# Advanced Machine Learning Techniques for 3D Semantic Segmentation & Precision Tree counting in UAV LiDAR and Airborne LiDAR Point clouds

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ACKNOWLEDGMENT

*We would like to express our sincere gratitude to "Société Topographie Informatique" for generously providing the data necessary for the completion of this work.*
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ACKNOWLEDGMENT

*This work was carried out under the auspices of the Hassan II Institute of Agronomy and Veterinary Medicine, within the Department of Cartography-Photogrammetry, School of Geomatics and Geodesy, to whom we would like to express our sincere thanks.*
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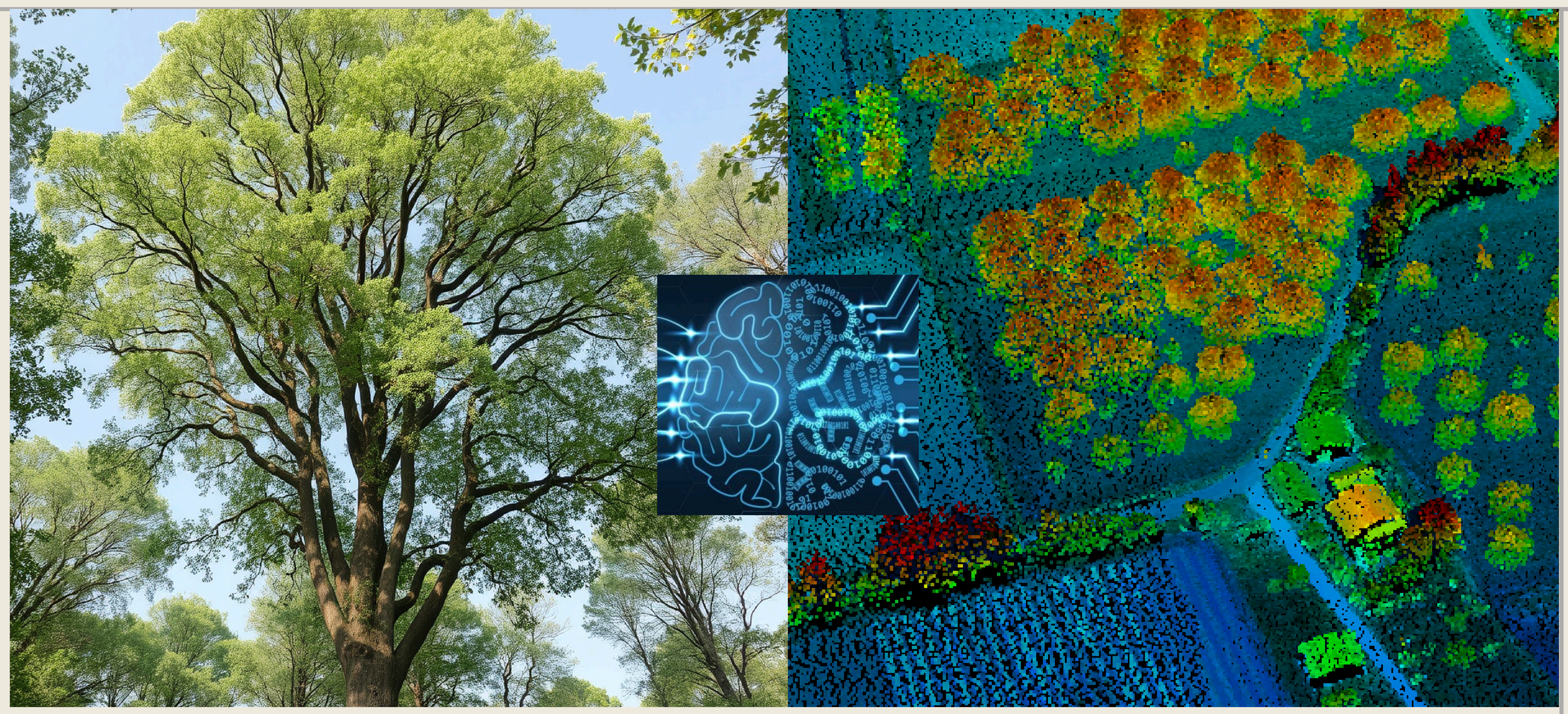
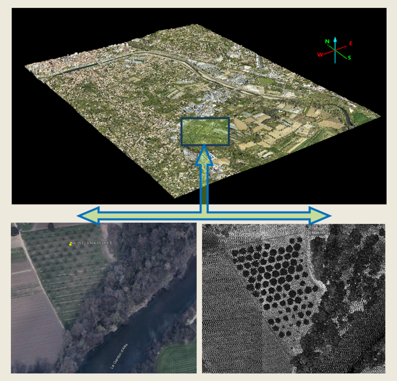


## 01. Introduction

Trees play an essential role in our lives, producing oxygen through photosynthesis and sequestering carbon dioxide to help combat climate change[1]. They provide shelter for many species, thus preserving biodiversity [2]. The challenge of accurately counting trees in large-scale environmental monitoring has been a persistent concern . Traditional manual methods are labor-intensive, time-consuming, and prone to human error, making them impractical for extensive forest inventories [3]. This study explores using LiDAR data and semantic segmentation to overcome these limitations. How can advanced technologies like LiDAR and machine learning improve the accuracy of tree counting?

## 02.Materials&Methods

Two point clouds were acquired for this work :



- The first dataset was collected in Ales in France, using the airborne lidar Galaxy T1000 from Teledyne Optech, mounted on a Piper Cheyenne II XL aircraft.

-This system has a pulse repetition frequency of 1000 kHz, producing a density of 20 pts/m² and up to 8 returns per pulse.

Figure 1: First dataset in Ales city

The second point cloud was acquired with the Zenmuse L2 lidar from DJI, installed on a Matrice 350 RTK drone.

This lidar has a density of 550 pts/m² and up to 5 returns per pulse, generating 6,408,198 points.

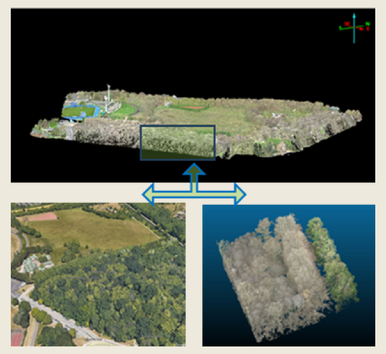


Figure 2: Second dataset of "la Garenne" leisure park

Both datasets were processed using CloudCompare version 2.13.0 on a workstation equipped with an NVIDIA RTX A5000 GPU.

### *Related literature*

[1] S. S. Ramanan, A. Arunachalam, A. K. Shanker, K. B. Sridhar, A. Keerthika, et S. B. Chavan, « Oxygen production potential of trees – unrealistic perception in India », Current Science, vol. 123, no 8, p. 957-958, 2022.

[2] T. S. Eisenman et al., « Urban trees, air quality, and asthma: An interdisciplinary review », Landscape and Urban Planning, vol. 187, p. 47-59, juill. 2019, doi: 10.1016/j.landurbplan.2019.02.010.

[3] M. Yang et al., « A Review of General Methods for Quantifying and Estimating Urban Trees and Biomass », Forests, vol. 13, no 4, Art. no 4, avr. 2022, doi: 10.3390/f13040616.

[4] M. Letard et al., « 3DMASC: Accessible, explainable 3D point clouds classification. Application to bi-spectral topo-bathymetric lidar data », ISPRS Journal of Photogrammetry and Remote Sensing, vol. 207, p. 175-197, janv. 2024, doi: 10.1016/j.isprsjprs.2023.11.022.

[5] Z. Xi et C. Hopkinson, « 3D Graph-Based Individual-Tree Isolation (Treeiso) from Terrestrial Laser Scanning Point Clouds », Remote Sensing, vol. 14, no 23, 2022, doi: 10.3390/rs14236116.

[6] C. Cabo, C. Ordóñez, C. A. López-Sánchez, et J. Armesto, « Automatic dendrometry: Tree detection, tree height and diameter estimation using terrestrial laser scanning », International Journal of Applied Earth Observation and Geoinformation, vol. 69, p. 164-174, juill. 2018, doi: 10.1016/j.jag.2018.01.011.

## 02.Materials&Methods

The method used for both airborne and UAV datasets is describing in Figure 5 below. After acquiring point clouds, we pre-process the data by removing noise points, coloring the points using photos taken simultaneously with two missions, normalizing the intensity to have a same scale of intensity, and selecting the area part of forest or parcel to obtain two representative sample subsets.

After the semantic segmentation of points using the "3dMasc" [4] machine learning method, we used the "Treeiso"[5] clustering method to isolate the trees, then separated the resulting file into elements to count trees, and finally compared the results obtained with those separated manually.

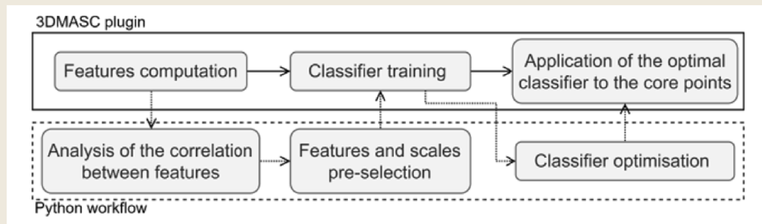



Figure. 3: Illustration of the 3D Multi-Attributes, Multi-Scale, Multi-Cloud (3DMASC) classification workflow.[4]

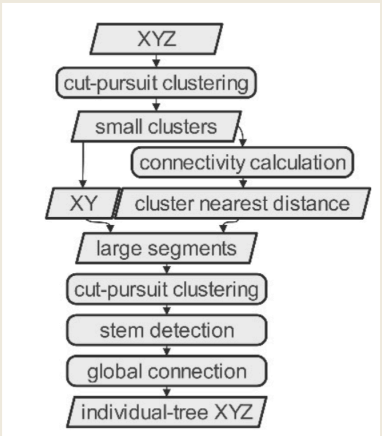



Figure 4 : treeiso's work [5]

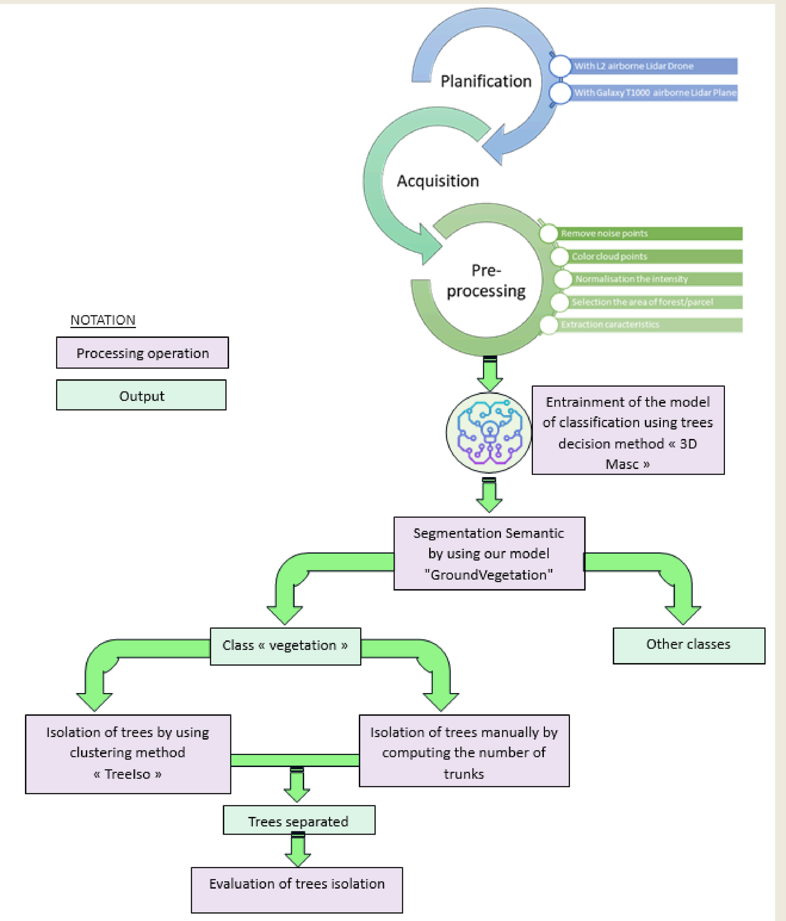


Figure 5: The general workflow of proposed approach

## 03. Results & Analysis

The results obtained for semantic segmentation and tree isolation are schematized in the figure 6 below.

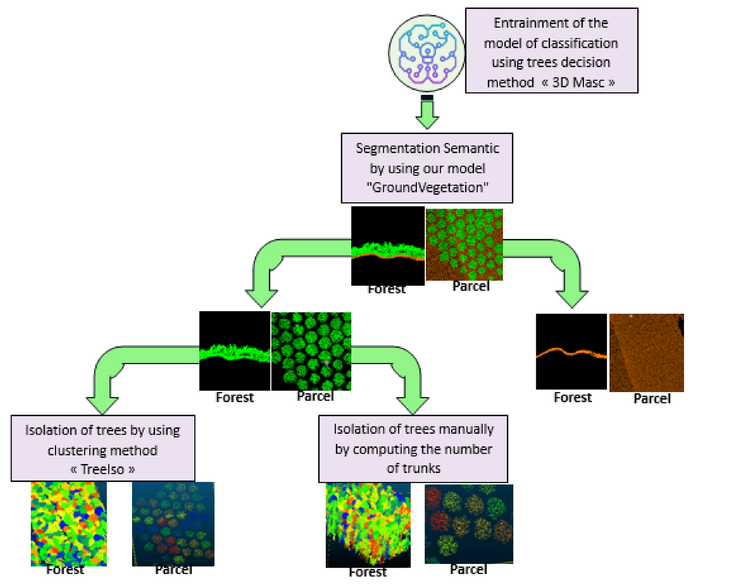


Figure 6: Semantic segmentation and tree isolation results.

The result of each operation can be detailed for each approach as below:

**A.Semantic segmentation**

The semantic segmentation was trained, tested and validated. For airborne LiDAR we obtained an overall accuracy of 0.99. The confusion matrix and the metrics of each class (precision, recall and F1-score) of our model "Ground Vegetation" is presented in the table I below. Additionally, for UAV LiDAR we attained an overall accuracy of 0.98 and a good metrics as outlined in table II below.

Table I: Matrix of confusion and the metrics of semantic segmentation for the first dataset in three classes: ground (2), medium vegetation (4) and high vegetation (5)

| | | Predicted | | | | | |
|---|---|---|---|---|---|---|---|
| | | Ground | Medium Vegetation | High Vegetation | Precision | Recall | F1-score |
| Real | Ground | 12978 | 20 | 5 | 0.99 | 1 | 0.99 |
| | Medium Vegetation | 90 | 210 | 76 | 0.77 | 0.56 | 0.65 |
| | High Vegetation | 32 | 41 | 8767 | 0.99 | 0.99 | 0.99 |

Table II: Matrix of confusion and the metrics of semantic segmentation for the first dataset in three classes: ground (2), medium vegetation (4) and high vegetation (5)

| | | Predicted | | | | | |
|---|---|---|---|---|---|---|---|
| | | Ground | Medium Vegetation | High Vegetation | Precision | Recall | F1-score |
| Real | Ground | 30905 | 1621 | 875 | 0.96 | 0.93 | 0.94 |
| | Medium Vegetation | 1019 | 54487 | 39678 | 0.77 | 0.57 | 0.66 |
| | High Vegetation | 411 | 14461 | 545229 | 0.93 | 0.97 | 0.95 |

**B. Isolation trees**

*Qualitative result :*

The qualitative results of the isolation trees method for both forest and parcel data with "TreeIso" method demonstrate its effectiveness in accurately isolating individual trees. The majority of trees have been well isolated correctly, as depicted in the figures 7 & 8 below.

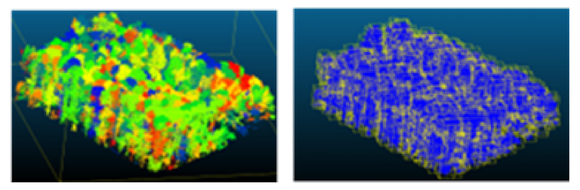


Figure 7: Isolation trees result obtained for forest's data with 'Treeiso' (left side) and manually isolation (right side).

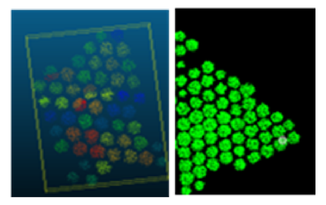


Figure 8: Isolation trees result obtained for parcel's data with 'Treeiso' (left side) and manually isolation (right side).

## 03. Results & Analysis

*Quantitative result :*

The 'TreeIso' method yields 80 falsely identified trees among 1185 trees for forest data, resulting in an error rate of approximately 0.06. The outcomes for the forest are detailed in Table V below. When applied to parcel data, the 'TreeIso' method indicates an additional 6 trees, indicating a misclassification: among 52 trees, three trees were segmented into two. The error rate for the parcel data is 0.10. The results for the parcel are provided in Table VI.

Table V: number of trees computed automatically and manually for forest data

| | Trees classified "Treeiso" | Trees classified manually |
|---|---|---|
| Number of trees | 1185 | 1105 |

Table VI: number of trees computed automatically and manually for parcel 'data

| | Trees classified "Treeiso" | Trees classified manually |
|---|---|---|
| Number of trees | 58 | 52 |

## 04. Discussion & Conclusion

This research presents a novel approach to semantic segmentation using the 3D MASC method and TreeIso for automatic tree isolation. Results demonstrate the effectiveness of these techniques for both forest and parcel datasets using airborne and UAV LiDAR. The TreeIso method significantly improves forest inventory by automating tree counting with an error rate of less than 10%, closely approximating manual observations.

Future research could focus on:

- Multi-source data integration for improved segmentation.
- Fine-tuning algorithm parameters for broader applications.
- Exploring real-time applications in environmental assessment and forest management.

The study also highlights potential comparisons with cutting-edge methods like 3DFin [6] for stem identification and tree height estimation using TLS data, alongside considerations for scalability, data privacy, and automation in forest inventory systems.