Precise Estimation of Urban Vegetation Carbon Stock Using Multi-Source LiDAR: A Case Study of East China Normal University

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Abstract: With the intensification of global climate change, accurately estimating vegetation carbon stock has become one of the keys to achieving carbon neutrality. This study combines multi-source LiDAR data and empirical carbon stock formulas to propose a comprehensive and reliable technical framework for the fine estimation of urban vegetation carbon stock. This framework includes: LiDAR data preprocessing, shrub extraction and volume calculation, tree segmentation, and carbon stock calculation. In particular, the study compares various commonly used tree segmentation algorithms and uses the layer stacking algorithm for tree segmentation in the study area, ultimately obtaining the total carbon stock in the study area to be 2,677,442.666 kg. Overall, this technical framework can effectively improve the accuracy and efficiency of traditional urban vegetation carbon stock estimation, providing technical support and data foundation for achieving carbon neutrality.

1 INTRODUCTION

Research on the carbon cycle in urban ecosystems has become a focal point in climate change mitigation strategies. Urban carbon storage is primarily composed of trees and shrubs, both playing an irreplaceable role in improving the living environment, maintaining ecological security, and achieving sustainable urban development (Creutzig et al., 2016). Traditionally, estimation of urban carbon stocks relied on field measurements. However, this method is highly subjective and laborious (Zhang et al., 2015). Meanwhile, although high-resolution satellite remote sensing images have significant spectral characteristics and rich texture information, they failed to provide data below the canopy and neglected the vertical spatial structure differences of vegetation, resulting in a lower accuracy in carbon stock estimation.

The rise of LiDAR (Light Detection and Ranging) technology has provided robust technical support for fine carbon stock estimation. LiDAR is characterized by its high resolution, strong penetrative ability, and high efficiency, allowing for the convenient acquisition of accurate three-dimensional structural information of urban vegetation. Additionally, LiDAR operates effectively under various environmental conditions and offers high precision and high-density data collection capabilities.

Since the majority of urban carbon storage comes from trees. Therefore, the accuracy of carbon stock estimation based on LiDAR largely depends on the precision of tree segmentation (Mei and Durrieu, 2004). Current tree segmentation algorithms can be primarily divided into two categories: tree segmentation based on Canopy Height Model(CHM) or point clouds.

For CHM-based tree segmentation, Hyyppä et al. (2001) were the first to apply the region-growing algorithm to the segmentation of LiDAR data in Nordic coniferous forests. Mei & Durrieu (2004) achieved a 90% accuracy using the watershed algorithm for tall and regularly spaced trees, but faced challenges of over-segmentation or under-segmentation in complex and dense forests. Koch et al. (2006) employed the flooding algorithm to segment coniferous and deciduous forests in Germany, achieving an accuracy of 61.7%. Chen et al. (2006) proposed a marker-controlled watershed tree segmentation algorithm, tested with an accuracy of 64.1% in the savannas of California, USA. Khosravipour et al. (2014) enhanced upon Chen et al.'s algorithm by removing CHM pits through

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overlapping point cloud subsets, achieving a segmentation accuracy of 74.2%. Besides, Kaartinen et al. (2012) introduced two new methods: multi-scale Gaussian Laplacian segmentation and CHM minimum curvature segmentation. Overall, CHM-based tree segmentation runs fast, although the interpolation process and canopy cover of tall trees can affect the results.

Tree segmentation algorithms based on point clouds are more straightforward, avoiding potential errors that may arise during CHM generation. Nevertheless, these methods require substantial computational resources and high-performance hardware. Early studies such as Morsdof et al. (2004) were the first to apply k-means clustering for tree segmentation, demonstrating the feasibility of this approach. Li et al. (2012) introduced a region-growing algorithm combined with threshold judgment, achieving an accuracy of 0.9 in California, USA, but the segmentation accuracy of this algorithm in deciduous forests was lower. Lu et al. (2014) introduced a bottom-up region-growing algorithm that marked trunk points and allocated distances topologically, achieving a recall rate of 0.84 and an accuracy of 0.97 in the deciduous forests of Pennsylvania, USA. Lin et al. (2017) used circle detection theory to extract individual tree locations, heights, and diameters at breast height, achieving an accuracy of over 90%. Aryey et al. (2017) developed layer stacking algorithm that clusters point clouds at 1-meter intervals, performing better than traditional algorithms in deciduous or leafless conditions. Paris et al. (2016) explored a combined method using CHM and point cloud space, accurately segmenting dominant trees by analyzing horizontal and vertical profiles of the point cloud, achieving an accuracy exceeding 92%.

This study utilizes multi-source LiDAR data to test and compare several commonly used tree segmentation algorithms, with the aim of proposing a comprehensive and reliable technical process for fine estimation of urban vegetation carbon stock. The results aim to serve as a guideline for future urban planning and sustainable development endeavors. This article is organized as follows: Section 2 will show the materials and methods in this research, Section 3 will display all the results and analysis, and Section 4 will provide the discussion and conclusions.

2 MATERIALS AND METHODS

2.1 Study Area

Study area in this research is East China Normal University (Minhang Campus), which is located on No. 500 Dongchuan Rd., Minhang District, Shanghai, China(Figure 1). Due to the large size of the study area, the campus is divided into eight zones based on the road, river, and vegetation characteristics. The campus is rich in tree species, dominated by camphor, bellflower, ginkgo, and luan. Also, it contains a variety of deciduous small trees. In terms of shrubs, they mainly composed of buxus sinica and rhododendron.

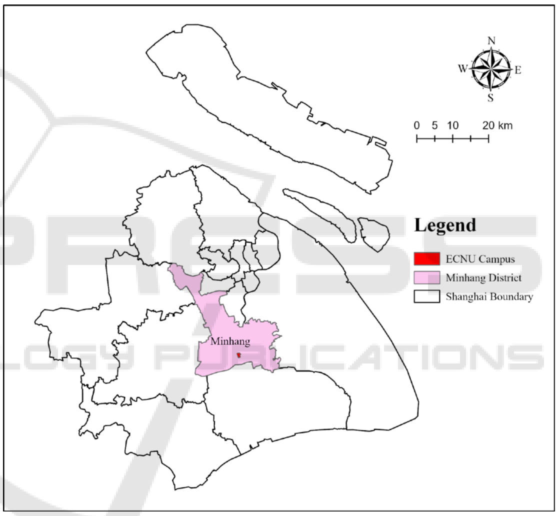


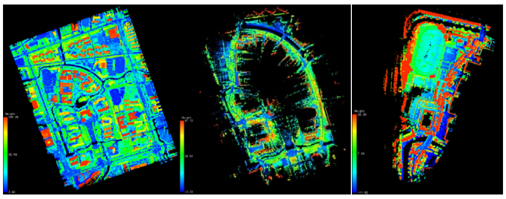
Figure 1: Study area (Picture credit: Original)

2.2 Data Source

This study contains three parts of LiDAR data, namely airborne, vehicle-mounted and backpack LiDAR. The detailed information of each data type is shown in Table 1 and data samples are shown in Figure 2.

Table 1: Detailed information of different types of LiDAR data

Data Type	Acquisition Device	Coordinate System	Point Density	File Format	File Size(G)	Range
Airborne	ECNU-ULS	UTM Zone 51N	Low	las	3.1	Entire campus
Vehicle-mounted	ECNU-MLS	UTM Zone 51N	High	las	13.7	Main roads only
Backpack	LiBackpack C50	Relative coordinates	High	ply	19.8	Entire campus



(a) (b) (c)

Figure 2: Sample LiDAR data: (a) Airborne LiDAR (entire campus area); (b) Vehicle- mounted LiDAR(main roads only); (c) Backpack LiDAR(part of Zone 5) (Picture credit: Original)

2.3 Technical Framework

The study harnesses multi-source LiDAR data and proposes a reliable technical framework for fine estimation of urban carbon stock. Four steps are involved in the technical framework (Figure 3), namely LiDAR data preprocessing, shrub extraction and volume calculation, tree segmentation methods and carbon stock calculation.

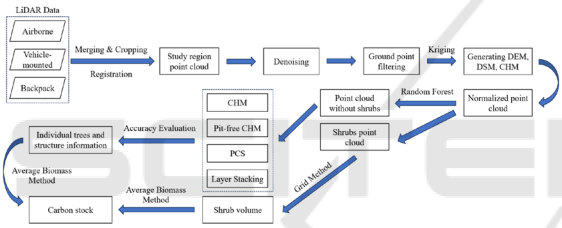


Figure 3: Techinical framework of the research (Picture credit: Original)

2.4 LiDAR Data Preprocessing

The LiDAR data preprocessing includes: 1) Multi-source data registration to UTM Zone 51N coordinate system, 2) Data merging and cropping, 3) LiDAR denoising, 4) Ground point filtering, 5) Kriging interpolation to generate DEM, DSM and CHM with the pixel size of 0.1m, 6)Point cloud normalization.

In this study, traditional automatic registration methods(e.g. Iterative Closest Point) are less effective due to the disparity in point density between aerial LiDAR data and other two forms of data. Therefore, in this study, a stepwise minimum spanning tree matching algorithm based on quadrant search is utilized for point cloud registration.

The algorithm primarily involves of three steps: extraction of tree locations, quadrant search-based minimum spanning tree matching, and registration. As the airborne and vehicle-mounted LiDAR data already had UTM coordinates, only the transformation matrix from backpack LiDAR data to UTM coordinates needs to be calculated. Firstly, the tree location points collected from the three LiDAR data are extracted, and then matched based on the topological similarity of the minimum spanning tree connected into a quadrant search, and matched by stepwise search, finally realizing the fusion of the LiDAR data collected by three different sensors.

2.5 Shrub Extraction and Volume Calculation

Shrubs constitute a crucial component of urban vegetation, playing an essential role in the calculation of urban carbon stock. The extraction of shrubs from the point cloud data was accomplished using the random forest algorithm, integrated within the LiDAR360 software. By manually selecting a small number of representative shrub point clouds to train the model and applying the model to the remaining data, all shrubs in the point cloud can be obtained. This approach substantially reduces the labor-intensive and time-consuming nature of manual selection.

The calculation of shrub volume uses the grid method, which is conceptually similar to calculus. Specifically, the process begins by projecting 3D point cloud data onto a 2D plane Then, the 2D plane is divided into small cells using a grid structure. The tallest point in each grid is recorded, multiplying by the grid cell size gives the volume of the shrub within that cell. The overall volume of shrub is calculated by adding the volumes of all the grid cells.

Therefore, the choice of grid size largely determines the accuracy of the result volume. If the grid is too small, many grid cells might fall into gaps between point cloud data points, leading to an underestimated volume, and vice versa. Thus, the selection of grid size should primarily be based on point density. Since shrubs in LiDAR data are primarily detected by high-density backpack LiDAR and vehicle-mounted LiDAR, a grid size of 0.1m is chosen for this study.

2.6 Tree Segmentation Methods

This study evaluated and compared four common tree segmentation methods: two region-based segmentation methods using CHM and pit-free CHM, region-growing and threshold judgment algorithm (PCS), and Layer Stacking algorithm which both directly based on point cloud.

1) CHM (Chen et al., 2006)

The Watershed Algorithm is used for CHM based segmentation (Figure 4). It is mainly based on the concept of immersion simulation. It first takes the complement of the CHM, where each local minimum represents a tree height point, and its influence area is called a catchment basin (the extent of the tree crown). At the junction of catchment basins, a dam is constructed to form the watershed that segments the tree crowns, thereby isolating individual trees.

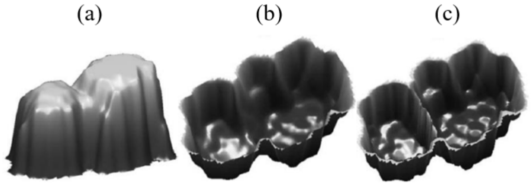


Figure 4: Watershed Algorithm (Picture credit: Original)

2) Pit-free CHM (Khosravipour et al., 2014)

However, black holes can form in the CHM as a result of some laser pulses passing through the tree crowns and reflecting back from the ground due to LiDAR's great penetration into the canopy. This phenomenon leads to an incomplete canopy surface and is referred to as pits.

Khosravipour et al. (2014) introduced a technique for generating pit-free CHM (Figure 5): First, an initial CHM (CHM00) is established. The normalized point cloud is then vertically stratified according to the ASPRS point cloud classification standards: low vegetation (0.5m < h ≤ 2.0m), medium vegetation (2.0m < h ≤ 5.0m), and high vegetation (h > 5.0m). For high vegetation, further stratification is done at 5-meter intervals. This results in the construction of CHMs for each layer (CHM02, CHM05, CHM10, ...). Finally, the CHMs of all layers are stacked, with each pixel in the result taking the maximum value of the corresponding x, y pixel position from all the layers, thereby generating a pit-free CHM and using the Watershed Algorithm for tree segmentation.

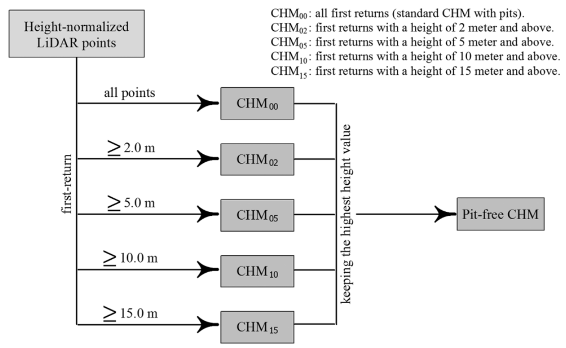


Figure 5: Methods for generating Pit-free CHM Picture credit: Khosravipour et al., 2014[1]

3) PCS (Li et al., 2012)

PCS algorithm makes the assumption that the tree apex is the local highest point in the LiDAR data. This point is used as a seed for region growing through iterative expansion. During each iteration, a threshold is used to determine whether a point belongs to an existing tree or represents a new tree apex. Points farther from the existing tree than the threshold are assigned to a new tree; points closer are categorized under the existing tree.

4) Layer Stacking (Ayrey et al., 2017)

Main steps of the Layer Stacking Algorithm are shown in Figure 6: (a) Vertically segment the point cloud starting from 0.5 meters with a certain interval (generally 1m) up to the highest point. (b) Applying K-means clustering algorithm to each layer. (c) Creating a 0.5m buffer polygon around each cluster. (d) Overlaying polygons of each layers. (e) Smoothing the overlap result using a window size of 1.5m. (f) Detecting the local maxima, which represent the center of the tree.

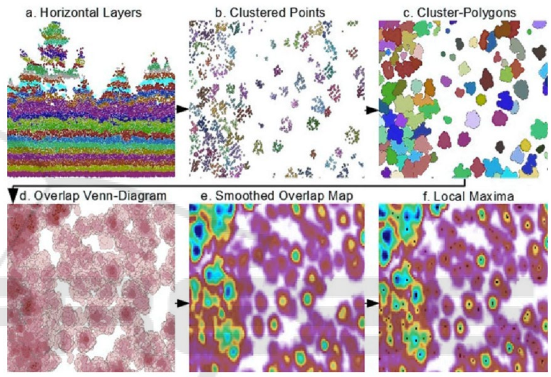


Figure 6: Main steps of Layer Stacking algorithm Picture credit: Ayrey et al., 2017[2]

There are three types of segmentation results (Figure 7): 1) True Positive (TP): The quantity of properly segmented trees. 2) False Positive (FP): The quantity of excessively segmented trees. 3) False Negative (FN): The quantity of unsegmented trees that are wrongly believed to be a component of other trees. To evaluate the accuracy of various tree segmentation methods on sample plots, the study used the following formulas to compute recall(r), precision(p), and F-score(F).

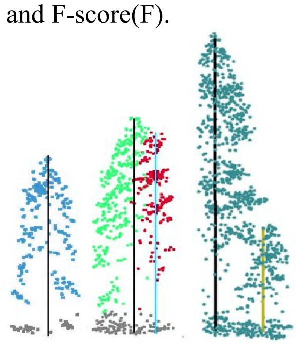


Figure 7: Three different types of segmentation results: (a) TP, (b) FP, (c) FN Picture credit: Original

$$r = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{1}$$

$$p = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{2}$$

$$F = 2 \times \frac{r \times p}{r + p} \tag{3}$$

2.7 Carbon Stock Calculation

After the tree segmentation process is finished, LiDAR360 may use the segmentation data to automatically determine each tree's diameter at breast height (DBH), crown width, tree height, and crown volume.

Carbon stock was calculated using the average biomass method of the sample plot inventory method, which is suitable for small to medium-scale plant biomass calculation in this study. Meanwhile, the anisotropic biomass growth equation is crucial for the measurement of carbon stock in trees. In order to guarantee the scientific validity of the carbon stock findings, the study selected common tree species in the campus, and constructed the biomass model of each tree species according to the local and adjacent areas of Shanghai. The carbon content coefficient was selected based on the average carbon content coefficient for forest trees, which is 0.5, as published by the IPCC. Finally, the following formulas were derived for calculating carbon stock in an individual tree (Zhong et al, 2019).

$$\textit{Soft broadleaf trees:}\ W = 0.01901D^{3.10510} \tag{4}$$

$$\textit{Hard broadleaf trees:}\ W = 0.10387D^{2.61147} \tag{5}$$

$$\textit{Coniferous:}\ W = 0.01639D^{2.01732}H^{-0.11744} + 0.06539D^{2.01732}H^{0.49425} \tag{6}$$

$$\textit{Carbon stock of trees:}\ C = W\alpha \tag{7}$$

In the formula, C, W, D, H, α respectively represent the carbon stock of trees, biomass, DBH, tree height and carbon content coefficient (0.5).

For the calculation of shrub carbon stock, considering that the distribution of shrubs on the campus is heterogeneous and difficult to distinguish, this study referenced the optimal models from previous research on the relationship between canopy volume and annual branch biomass of different shrubs in Shanghai. The study chose the common shrubs on the campus (Buxus sinica and Rhododendron) as the representative shrubs and averaged their carbon stock models to calculate the carbon stock of all shrubs on the campus (Fang, 2013).

$$\textit{Shrubs:}\ W = \left(\frac{820.78 \times V^{0.227} + 1046.8 \times V^{0.4022}}{1000}\right) \times 0.5 \tag{8}$$

$$\textit{Carbon stock of shrubs:}\ C = W\alpha \tag{9}$$

In the formula, C, W, V, α respectively represent the carbon stock of shrubs, biomass, shrub volume and carbon content coefficient (0.5).

3 RESULTS

3.1 Selecting the Best Tree Segmentation Method

A total of six sample plots (four broadleaf and two coniferous) were selected in this research to evaluate the four segmentation methods' accuracy, and the results are shown in Table 2.

Table 2: Accuracy evaluation results of different segmentation algorithms (Picture credit: Original)

Sample plot ID	Segmentation algorithm	Actual trees	Segment Trees	TP	FN	FP	r	p	F
1 Broadleaf	Layer stacking	40	42	33	7	9	.825	.788	.805
	PCS		50	27	13	23	.675	.540	.600
	CHM		52	22	18	30	.550	.423	.478
	Pit-free CHM		47	31	9	16	.775	.660	.713
2 Broadleaf	Layer stacking	58	53	43	15	10	.741	.811	.775
	PCS		66	39	19	27	.672	.591	.629
	CHM		58	33	25	25	.569	.569	.569
	Pit-free CHM		51	39	19	12	.672	.765	.716
3 Broadleaf	Layer stacking	40	40	32	8	9	.800	.780	.790
	PCS		34	20	20	14	.500	.588	.541
	CHM		43	25	15	18	.625	.581	.602
	Pit-free CHM		41	28	12	13	.700	.683	.691

4 Broadleaf	Layer stacking	61	59	48	13	11	.787	.814	.800
	PCS		60	41	20	19	.672	.683	.678
	CHM		71	33	28	38	.541	.465	.500
	Pit-free CHM		64	38	23	26	.623	.594	.608
5 Coniferous	Layer stacking	100	95	88	12	7	.880	.926	.903
	PCS		53	23	47	30	.329	.434	.374
	CHM		113	84	16	29	.840	.743	.789
	Pit-free CHM		101	91	9	10	.910	.901	.905
6 Coniferous	Layer stacking	72	69	64	8	5	.889	.928	.908
	PCS		40	40	29	43	11	.403	.725
	CHM		85	85	62	10	23	.861	.729
	Pit-free CHM		74	74	67	5	7	.917	.892

Sample plots 1-4 are broadleaf forest plots. Due to the uncertainty and complexity of the canopy morphology of broadleaf tree, the highest overall accuracy was only 80.5%. According to the F-score results from different segmentation methods, layer stacking can achieve around 80% accuracy even when facing the challenges of varied morphology, multiple branches, and numerous vertices of broadleaf tree species. This method provides the best overall segmentation performance, followed by pit-free CHM, PCS, and CHM.

Sample plots 5-6 are dense coniferous forest samples on the southeast side of the campus. Compared to broadleaf plots, the morphological differences in coniferous tree species are smaller, allowing for a maximum overall accuracy of up to 90.8%. Based on the F-score results from different segmentation methods, both layer stacking and pit-free CHM provided the best segmentation performance, each achieving over 90% accuracy. However, in the densely populated coniferous forest areas of the campus, the PCS algorithm performed the poorest with an accuracy of only 37.4%. This is because the distance threshold d=1.5m, which is relatively more suitable for broadleaf plots, failed to segment the closely spaced coniferous trees, resulting in very poor segmentation results.

Therefore, in the tree segmentation task for urban trees, the layer stacking algorithm should be prioritized in areas with diverse and unstable tree morphology, such as broadleaf areas or mixed broadleaf-coniferous areas. In areas with stable tree morphologies, such as coniferous areas, the faster pit-free CHM segmentation method should be preferred.

3.2 Number of Trees Segmented and Shrub Volume in Each Zone

Since the campus is dominated by broadleaf trees, layer stacking method was chosen for tree segmentation. The results of the number of trees and shrub volume obtained in each area of the campus are shown in Table 3.

Table 3: Number of tree segmented and shrub volume in each zone (Picture credit: Original)

Zone ID	Segment Trees	Shrub Volume(m^3)
1	741	2861.840
2	1921	2866.460
3	1283	6910.606
4	1092	6602.009
5	1336	6539.478
6	711	4881.820
7	748	4355.723
8	600	2953.506

3.3 Carbon Stock Calculation and Analysis

After substituting the shrub volume and the morphological parameters of each tree into the carbon stock equation, the carbon stock results for each area can be calculated and shown in Table 4.

Table 4: Summary of carbon stock (Picture credit: Original)

Zone ID	Total carbon stock(kg)	Tree carbon stock(kg)	Shrub carbon
1	256138.422	256130.744	7.678
2	83378.314	83370.632	7.682
3	446909.511	446893.057	16.454
4	377898.048	377877.747	20.301
5	735757.340	735746.870	10.470

6	239094.774	239085.395	9.379
7	259546.127	259537.141	8.986
8	278720.130	278712.361	7.769
Total	2677442.666	2677353.950	88.719

To analyze the spatial distribution of carbon stock within the campus, the study drew a carbon stock map under the 50m×50m grid (Figure 8(a)) and the map of carbon stock density in different zones (Figure 8(b)). There are significant differences in the size and density of carbon storage across various campus areas. Generally, the carbon stock is smaller in areas with dense buildings and open areas (e.g. playgrounds), and the larger carbon stock is mainly in areas where trees are concentrated (e.g. both sides of the main road and the green spaces).

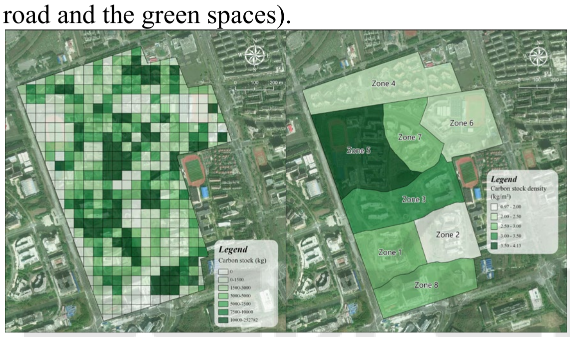


Figure 8: (a) Carbon stock map under 50m×50m Grid, (b) Carbon stock density in different zones
Picture credit: Original

4 CONCLUSION

This study establishes a comprehensive and reliable technical framework for the fine estimation of urban vegetation carbon stock by utilizing multi-source LiDAR data. This framework includes following steps: This framework includes: LiDAR data preprocessing, shrub extraction and volume calculation, tree segmentation, and carbon stock calculation. Specifically, after data preprocessing, the study first uses a random forest model to extract shrubs from the point cloud and employs a grid method to calculate their volume. Subsequently, by comparing four different tree segmentation algorithms across six sample plots, the layer stacking algorithm, which demonstrates superior accuracy and stability in both coniferous and broad-leaved forests, is selected for tree segmentation in the study region. After obtaining the morphological parameters of individual trees, the study builds biomass models suitable for the vegetation in the study area using the average biomass method, and calculates the final carbon storage to be 2,677,442.666 kg.

The technical framework proposed in this study is universally applicable to the accurate estimation of urban vegetation carbon stock. Additionally, due to the rich semantic information contained in LiDAR data, the research data (such as the morphological parameters of individual trees) can be widely applied to other forestry applications. This provides technical and data support for helping achieve dual carbon goals and formulate related policies.

However, this study also has certain limitations. The formulae used to calculate carbon stocks for different species of trees may vary, and the study's lack of species differentiation may have contributed to some degree of error in the carbon stock conclusion. Future research could consider incorporating street view images or high-resolution remote sensing images for tree species identification, thus building biomass models for different species and further refining the precision of carbon stock calculations.

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