# A Novel Approach for Individual Tree Structural Parameter Extraction from ALS Data

Yanan Liu [1], Ai Zhang [1], Peng Gao [1], Mengxue Xu [1], Pingbo Hu [1], Tao Yuan [2]

[1] School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing 100044, China - liuyanan@bucea.edu.cn (Y.L.), 2108570023082@stu.bucea.edu.cn (A.Z.), 2108570022088@stu.bucea.edu.cn (P.G.), 2108160224004@stu.bucea.edu.cn (M.X.), hupb@whu.edu.cn (P.H.)

[2] Beijing Institute of Engineering Geology, Beijing 100083, China - 414061370@qq.com (T.Y.)

**Keywords:** Structural parameter, Individual tree, Segmentation, Extraction, YOLO, Point cloud.

**Abstract**

Estimating tree-level structural parameters from airborne laser scanning (ALS) point cloud is essential for sustainable and efficient forest management. This task is currently carried out through labour-intensive and time-consuming manual efforts, particularly in complex forest with overlapping canopies. This paper presents a novel approach for individual tree extraction utilizing an improved YOLO-based model, along with advanced algorithms for structural parameter calculation. The enhanced model, named CCD-YOLO, introduces several key improvements for individual tree segmentation (ITS) by leveraging a newly created ITS dataset. It replaces the C2F module with a CReToNeXt module to enhance feature extraction. A convolutional block attention module (CBAM) is added to highlight crown features and reduce background noise, while a Dynamic Head enables adaptive multi-layer fusion, boosting segmentation accuracy. Additionally, a denoising process is applied, ensuring more accurate and reliable measurements for vertical parameters. Lastly, an improved convex hull algorithm is employed to better accommodate the irregular shapes of tree crowns. The experimental results were evaluated in a dense forest through both internal and external consistency assessments, demonstrating significant performance enhancements. For the individual tree segmentation, the proposed approach achieved a precision of 82.4%, a recall of 72.8%, and an F1 score of 77.9%. In terms of parameter estimation, the accuracy for tree height, crown width, and crown area was 0.82, 0.60, and 0.99, respectively, with corresponding RMSE values of 1.25, 1.01, and 1.16. These results highlight the effectiveness of the proposed method in improving both segmentation and parameter estimation accuracy.

## 1. Introduction

Forests are a vital component of terrestrial ecosystems, accounting for approximately 77% of the global carbon stock. As the largest carbon sink, forests are essential for maintaining the global carbon cycle and alleviating climate change (Cao et al., 2021). Therefore, accurate monitoring and effective management of forest resources are essential.

Tree structural parameters are the core focus of forest resource surveys, as they provide insights into the spatial arrangement and growth health of trees. These parameters typically include tree height, diameter at breast height (DBH), and crown parameters such as crown width, crown area, and crown volume. Traditionally, forest resource surveys rely on field investigations, where individual tree parameters are measured within sample plots. While these methods provide detailed tree-level information, they are time-consuming, labour-intensive, and limited in scope, especially in inaccessible areas.

LiDAR (Light Detection and Ranging) systems, especially airborne laser scanning (ALS), are capable of efficiently and accurately retrieving three-dimensional forest structural information over large areas. ALS has been widely used to estimate forest carbon stocks and biomass in large forest scenes, significantly enhancing the efficiency of forest resource assessments (Luo et al., 2021). However, challenges remain in accurately acquiring individual tree morphological parameters due to the low point density and occlusion caused by overlapping tree crowns, especially in complex forest environments.

## 2. Related Work

The extraction of individual tree structural parameters involves two primary steps: individual tree segmentation and structural parameter extraction. Accurate tree segmentation is crucial for parameter estimation, as segmentation accuracy directly impacts the precision of the extracted parameters.

### 2.1 Individual Tree Segmentation

Traditional tree segmentation methods based on ALS can generally be categorized into two main approaches: 2D image segmentation and 3D point cloud segmentation.

The 2D image segmentation approach employs canopy height model (CHM) raster images to represent the upper canopy contour, where local maxima are extracted as treetops to facilitate the segmentation of individual trees (Kaartinen et al., 2012). Typical approaches consist of Watershed Algorithms (Dalponte et al., 2014), Region Growing Algorithms (Zhen et al., 2014), and other 2D image segmentation techniques (Zhou et al., 2020). However, the accuracy of these approaches is limited by the local maximum detection, which can lead to both false positives and false negatives.

By comparison, 3D point cloud based approaches, including Mean-shift Clustering (Ferraz et al., 2012), Graph-based Segmentation (Dong et al., 2020), and Spectral Clustering (Pang et al., 2021), are able to exploit the spatial structure of point clouds. These methods generally achieve higher accuracy but rely heavily on prior knowledge of forest characteristics, and they require manual parameter adjustment according to factors such as forest type and developmental stage. This lack of generalizability, coupled with the complex tuning process, limits their applicability and transferability across different forest environments.

Recent advances in deep learning (DL) have demonstrated that both direct and indirect approaches applied to 3D point clouds can achieve efficient individual tree segmentation in complex forest environments, offering broad application prospects. The direct approach begins with the segmentation or classification of 3D point clouds into distinct components through networks like PointNet++ (Krisanski et al., 2021) and 3D U-Net (Henrich et al., 2024), followed by clustering to further refine the segmentation. Due to their high dimensionality and irregular structure, 3D point clouds impose greater computational complexity, which makes training and inference more difficult. Such direct approaches are generally applied within terrestrial or mobile LiDAR systems. For the latter, advanced networks such as Swin Transformer (Liu et al., 2021b), Faster R-CNN (Liu et al., 2021a), YOLO (Wang et al., 2022), and U-Net (Freudenberg et al., 2022) employed for segmenting 2D images generated from 3D point clouds. By exploiting the representational capacity of advanced network architectures, these methods automatically capture and extract complex spatial features, ultimately achieving precise delineation of the upper canopy. Especially, the YOLO model demonstrates a clear advantage in faster execution, which contributes to the efficient accomplishment of detection and segmentation tasks.

To improve detection speed and accuracy, the YOLO models (Ali and Zhang, 2024) and its variants (Chen et al., 2023) have been enhanced through the integration of multi-scale detection, attention mechanisms, loss function refinements, and data augmentation techniques (Nan et al., 2024; Zhao et al., 2024). With these enhancements, the model is capable of capturing fine details, suppressing background interference, and adapting to diverse canopy characteristics, thereby serving as an effective tool for crown detection.

### 2.2 Structure Parameter Extraction

The structural parameters of individual trees form the foundation of forest spatial structure analysis, providing critical data for forest resource surveys and ecological research. Key parameters typically measured in field surveys include diameter at breast height (DBH), tree height, height to the lowest live branch, and crown width. More complex parameters such as biomass and tree volume require tree felling for accurate measurement (Krůček et al., 2020).

In recent years, there has been a growing focus on automating forest parameter extraction, particularly through the use of ALS data. The extraction of individual tree parameters can be classified into two categories (Zhao, 2022). Direct extraction methods involve obtaining parameters such as tree height, crown projection area, surface area, and volume directly from the segmentation results. For parameters that cannot be directly obtained from segmentation, growth equations or empirical models are used to estimate parameters like DBH, volume, and biomass.

However, these two approaches are not entirely independent. The effectiveness of both approaches is influenced by factors such as data density and acquisition conditions. The accuracy of parameter estimation is thus dependent on the quality of the segmentation and the characteristics of the ALS data.

## 3. Methodology

This study aims to perform individual tree segmentation using an improved YOLO model, and subsequently extract the structural parameters of individual trees. The overall pipeline, as illustrated in Figure 1, comprises three main components: data preparation (Section 3.1), structural parameter extraction (Section 3.2), and accuracy evaluation (Section 3.3).

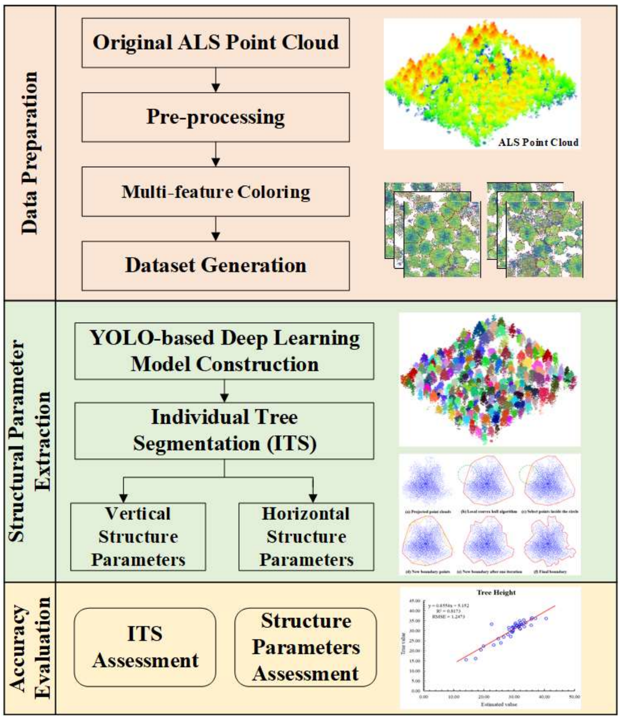



Figure 1. Flowchart of the proposed approach.

### 3.1 Data Preparation

**3.1.1 Pre-processing:** The construction of the individual tree segmentation dataset relies on a systematic pre-processing of the original ALS point cloud, which mainly includes point cloud denoising, ground filtering, height normalization, and the generation of multi-feature point cloud maps.

Statistical Outlier Removal (SOR) filtering (Li et al., 2016) and Cloth Simulation Filtering (CSF) (Zhang et al., 2016) are used to eliminate noise outliers and ground points, respectively. To generate the ITS map dataset, the CSF result is first normalized, and then a multi-feature coloring method is employed to extract the multidimensional features of the point clouds. In the construction of multi-feature point cloud maps, the processed point clouds are first vertically stratified by height, and the point density and intensity values are calculated for each height interval. Based on these values, density and intensity colorized point clouds are generated and visualized through color mapping. The RGB mean values of the two colorized point clouds are then fused to produce multi-feature data that represent comprehensive multidimensional information. Finally, the colorized point clouds are projected onto the ground to generate a complete multi-feature point cloud map that fully reflects three-dimensional structural characteristics (Liu et al., 2025).

**3.1.2 Dataset Generation:** To meet the input requirements of the YOLO deep learning network, the generated multi-feature point cloud maps were divided into fixed-size patches of 512 × 512 pixels, with a 64-pixel overlap between adjacent patches to ensure spatial continuity and preserve edge features during subsequent processing. Image annotation was performed using the LabelMe tool, which produced JSON files containing tree locations, anchor box dimensions, and class labels. Meanwhile, to mitigate the risk of over-fitting, data augmentation strategies such as flipping, rotation, and the addition of Gaussian noise were applied.

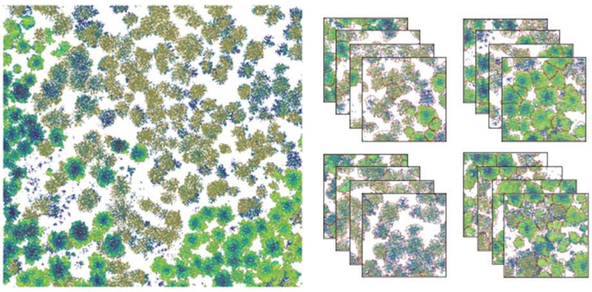


Figure 2. Multi-feature map and ITS Dataset with labelled mark.

### 3.2 Structural Parameter Extraction

**3.2.1 Individual Tree Segmentation:** To overcome challenges posed by crown overlap and heterogeneous backgrounds in dense forests, an improved YOLO model is proposed for ITS using ALS point clouds. The model can effectively extract the location and boundary information of trees in dense forests, thereby improving detection and segmentation accuracy while minimizing both false positives and false negatives. Built upon the YOLOv8 architecture, the proposed model, as shown in Figure 3, incorporates advanced modules incorporates advanced modules such as CReToNeXt (Cross Residual Transformer Network Extended), CBAM (Convolutional Block Attention Module), and a Dynamic Head.

The CReToNeXt module (Xu et al., 2022) replaces the original C2F module to enhance feature extraction and multi-scale fusion. The CBAM (Woo et al., 2018) is integrated into the backbone network to emphasize critical regions and reduce background noise. Additionally, a Dynamic Head (Dai et al., 2021) optimizes feature layer weighting and fusion, improving accuracy in detecting target positions and boundary changes. Further details of the improved model architecture can be found in (Liu et al., 2025).

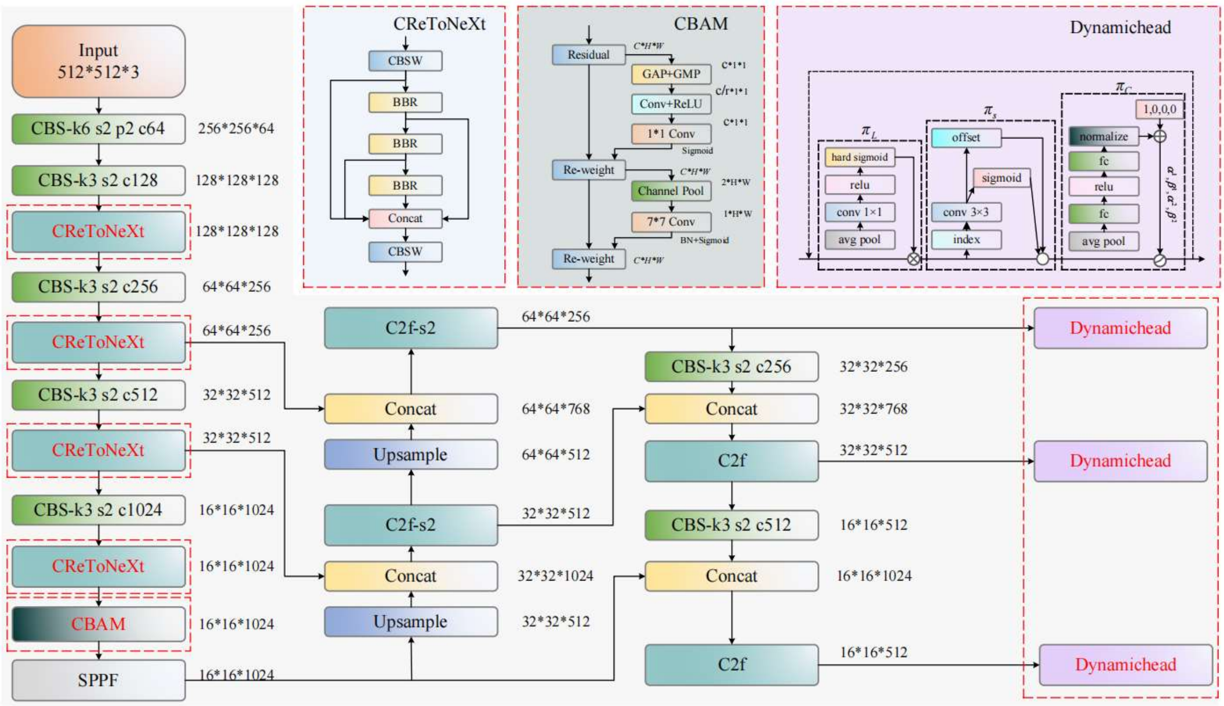



Figure 3. Framework of the proposed model.

**3.2.2 Structural Parameter Extraction:** Tree structural parameters are categorized into horizontal and vertical metrics, which respectively describe the morphological characteristics in the vertical (height-related) and horizontal (crown spatial distribution) dimensions. Vertical parameters, such as tree height, reflect growth status and biomass allocation, while horizontal parameters, on the other hand, including crown width and area, describe the spatial distribution and extent of the tree canopy, helping assess site conditions, light distribution, and tree competition. Accurately measuring these parameters is essential for forest management and ecological studies.

**Tree Location and Height Extraction:** The tree location and height in ALS cloud data are typically determined by the tree top (Yang et al., 2016). Traditionally, the maximum Z-coordinate (tree top) within a point cluster determines tree height, but this approach is sensitive to noise. To remove outliers, this method first applies spatial clustering (Fu et al., 2022) to isolate tree point clouds from the proposed CCD-YOLO, and then the tree top is identified as the highest point (maximum Z-value). This two-step process—clustering followed by maximum value extraction—ensures precise localization of tree positions (XY coordinates) and reliable height estimation (Z-coordinate).

**Crown Width and Area Extraction:** Crown width (maximum horizontal span) and crown area (ground projection area) are computed using an iterative progressive convex hull algorithm. The commonly used convex hull methods struggle with irregular crown shapes and internal gaps, especially in dense forests. To overcome this limitation, an iterative progressive algorithm (Dong et al., 2018) is adopted, as illustrated in Figure 4. This approach projects the point cloud onto the Z-axis and applies a local convex hull algorithm to construct a more accurate boundary. For edges exceeding a set threshold, a circular region is constructed using the edge as the diameter, and boundary points are identified based on the largest angle formed with the endpoints. This iterative procedure is repeated until all edges are smaller than the threshold or no points remain within the circular region. The proposed method can refine the crown boundary, minimize gaps, and enhance the accuracy of crown width and area calculations.

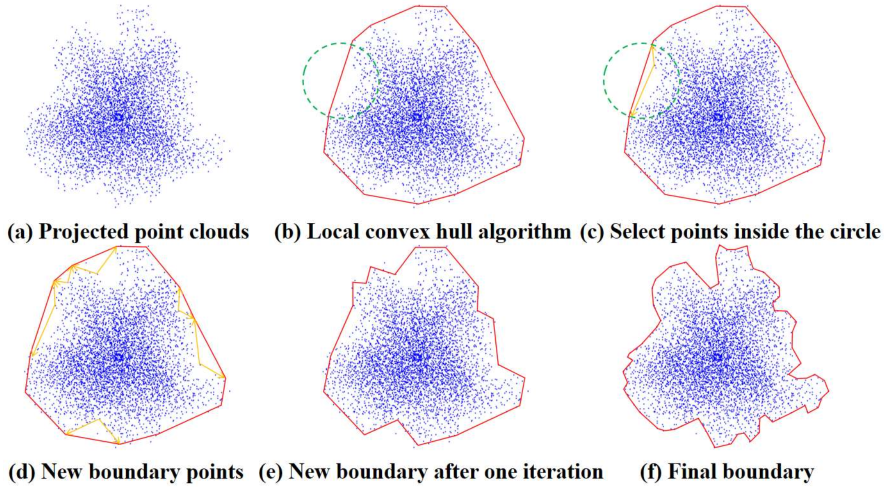



Figure 4. Process of the Iterative Convex Hull Algorithm.

### 3.3 Accuracy Evaluation

The performance of the proposed methodology was rigorously assessed through two parallel evaluations: (1) individual tree segmentation accuracy and (2) structural parameter estimation accuracy. Both evaluations employed statistical metrics and visual assessment to ensure objective results.

**3.3.1 Individual Tree Segmentation:** Segmentation accuracy was quantified using Precision, Recall, F1-Score, and Average Precision (AP). These metrics were calculated based on the overlap between predicted and ground-truth tree boundaries: The equations for these metrics are:

$$Precision = \frac{TP}{TP + FP} \times 100\% \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \quad (2)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (3)$$

$$AP = \int_0^1 P(R)dR \quad (4)$$

Where ***TP*** (True Positive) denotes the number of correctly detected (or segmented) trees, while ***FP*** (False Positive) and ***FN*** (False Negative) represent the number of incorrectly detected and missed trees, respectively. ***P(R)*** indicates the precision at different recall levels.

**3.3.2 Structural Parameter Extraction:** The accuracy of forest vertical and horizontal parameter extraction was evaluated using the coefficient of determination ($R^2$) and Root Mean Square Error (***RMSE***). The equations are defined as:

$$R^2 = 1 - \sum_{i=1}^{n}(x_i - y_i)^2 / \sum_{i=1}^{n}(x_i - x_m)^2 \quad (5)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2 / n} \quad (6)$$

Where $x_i$ and $y_i$ are the $i$-th ground-truth and predicted values, $x_m$ is the mean of ground-truth values, $n$ is the sample size.

## 4. Results and Discussion

### 4.1 Results of Individual Tree Segmentation

To evaluate the performance of the CCD-YOLO model, the ITS dataset was randomly divided into training/validation and test sets at a 7:3 ratio. The training utilized the Adam optimizer with PyTorch 1.12 on an NVIDIA GeForce RTX 3080 GPU, achieving optimal performance after 300 epochs. Additionally, the hyperparameters in CCD-YOLO, including momentum, learning rate, and weight decay, are set to 0.937, 0.01, and 0.0005, respectively. As shown in Figure 5, the segmentation results were obtained using the proposed method. To enable intuitive distinction of individual trees, each tree was assigned a unique random color.

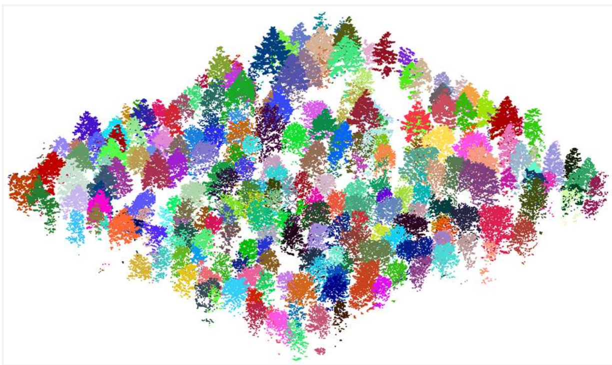


Figure 5. Oblique view of segmentation result.

Figure 5 illustrates that adjacent trees are distinguished by different colors and clear boundaries, confirming the effectiveness of the algorithm in individual tree segmentation, with 174 out of 239 trees fully extracted. While preserving the natural morphology and spatial structure of trees, the method significantly reduces over-segmentation (fragmented crowns) and under-segmentation (missed trees), thereby ensuring the reliable extraction of complete tree point clouds. A locally enlarged segmentation result is shown in Figure 6.

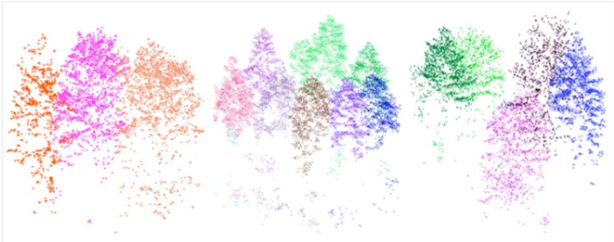
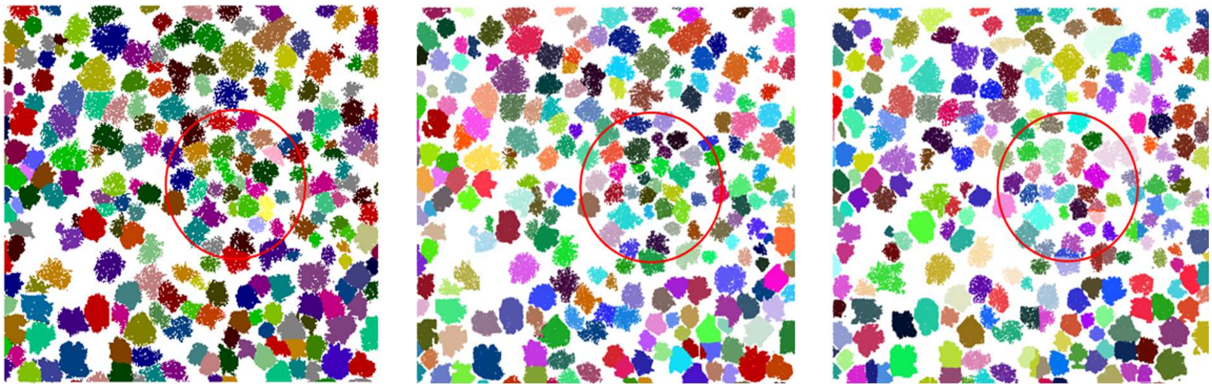


Figure 6. Visualization of detailed tree segmentation results.

In addition, a comparison map between the original YOLO model and its improvement are shown in Figure 7.

As shown in Figure 7, the proposed model demonstrates a strong accuracy in locating individual trees and performs well in boundary segmentation by precisely capturing crown edges, achieving high consistency with the ground truth in most areas. This underscores the model's sensitivity to boundary details and its precision in segmentation. Even in cases of crown overlap and occlusion, the proposed model effectively restores tree crown shapes, showcasing its adaptability to complex scenarios. In contrast, the original YOLOv8 model locates most trees accurately but still experiences some misclassifications and missed detections. While crown segmentation generally aligns with expected contours, some areas show noticeable over-segmentation, resulting in excessive fragmentation.



**(a) Ground truth ITS data** **(b) Improved YOLO Model** **(c) YOLOv8**

Figure 7. ITS results between YOLO and CCD-YOLO.

| Models | Tree Boundary Segmentation | | | |
|---|---|---|---|---|
| | **Precision** | **Recall** | **F1** | **AP** |
| YOLOv8 | 77.9 | 71.8 | 74.7 | 79.9 |
| YOLOv8+CReToNeXt | 80.9 | 75.4 | 78.1 | 82.4 |
| YOLOv8+CBAM | 79.9 | 68.3 | 73.6 | 78.9 |
| YOLOv8+Dynamic Head | 79.0 | 70.3 | 74.4 | 79.7 |
| YOLOv8+CReToNeXt +CBAM | 80.7 | 72.9 | 76.6 | 81.2 |
| YOLOv8+CReToNeXt +Dynamic Head | 80.9 | 74.2 | 77.4 | 82.3 |
| YOLOv8+CBAM +Dynamic Head | 77.8 | 71.0 | 74.2 | 79.3 |
| YOLOv8+CReToNeXt +CBAM +Dynamic Head **(Proposed CCD-YOLO)** | **82.4** | **72.8** | **77.9** | **83.0** |
| YOLOv11 | 81.0 | 71.5 | 77.6 | 82.3 |

Table 1. Quantitative assessment of the proposed CCD-YOLO.

As shown in Table 1, the CReToNeXt, CBAM, and Dynamic Head modules play a significant role in enhancing crown detection accuracy and boundary segmentation performance. Each module contributed incremental improvements, but their combined integration into the YOLO framework yielded synergistic gains. Compared to the baseline YOLO model, the proposed CCD-YOLO achieved a 3.5% increase in precision, 4.4% higher recall, and a 4.1% improvement in F1 score, significantly reducing both omission and commission errors. This underscores the model’s enhanced robustness and adaptability to complex forest environments. Compared to YOLOv11, the latest advancement the latest advancement in the YOLO series, the proposed model showed gains in precision (1.4%), F1 score (1.3%), and AP@0.5 (0.7%), demonstrating a clear advantage in segmentation accuracy.

### 4.2 Results of Structural Parameter Extraction

The proposed method was validated using 45 randomly selected trees, with structural parameters (tree height, crown width, and crown area) derived from the segmentation results compared against manually acquired reference data. Performance was quantified using the coefficient of determination (***$R^2$***) and Root Mean Square Error (***RMSE***). The comparative analysis between extracted parameters and reference values is as follows.

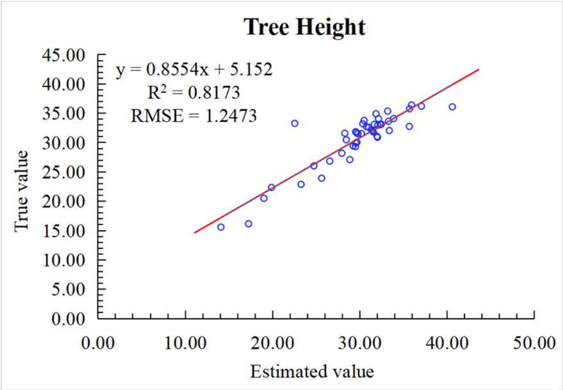



Figure 8. Comparison of the tree height structural parameter.

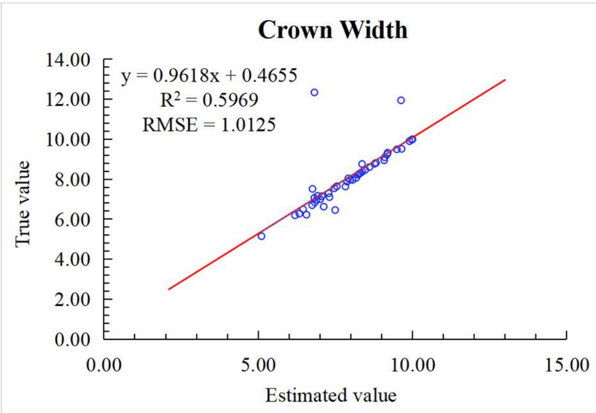



Figure 9. Comparison of the crown width structural parameter.

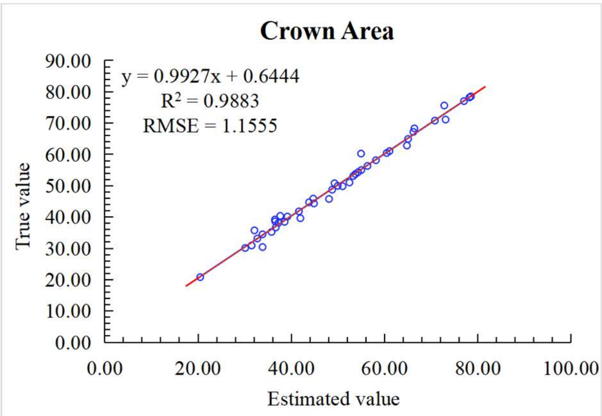



Figure 10. Comparison of the crown area structural parameter.

It can be seen from Figure 8 to Figure 10 that the results demonstrate strong consistency between extracted parameters and manual reference measurements: tree height ($R^2$ = 0.82, ***RMSE*** = 1.25), crown width ($R^2$ = 0.60, ***RMSE*** = 1.01), and crown area ($R^2$ = 0.99, ***RMSE*** = 1.16). These findings highlight the effectiveness and reliability of the proposed method in extracting forest structural parameters from ALS point clouds. However, some crown edges were not effectively identified or extracted, thereby affecting the accuracy of the estimates, as shown in Figure 11.

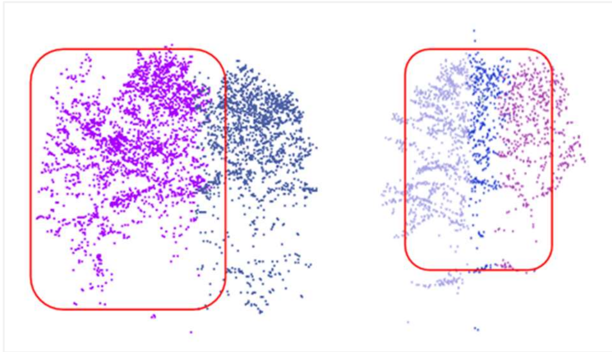


Figure 11. Difficult instances to segment.

## 5. Conclusion and Future Work

The paper presents an improved YOLO-based model for individual tree segmentation and structure parameter extraction from ALS data. The proposed CCD-YOLO model, enhanced with the modules of CReToNeXt, CBAM, and Dynamic Head, demonstrates superior accuracy and robustness in detecting tree positions and segmenting crown boundaries. In addition, an iterative progressive algorithm is employed to precisely extract vertical and horizontal structural parameters, ensuring reliable and accurate measurements.

However, CCD-YOLO still exhibits certain limitations in individual tree segmentation, which are primarily reflected in the misclassification of shrubs (non-trees) and the over-segmentation of dense canopies. To address these issues, future work will focus on integrating multi-source data and refining post-processing techniques, thereby further improving segmentation accuracy and parameter estimation in complex forest environments.

## Acknowledgments

This work was supported by the R&D Program of Beijing Municipal Education Commission (No. KM202410016006), the Pyramid Talent Training Project for Beijing University of Civil Engineering and Architecture (No. JDYC20220824), the Fundamental Research Funds for Beijing University of Civil Engineering and Architecture (No. Y2207), and the National Natural Science Foundation of China (No. 42001379).

## References

Ali, M. L. and Zhang, Z.: The YOLO Framework: A Comprehensive Review of Evolution, Applications, and Benchmarks in Object Detection, Computers, 13, 2024.

Cao, Y., You, W. B., Wang, F. Y., Wu, L. Y., and He, D. J.: Research progress on carbon storage of coarse woody debris in forest ecosystems, Acta Ecologica Sinica, 41, 7913-7927, 2021.

Chen, Y., Xu, H., Zhang, X., Gao, P., Xu, Z., and Huang, X.: An object detection method for bayberry trees based on an improved YOLO algorithm, International Journal of Digital Earth, 16, 781-805, 2023.

Dai, X., Chen, Y., Xiao, B., Chen, D., Liu, M., Yuan, L., and Zhang, L.: Dynamic Head: Unifying Object Detection Heads with Attentions, 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 20-25 June 2021, 7369-7378, Dalponte, M., Ørka, H. O., Ene, L. T., Gobakken, T., and Næsset, E.: Tree crown delineation and tree species classification in boreal forests using hyperspectral and ALS data, Remote Sensing of Environment, 140, 306-317, https://doi.org/10.1016/j.rse.2013.09.006, 2014.

Dong, T., Zhang, X., Ding, Z., and Fan, J.: Multi-layered tree crown extraction from LiDAR data using graph-based segmentation, Computers and Electronics in Agriculture, 170, 105213, https://doi.org/10.1016/j.compag.2020.105213, 2020.

DONG, Y., LI, Y., LI, P., and LYU, Y.: Tree crown outline points extracting and volume calculation based on improved convex hull algorithm, EngineeringofSurveyingandMapping, 27, 66-71, 10.19349/j.cnki.issn1006-7949.2018.08.012, 2018.

Ferraz, A., Bretar, F., Jacquemoud, S., Gonçalves, G., Pereira, L., Tomé, M., and Soares, P.: 3-D mapping of a multi-layered Mediterranean forest using ALS data, Remote Sensing of Environment, 121, 210-223, https://doi.org/10.1016/j.rse.2012.01.020, 2012.

Freudenberg, M., Magdon, P., and Nölke, N.: Individual tree crown delineation in high-resolution remote sensing images based on U-Net, Neural Computing and Applications, 34, 22197-22207, 10.1007/s00521-022-07640-4, 2022.

Fu, H., Li, H., Dong, Y., Xu, F., and Chen, F.: Segmenting Individual Tree from TLS Point Clouds Using Improved DBSCAN, Forests, 13, 10.3390/f13040566, 2022.

Henrich, J., van Delden, J., Seidel, D., Kneib, T., and Ecker, A. S.: TreeLearn: A deep learning method for segmenting individual trees from ground-based LiDAR forest point clouds, Ecological Informatics, 84, 2024.

Kaartinen, H., Hyyppä, J., Yu, X., Vastaranta, M., Hyyppä, H., Kukko, A., Holopainen, M., Heipke, C., Hirschmugl, M., Morsdorf, F., Næsset, E., Pitkänen, J., Popescu, S., Solberg, S., Wolf, B. M., and Wu, J.-C.: An International Comparison of Individual Tree Detection and Extraction Using Airborne Laser Scanning, Remote Sensing, 4, 950-974, 2012.

Krisanski, S., Taskhiri, M. S., Gonzalez Aracil, S., Herries, D., Muneri, A., Gurung, M. B., Montgomery, J., and Turner, P.: Forest Structural Complexity Tool—An Open Source, Fully-Automated Tool for Measuring Forest Point Clouds, Remote Sensing, 13, 2021.

Krůček, M., Král, K., Cushman, K. C., Missarov, A., and Kellner, J. R.: Supervised Segmentation of Ultra-High-Density Drone Lidar for Large-Area Mapping of Individual Trees, Remote Sensing, 12, 10.3390/rs12193260, 2020.

LI, P., WU, H. e., JING, J., and LI, R.: Noise classification denoising algorithm for point cloud model, Computer Engineering and Applications, 52, 188-192, 2016.

Liu, Y., Zhang, A., and Gao, P.: From Crown Detection to Boundary Segmentation: Advancing Forest Analytics with Enhanced YOLO Model and Airborne LiDAR Point Clouds, Forests, 16, 10.3390/f16020248, 2025.

Liu, Y., Sun, P., Wergeles, N., and Shang, Y.: A survey and performance evaluation of deep learning methods for small object detection, Expert Systems with Applications, 172, 114602, https://doi.org/10.1016/j.eswa.2021.114602, 2021a.

Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., and Guo, B.: Swin Transformer: Hierarchical Vision Transformer using Shifted Windows, 2021 IEEE/CVF International Conference on Computer Vision (ICCV), 10-17 Oct. 2021, 9992-10002, 10.1109/ICCV48922.2021.00986,

LUO, H.-b., YUE, C.-r., ZHANG, G.-f., LONG, F., YANG, W.-j., and XU, W.-t.: Application of Airborne LiDAR in Inversion Forest Leaf Area Index at Different Regional Scales, Journal of West China Forestry Science, 50, 33-40, 2021.

Nan, G., Zhao, Y., Lin, C., and Ye, Q.: General Optimization Methods for YOLO Series Object Detection in Remote Sensing Images, IEEE Signal Processing Letters, 31, 2860-2864, 2024.

Pang, Y., Wang, W., Du, L., Zhang, Z., Liang, X., Li, Y., and Wang, Z.: Nyström-based spectral clustering using airborne LiDAR point cloud data for individual tree segmentation, International Journal of Digital Earth, 14, 1452-1476, 2021.

Wang, Y., Bashir, S. M. A., Khan, M., Ullah, Q., Wang, R., Song, Y., Guo, Z., and Niu, Y.: Remote sensing image super-resolution and object detection: Benchmark and state of the art, Expert Systems with Applications, 197, 116793, https://doi.org/10.1016/j.eswa.2022.116793, 2022.

Woo, S., Park, J., Lee, J.-Y., and Kweon, I.-S.: CBAM: Convolutional Block Attention Module, ArXiv, abs/1807.06521, 2018.

Xu, X., Jiang, Y., Chen, W., Huang, Y.-L., Zhang, Y., and Sun, X.: DAMO-YOLO : A Report on Real-Time Object Detection Design, ArXiv, abs/2211.15444, 2022.

Yang, B., Dai, W., Dong, Z., and Liu, Y.: Automatic Forest Mapping at Individual Tree Levels from Terrestrial Laser Scanning Point Clouds with a Hierarchical Minimum Cut Method, Remote Sensing, 8, 10.3390/rs8050372, 2016.

Zhang, W., Qi, J., Wan, P., Wang, H., Xie, D., Wang, X., and Yan, G.: An Easy-to-Use Airborne LiDAR Data Filtering Method Based on Cloth Simulation, Remote Sensing, 8, 2016.

Zhao, L.: Application and Prospect of Airborne Lidar in Forest Resource Parameter Acquisition, Forestry Science and Technology Information, 54, 71-73, 2022.

ZHAO, Z., LI, D., ZHAO, D., CHENG, Z., and GUO, X.: Canopy Segmentation and Biomass Estimation Based on Deep Learning, Forest Engineering, 40, 145-155, 2024.

Zhen, Z., Quackenbush, L., and Zhang, L.: Impact of Tree-Oriented Growth Order in Marker-Controlled Region Growing for Individual Tree Crown Delineation Using Airborne Laser Scanner (ALS) Data, Remote Sensing, 6, 555-579, 2014.

Zhou, Y., Wang, L., Jiang, K., Xue, L., An, F., Chen, B., and Yun, T.: Individual tree crown segmentation based on aerial image using superpixel and topological features, Journal of Applied Remote Sensing, 14, 022210 - 022210, 2020.