Voxel-based Urban Vegetation Volume Analysis with LiDAR Point Cloud

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1. Abstract

The 3D volume and spatial distribution of urban vegetation are highly related to the delivery of multiple ecosystem services. However, due to the intricate vegetation structure, little research has been conducted to visualize and model the 3D spatial structure of urban vegetation. This study proposes an automated voxel-based modeling method to visualize and quantify the urban vegetation volume with LiDAR point cloud and performs a case study of the No.6 Middle School campus in Hengyang City, Hunan Province, China. The PointCNN model is used to perform semantic segmentation of the LiDAR data to extract the tree points. Then the points are voxelized into a 3D volume model with 1m×1m×1m cells. The result shows that the total vegetation volume of the area is 61,192m³, accounting for 37.28% of the total voxelized study area. The green space in front of the north teaching buildings has the largest proportion of vegetation volume, 19,366m³, accounting for 68.37% of the vegetation volume of the whole campus, due to the diverse vegetation and complex structure. The automated segmentation voxel modeling process could provide an efficient way to represent the spatial distribution of urban greenery. With an adjustable voxel size, the model could be adapted to various scales from regional to neighborhood. The model could also be used to analyze the green space structure at the human scale, as well as the interactions between green space and the surrounding environment, and to provide spatial data for the evaluation of multiple ecosystem services.

2. Introduction

3D vegetation modeling is an indispensable part of real-world scene digitalization. However, due to the intricate vegetation structure, large-scale 3D vegetation modeling and analysis are often time-consuming and complex (Xu et al. 2021). Vegetation modeling with complex mesh surfaces often leads to large model sizes and a time-consuming analysis process. Unlike the triangular mesh model, the voxel model is composed of voxel grid cells, which can express the model's internal features and facilitate spatial analysis (Table 1). Currently, the voxel-based 3D models have been widely used in medical image analysis and terrain modeling, but rarely used in urban fabric analysis.

Table 1. Comparison of different vegetation modeling types

Vegetation model	Type	Description	Advantage	Disadvantage
	Simple geometric model	Vegetation model represented by simple geometries	A simple model for quick visualization	As a simple axis symmetry geometry. model, it cannot reflect the complex canopy morphology, anisotropy, or internal characteristics of the canopy.
	Triangular mesh model	Tree canopy and trunk simulated by irregular triangular mesh models	A mesh model could have a more detailed expression of canopy branch and leaf details	To improve the display and processing speed, triangular mesh models usually contain only the outer surface, ignoring the internal structure of the vegetation.
	Voxel model	Vegetation models constructed with cubic grid voxels	A voxel model could reflect the internal characteristic and facilitate spatial analysis operations	Voxel models with high resolution or large scenes will occupy enormous computer resources and affect the processing speed of analytical calculations and visualization.

A voxel model contains complete 3D spatial information, which could be used to solve the complex problems caused by the geometry and topology of vegetation morphology. Recently, voxel modeling has been applied to the structure study of individual trees. Hosoi (2013) and Omasa (2008) used portable scanning LiDAR data to obtain the 3D point cloud of a single tree, converted them into voxels, and analyzed the correlation between the volume and the value of leaf area density. Anderson (2018) built an urban green space voxel model by using LiDAR waveforms based on the Cranfield triangle in London, and then visualized the volumetric nature with a technic combination of GIS, Minecraft, 3D printing and CNC machining. Wang (2020) tested different voxel sizes to obtain an estimation model of forest canopy height using full-waveform airborne LiDAR data. However, voxel modeling techniques have not been widely used yet, as there is no standardized modeling process method, and the point cloud classification process is often time-consuming and requires intensive work.

Semantic segmentation is a computer vision task to label specific regions of a 2D image or a 3D image/point cloud. Convolutional Neural Networks (CNNs) are a particular type of neural network that can be applied to various computer vision tasks. The PointCNN model has been proposed as a simple and general framework for feature learning from irregular and unordered point cloud data (Dmitry 2019, ESRI 2022). The core of PointCNN is the X-Conv operator, which can weight and permutes the input point cloud and features before applying a typical convolution (Li Y et al. 2018). The Point CNN model could achieve a precision of 0.975, a 0.966 recall and a 0.971 F1-score based on the UK Environment Agency's open airborne LiDAR datasets (ESRI 2022).

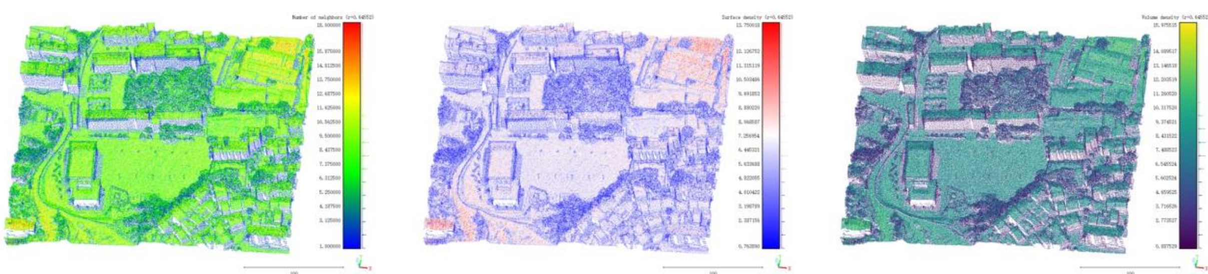
In this study, by adopting PointCNN as an automatic semantic segmentation tool, we propose an automated voxel-based modeling method to visualize and quantify the urban vegetation distribution. It works in 3D space from the LiDAR point cloud and is performed with a case study of the Hengyang No.6 Middle School in Hunan Province, China.

3. Method and Data

Study areas: Hengyang No.6 Middle School's campus covers about 32,000 m^2, with a 4,000 m^2 building ground area. It has several teaching buildings, an office, a laboratory, several student apartments, a canteen, and a playground. The school is located next to the residential district, south of Qinghua Mountain, north of a business park and west of a construction site.

Figure 1. The location of the study area in Hengyang

Point cloud semantic segmentation: An airborne LiDAR dataset covering the site is selected and processed to obtain the site information. The LAS dataset contains 647,575 points with a volume of 268m × 304m × 41m.



Number of neighbors Surface density Volume density

Figure 2. The original point cloud data

The intricate layered structure of the vegetation makes it difficult to analyze by traditional methods. Therefore, in this study, we select the PointCNN model to process the point cloud data by adopting ArcGIS API for Python on an NVIDIA GeForce RTX 2060 graphic card for the semantic segmentation of the LAS dataset. The point cloud data is segmented into 4 classes (trees/high-vegetation, building, ground and other) (Table 2).

Table 2. Results of the point cloud classification

Code	Classification	Accumulated Points	Percentage (%)	Z min (m)	Z max (m)
1	Other	54248	8.38	50.29	86.86
2	Ground	196390	30.33	50.35	81.93
5	Trees / High-vegetation	177938	27.48	52.66	88.78
6	Buildings	218999	33.82	50.05	91.25

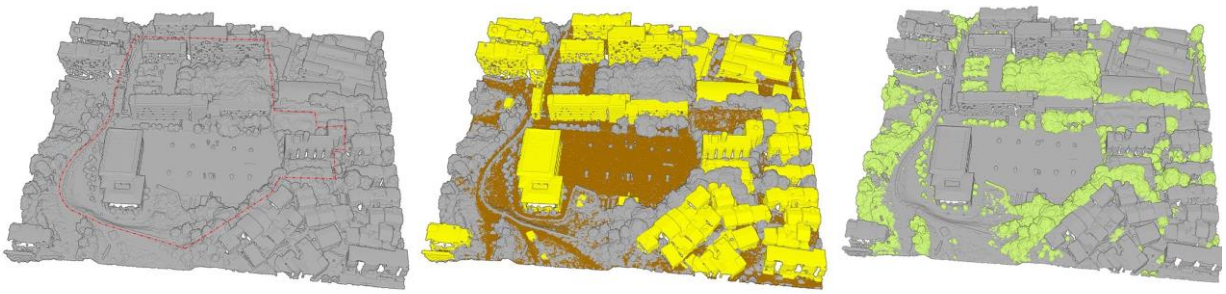


Figure 3. Visualization of the point cloud classification

Point cloud voxelization: The original coordinates of the point cloud are converted to voxel coordinates and the point cloud is visualized in voxels.

1) Establish the voxel coordinate system, determine the minimum values of the point cloud on the X, Y, and and Z axes as (X_{min}, Y_{min}, Z_{min}), and all integers no less than 0;

2) Set the voxel gird size as (Δi, Δj, Δk) based on the range and resolution of the point cloud. The size determines the voxelization results and the similarity with the point cloud;

3) Determine the correspondence between the points and voxels, convert all the points into voxel coordinates by the equation (1) and identify the voxel positions, where Int is a function to round off at one decimal place and (i, j, k) are the voxel coordinates of the integers (Hosoi and Omasa 2006).

$$\begin{cases} i = Int\left(\frac{X - X_{min}}{\Delta\, i}\right) \\ j = Int\left(\frac{Y - Y_{min}}{\Delta\, j}\right) \\ k = Int\left(\frac{Z - Z_{min}}{\Delta\, k}\right) \end{cases} \tag{1}$$

Due to the need for vegetation analysis, the voxel grid cell size is set to 1m × 1m × 1m. The vegetation points are then voxelized into a 3D volume model by using MagicaVoxel, an open-source voxel-based modeling tool for visualization and analysis (Figure 4&5).

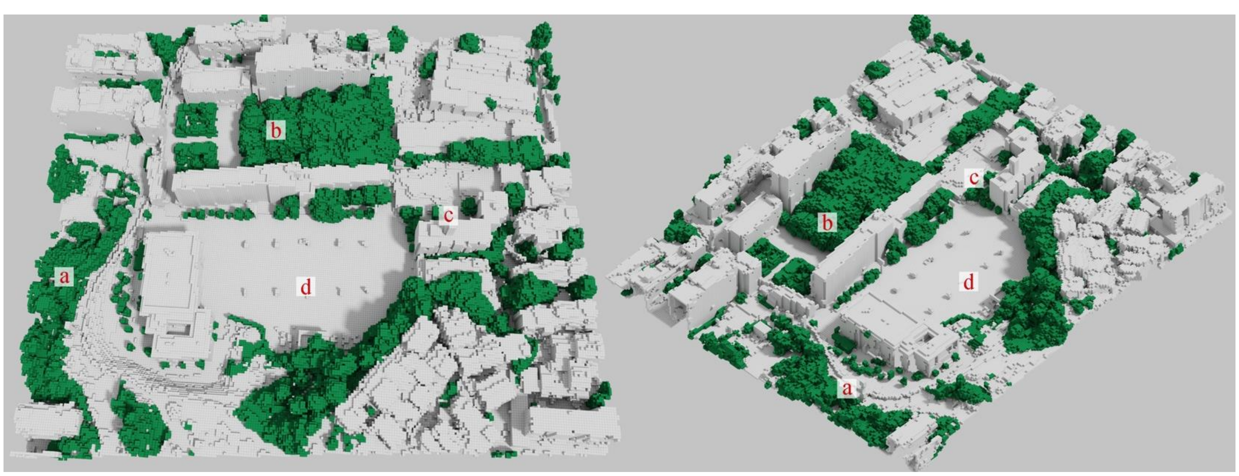


Figure 4. The 3D volume model of 1 m × 1 m × 1m voxel cell

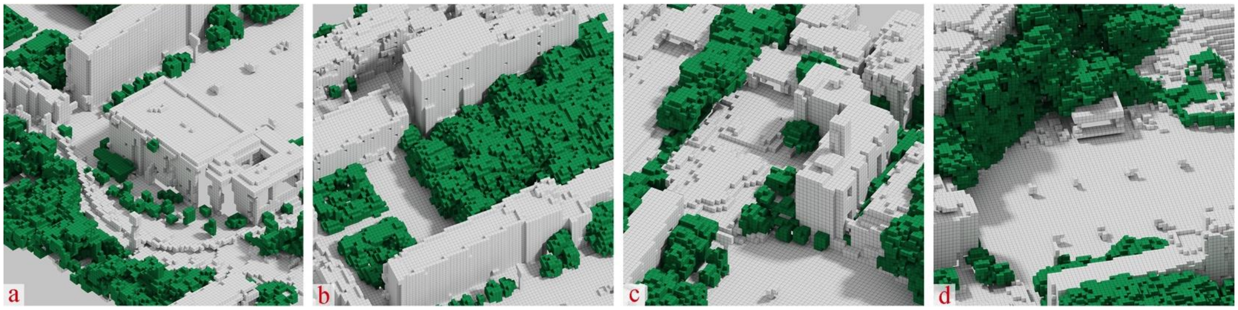


Figure 5. Details of the voxel model ([a] West Laboratory Building， [b] North Teaching Buildings， [c] Student Apartments And Canteens， [d] Playground)

4. Results

The model shows that the total vegetation volume of study area is 61,192m³, accounting for 37.28% of the total voxelized study area. The accumulated vegetation volume within school area is 28,325m³, accounting for 46.29% of the accumulated spatial green volume of the study area; among them, the north teaching building neighbourhood has the largest proportion of vegetation volume, 19,366m³, accounting for 68.37% of the vegetation volume of the whole school area, due to the diverse vegetation and slightly complex structure. The vegetation level of this part is mainly tall trees and lawns, with grass and flowerbeds. The west laboratory building neighbourhood has the least amount of vegetation, with only some low shrubs. The playground is backed by a hill and dominated by a dense tree canopy, thus it has a rich vegetation level (Table 3).

Table 3. Results of vegetation volume in the study area

Study Area	Vegetation Volume	Percentage
School Area	28325 m³	46.29 %
North Teaching Building Neighbourhood	19366 m³	31.65 %
West Laboratory Building Neighbourhood	642 m³	1.05 %
Student Apartments and Canteen	1110 m³	1.81 %
Playground	7207 m³	11.78 %
Others	32867 m³	53.71 %
Total	61192 m³	100.00 %

Based on the semantic segmentation and voxelization process, the voxel vegetation model could be used to visualize the complex spatial volume of urban vegetation from tree tops to the ground (Figure 6) as an effective way to represent the spatial distribution of vegetation in 3D (Figure 7). The adjustable voxel size could make the model adaptable to various analysis needs (Figure 8). The low-resolution model could be used to illustrate the basic spatial distribution of the site, and has a fast response time. The high-resolution model could give more detailed information, but is slower for calculation and visual processing. The voxel vegetation model can also be combined with Virtual Reality technology and used for related research on the visible green index, visual preferences and mental health assessment of people in the environment (Figure 9).

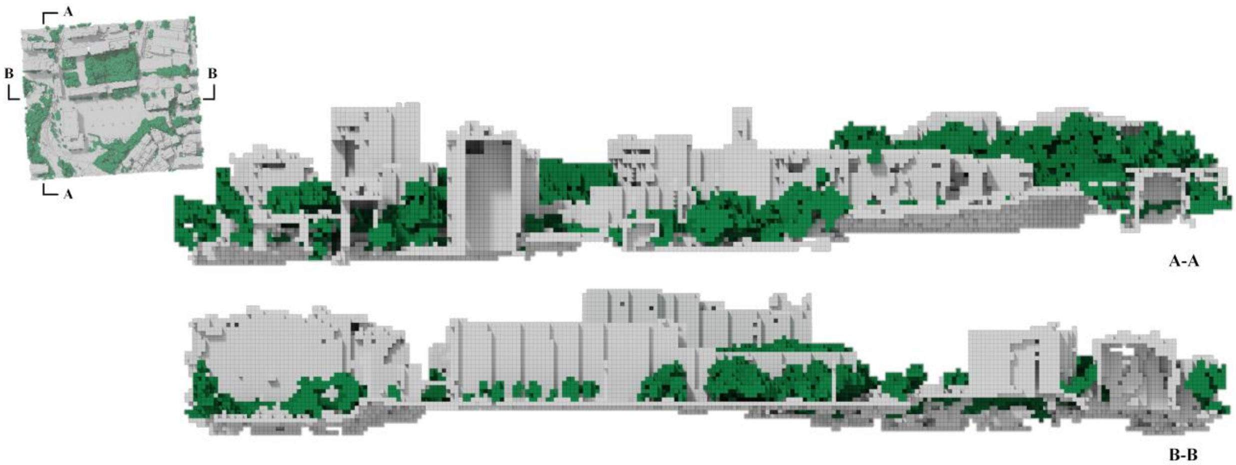


Figure 6. Spatial structure from tree tops and roofs to the ground

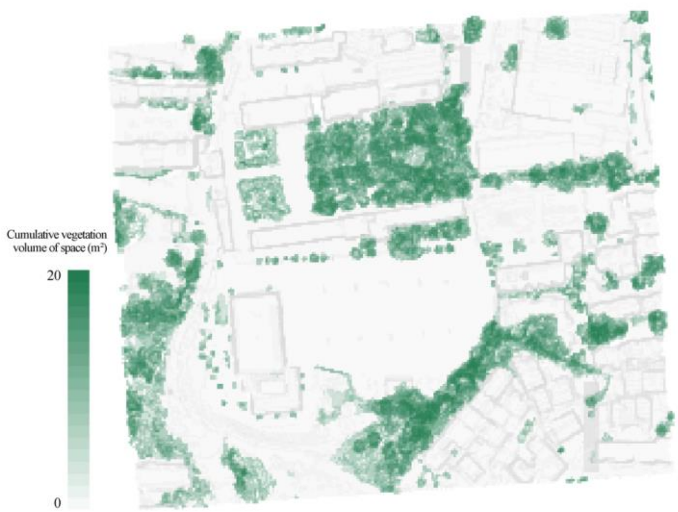


Figure 7. The cumulative vegetation volume per voxel gird in vertical space

Figure 8. Models with different voxel sizes

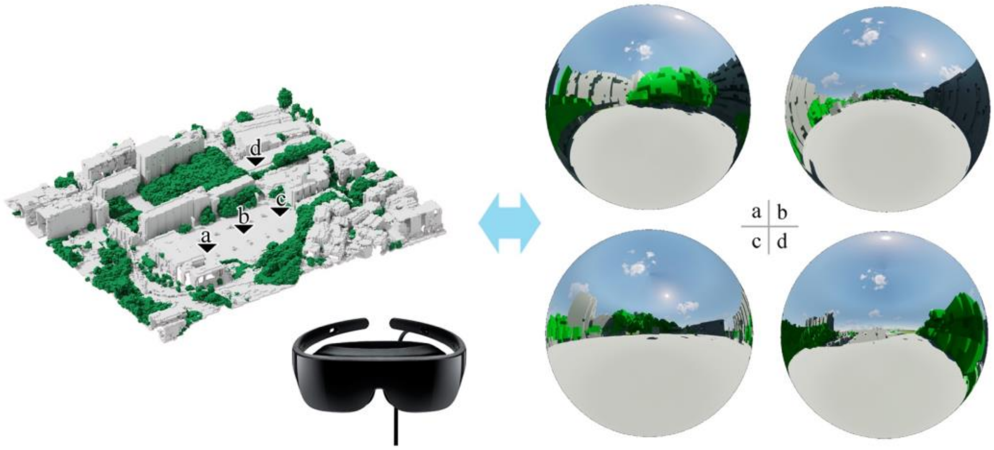
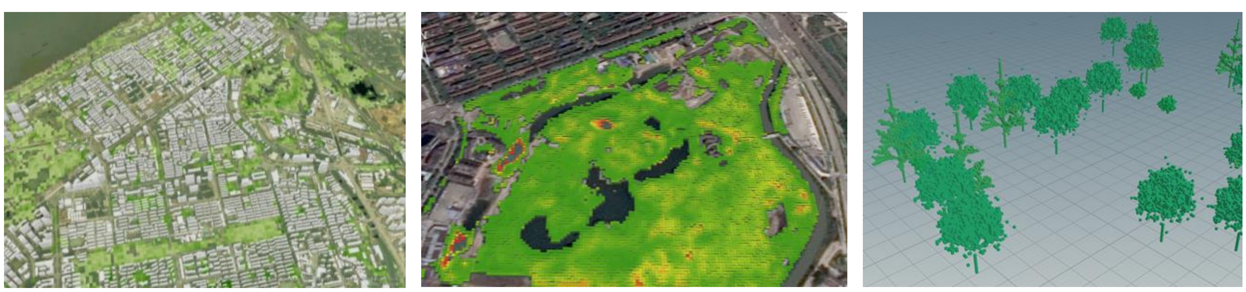


Figure 9. Models with Virtual Reality technology

5. Discussion and Conclusion

The model could have various potential applications. The voxel vegetation model can be used to analyze 3D structural characteristics and ecosystem services of urban green space in response to the development trend of increasingly complex vertical spatial changes in urban structure.

Various scale representation: With the adjustable voxel size, the voxel vegetation model could be adapted to multiple scales from regional green infrastructure to individual tree structure analysis. The voxel grid could have different horizontal and vertical unit lengths to reflect the vegetation space's subtle changes (Figure 10).



Regional scale (Voxel size: 15 m × 15 m × 1m)	Neighborhood scale (Voxel size: 6m × 6 m × 1m)	Individual trees (Voxel size: 0.1m^3)

Figure 10. Voxel vegetation model in different scales

3D vegetation volume calculation: The voxel model can be used as the basis for the calculation of 3D vegetation volume, and analysis of the vegetation volume of urban green space. The existing 2D green space measurement and assessment indicators could be extended to 3D green space for statistical analysis, monitoring and assessment of urban green space (Table 4).

Table 4. 2D and 3D urban green space evaluation indicators

2D green space indices	3D green space indices
Green area (m^2): The total area of green space in the build-up areas of a city.	**Green volume (m^3):** The total 3D volume of green space in the build-up areas of a city.
Green space ratio (%): $$\lambda_G = \left(\frac{A_{G1} + A_{G2} + A_{G3'} + A_{XG}}{A_L}\right) \times 100\%$$	**3D Green space ratio (%):** $$\lambda_{VG} = \left(\frac{V_{G1} + V_{G2} + V_{G3'} + V_{XG}}{V_L}\right) \times 100\%$$
Per capita green area (m^2/pp): $$A_{Gm} = \frac{A_{G1} + A_{G2} + A_{G3'} + A_{XG}}{N_p}$$	**Per capita green volume (m^3/pp):** $$V_{Gm} = \frac{V_{G1} + V_{G2} + V_{G3'} + V_{XG}}{N_p}$$
λ_G: Green space area ratio (%) A_{G1}, A_{G2}, A_{G3}, A_{XG}: Areas of different kinds of green space listed in Chinese Standard CJJT 85-2017 (m^2) A_L: Area of urban land (m^2) A_{Gm}: Per capita green area (m^2/pp) N_p: Population size	λ_{VG}: Green space volume ratio (%) V_{G1}, V_{G2}, V_{G3}, V_{XG}: Volumes of different kinds of green space listed in Chinese Standard CJJT 85-2017 (m^2) V_L: Volume of urban fabric (m^3) V_{Gm}:Per capita green volume (m^3/pp)

3D landscape pattern analysis: Landscape pattern refers to the spatial arrangement of different sizes and shapes of landscape elements. Traditional landscape pattern indices are calculated in 2D, which could not reflect the vertical changes of the landscape. Based on the voxels with both horizontal and vertical distributions, we can add a vertical dimension for the 2D landscape pattern indices to realize the expression of 3D landscape patterns. Some 3D landscape metric examples are listed in Table 5.

Table 5. 3D Landscape metric example

3D landscape metrics	Definition	Description
Patch Volume	$Vol = \sum V_k = nV \times V$	This index indicates the volume of each patch. V_k:Volume of the kth voxel in the patch; V: Volume of individual voxel; nV:Number of voxels that make up the patch.
3D Landscape Shape Index	$LSI = \frac{\sqrt{\text{Area}/6}}{\sqrt[3]{\text{Vol}}}$	This index indicates the deviation of the patch shape from the standard cube. $Area$: Surface area of a patch; Vol: Volume of a patch.
Percentage of the Landscape Volume	$\text{PLAND} = \frac{CV}{TV} \times 100$	This index indicates the proportion of the target class in the landscape. CV: Volume of the target class; TV: Total volume of the landscape.

3D simulation of vegetation growth and expansion: In the local scale, the volume change of green space is represented by the process of plant growth and change; while in the regional scale, it is closely related to the evolution of the increase and decrease of various urban land types. Various studies have been performed based on 2D cellular automata (CA) models to simulate the change of land use types. With the voxel model, the calculation rules can be extended to 3D urban space, which could be used to construct a 3D spatial cellular automata model for the urban green space.

3D spatial ecological process analysis and ecosystem services assessment: Ecosystem services such as climate regulation, air purification and hydrological regulation are closely related to the vegetation's 3D spatial structure. Most current ecosystem service assessment models such as InVEST use the 2D raster as data input, and could not reflect the vertical distribution of ecosystem services. The voxel vegetation model could be used to provide a data source for the assessment of multiple ecosystem services provided by 3D green space, and to establish corresponding ecosystem service assessment methods and processes in 3D. For example, with the vegetation voxel model describing the spatial layout of the green space and vegetation biomass indices, the amount of urban vegetation's carbon fixation and oxygen release can be calculated more accurately.

Some restrictions still exist and further refinements are still needed. Currently, the semantic segmentation results of the PointCNN model contain a few errors, which need to adjust manually. The ground living plants and the trees near the building are the challenging part of the automated recognition process (Figure 11). Local labeled semantic point cloud data could be used to train the PointCNN model to improve the accuracy of the semantic segmentation results.

Figure 11. The manual adjustments in the classification results

6. Acknowledgment

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