inspired by Logistic Regression in Rare Events Data, King, Zen, 2001.

Fig 8: Class weights given by sklearn are better than preset