

Individual Tree Crown Delineation and Species Classification in Urban Landscapes from Multi-Source Remote Sensing by Integrating SAM and Watershed Segmentation

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Abstract

Urban trees enhance the urban environment through various ecosystem services. Individual tree delineation and species classification provide information on the location, structure, and species of each tree from remote sensing datasets, offering valuable data support for efficient and refined urban greening management. However, existing individual tree delineation algorithms developed based on single-source remote sensing datasets struggle to address the complexity of urban green landscapes, such as conifer-broadleaf mixtures, tree-shrub complexes. Additionally, the relationship between classification accuracy and individual tree delineation quality remains unclear. This study integrates the Segment Anything Model (SAM) and Marker-Controlled Watershed Segmentation (MCWS), combining imagery and LiDAR features, to optimize individual tree delineation in complex urban landscapes. Species classification was then performed on crown datasets from different algorithms to investigate how classification accuracy responds to varying crown qualities. The results demonstrate that the proposed SAM-WS algorithm effectively enhances individual tree delineation accuracy, achieving the highest F1-Score of 0.75, with improvements of 0.20 and 0.27 over SAM and MCWS, respectively. The classification accuracy based on SAM-WS crowns was the highest among all algorithm-derived crown datasets, with an Overall Accuracy (OA) of 0.79 and a Kappa of 0.64. As the average F1-Score of crown delineation dropped from 1.00 to 0.48, the OA for classification decreased from 0.86 to 0.74, and Kappa from 0.77 to 0.38. Additionally, the classification accuracy of conifers and shrubs was more sensitive to the crown quality. This research offers new methodologies and insights into the application of remote sensing-based urban vegetation monitoring.

1. Introduction

Urban trees constitute an important component of urban ecosystems by providing multiple ecosystem service functions, including mitigation of the urban heat island effect (Li et al., 2024), conservation of biodiversity (Turo and Gardiner, 2020), and provision of recreational spaces (Rojas-Rueda et al., 2019). Accurate monitoring of urban trees plays a crucial role in quantifying their maintenance costs and service values, thereby supporting the sustainable management of urban greening (Klobucar et al., 2020).

Achieving fine-scale urban vegetation monitoring requires individual-tree-level information on tree location, structure, and species (Ottoy et al., 2025). However, conventional field surveys are both time- and labor-intensive, and plot-based surveys may also introduce uncertainties due to sampling bias (Sharma et al., 2025). Advances in high-resolution and multi-source remote sensing have made it increasingly feasible to obtain such information efficiently from neighbourhood to city scales. Optical imagery provides spectral and textural information on trees, whereas LiDAR captures their vertical structural characteristics, thereby promoting individual tree crown delineation and species classification from remote sensing data (Guo et al., 2021; Zheng et al., 2025).

Individual tree delineation refers to the extraction of each tree crown extent from imagery or point cloud (Jaskierniak et al., 2021; Tong and Zhang, 2025). Existing individual tree delineation methods can generally be divided into process-based methods and deep learning methods (Zheng et al., 2025).

Process-based methods mainly achieve delineation by applying manually defined rules based on crown characteristics, such as watershed segmentation (Jing et al., 2012), distance threshold (Li et al., 2012), and kernel density estimation (Jaskierniak et al., 2021); deep-learning methods for individual tree delineation mainly rely on neural networks to learn discriminative features directly from the imagery or point cloud, such as Mask R-CNN (Hao et al., 2021), Segment Anything Model (SAM) (Kirillov et al., 2023), and StarDist (Tong and Zhang, 2025).

Existing algorithms can accurately capture crown boundaries in forests with simple species composition and single-layer canopy structure. However, a unimodal remote sensing dataset is often insufficient to fully characterize complex forest attributes (Ball et al., 2023; Ma et al., 2022). For example, Marker-Controlled Watershed Segmentation (MCWS) based on LiDAR-derived height products typically detects local maxima as treetop markers and delineates crowns according to height variations within the canopy surface, but it tends to over-segment broadleaf crowns with multiple treetop structures (Qin et al., 2022). In contrast, image-based methods such as Mask R-CNN and SAM can exploit spectral and textural differences between adjacent crowns, as well as between crowns and the background, for individual tree delineation (Afsar et al., 2024; Hao et al., 2021). Nevertheless, their performance is often limited in forests with high canopy closure (Zhu et al., 2025).

Urban green landscapes are often characterized by conifer-broadleaf mixtures, tree-shrub complexes, and locally high canopy closure (Man et al., 2025), making it difficult to directly apply existing algorithms to individual tree crown delineation in

urban vegetation. Therefore, it is necessary to integrate the complementary advantages of multi-source sensors and jointly exploit crown structural, color, and textural features to develop a novel individual tree delineation algorithm suitable for urban green landscapes.

With the development of individual tree delineation techniques, tree species classification has gradually evolved from the stand or pixel scale to the individual tree scale (Chen et al., 2024). Crowns derived from either algorithmic delineation or visual interpretation were used as samples for feature extraction and for classifier training and validation, allowing crown structural information to be incorporated to improve classification accuracy (Dalponte et al., 2014). This also implies that the quality of crown delineation can influence subsequent classification performance. However, research comparing individual tree classification accuracy under varying crown qualities delineated by different algorithms is still limited.

This study developed a new SAM-WS algorithm for complex urban vegetation landscapes by integrating MCWS and SAM with both imagery and LiDAR data, and validated its accuracy in eight urban plots across two study areas. Subsequently, species classification was conducted based on the crowns delineated by different algorithms, and the differences in classification accuracy based on varying delineation crowns were compared.

2. Datasets and Methods

2.1 Study area

This study was conducted in two areas: the Xianlin Campus of Nanjing Normal University (NNU) in Nanjing, China (32°06'~32°07' N, 118°53'~118°54' E), and Cooling Town in Mount Lushan, China (29°29'~29°36' N, 115°55'~116°01' E). Both areas are situated in the subtropical monsoon climate zone. The landform of Nanjing is mainly composed of plains and low hills with gentle terrain, whereas Mount Lushan is characterized by hilly and mountainous landscapes with steeper topography.

The vegetation in the study areas is dominated by planted urban greenery, with conifer-broadleaf mixtures and tree-shrub mosaics, which pose challenges for individual tree segmentation and classification. The dominant tree species on the NNU campus include *Platanus acerifolia*, *Camphora officinarum*, *Osmanthus fragrans*, *Koelreuteria bipinnata*, and *Metasequoia glyptostroboides*, whereas those in Cooling Town include *Platanus acerifolia*, *Pinus hwangshanensis*, *Chamaecyparis obtusa*, and *Cryptomeria japonica*. The inventoried shrubs mainly include species that can be delineated as distinct individuals, such as *Osmanthus fragrans* and *Photinia serratifolia*, whereas dense shrub thickets were not considered.

2.2 Data acquisition and preprocessing

The UAV LiDAR point cloud and high-resolution RGB orthomosaic imagery of the NNU campus were obtained from the Yangtze River Delta Science Data Center, National Earth System Science Data Sharing Infrastructure, National Science & Technology Infrastructure of China (<http://geodata.nnu.edu.cn/>). Acquired in July 2022, the point cloud density exceeded 600 pts/m², and the imagery ground sampling distance (GSD) was 0.012 m. Correspondingly, the UAV LiDAR and high-resolution RGB imagery of Cooling Town were acquired in September 2022 using a DJI Matrice 300 RTK UAV equipped with a DJI Zenmuse L1 LiDAR sensor and its accompanying camera. The point cloud density exceeded 250 pts/m², and the imagery GSD was 0.033 m.

The imagery was resampled to a uniform spatial resolution of 0.033 m and subsequently enhanced using a 5% percent clip stretch. The point cloud was proportionally resampled to a density exceeded 200 pts/m², and then processed by spatial statistical denoising, cloth simulation filtering, and height normalization. Finally, rasterization was performed in point clouds to derive a digital surface model (DSM) and a canopy height model (CHM) at a spatial resolution of 0.1 m.

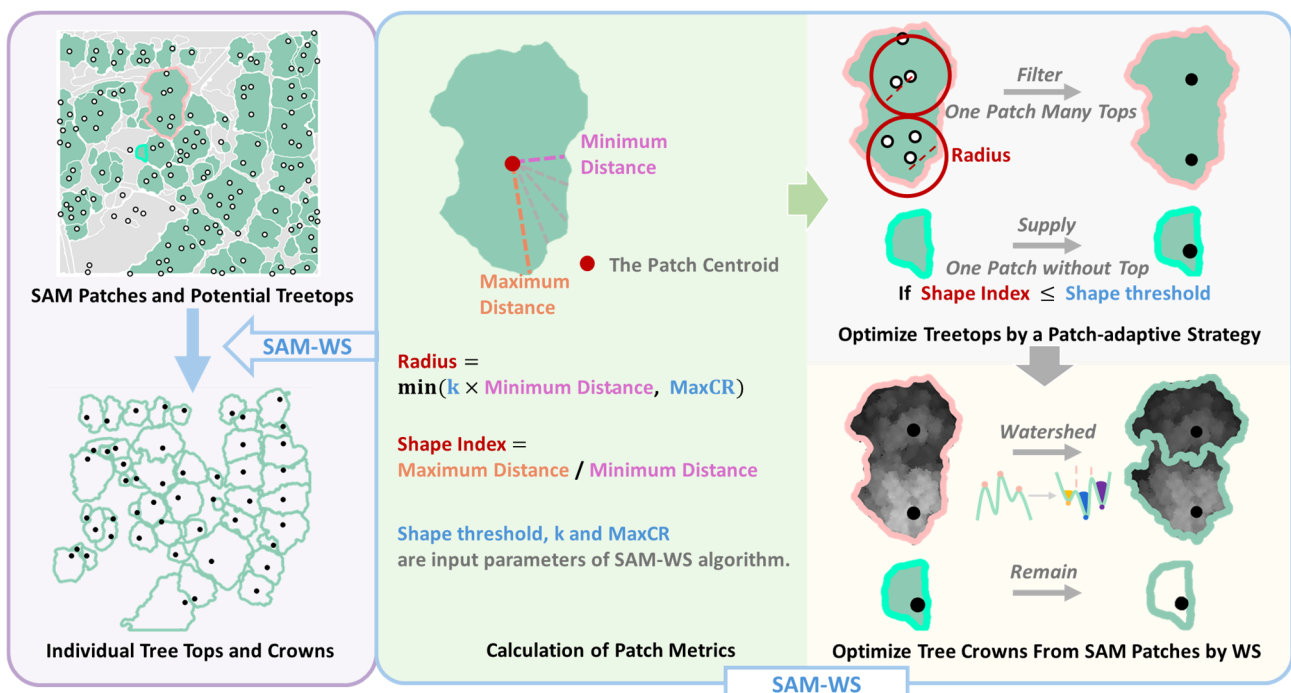


Figure 1. SAM-WS algorithm

Field surveys were conducted in Cooling Town and the NNU campus in August 2023 and July 2024, respectively. Four 50 × 50 m plots were selected in each study area, yielding eight plots in total. All 367 trees within the plots were used to evaluate the accuracy of individual tree segmentation algorithms. In addition, 361 samples surrounding the plots were sampled according to the species composition within the plots, yielding 728 samples for training and validating the classification model. Tree locations were recorded using a GNSS receiver and checked against high-resolution imagery. Reference crown boundaries were delineated by visual interpretation, and species were identified using the FlowerMate application, the Plant Photo Bank of China (<https://www.ppbc.cn/>), and consultations with local horticultural staff.

2.3 Individual tree delineation

A new individual tree delineation algorithm called SAM-WS was developed in this study (Figure 1). To improve delineation performance in urban green landscapes with conifer-broadleaf mixtures and tree-shrub mosaics, the SAM-WS algorithm combines SAM and MCWS by integrating high resolution imagery with LiDAR point cloud. The algorithm generally consists of three steps: (1) initial extraction of treetops and SAM patches; (2) patch-adaptive treetop optimization; and (3) treetop-controlled crown optimization.

2.3.1 Initial extraction of treetops and SAM patches: Initial treetops were detected from the point cloud using local maximum filtering. The filter window size was tuned for each plot, and a circular window with a radius of 1.5 m was found to be suitable for most scenes. Canopy patches were extracted from high-resolution RGB imagery using SAM via the samgeo package (Wu and Osco, 2023). The ViT-H backbone of SAM was used to automatically generate image masks. Three hyperparameters, namely *pred_iou_thresh*, *stability_score_thresh*, and *stability_score_offset*, were optimized through grid search to determine the optimal parameter combination for each plot. Threshold-based post-processing was then applied to retain only tree and shrub patches from the full-scene patches, based on a green-pixel fraction >30%, a mean CHM height >2 m, and a maximum-to-mean CHM ratio below a predefined threshold. The resulting initial treetops and SAM patches were used as inputs for the subsequent optimization steps.

2.3.2 Patch-adaptive treetop optimization: The patch-adaptive treetop optimization was designed to refine the initial treetops into final individual treetops according to the size and shape of each SAM-derived patch and the number of initial treetops within it. The optimization was performed as follows: (1) if a tree or shrub patch contained two or more initial treetops, an adaptive search-window radius based on the patch size was used for further LMF to reduce redundant treetops (Equation 1); (2) if the patch contained a single initial treetop, the treetop was preserved; (3) if the patch contained no initial treetops but had a reasonable shape (*Shape Index* ≤ *Shape Threshold*), the location of the highest DSM cell within the patch was added as a treetop (Equation 2); and (4) for non-tree/shrub patches, all initial treetops within the patch were removed.

$$Radius = \min(k \times MinDis, MaxCR) \quad (1)$$

$$Shape\ Index = MaxDis/MinDis \quad (2)$$

Where *MaxDis* and *MinDis* denote the maximum and minimum distances from the patch centroid to the patch boundary, respectively; *min()* represents the minimum operator; and *Shape*

Threshold, *k*, and *MaxCR* are input parameters adjusted according to the crown structure in each plot. *MinDis* served as the primary indicator of patch size and was combined with the adjustment factor *k* and the maximum crown radius observed in each plot (*MaxCR*) to account for variations in crown morphology. A patch was considered to have a reasonable crown-like shape when its *Shape Index* was less than or equal to the plot-specific *Shape Threshold*.

2.3.3 Treetop-controlled crown optimization: Using the final individual treetops as markers, the SAM patches were further refined by MCWS to produce the final individual tree crown delineation results. The specific steps were as follows: (1) if a tree or shrub patch contained two or more final treetops, these treetops were used as markers for MCWS to segment the DSM, and the resulting boundaries were used to replace the patch; (2) if a patch contained a single final treetop, it was directly retained as the final crown boundary; and (3) if a patch contained no treetops, the patch was removed.

2.3.4 Comparison with baseline methods: The crown delineation results produced by SAM-WS were compared with those generated by SAM (Wu and Osco, 2023) and MCWS (Chen et al., 2006) to assess its improvement over the baseline algorithms. The tree- and shrub-covered regions derived in 2.3.1 were used to filter the outputs of SAM and MCWS, since these algorithms cannot distinguish trees from other urban objects, such as buildings and streetlights.

2.4 Individual tree classification

Individual tree classification was performed after crown delineation. The delineated crown results were regrouped into four classes: broadleaf trees, coniferous trees, shrubs and non-tree/shrub objects. A random forest classifier was adopted due to its widespread use in recent individual tree classification studies (Qin et al., 2022; Xu et al., 2020).

To minimize the influence of crown delineation quality on classifier training, 361 additional samples were manually collected around the plots through visual interpretation to train the random forest classifier, including 349 reference crowns and 12 non-tree/shrub samples. The trained classifier was then applied separately to four crown datasets within the plots, derived from visual interpretation, SAM-WS, SAM, and MCWS, respectively, and the resulting classification accuracies were compared.

For individual tree crown classification, 42 features were extracted, including 20 imagery features and 22 point-cloud features (Table S1). The imagery features mainly comprised the mean and standard deviation of the RGB bands, vegetation indices, and texture metrics, whereas the point-cloud features characterized the height distribution, intensity distribution, and structural attributes of the crown point cloud. Ten-fold cross-validation combined with grid search was used to optimize the hyperparameters and rank feature importance, based on which the optimal feature subset and hyperparameter combination were selected.

2.5 Accuracy evaluation

The accuracy of individual tree delineation was evaluated using Recall, Precision, and F1-Score, which were calculated based on the counts of True Positives (TP), False Positives (FP), and False Negatives (FN). Additionally, the accuracy of individual tree classification was assessed using Overall Accuracy (OA),

Cohen's Kappa (Kappa), User's Accuracy (UA), and Producer's Accuracy (PA), all derived from the confusion matrix.

3. Result

3.1 Individual tree delineation

The SAM-WS algorithm achieved the highest individual tree delineation accuracy, with an F1-score of 0.75, exceeding those of SAM and MCWS by 0.20 and 0.27, respectively. It also achieved the highest Recall and Precision, with values of 0.70 and 0.81, respectively (Figure 2). Relative to SAM, SAM-WS improved Recall and Precision by 0.25 and 0.10, respectively. Compared with MCWS, the improvements reached 0.27 and 0.27.

Three representative plots with simple, moderate, and complex vegetation conditions were selected to visually compare the delineation results of different algorithms (Figure 3). SAM exhibits an under-segmentation tendency for contiguous broadleaf trees; MCWS tends to over segment broadleaf trees while missing conifers and shrubs. In contrast, SAM-WS mitigates these issues and provides better crown delineation for broadleaf trees, conifers, and shrubs, resulting in tree composition and spatial distribution patterns that are more consistent with the visual interpretation of the plots.

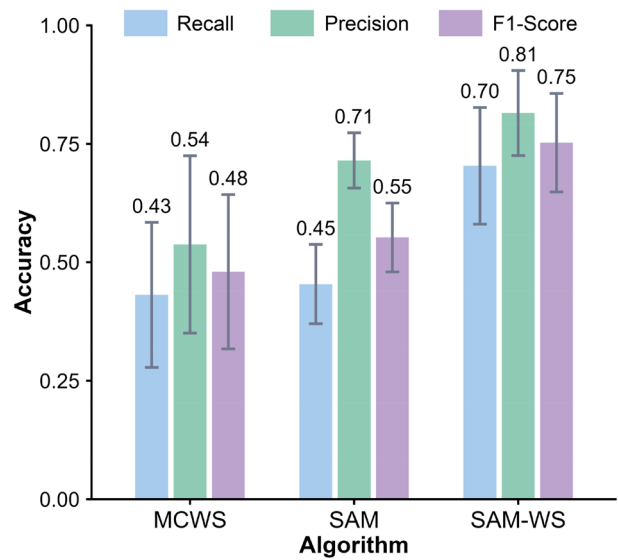


Figure 2. Accuracy of individual tree delineation among different algorithms

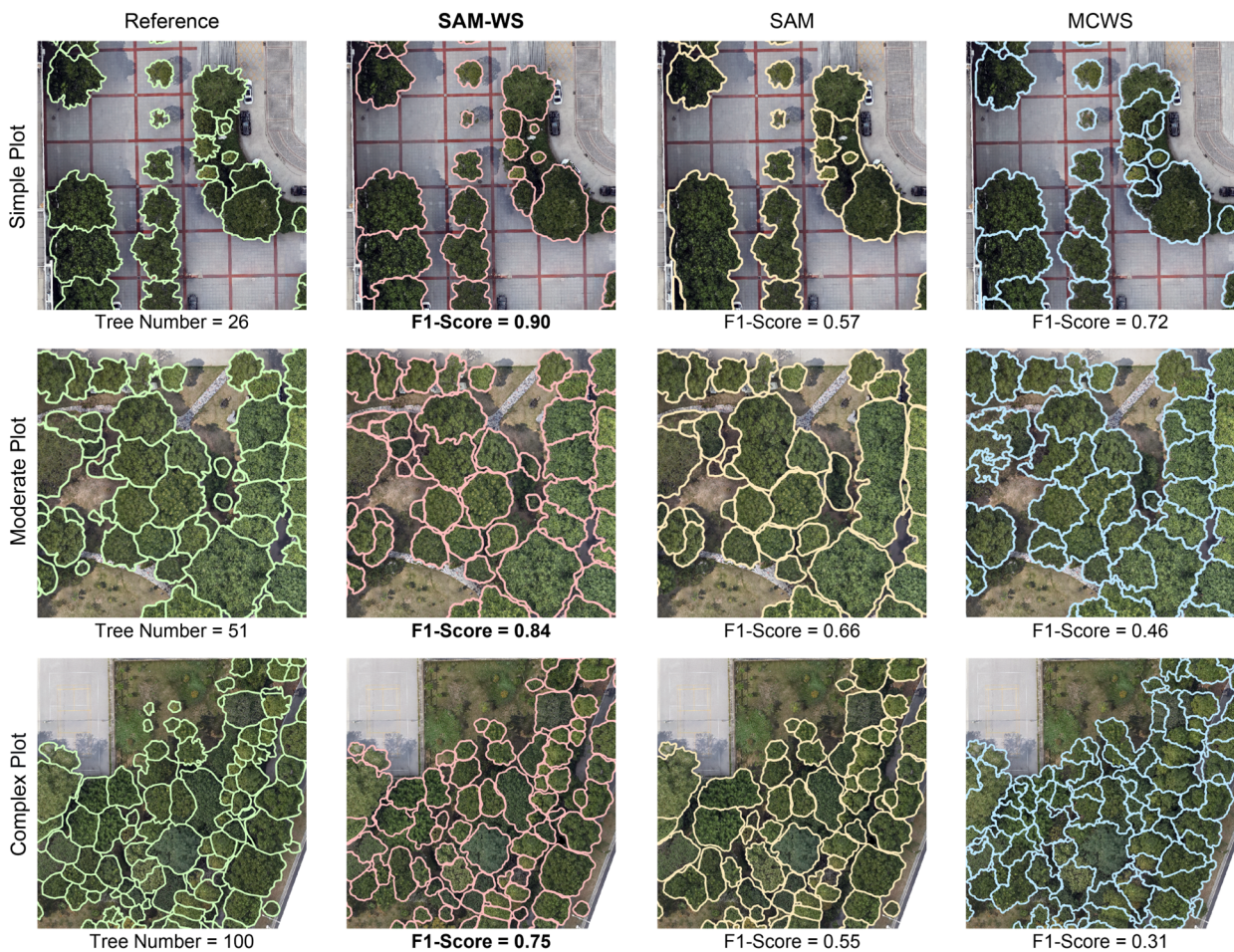


Figure 3. Visualization of individual tree delineation results in typical plots

3.2 Individual tree classification

For classification, the reference crowns achieved the highest accuracy, with an OA of 0.86 and a Kappa of 0.77. Among the algorithm-delineated crown datasets, SAM-WS crowns yielded the best performance (OA = 0.79, Kappa = 0.64), slightly outperforming SAM crowns (OA = 0.79, Kappa = 0.63), whereas MCWS crowns had the lowest accuracy (OA = 0.74, Kappa = 0.38).

Broadleaf trees generally achieved higher classification accuracy than conifers and shrubs, with both PA and UA remaining above 0.80 across all crown datasets. For conifers, PA and UA ranged from 0.54 to 0.88 and from 0.52 to 0.88, respectively. For shrubs, PA ranged from 0.38 to 0.74, while UA ranged from 0.75 to 0.87 (Table 1).

Database	Class	PA	UA	OA	Kappa
MCWS Crowns	Broadleaf	0.84	0.82	0.74	0.38
	Conifer	0.54	0.52		
	Shrub	0.38	0.75		
	Non tree/shrub	0.00	0.00		
SAM Crowns	Broadleaf	0.85	0.82	0.79	0.63
	Conifer	0.81	0.78		
	Shrub	0.53	0.76		
	Non tree/shrub	0.25	0.17		
SAM-WS Crowns	Broadleaf	0.83	0.85	0.79	0.64
	Conifer	0.83	0.76		
	Shrub	0.55	0.72		
	Non tree/shrub	0.20	0.33		
Reference Crowns	Broadleaf	0.89	0.87	0.86	0.77
	Conifer	0.88	0.88		
	Shrub	0.74	0.87		
	Non tree/shrub	1.00	0.00		

Table 1. Accuracy of tree species classification in different crown datasets

4. Discussion

4.1 Advantages of our algorithm

To improve individual tree delineation accuracy in complex urban green landscapes, this study developed an optimization SAM-WS algorithm that integrates MCWS and SAM by combining imagery and LiDAR data. Delineation accuracy was evaluated in eight plots and compared with that of SAM and MCWS. The results demonstrated that the SAM-WS algorithm could improve individual tree delineation accuracy in urban green landscapes characterized by conifer-broadleaf mixtures, tree-shrub complexes, and locally high canopy closure.

To address the issues of uneven delineation of coniferous and broadleaf trees and the omission of shrubs in process-based methods such as MCWS, the integration of SAM enables the SAM-WS algorithm to pre-segment coniferous, broadleaf, and shrub patches within a scene by capturing visual differences among adjacent crowns. By incorporating subsequent patch-by-patch optimization, the algorithm reduces delineation errors caused by differences in crown morphology and partial occlusion, thereby improving the identification of trees in conifer-broadleaf mixed areas and shrubs with only partially visible crowns. In some parts of the scene, such as continuous rows of broadleaved street trees, adjacent crowns show neither clear gaps nor obvious

visual differences. In such cases, MCWS is applied to capture height variations on the canopy surface and refine the SAM-derived canopy patches.

The studies by Lei et al. (2025) and Qin et al. (2022) also improved tree delineation accuracy on the basis of watershed segmentation through the integration of image features. Together with the present study, these works support the feasibility of data fusion strategies for individual tree delineation in complex stands.

4.2 Influence of delineation on classification

The study compared the accuracy of tree species classification based on reference crowns, SAM-WS crowns, SAM crowns, and MCWS crowns. The results indicate that the accuracy of individual tree species classification is influenced by crown quality, particularly evident in coniferous trees and shrubs.

Chen et al. (2024) noted that interspecific similarity and intraspecific variability are key factors influencing remote sensing-based tree species classification. Crown delineation errors further exacerbate this phenomenon, leading to a decline in tree species classification accuracy (Dalponte et al., 2014). For instance, over-segmentation of broadleaved trees and under-segmentation of coniferous trees can result in crown sizes of different species becoming increasingly similar. Meanwhile, inaccurate crown boundaries may cause confusion in color and texture features among adjacent crowns of different species (Lei et al., 2025).

4.3 Limitations and future work

Regarding individual tree segmentation, constrained by the limitation of watershed algorithm, the SAM-WS method only addresses cases where shrub crowns are partially occluded, while shrubs that are completely occluded remain difficult to identify. In the future, multi-source data need to be fused using a point-cloud-based processing approach, rather than relying solely on surface height information, to capture forest stratification and species-specific features. This is essential for improving the accuracy of individual tree delineation and classification in forests with complex canopies and diverse tree species (Hamraz et al., 2017; Liu et al., 2026).

Additionally, current accuracy assessment methods for individual tree classification exhibit some limitations. Specifically, when crown delineation is inaccurate, the species occupying the majority area within a crown sample is typically assigned as the label for that sample (Steier et al., 2024). This approach overlooks the mixing of multiple species within a single crown sample, making it difficult to adequately quantify the uncertainty in individual tree species classification. Therefore, future work should focus on developing a more robust accuracy assessment framework to account for species mixing within crown samples from delineation algorithms, ultimately supporting more reliable evaluation of individual tree species classification results.

5. Conclusion

To achieve large-scale, fine-grained monitoring of urban trees, this study proposes a new SAM-WS algorithm for individual tree delineation and examines the effect of crown delineation quality on crown classification. Results show that SAM-WS improves the performance of individual tree delineation, and tree crown delineation quality indeed affects crown-level classification. The SAM-WS algorithm is well suited to complex urban green

landscapes with conifer-broadleaf mixtures and tree-shrub complexes, yielding tree composition and spatial distribution patterns that more closely match the ground truth. By integrating multi-source data and coupling the deep learning model with the traditional algorithm, this work offers a new framework to urban individual tree delineation and classification.

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Appendix

Source	Features
	R_mean, G_mean, B_mean, R_std, G_std, B_std (Chen et al., 2024)
Imagery	VARI, NGRDI (Gitelson et al., 2002); GLA (Louhaichi et al., 2001); ExG, ExGR, VEG (Hamuda et al., 2016). Mean, Entropy, Contrast, Second moment, Homogeneity, Dissimilarity, Variance, Correlation (Haralick et al., 1973).
	H_mean, H_std, H_cv, H_p25, H_p50, H_p75, H_iq, I_mean, I_std, I_cv, I_p25, I_p50, I_p75, I_iq (Liu et al., 2017).
LiDAR	Tree height, Crown projection area, Crown width, Crown length, Crown volume, Crown length ratio; Crown volume ratio (Liu et al., 2017); Crown aspect ratio (Jucker et al., 2025).

Table S1. Features for tree species classification