

Assessment of tree detection and segmentation pipelines for terrestrial laser scanning dataset of orange orchards

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Abstract

This paper discusses the challenges faced by current tree segmentation pipelines in accurately detecting and performing coarse-to-fine segmentation of individual trees from terrestrial laser scanning (TLS) point clouds acquired in fruit-bearing crops such as orange orchards. Most pipelines for tree detection and individual tree segmentation were originally developed for forest environments, particularly boreal and temperate forests. Consequently, tropical forests and trees with more complex structures pose a challenge. For instance, orange, coffee, and lime crops present dense and overlapping canopies, which differ from those of boreal and managed forests. Our discussion is supported by a study aiming to detect and segment trees in an orange orchard using raster-based, point cloud-based, and hybrid algorithms. The results highlight the advantages and disadvantages in performance across the pipelines. Although stem detection is generally a more stable and accurate method for identifying tree positions, we concluded that approaches based on canopy height models (CHM) for tree detection and raster-based segmentation tend to provide more comprehensive results for orange crop trees. These methods offer better performance in cases where the canopy structure is complex, compared to those that rely on stem detection and clustering segmentation techniques.

1. Introduction

The integration of advanced remote sensing techniques in digital agriculture enables continuous and reliable information for crop management and monitoring. For instance, close-range techniques based on terrestrial laser scanning (TLS) or mobile laser scanning (MLS) data offer high-resolution, three-dimensional information that supports the analysis at the individual level. TLS can be used to obtain tree structural parameters (Rivera et al., 2023), such as canopy height, biomass, and canopy architecture (e.g. number of branches and fruits), among others (Hyypä et al., 2001; Yrttimaa et al., 2024).

Despite the substantial advances in close-range LiDAR data acquisition (e.g., TLS, MLS) and processing, especially for forest environments, challenges remain when applying tree detection and segmentation algorithms for agricultural trees, such as orchard trees (e.g., orange, coffee). One important task that requires greater precision is the segmentation of individual trees in point clouds for the estimation of accurate per-tree information, such as canopy structure parameters, which supports yield estimation, health monitoring, and targeted interventions (Castanheiro et al., 2023; Rivera et al., 2023; Silva et al., 2024). Therefore, several studies have presented automated methods for extracting individual trees from the LiDAR point clouds (Zhen et al., 2016). Most of the methods were developed and validated, particularly in boreal (Yrttimaa et al., 2019) and managed (Krisanski et al., 2021) forests. While these approaches have shown consistent results in such environments, their application in more complex vegetated structures, such as agricultural environments, remains challenging.

Errors and noise resulting from the tree segmentation process are the main sources of inaccuracies when estimating tree parameters from point clouds, such as canopy height. In citrus orchard systems, where trees have irregular crown shapes and interlacing branches of neighbouring trees and occluded stems, traditional

segmentation algorithms designed for boreal and temperate tree species may struggle to accurately delineate individual trees.

In this work, we discuss the challenges associated with tree detection and individual tree segmentation for structurally complex trees, such as those found in fruit-bearing crops. Our focus is on raster-based, point cloud-based, and hybrid detection and segmentation algorithms. To support this discussion, we present a case study conducted in four orange orchard plots with varying tree spacing. The performance of the tree detection and segmentation algorithms was evaluated using one raster-based method (Point Cloud Tools), one point cloud-based method (3DFin), and one hybrid method (LiPheKit).

2. Background

According to Deng et al. (2024), tree segmentation methods can be grouped into three main categories: (1) raster-based methods (2D), (2) point cloud-based methods (3D), and (3) hybrid methods.

Raster-based techniques rely on 2D representations derived from 3D point clouds, such as the canopy height model (CHM). Individual trees are segmented by applying a local maximum filter (Koch et al., 2006) or watershed segmentation (Yun et al., 2021) on raster images derived from point clouds. Point Cloud Tools (Yrttimaa et al., 2021) and PyCrown (Zörner et al., 2028) are examples of raster-based approaches. These methods adapt classical image processing algorithms to delineate individual trees. An example is the marker-controlled watershed segmentation, which interprets the CHM as a surface where treetops are local maxima and crown boundaries follow ridge lines between adjacent canopy regions. This technique is implemented in Point Cloud Tools, where individual trees are automatically detected in forest environments. Another popular strategy is the application of region-growing algorithms. PyCrown identifies initial tree locations as local maxima in the CHM and applies a region-growing algorithm, expanding the

crown by adding neighbouring pixels according to four conditions: (i) the pixel height must be greater than 70% of the seed height, (ii) greater than 55% of the current crown's mean height, (iii) less than 105% of the seed height, and (iv) located within a maximum distance (typically 10 m) from the seed point. This region-growing approach continues until no additional pixels satisfy the conditions. However, the small tree covered by bigger trees cannot be detected in raster-based methods (Deng et al., 2024).

PyCrown identifies initial tree locations as local maxima in the CHM and applies a region-growing algorithm, expanding the crown by adding neighbouring pixels that meet height and distance thresholds relative to the seed and crown mean height, until no more pixels satisfy the conditions.

To address the limitations of raster-based methods, such as accuracy in tree positioning and limited subcanopy detection, point cloud-based methods operate directly in 3D space, for instance, using clustering algorithms (e.g., k-means, HDBSCAN), geometric model fitting to isolate tree structures, and voxel-based segmentation (e.g., 3DFin). More recently, deep-learning methods have been proposed, such as the Forest Structural Complexity Tool (FSCT). For instance, FSCT (Krisanski et al., 2021) uses PointNet++ for point cloud classification and extracts stem points, which are horizontally sliced and clustered using HDBSCAN. Then, cylinders are fitted using RANSAC, and trees are detected based on cylinder orientation and spatial proximity. Finally, the vegetation points are assigned to the nearest identified tree stem, completing the individual tree extraction process. However, point cloud-based methods are generally computationally demanding. This is especially true for deep learning models, which typically require thousands (or more) of labelled samples and significantly more processing time.

Hybrid segmentation methods aim to combine the strengths of both 2D and 3D data sources to improve the detection and delineation of individual trees. Unlike raster-based or fully 3D approaches, hybrid methods often follow a coarse-to-fine strategy, where one representation provides an initial estimate that is later refined using the other. While some methods begin with CHM-based segmentation (Fu et al., 2024), others start with tree detection and localisation (Santos et al., 2024). This flexibility enables more robust handling of complex tree structures, mainly in scenarios where overlapping canopies and occlusions pose challenges that cannot be fully addressed by either 2D or 3D approaches alone. For instance, the LiPheKit package (Wittke et al., 2024) determines tree locations using a stem detection algorithm originally proposed by Liang et al. (2011), where stems are identified by analysing the flatness of a point and its neighbourhood, along with the orientation of its normal vector. The fine segmentation steps rely on the algorithm developed by Hakula et al. (2023), which performs layer-by-layer DBSCAN clustering on 2D projections of the point cloud at different heights. As such, this method can be considered hybrid, since part of the process is conducted in 2D space, while subsequent steps are carried out using the full 3D point cloud (see Section 3.2 for more details).

The mentioned approaches were mostly tested for detecting and segmenting trees in forest and urban areas. In such environments, the tree stems are often fully mapped with a TLS. In the context of an agricultural environment, different crop types, such as fruit orchards and plantations, present high high-density canopy and interlacing branches that may require further studies about the segmentation strategies (Wang et al., 2025).

3. Experiments

3.1 Datasets

Although close-range LiDAR data can be acquired by different methods, either static or mobile, we decided to use TLS to evaluate the segmentation algorithms, since it can provide higher spatial resolution and better stem mapping, which are often essential for most tree segmentation algorithms. Data collection was performed using a *FARO Focus Premium 70* TLS, which has a field of view of $300^\circ \times 360^\circ$. The TLS was configured to collect up to 400,000 points per second (1/5 of the maximum possible), with a 4x quality to store the point coordinates. Figure 1 shows the *FARO Focus Premium 70* TLS placed in an orange orchard.



Figure 1. *FARO Focus* laser scanner in an orange orchard.

The experimental data were collected from orange crops. Orange orchards are typically arranged in a systematic pattern. The canopy of a mature orange tree is quite dense, covering the whole tree, as shown in Figure 1. These characteristics are also present in other crops, such as lime and coffee.

The test area consists of four orange crop plots located in Brazil. These selected plots show different tree spacing patterns, enabling the evaluation of methods in a complex agricultural environment. Figure 2 shows the TLS point clouds obtained in the test area: (a) plot A, (b) plot B, (c) plot C, (d) plot D, which were colourised considering the Z coordinates. Plot A presents mature trees, resulting in overlapping crowns, which increase the challenge in delineating the crown. Plots B and D contain trees of varying heights, including both young and mature individuals. In plot B, partial occlusion of trees located at the end of the row increases the challenge of detecting individual trees. Plot C shows a more regular distribution of similarly sized trees.

To enable a comparative analysis of the methods' performance in orange orchards versus forests, we also tested the selected algorithms in a boreal forest plot located in Evo, Finland (Yrttimaa et al. 2020). This dataset, which was made publicly available by the University of Eastern Finland (2021), was acquired using a Leica RTC360 3D laser scanner (Leica Geosystems, St. Gallen, Switzerland) with a field of view of $300^\circ \times 360^\circ$. A multi-scan approach with five separate scanning positions was used to capture a detailed point cloud of the plot-level area analysed in this study (Plot 1002). This plot represents the type of environment for which most of these pipelines were originally developed and optimised. Unlike citrus orchards, boreal forests typically feature straight stems, sparse understory vegetation, and minimal canopy overlap. The forest plot used here contains a predominantly mature forest structure, with 92 tall and dominant trees, 15 smaller trees, and 30 young trees at an early growth stage, many of which have only thin branches without developed foliage. Figure 3 shows the boreal forest plot used in the analysis.

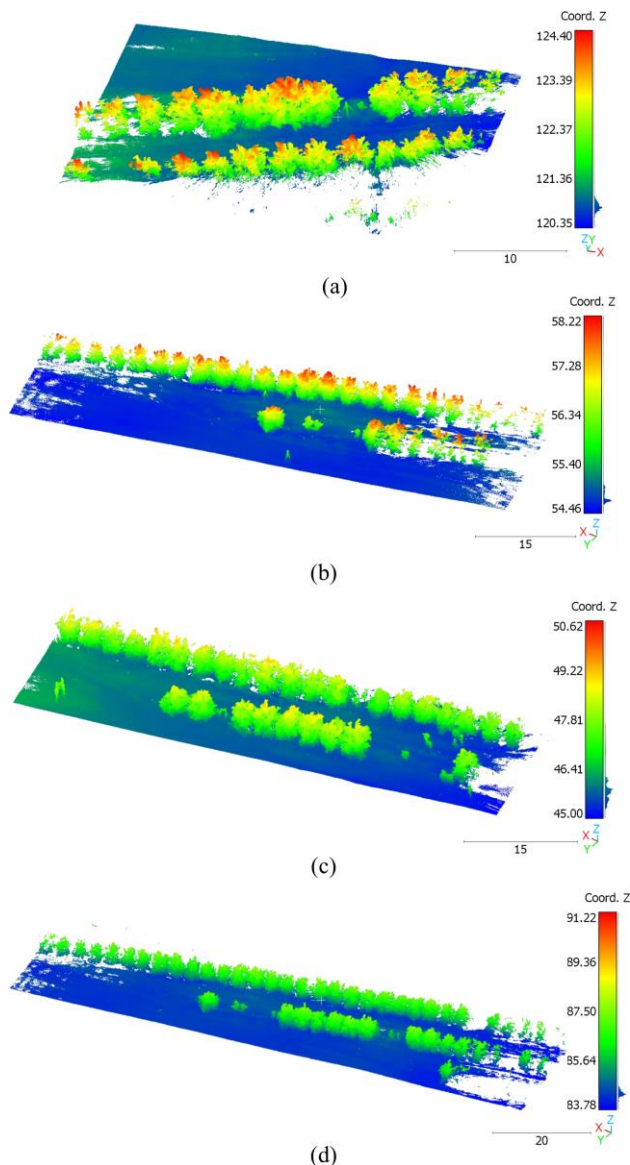


Figure 2. Point clouds obtained with *FARO Focus* in (a) plot A, (b) plot B, (c) plot C, and (d) plot D. Z coordinate unit: meters.



Figure 3. The EVO forest in Finland.

3.2 Methods

To support our discussion on the effectiveness of raster-based, point cloud-based, and hybrid methods in those challenging agricultural environments, we select three methods: Point Cloud Tools (Yrttimaa, 2021), 3DFin (Laino et al., 2024), and LiPheKit (Campos et al., 2024; Wittke et al., 2024). Before applying these segmentation approaches, preliminary processing steps were performed to generate the digital terrain model (DTM) and CHM using the cloth simulation filter (CSF) tool (Zhang et al., 2016) to segment ground points, which were used to generate the DTM with 20 cm resolution. The CHM was generated by subtracting the raw point cloud from the mesh. This preprocessing provided input data for the methods discussed in the following sections.

3.2.1 Point Cloud Tools

The Point Cloud Tools (Yrttimaa et al., 2021) approach employs a raster-based canopy segmentation approach. The tree top locations area was initially identified in CHM using a variable window filter approach. These tree tops are used as seeds for the subsequent watershed segmentation, which delineates individual crown segments. The method then employs a point-in-polygon approach in the XY-plane to extract points belonging to each crown segment, partitioning the point cloud into smaller samples that represent individual trees or groups of trees where crowns overlap.

3.2.2 3DFin

3DFin (Laino et al., 2024) is a pipeline designed for forest inventories using TLS. This pipeline consists of four steps: (1) height-normalisation of the point cloud, (2) identification of stems within the user-provided horizontal stripe, (3) tree individualisation based on point-to-stem distances, and (4) computation of stem diameters at different section heights. The 3DFin (Laino et al., 2024) pipeline includes denoising steps that combine voxelization and DBSCAN clustering. Voxel grids with varying resolution are employed to differentiate trunk-like structures from noise or foliage, and clusters are selectively retained based on their size and geometric consistency. This enables robust estimation of tree height and structure while minimising the inclusion of non-relevant points such as nearby trees or canopy artefacts. At the end, small clusters are discarded, and from the remaining voxels associated with each tree, a cylindrical volume around the estimated trunk axis is defined. The highest voxel within this volume is then used to determine the tree height.

3.2.3 LiPheKit

LiPheKit is a point cloud processing package developed to extract individual tree time series from a permanent laser scanning (PLS) dataset, as described by Wittke et al. (2024). The input for its coarse-to-fine tree segmentation algorithm is the tree position, which is automatically identified using either stem or canopy height detection. Since stem detection in orange orchards is particularly challenging due to high levels of occlusion and low stem continuity (Castanheiro et al., 2023), in this study, we explored a canopy-based approach, in which tree positions are detected based on local maxima in a CHM (similar to the Point Cloud Tool pipeline). After tree detection, individual trees are first coarsely segmented from the original point cloud using the tree map and a cylinder-based clipping approach. This process produces initial individual tree point clouds that may include neighbouring noise, depending on the size of the cylinder buffer. User input is required to define the optimal radius for the buffer to minimise noise while preserving the tree structure. In a second step, a fine-segmentation algorithm is performed considering the points within the cylinder buffer of each tree, aiming to remove

noise and neighbouring points from other trees. The fine segmentation algorithm (Hakula et al, 2023) begins by dividing the input point cloud into horizontal layers. Each layer is then projected onto the XY-plane, and the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm is applied independently to identify clusters. Tree locations are estimated by fitting vertical lines through these clusters, using local maxima of the Z-coordinates as auxiliary information. For each detected tree, a corresponding set of points is extracted and used as initial training data for a Fuzzy k-Nearest Neighbours (FkNN) classifier, which then assigns all points belonging to the target individual trees. This algorithm can be classified as a hybrid method, as certain steps, such as DBSCAN clustering, are performed in 2D space, while subsequent operations are carried out in the 3D point cloud.

To evaluate the performance of the segmentation methods, we compared the segmented tree with the reference trees that were manually identified in each plot. If a tree is correctly detected, it is a true positive (TP); if a tree is not detected but assigned to a nearby tree, it is called a false negative (FN); and if a tree exists but was partially segmented from the point cloud, it is called a false positive (FP). Then, we calculated the recall (r), precision (p) and F1-score (F) as shown in Equations 1, 2, and 3, respectively.

$$r = \frac{TP}{TP + FN} \quad (1)$$

$$p = \frac{TP}{TP + FP} \quad (2)$$

$$F = \frac{2rp}{r + p} \quad (3)$$

4. Results and discussion

4.1 Tree detection

4.1.1 Method based on canopy detection

Both Point Cloud Tools and LiPheKit used the CHM to locate individual trees on the orange crop plots. Despite the complexity of the orange trees, their canopy is well represented in CHM, allowing for a reliable detection of treetops. As a result, these approaches were able to identify individual trees even with sparse points due to partial occlusion. Overall, stem detection enables more accurate tree position estimation, as stems are more stable than canopies. Tree canopies are subject to constant changes due to weather conditions (e.g., wind) and natural vertical and horizontal growth (Zhen et al., 2016). Although canopy-based detection may introduce greater bias in estimating the true position of the tree and its stem, it still provides sufficiently reliable input to serve as a seed for segmentation algorithms, especially in complex tree structures, where the stem is occluded due to high foliage density that hinders TLS laser beam penetration. Figure 4 show example of three trees with varying point densities due to TLS position: (a) a single tree mapped from multiple scans, resulting in a complete crown mapping and higher density point cloud, (b) a tree mapped mainly from the front, and (c) a tree located at the end of the row with lower point density due to occlusion by a neighbouring tree.

Point Cloud Tools was also able to detect young trees, which generally have smaller crowns. Therefore, this method could identify trees with variations in crown size. This is because,

unlike forests with vertically stratified canopies, orange orchards exhibit lateral crown overlap. Trees are planted in very close proximity but do not significantly overshadow one another, which is often the main issue when applying raster-based methods on complex forests. In contrast, these small trees were not detected by LiPheKit as its parameters were set to consider only treetops more than 2 m in height to avoid the detection of non-vegetation objects such as humans and tripods presented in the scene.

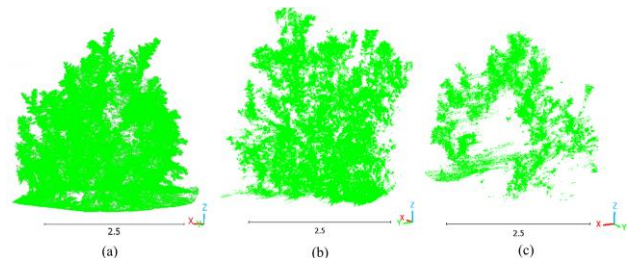


Figure 4. Example of trees with different dense canopies: (a) a single tree mapped with a complete crown mapping and higher density point cloud, (b) a tree mapped only from the front, and (c) a tree located at the end of the row with lower point density.

To access the tree detection performance, we calculated recall (r), precision (p), and F1-score (F) based on the comparison between detected trees and reference data, as shown in Table 1.

	Point Cloud Tools				LiPheKit			
	A	B	C	D	A	B	C	D
r	0.90	0.90	0.88	0.90	0.93	0.86	0.90	1
p	0.77	0.67	0.42	0.52	0.60	0.50	0.59	0.63
F	0.83	0.76	0.56	0.65	0.73	0.63	0.71	0.77

Table 1. Evaluation metrics (recall - r , precision - p , and F1-score - F) for the Point Cloud Tool and LiPheKit approach, based on the comparison between the detected and reference tree positions.

As shown in Table 1, the recall values remained high, indicating that most of the trees present in the point clouds were detected. However, precision values were lower due to over-segmentation. Over-segmentation means that multiple peaks were detected for a single tree. This can occur due to the structural characteristics of orange orchards, combined with the presence of trees of varying sizes (both young and mature) within the same plot, which makes parameterisation particularly challenging. A larger search window can result in the detection of trees with dominant peaks. In comparison, a smaller window allows the detection of smaller trees, but may confuse multiple peaks within a single large crown as separate trees. This issue is prevalent in orange orchards, where a single orange tree with irregular canopies may have more than one local maximum in the CHM due to the presence of two or more peaks in its crown. Additionally, small trees are present in these orchards, further increasing the challenge of parameter tuning for accurate segmentation.

The F1-scores varied from 0.56 (Plot C) to 0.83 (Plot A). These results show that the method is effective at detecting existing trees, but it struggles with delineating individual tree crowns in such a complex environment as an orange orchard. Therefore, strategies need to be employed to improve the overall accuracy of the approach. Some works apply a technique to merge tops located within a distance from a stem, assuming they belong to the same tree, avoiding over-segmentation. For instance, Point Cloud Tools employs a filtering step based on stem positions and the detected canopy locations to merge trees. However, for crops

such as oranges, coffee and lemons, this strategy becomes difficult to employ since the stems are often not mapped in TLS data.

In the forest plot, Point Cloud Tools detected 76 trees, while LiPheKit canopy-based approach identified 72 trees, capturing most of the dominant and mature trees. In this environment, the canopy-based detection methods tend to identify more dominant trees, while smaller trees are more frequently occluded in raster data by the canopy of taller trees. As a result, raster-based methods usually detect more than 80% of the trees in mature plots. In the tested methods, Point Cloud Tools detected 82% and LiPheKit 78% of these trees.

4.1.2 Method based on stem detection

A total of 7, 1, 11, and 9 trees were detected with 3DFin in plot A, plot B, plot C, and plot D, respectively. Furthermore, some confusion occurred in plot C, where humans present in the scene were detected as trees (e.g., trees 1, 3, 5, 6, 9, 11). The performance of 3DFin for tree detection was limited since this approach relies on detecting the stem. In orange orchards, the trunks are not vertical as in the boreal forest, and, due to the dense canopy, the trunks are not often visible in the point cloud, reducing the performance of stem-based tree detection. Figure 5 shows the tree detected with 3DFin in (a) plot A, (b) plot B, (c) plot C, and (d) plot D.

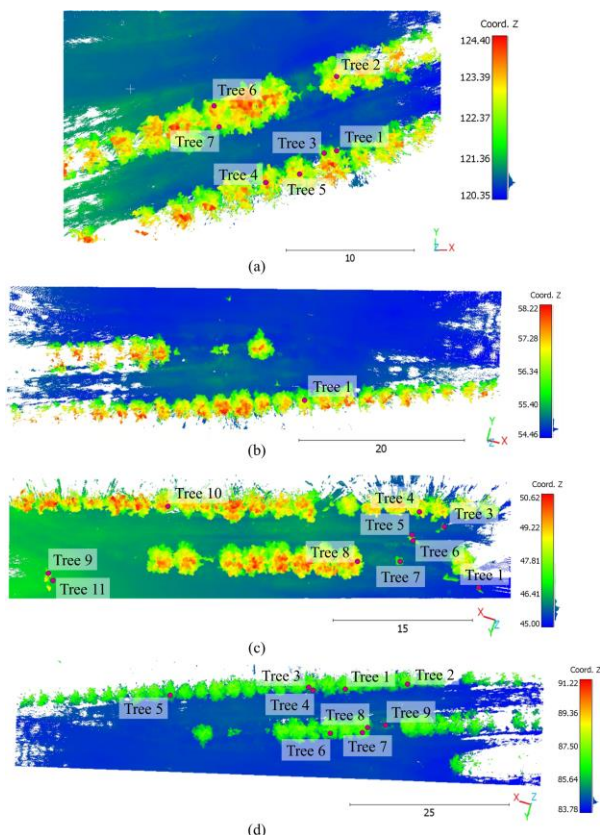


Figure 5. Trees detected with 3DFin in (a) plot A, (b) plot B, (c) plot C, and (d) plot D.

Despite the limited performance, a few trees were detected in the orchard plots. Some of these detections were young trees, such as tree 7 in plot C and tree 9 in plot D, where the stems were visible and mapped. Additionally, trees with sparser canopies were also detected, since gaps in the canopy enabled some laser pulses to reach the trunk, enabling the 3DFin approach to detect the trees. Figure 6 shows two profiles of (a) a tree detected using

3DFin, where the trunk is visible, and (b) a tree with a dense canopy, which was not detected.

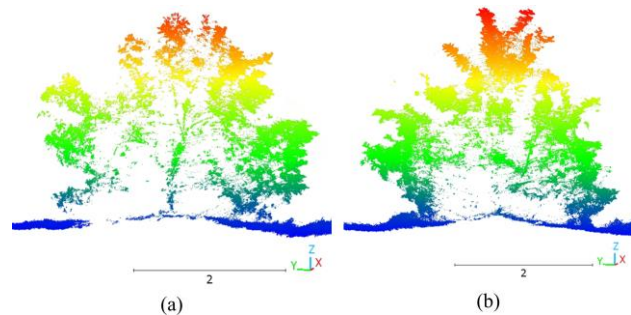


Figure 6. Example of (a) a tree with a sparse canopy and (b) a dense canopy.

When applied in a forest environment, both 3DFin and LiPheKit stem-based approaches resulted in more consistent results. The LiPheKit pipeline, when using the stem detection approach, detected not only the dominant and mature trees but also the smaller trees and even young trees at early growth stages, resulting in 106 out of 111 trees (95.5% of the reference trees). 3DFin was able to identify 88 trees, capturing most of the dominant trees but missing young trees at early growth stages, which would require better parameterisation to detect thinner stems.

These findings show that when stems are visible, the stem detection can outperform the canopy-based approach, as it was able to detect smaller trees often occluded by the canopy of taller trees. Moreover, these results highlight how forest environments pose different challenges in terms of point cloud data processing compared to agricultural orchards. While citrus crops have more uniform and well-spaced trees, boreal forests present irregularly distributed trees with vertical structures and smaller trees in the understory. Figure 7 shows (a) a top view, in which the blue points are the tree detected by 3DFin, and (b) the detected sections along the detected stem.

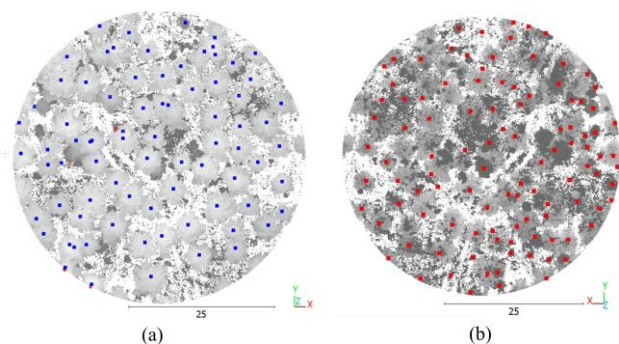


Figure 7. Tree detection in a boreal forest plot with (a) 3DFin and (b) LiPheKit stem-based approach.

4.2 Segmentation

4.2.1 Methods based on raster images

Methods based on raster images provided better results for crop delineation. By using CHM and tree position based on canopy top detection, Point Cloud Tools delineate the tree crown, enabling better identification of individual tree boundaries and canopy structures. Figure 8 shows the tree detected using Point Cloud Tools in (a) plot A, (b) plot B, (c) plot C, (d) plot D. The dark blue points are from the original TLS point cloud, the green points correspond to the segmented tree points identified by the

Point Cloud Tools method, and the yellow boxes represent the bounding volumes assigned to each detected tree.

Despite the consistent results achieved using raster images for segmentation, some challenges remain in accurately delineating individual tree crowns from point cloud data. Figure 9 shows examples of (a) over-segmentation, where a single tree was incorrectly divided into multiple segments due to multiple peaks in the canopy, as previously discussed in Section 4.1.1, (b) incorrect crown delineation, where parts of a tree's crown were assigned to a neighbouring tree and (c) under-segmentation, where two adjacent trees were grouped as a single tree.

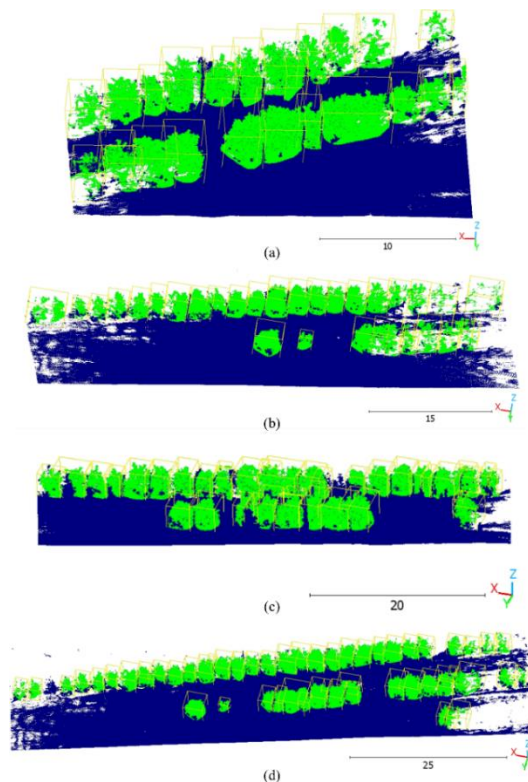


Figure 8. Point Cloud Tools results: the tree detected in (a) plot A, (b) plot B, (c) plot C, (d) plot D, in which the green points correspond to the segmented tree points identified by the Point Cloud Tools method, and the yellow boxes represent the bounding volumes assigned to each detected tree.

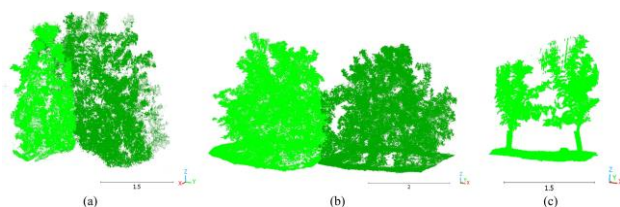


Figure 9. Examples of (a) over-segmentation of a tree, (b) incorrect crown delineation, for instance, and (c) under-segmentation.

The incorrect delineation often occurred in lateral overlapping between canopies, which are common in densely orange orchards. This issue is illustrated in Figure 9(c), where parts of one crown were assigned to a neighbouring tree, despite the correct identification of both trees. This error can affect the individual tree volume estimation, for instance. Therefore, a post-processing strategy is needed to correctly delineate the tree crown.

Point Cloud Tools detected young trees, but in some cases, neighbouring small trees were grouped as a single tree; an example is shown in Figure 9(d). This under-segmentation typically occurred due to interlacing branches between neighbouring trees or high canopy proximity, making it difficult for a raster-based algorithm to separate them into distinct trees. In this case, conditions based on expected crown size can be incorporated into the algorithm. Since small trees tend to have smaller and less complex canopies, adapting the segmentation thresholds accordingly could avoid the merging of nearby small trees.

The percentage of points from manually segmented trees that were correctly included within the boundaries of the segmentation generated by the algorithm was calculated. For trees whose segmentation was assessed as correct using Point Cloud Tools, approximately 99% of the points from the automatically segmented tree fell within the manually segmented tree. In contrast, for trees with segmentation errors, such as over- or under-segmentation, this percentage was approximately 65%.

4.2.2 Methods based on point cloud

Point cloud-based methods delineate the tree by analysing the spatial distribution and the characteristics of the 3D points. LiPheKit and 3DFin segmentation methods, which are based on clustering, rely on the assumption of vertical tree structures relative to the stem or canopy positions.

For instance, in the case of LiPheKit, which applies Hakula et al. (2023) algorithm, after identifying tree locations using local maxima, a vertical line fitting algorithm is applied to the extended set of all clusters detected by DBSCAN at each layer. Each cluster is assigned a vertical line through its centre. Inliers are then identified by selecting clusters whose centres lie within half of their effective radius from the fitted line. However, in orange orchards, the trees tend to have a more pronounced horizontal structure than vertical, which can lead to multiple vertical lines being fitted to different clusters belonging to the same tree. This makes parameter tuning, such as setting appropriate thresholds for the maximum distance from the cluster centre to the line versus minimum distance between trees, particularly challenging in this context.

Similarly, 3DFin relies on identifying potential stems represented by a vertical axis from the upward to the base point. This line becomes the reference for clustering points around the detected stem. Points are grouped based on their proximity to the stem axis, in which points falling within a given radial distance from the stem line are associated with that tree. The point cloud spacing both within and between orange trees is often similar, which poses more challenges for clustering points belonging to the same tree.

In contrast, in the boreal forest environment, these methods performed well, as expected, due to the presence of well-defined vertical stems and more distinct spacing between individual trees.

5. Conclusion

This study presented a discussion and evaluated the performance of different tree detection and segmentation pipelines, originally developed for boreal and temperate forests, when applied to orange orchards. The results demonstrated that canopy-based methods outperform stem-based approaches in detecting individual mature trees in citrus environments. Stem-based approaches rely on the detection of stems and vertical structures

for segmenting trees, which are mostly occluded by the dense canopy of mature trees. On the other hand, when orange trees are still young and the canopy is sparse, stem-based methods can still identify individual trees, while canopy-based methods may not detect them, depending on the parameterisation of the window search.

Although these challenges are well-known and have been discussed by the original developers, our findings highlight that further improvements are still needed in tree segmentation using point clouds from citrus orchards. These challenges must be considered when developing more robust and adaptable tree segmentation workflows for agricultural applications. An accurate tree segmentation can support subsequent steps such as calculating tree height, crown dimensions, and other structural metrics for monitoring and management.

For future work, it is recommended to extend the analysis to more algorithms and agricultural environments with different crop structures. The evaluation of approaches for tree detection and segmentation across different crops with different algorithms can potentially help identify crop-specific challenges. In addition, different data acquisition methods, such as UAV-based, need to be considered in the discussion. For instance, terrestrial platforms, either static or mobile, tend to result in greater occlusion of treetops, while UAV-based data often has occlusion of trunks. Finally, based on our review and benchmark, we conclude that hybrid approaches that combine both stem and canopy information need to be further explored. This type of approach could provide a more robust and flexible solution, improving segmentation performance across the tree development stages in a citrus orchard.

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References

- Campos, M., Echriti, R., Ruoppa, L. and Wittke, S., 2024. Liphekit. *Zenodo*. Available in: <https://zenodo.org/records/13763734>
- Castanheiro, L.F., Tommaselli, A.M.G., Garcia, T.A.C., Campos, M.B. and Kukko, A., 2023. Point Cloud Registration Using Laser Data from an Orange Orchard. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 48, pp.71-77. <https://doi.org/10.5194/isprs-archives-XLVIII-1-W1-2023-71-2023>
- Deng, S., Jing, S. and Zhao, H., 2024. A hybrid method for individual tree detection in broadleaf forests based on UAV-LiDAR data and multistage 3D structure analysis. *Forests*, 15(6), p.1043.
- Fu, Y., Niu, Y., Wang, L. and Li, W., 2024. Individual-tree segmentation from UAV-LiDAR data using a region-growing

segmentation and supervoxel-weighted fuzzy clustering approach. *Remote Sensing*, 16(4), p.608.

- Hakula, A., Ruoppa, L., Lehtomäki, M., Yu, X., Kukko, A., Kaartinen, H., Taher, J., Matikainen, L., Hyypä, E., Luoma, V. and Holopainen, M., 2023. Individual tree segmentation and species classification using high-density close-range multispectral laser scanning data. *ISPRS Open Journal of Photogrammetry and Remote Sensing*, 9, p.100039.
- Krisanski, S., Taskhiri, M.S., Gonzalez Aracil, S., Herries, D., Muneri, A., Gurung, M.B., Montgomery, J. and Turner, P., 2021. Forest structural complexity tool—an open source, fully-automated tool for measuring forest point clouds. *Remote Sensing*, 13(22), p.4677.
- Koch, B., Heyder, U. and Weinacker, H., 2006. Detection of individual tree crowns in airborne lidar data. *Photogrammetric Engineering & Remote Sensing*, 72(4), pp.357-363.
- Laino, D., Cabo, C., Prendes, C., Janvier, R., Ordonez, C., Nikonovas, T., Doerr, S. and Santin, C., 2024. 3DFin: a software for automated 3D forest inventories from terrestrial point clouds. *Forestry: An International Journal of Forest Research*, 97(4), pp.479-496. <https://doi.org/10.1093/forestry/cpae020>
- Liang, X., Litkey, P., Hyypä, J., Kaartinen, H., Vastaranta, M. and Holopainen, M., 2011. Automatic stem mapping using single-scan terrestrial laser scanning. *IEEE Transactions on Geoscience and Remote Sensing* 50, 661–670, <https://doi.org/10.1109/TGRS.2011.2161613> (2011).
- Rivera, G., Porras, R., Florencia, R. and Sánchez-Solís, J.P., 2023. LiDAR applications in precision agriculture for cultivating crops: A review of recent advances. *Computers and electronics in agriculture*, 207, p.107737.
- Santos, R. C., Da Silva, M. F., Tommaselli, A. M. G., and Galo, M., 2024. Automatic Tree Detection/Localization in Urban Forest Using Terrestrial Lidar Data. *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, 4522–4525. <https://doi.org/10.1109/IGARSS53475.2024.10642701>
- Silva, M. F., César Dos Santos, R., and Galo, M., 2024. Detection and Segmentation of Orange Fruit in 3D Point Clouds Generated by a Terrestrial Lidar System. *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, 4196–4199. <https://doi.org/10.1109/IGARSS53475.2024.10642606>
- University of Eastern Finland, National Land Survey of Finland, University of Helsinki, Yrttimaa, T., Vastaranta, M., Saarinen, N., Kankare, V., Luoma, V., & Hyypä, J. (2021). Terrestrial laser scanning point clouds from Evo test site, 37 sample plots, autumn 2019 (Version 1). University of Eastern Finland, Metsätieteiden osasto. <https://doi.org/10.23729/b6c7c1bc-69a9-401d-aad2-af4b0c062a25>
- Wang, S., Ji, J., Zhao, L., Li, J., Zhang, M. and Li, S., 2025. Canopy Segmentation of Overlapping Fruit Trees Based on Unmanned Aerial Vehicle LiDAR. *Agriculture*, 15, 295. <https://doi.org/10.3390/agriculture15030295>
- Wittke, S., Campos, M., Ruoppa, L., Echriti, R., Wang, Y., Gołoś, A., Kukko, A., Hyypä, J. and Puttonen, E., 2024.

LiPheStream-A 18-month high spatiotemporal resolution point cloud time series of Boreal trees from Finland. *Scientific Data*, 11(1), p.1281. <https://doi.org/10.1038/s41597-024-04143-w>

Yrttimaa, T., Saarinen, N., Kankare, V., Liang, X., Hyypä, J., Holopainen, M. and Vastaranta, M., 2019. Investigating the feasibility of multi-scan terrestrial laser scanning to characterize tree communities in southern boreal forests. *Remote Sensing*, 11(12), p.1423.

Yrttimaa, T., Luoma, V., Saarinen, N., Kankare, V., Junttila, S., Holopainen, M., Hyypä, J. and Vastaranta, M., 2020. Structural changes in boreal forests can be quantified using terrestrial laser scanning. *Remote Sensing*, 12(17), p.2672. <https://doi.org/10.3390/rs12172672>

Yrttimaa T., 2021. Automatic Point Cloud Processing Tools to Characterize Trees (Point-Cloud-Tools). Zenodo. <https://doi.org/10.5281/zenodo.5779288>.

Yrttimaa, T., Junttila, S., Luoma, V., Pyörälä, J., Puttonen, E., Campos, M., Hölttä, T. and Vastaranta, M., 2024. Tree height and stem growth dynamics in a scots pine dominated boreal forest. *Trees, Forests and People*, 15, p.100468.

Yun, T., Jiang, K., Li, G., Eichhorn, M.P., Fan, J., Liu, F., Chen, B., An, F. and Cao, L., 2021. Individual tree crown segmentation from airborne LiDAR data using a novel Gaussian filter and energy function minimization-based approach. *Remote Sensing of Environment*, 256, p.112307.

Zhen, Z., Quackenbush, L.J. and Zhang, L., 2016. Trends in automatic individual tree crown detection and delineation—Evolution of LiDAR data. *Remote Sensing*, 8(4), p.333.

Zörner, J., Dymond, J.R., Shepherd, J.D., Wiser, S.K., Bunting, P., Jolly, B., 2018. Lidar-based regional inventory of tall trees - Wellington, New Zealand. *Forests* 9, 702-71. <https://doi.org/10.3390/f9110702>