

## From Peaks to Crowns: A Morphology-Based UAV-LiDAR Framework for Individual Tree Segmentation

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### Abstract

Recognising individual trees has important applications in forest ecology and management. Conventional individual tree segmentation methods tend to favour dominant trees with pronounced canopy surface features but have limited capability in detecting subdominant trees that are partially occluded or have smaller crowns. To mitigate this issue, we propose a morphology-based method for individual tree segmentation. First, a treetop extraction method is developed based on morphological criteria. Candidate treetops are initially detected using local maximum filtering, followed by classification and validation through vertical profile analysis integrated with crown morphological characteristics. Subsequently, the extracted treetops serve as seed points to guide individual tree crown delineation within a Min-cut/Max-flow graph cut framework, leveraging the spatial relationships among points. Our method enhances the detection of subdominant trees, with detection rates climbing to 90–95%, and achieves an average F-score of 0.8 for crown delineation, which outperforms the other methods by 0.24 points. By integrating treetop information with local crown features, the proposed method improves the detection and segmentation accuracy of subdominant trees in complex forest environments, supporting overstory structure analysis and individual tree inventory in intricate forests.

### 1. Introduction

Accurate forest inventory serves as a cornerstone for biomass estimation, carbon stock assessment, and forest management (Li et al., 2025). As an active remote sensing technology, LiDAR (Light Detection and Ranging) facilitates the precise acquisition of three-dimensional forest structural data (Guo et al., 2021). Among its various applications, UAV-LiDAR, distinguished by its high resolution and remarkable adaptability, has become an indispensable tool for individual tree detection, crown delineation, and the analysis of forest stand spatial configurations (Liu et al., 2018). Compared to region-scale approaches, individual tree analysis provides more detailed information on tree location, height, and crown morphology, offering a more reliable foundation for characterizing the complex three-dimensional structure of forests.

The overstory layer, which makes the most efficient use of light and displays the most pronounced crown morphology, accounts for much of the variability in carbon storage (Ullah et al., 2024). However, current individual tree segmentation (ITS) methods often prioritize dominant trees with clear canopy features, while failing to detect subdominant trees that are nearby, partially occluded, and have less visible crowns. This issue arises from both the natural traits of subdominant trees and the limitations of LiDAR data. Subdominant trees typically have smaller crowns, which may be partially hidden within the canopy. Additionally, the close spacing between trees, crown overlap, and the decreasing LiDAR point density from the upper canopy down exaggerate the differences in point cloud representation between dominant and subdominant trees.

Traditional ITS method usually employs the canopy height model (CHM). They first detect treetops by finding local maxima, then apply techniques like region growing or watershed

algorithms to delineate crowns. However, the success of these methods depends on the CHM's resolution and smoothing settings (Rodríguez-Puerta et al., 2022). Choosing inappropriate resolution or smoothing can either fail to suppress false peaks or merge nearby crowns too much. In complex forests with mixed species or varying crown sizes, a single optimal parameter is rarely available. As a result, this method works well for dominant trees but is less effective for subdominant trees.

To transcend the reliance of CHM-based methods on surface-level peak features, researchers have progressively shifted their analytical focus from the two-dimensional canopy surface to the three-dimensional point cloud. Relevant studies can be divided into two main approaches. The first category builds upon initial CHM segmentation by incorporating vertical point cloud information. For instance, Paris et al. (2016) combined CHM data with point cloud spatial data, improving dominant tree detection and crown delineation, then identifying subdominant trees through vertical profile analysis. Harikumar et al. (2019) projected the three-dimensional points segmented by CHM onto a new Euclidean space and utilized the three-dimensional information to achieve joint detection and segmentation of dominant and subdominant trees. Duncanson et al. (2014) used watershed segmentation on the CHM, followed by vertical binning and trough analysis of LiDAR returns within the segmented regions. Later studies have performed segmentation directly within the point cloud or voxel space. For example, Dai et al. (2018) used SVM classifiers trained on manually annotated samples to recognize subdominant clusters. Yu et al. (2024) combined crown contours with vertical profile analysis to detect subdominant clusters. However, these methods depend on the quality of the initial segmentation. If the initial labels are fragmented or incomplete, even when under-segmentation is detected, reconstructing full trees remains impossible.

In summary, existing methods for ITS have several key limitations. Firstly, many rely on tree top peaks or initial CHM segmentation, which can lead to missed detections when subdominant trees are weakly visible on the canopy surface. Secondly, in the case of severe interlaced tree crowns and blurred boundaries, existing methods are difficult to accurately depict the morphological relationship between dominant trees and secondary dominant trees. Finally, most studies focus on coniferous forests, with insufficient testing in mixed forests that have more complex canopy structures and diverse species. To overcome these issues, this study proposes a morphology-based method for ITS, improving the detection and delineation of subdominant trees in complex forests.

## 2. Methodology

### 2.1 Dataset

The study area is situated in Fengshushan Forest Farm, Jiangxi Province, central China. The terrain is mainly composed of gently undulating hills and low mountains, with elevations ranging from 150 to 600 meters. The region experiences a subtropical monsoon climate. The dominant tree species are Chinese fir (*Cunninghamia lanceolata* (Lamb.) Hook.), Formosan sweetgum (*Liquidambar formosana* Hance), and Camphor tree (*Cinnamomum camphora* (L.) Presl). Four 30 m × 20 m sample plots are established, encompassing both pure Chinese fir plantations and mixed forests of Chinese fir and sweetgum. Sample plot information see Table 1.

Table 1. Sample plot information table

| Sample Plots | Stand type                 | Number of trees | Average tree height (m) | Average tree spacing (m) |
|--------------|----------------------------|-----------------|-------------------------|--------------------------|
| Plot1        | C. lanceolata/L. formosana | 58              | 21.5                    | 2.8                      |
| Plot2        | C. lanceolata/L. formosana | 64              | 19                      | 2.4                      |
| Plot3        | C. lanceolata monoculture  | 86              | 17.3                    | 2.1                      |
| Plot4        | C. lanceolata monoculture  | 120             | 13.3                    | 1.8                      |

### 2.2 Data acquisition and preprocessing

This study uses UAV-LiDAR data acquired by the DJI M300 equipped with the L1 LiDAR scanner. The flight altitude was approximately 100 m, with a speed of 6 m/s, a strip overlap of around 70%, and an average point density of around 200 pts/m<sup>2</sup>. High-resolution RGB UAV imagery was captured by the DJI Mavic 3E, achieving a ground resolution of 2-3 cm at an altitude of approximately 100 m. Both the imagery and LiDAR point clouds were collected simultaneously, ensuring spatial and temporal consistency.

LiDAR point cloud preprocessing was conducted using LiDAR360 software (V8.0, GreenValley International, Beijing, China). The raw UAV point cloud was first resampled at a fixed sampling rate, followed by the removal of noise points using a statistical outlier removal method. Ground and non-ground points were then separated using the Cloth Simulation Filtering (CSF) algorithm (Zhang et al., 2016).

To evaluate the accuracy of individual tree segmentation, reference crown boundaries were acquired for each sample plot. Individual tree crown polygons were manually delineated

through visual interpretation. The corresponding results are shown in Figure 1. This work relied on high-resolution RGB imagery. The imagery was generated using DJI Terra software (v3.7.0, DJI Inc., Shenzhen, China).

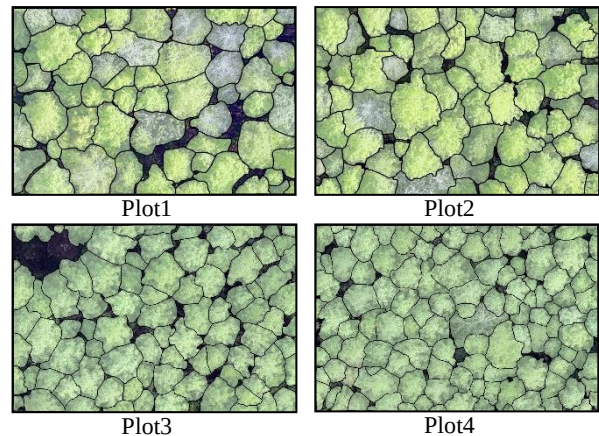


Figure 1. Reference crown boundaries

### 2.3 Treetop extraction

This study developed a detect-then-verify treetop detection framework based on crown profile morphology. The framework consists of three components: super-segmentation, potential treetops classification, and potential treetop identification.

**2.3.1 Super-segmentation:** A small-scale search strategy is employed on the crown surface point cloud to enhance the sensitivity of local maximum detection for treetops with subordinate heights. This method deliberately introduces over-segmentation, thereby improving the retention of treetop points. Candidate treetops are generated as a result. As shown in Figure 2a.

**2.3.2 Potential treetop classification:** To eliminate false treetops caused by canopy undulations and noise, while retaining subdominant treetop points as much as possible, a neighbourhood competition-driven profile discrimination approach is used to classify candidate treetops. Specifically, the candidate points are first sorted in descending order of elevation. Then, each highest candidate point is selected as a reference point, and neighbouring candidate points within a radius  $R$  are searched. Local profiles are constructed for each reference-neighbour pair and assessed. Once a neighbouring point is identified for removal, it is excluded from subsequent comparisons. As shown in Figure 2b.

Point Pair Discrimination Based on Geometrical Relationships of Crown Profiles. For each candidate point pair  $p_i = (x_i, y_i, z_i)$  and  $p_j = (x_j, y_j, z_j)$ , the corresponding profile point cloud is extracted along the line connecting the two points. The profile coordinates are then transformed to  $(d_i, z_i)$  and  $(d_j, z_j)$ , with the center of the two points as the origin. Subsequently, surface points are extracted from the 2D profile  $(d, z)$ , and a spline curve is fitted to obtain a continuous crown profile  $z = f(d)$ . The minimum valley point  $d_v$  (i.e., the main valley point) of  $f(d)$  is identified within the interval  $[min(d_i, d_j), max(d_i, d_j)]$ . Segmentation nodes are then constructed using the curve endpoints and retained valley point positions to delineate structural intervals. If  $d_i$  and  $d_j$  fall within different intervals, they are classified as belonging to different canopy structural units, and  $p_j$  is retained as an independent treetop. If  $d_i$  and  $d_j$  fall within the same interval, further classification is required to

distinguish between false treetops and structurally significant non-dominant tree candidates. To this end, we introduce two types of interpretable potential treetops: shoulder-type and bottom-type potential treetops.

Shoulder-type treetops are used to characterize local protrusions along the canopy edge. The slope magnitude along the crown profile  $f(d)$  is defined as  $s(d) = |f'(d)|$ . If a smooth feature point  $d_m$  (i.e., a local minimum of  $s(d)$ ) exists within the neighbourhood of candidate point  $p_j$ , then  $p_j$  is classified as shoulder-type. Bottom-type treetops are used to describe candidate points near canopy depressions. If  $p_j$  is located close to the minimum point  $(d^*, z^*)$  of the crown profile  $f(d)$  both horizontally and vertically, i.e., satisfying  $(|d^* - d_j| < 0.5 * |d_i - d_j|) \cap (|z^* - z_j| < 0.5 |z_i - z_j|)$ , then  $p_j$  is classified as bottom-type.

Finally, all candidate points that do not pass the discrimination criteria are discarded. Independent treetops are directly retained, while shoulder-type and bottom-type candidate points are collectively output as the verification set  $T$ .

**2.3.3 Potential Treetop Verification:** For the candidate treetop set  $T$  output in the previous step, a multi-directional veto-based validation is applied to suppress false treetops caused by branch bifurcations. First, the set  $T$  is sorted in descending order of height. For each candidate point  $p_s$ , confirmed treetops within

a horizontal radius  $R$  are retrieved, and the neighbourhood is divided into four sectors based on azimuth. In each sector, the nearest representative point  $p_k$  to  $p_s$  is selected, and a one-vote veto validation is performed in order of increasing distance.

When  $|p_k - p_s|_{xy} < r$ , the candidate point  $p_s$  is directly classified as a non-treetop due to neighbouring suppression.

When  $|p_k - p_s|_{xy} \geq r$ , a profile is extracted along the line connecting the point pair  $(p_k, p_s)$ , and the crown profile curve  $f(d)$  is fitted. The local minimum values on both sides of  $p_k$  and  $p_s$  are used to determine the left and right envelope valley points, thereby defining the region of interest (ROI). Within the ROI, multi-scale clustering propagation with directional constraints is performed using  $p_k$  and  $p_s$  as seeds: if, at any scale, the downward path between two clusters remains nearest-neighbour ( $d_{path} < \delta$ ), the two clusters are considered to belong to the same structural unit, and  $p_s$  is vetoed. For candidate points that are not vetoed, vertical binning is performed along the  $z$ -axis for the cluster seeded at  $p_s$ . If the vertical coverage (the proportion of bins occupied by points) of this cluster exceeds  $\eta$ , and the longest continuous occupied bins  $M \geq m$ ,  $p_s$  passes the treetop validation in that direction. Only when all four sector directions pass the validation is  $p_s$  confirmed as a treetop and added to the treetop set  $T$ .

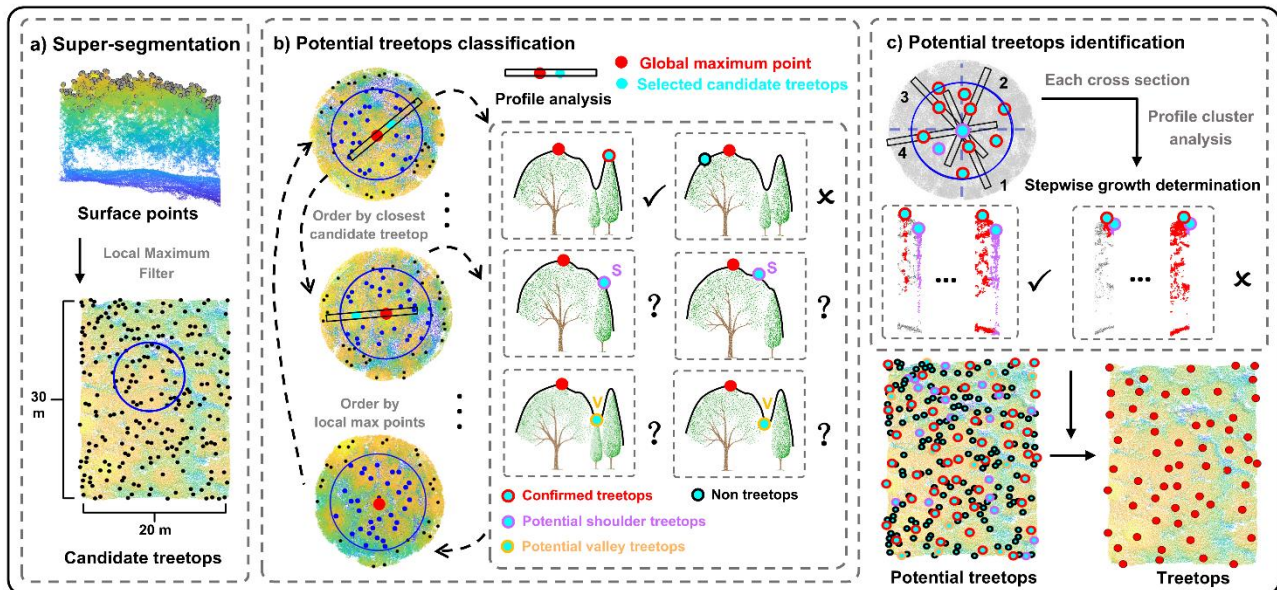


Figure 2. Workflow of the treetop extraction method

## 2.4 Tree Crown Delineation

Graph-cut is a graph-based clustering method that achieves segmentation by partitioning points or pixels into distinct clusters (Shi and Malik, 2000). Its core principle lies in constructing a graph that captures the relationships among data points and then performing graph partitioning using eigenvectors or optimization criteria. In LiDAR point clouds, graph nodes represent individual points, and edge weights are typically defined based on Euclidean distances in three-dimensional space.

In this study, we adopt a Min-cut/Max-flow framework for crown delineation (Lee et al., 2017). Within this framework, the extracted treetops are set as foreground seed nodes, while the remaining points are treated as unlabelled nodes. Edge weights

between nodes are defined according to their Euclidean distances in 3D space. By solving the minimum cut problem, the graph is partitioned into multiple subgraphs, each corresponding to an independent crown unit.

Figure 3 illustrates the complete workflow of the tree crown delineation. First, a graph model is constructed from the point cloud, with edges established based on spatial adjacency relationships. Edge weights are then calculated according to point-wise distances. Next, the minimum cut is solved using the treetops as prior information. Finally, the crown segmentation results are obtained.

By integrating treetop prior information with global graph optimization, the method achieves strong adaptability in

structurally complex forests. This combination effectively overcomes the over-segmentation or under-segmentation issues

commonly encountered by traditional methods in cases of crown overlap or ambiguous boundaries.

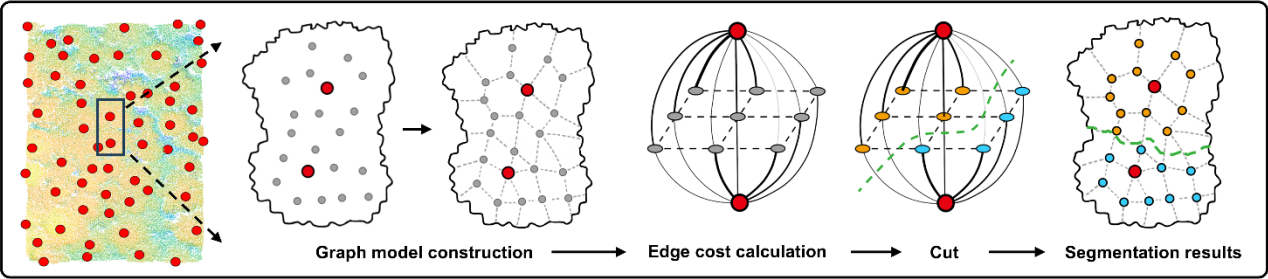


Figure 3. Workflow of the crown delineation

### 2.5 Accuracy Evaluation

Segmentation accuracy was assessed by manually delineating individual tree crowns using a Digital Orthophoto Map and point cloud data as reference. In the evaluation, True Positive (TP), False Positive (FP), and False Negative (FN) represent the number of correctly identified, incorrectly segmented, and missed trees, respectively. Based on these, Precision, Recall, and F-score are calculated. See equations 1 to 3.

Treetop detection evaluation. The treetops extracted by each method are overlaid onto the reference crown boundaries for a point-to-polygon matching. If only one treetop is detected within a reference crown, it is counted as TP. If multiple treetops are detected within the same reference crown, the one closest to the centre of the reference crown is considered TP, and the others are counted as FP. If no treetop is detected within the reference crown, it is counted as FN.

Crown delineation evaluation. We adopt a unified Intersection over Union (IOU) instance matching criterion. The evaluation involves polygon-to-polygon matching between the predicted crown projection polygons and the reference crown polygons in the planar domain. For each reference tree, the predicted instance with the highest intersection IOU is selected as the corresponding instance. If the maximum IOU is  $\geq 0.5$ , it is counted as TP; otherwise, the reference tree is counted as FN. Predicted instances that do not achieve this threshold with any reference tree are counted as FP.

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

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

$$F\text{-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

## 3. Results

### 3.1 Treetop extraction results

Figure 4 shows the treetop detection results for plots 1 to 4. As shown in Table 2, our method outperforms others in terms of stability and overall performance, with an average F-score improvement of 18%. The F-score for our method consistently ranges from 0.90 to 0.93, and it maintains high recall and precision even in mixed forests. With treetop detection rates ranging from 90% to 95%, our method's advantage becomes even more pronounced in high-density stands. In contrast, other methods generally show decreased performance as density increases. For example, in Plot 4, other methods FN an average of 56 trees, highlighting that high density is a major factor contributing to missed detections. Overall, our method performs

well in both mixed and pure forests, demonstrating its strong adaptability to various stand types and canopy structures.

Overall, our method performs well in both mixed and pure forests, demonstrating strong adaptability to diverse stand types and canopy structures. Compared with traditional methods (e.g., LMF and TREETOP), our method significantly reduces FN in high-density environments, confirming its effectiveness in complex forest settings.

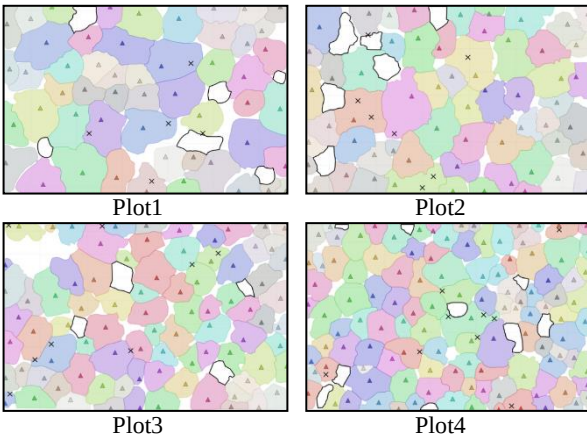


Figure 4. Treetop detection results using our method. “▲” and “x” denote correctly and incorrectly matched treetops, respectively. Whereas unfilled polygons with black outlines represent regions where no treetop was matched, coloured filled polygons indicate areas with matched treetops.

Table 2. Comparison of treetop extraction methods

| Sample plots | Methods     | TP        | FP       | FN       | Recall      | Precision   | F-score     |
|--------------|-------------|-----------|----------|----------|-------------|-------------|-------------|
| Plot1        | LMF         | 43        | 9        | 15       | 0.74        | 0.83        | 0.78        |
|              | LMFx        | 40        | 1        | 18       | 0.69        | 0.98        | 0.81        |
|              | LMFauto     | 43        | 1        | 15       | 0.74        | 0.98        | 0.84        |
|              | TREETOP     | 35        | 0        | 23       | 0.6         | 1           | 0.75        |
|              | <b>Ours</b> | <b>52</b> | <b>5</b> | <b>6</b> | <b>0.9</b>  | <b>0.91</b> | <b>0.9</b>  |
| Plot2        | LMF         | 46        | 7        | 18       | 0.72        | 0.87        | 0.79        |
|              | LMFx        | 45        | 5        | 19       | 0.7         | 0.9         | 0.79        |
|              | LMFauto     | 46        | 5        | 18       | 0.72        | 0.9         | 0.8         |
|              | TREETOP     | 36        | 5        | 28       | 0.56        | 0.88        | 0.69        |
|              | <b>Ours</b> | <b>58</b> | <b>7</b> | <b>6</b> | <b>0.91</b> | <b>0.89</b> | <b>0.9</b>  |
| Plot3        | LMF         | 60        | 6        | 26       | 0.7         | 0.91        | 0.79        |
|              | LMFx        | 51        | 1        | 35       | 0.59        | 0.98        | 0.74        |
|              | LMFauto     | 51        | 1        | 35       | 0.59        | 0.98        | 0.74        |
|              | TREETOP     | 31        | 5        | 55       | 0.36        | 0.86        | 0.51        |
|              | <b>Ours</b> | <b>82</b> | <b>8</b> | <b>4</b> | <b>0.95</b> | <b>0.91</b> | <b>0.93</b> |
| Plot4        | LMF         | 80        | 8        | 40       | 0.67        | 0.91        | 0.77        |

|             |            |          |          |             |             |             |
|-------------|------------|----------|----------|-------------|-------------|-------------|
| LMFx        | 73         | 4        | 47       | 0.61        | 0.95        | 0.74        |
| LMFauto     | 71         | 3        | 49       | 0.59        | 0.96        | 0.73        |
| TREETOP     | 31         | 3        | 89       | 0.26        | 0.91        | 0.4         |
| <b>Ours</b> | <b>111</b> | <b>9</b> | <b>9</b> | <b>0.93</b> | <b>0.93</b> | <b>0.93</b> |

### 3.2 Tree Crown delineation results

Figure 5 presents the crown delineation results for the four sample plots, and Table 3 summarizes the evaluation based on crown. The proposed morphology-based method outperformed the other methods, achieving an average F-score of 0.80, which is 0.24 points higher than the other methods' mean of 0.56. The method showed strong stability, with F-scores ranging from 0.78 to 0.83, indicating good adaptability to different stand structures.

For broadleaf-dominated plots (Plot 1 and Plot 2), the method reduced oversegmentation. It produced low FP (9 in Plot 1, 14 in Plot 2) and fewer FN. Recall, Precision, and F-score were highest in these plots: 0.83, 0.84, and 0.83 for Plot 1, and 0.80, 0.78, and 0.79 for Plot 2. These results show the method's effectiveness in reducing crown splitting in broadleaved stands. For conifer plots (Plot 3 and Plot 4), the method controlled undersegmentation. False negatives dropped to 15 in Plot 3 and 27 in Plot 4, significantly lower than other methods, improving tree separation. Recall reached 0.83 and 0.78, with high Precision (0.79 and 0.78), showing the method's ability to balance both metrics in dense conifer stands.

In summary, the proposed method reduces oversegmentation in broadleaf sample plots and undersegmentation in conifer sample plots, providing accurate and consistent results across different canopy structures.

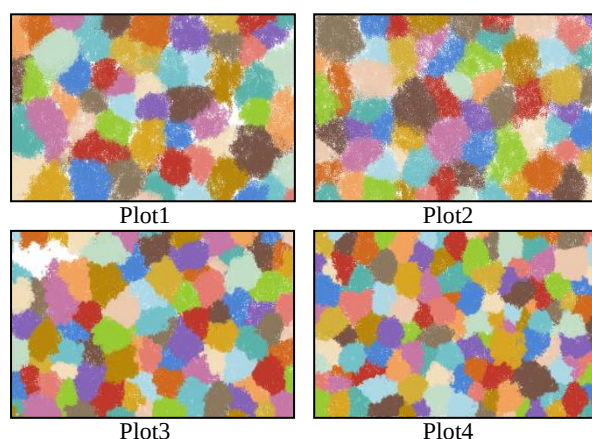


Figure 5. Tree Crown delineation results using our method. Different colours represent different individual trees.

Table 3. Comparison of Tree Crown delineation methods

| Sample plots | Methods      | TP        | FP        | FN        | Recall      | Precision   | F-score     |
|--------------|--------------|-----------|-----------|-----------|-------------|-------------|-------------|
| Plot1        | MCWS         | 35        | 17        | 23        | 0.6         | 0.67        | 0.64        |
|              | Dalponte2016 | 27        | 25        | 31        | 0.47        | 0.52        | 0.49        |
|              | Silva2016    | 32        | 20        | 26        | 0.55        | 0.62        | 0.58        |
|              | Li2012       | 35        | 11        | 23        | 0.6         | 0.76        | 0.67        |
|              | <b>Ours</b>  | <b>48</b> | <b>9</b>  | <b>10</b> | <b>0.83</b> | <b>0.84</b> | <b>0.83</b> |
| Plot2        | MCWS         | 33        | 20        | 31        | 0.52        | 0.62        | 0.56        |
|              | Dalponte2016 | 29        | 22        | 35        | 0.45        | 0.57        | 0.5         |
|              | Silva2016    | 34        | 19        | 30        | 0.53        | 0.64        | 0.58        |
|              | Li2012       | 34        | 18        | 30        | 0.53        | 0.65        | 0.59        |
|              | <b>Ours</b>  | <b>51</b> | <b>14</b> | <b>13</b> | <b>0.8</b>  | <b>0.78</b> | <b>0.79</b> |
| Plot3        | MCWS         | 43        | 23        | 43        | 0.5         | 0.65        | 0.57        |
|              | Dalponte2016 | 34        | 28        | 52        | 0.4         | 0.55        | 0.46        |

|       |              |           |           |           |             |             |             |
|-------|--------------|-----------|-----------|-----------|-------------|-------------|-------------|
| Plot4 | Silva2016    | 42        | 24        | 44        | 0.49        | 0.64        | 0.55        |
|       | Li2012       | 40        | 15        | 46        | 0.47        | 0.73        | 0.57        |
|       | <b>Ours</b>  | <b>71</b> | <b>19</b> | <b>15</b> | <b>0.83</b> | <b>0.79</b> | <b>0.81</b> |
|       | MCWS         | 62        | 26        | 58        | 0.52        | 0.7         | 0.6         |
|       | Dalponte2016 | 47        | 33        | 73        | 0.39        | 0.59        | 0.47        |
| Plot4 | Silva2016    | 50        | 38        | 70        | 0.42        | 0.57        | 0.48        |
|       | Li2012       | 72        | 17        | 48        | 0.6         | 0.81        | 0.69        |
|       | <b>Ours</b>  | <b>93</b> | <b>26</b> | <b>27</b> | <b>0.78</b> | <b>0.78</b> | <b>0.78</b> |

## 4. Discussion

### 4.1 Advantages of our method

**4.1.1 Multi-constraint verification strategy for treetop extraction:** LMF detects treetops on a CHM. It is simple to implement and computationally efficient, making it suitable for rapid extraction over large areas. However, at small scales, it is affected by canopy undulations, inconspicuous treetops, and the lack of height dominance in subdominant trees, which often lead to omission errors (Lai et al., 2025).

LMFx and LMFauto introduce adaptive window mechanisms to improve parameter adaptability, yet their performance remains constrained by CHM smoothing scales and the stability of local maxima. As shown in Table 2, LMFx and LMFauto outperform LMF in mixed forests, whereas LMF performs slightly better in coniferous forests. TREETOPS preserves multi-layer height information through hierarchical segmentation and stacking, offering some adaptability to multi-layer canopies. However, in scenes with overlapping canopies, it tends to merge adjacent structures, often resulting in under-segmentation.

To address the difficulty of detecting subdominant treetops, this study adopts a detect-then-verify approach, which effectively improves the detection rate of subdominant trees. Additionally, existing individual tree segmentation methods are generally sensitive to the initial selection of seed positions and the number of clusters (Li et al., 2023). Our method provides a verifiable treetop extraction mechanism, offering more reliable seed priors for subsequent segmentation and thereby enhancing the stability of the segmentation results.

**4.1.2 To mitigate error propagation, we directly utilize the surface point cloud:** Existing individual tree segmentation methods typically rely on the Digital Surface Model or the CHM normalized from the Digital Terrain Model. However, both approaches inevitably depend on interpolation and smoothing, which may weaken the local convexity and fine details of tree crowns while introducing scale-dependent errors (Lei et al., 2025). In mountainous areas with pronounced terrain relief, normalization can further lead to treetop displacement and crown shape distortion due to variations in ground elevation within the crown (Liu et al., 2024). To suppress the propagation of such errors, we perform treetop detection and crown segmentation directly on the surface point cloud, thereby minimizing the cumulative effects of normalization errors.

### 4.2 Limitations of our method

Treetop verification is performed using geometric verification with multiple constraints. When understory returns are insufficient, this verification may become overly strict, leading to the erroneous removal of true treetops and subsequently inducing under-segmentation in crown delineation. As sensor penetration capabilities improve, particularly with the increasing availability of high-density LiDAR systems, this limitation is expected to be alleviated (Tamimi., 2025).

In addition, the current framework relies primarily on purely geometric information, with a focus on point-wise distances and the consistency of local structures. While this geometric basis ensures computational efficiency and generalizability, it does not fully exploit the rich spectral and textural information increasingly available from multispectral or hyperspectral LiDAR systems. Future work could incorporate explicit constraints based on color, texture, and spectral differences, which would further enhance the robustness of treetop verification and improve the accuracy of crown boundary delineation, particularly in structurally complex or species-diverse forest environments.

## 5. Conclusion

For applications in complex forest stands, we propose a detect-then-verify framework for ITS. By integrating treetop information with local crown morphological features, the method advances the detection of subdominant trees and elevates overall tree detection rates, thereby enhancing the reliability of overstory crown segmentation under high density conditions. Experimental results reveal consistent performance gains across all samples plots, with particularly pronounced improvements in mixed forests, alongside stable performance in other high-density environments. In treetop extraction, our method achieves a detection rate of 90–95% and an F-score ranging from 0.90 to 0.93. This represents an 18% improvement over other methods. For crown delineation, the Min cut/Max flow framework attains an average F score of 0.80, outperforming other methods by 0.24 points. Collectively, these findings collectively highlight the practical value of the proposed approach for precision forest management. The method provides robust support for overstory structure analysis and individual tree inventory in structurally complex forest environments.

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