2D-BŐL 3D-BE

A városi zöldfelületek vizualizációs és elemzési módszereinek áttekintése különböző léptékekben

TRANSFORMING FROM 2D TO 3D

A Review of Urban Green Space Visualization and Analysis Methods at Different Scales

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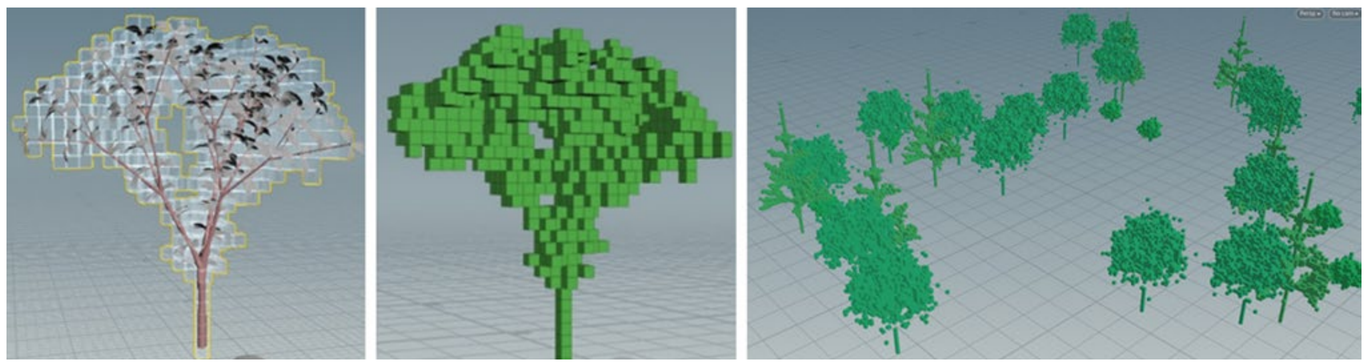

ABSZTRAKT

A városi információs modellezés, valamint az intelligens városok fejlődésével a hagyományos 2D-alapú várostervezési folyamat napjainkban 3D-s panorámás, térbeli tervezéssé alakul át. A jelenlegi városi zöldterületek modellezési és elemzési módszerei nagyrészt 2D-s tájmintákra és mutatókra támaszkodnak, amelyek nem képesek kifejezni a zöldterületek vertikális jellemzőit. Jelen tanulmány áttekinti a zöldterületek 3D környezetben történő modellezésére általánosan használt módszereket, és elemzi alkalmazhatóságukat. Három különböző léptékű – térségi, települési és objektum szintű - esettanulmányt tárgyal, majd mélytanuláson és parametrikus modellezési eszközökön alapuló automatizált modellezési és elemzési eljárást épít fel mindegyikhez. A három esettanulmány a következő módszereket veszi sorra: országos léptékű 3D vegetációs térfogat becslése a GEDI segítségével Kína különböző városaira, voxel-modellek építése LiDAR pontfelhőadatok alapján egy középiskolai campus zöldfelületeire, valamint L-rendszer generatív algoritmusok alkalmazása a fák növekedésének szimulálására és előrejelzésére egy kollégiumi területen. A javasolt 3D zöldterületi modellezési és elemzési módszerek támogathatják a zöldterületek és zöldfelületek 3D modellezési és elemzési igényeit különböző léptékekben.

Kulcsszavak: városi zöldfelület, tájmodellezés, 3D vegetációs térfogat ⦿

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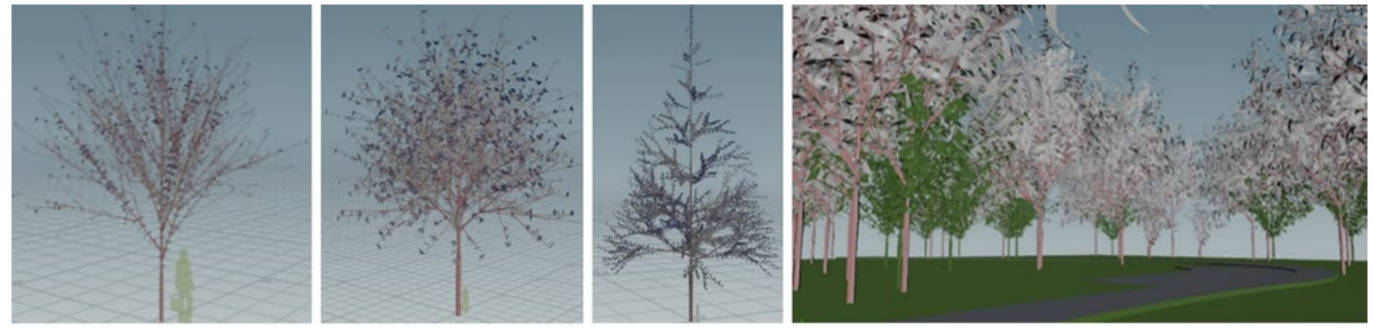
◂◂**Figure 1:** Voxel modeling of plants
Figure 2: Generative plant modeling based on L-system



ABSTRACT

With the development of city information modeling, digital twins, and smart cities, traditional 2D-based urban planning progress is now being transformed into 3D panoramic spatial planning. Current urban green space modeling and analysis methods largely rely on 2D landscape patterns and indicators, which cannot express the vertical characteristics of green spaces. This study reviews the commonly used methods for modeling green spaces in 3D environments and analyzes their applicability. Three case studies at different scales – regional, community, and site – are discussed, and an automated modeling and analysis process for each case study based on deep learning and parametric modeling tools is then constructed. The three case studies include the estimation of national-scale 3D vegetation volume using GEDI for different cities in China, the construction of voxel models for green spaces in a middle school campus based on LiDAR point cloud data, and the application of L-system generative algorithms for simulating and predicting tree growth in the dormitory area. The proposed 3D green space modeling and analysis methods could support green space's 3D modeling and analysis needs at different scales.

Keywords: urban green space, landscape modeling, 3D vegetation volume

1. INTRODUCTION

Urban green space contains 3D spatial vegetation structures, diverse plant types, and is continuously evolving over time. In urban green space planning and management practice, vegetation assessment primarily relies on 2D indicators, such as green area ratio and green area per capita, which cannot capture the spatial characteristics and comprehensive ecological benefits of green spaces [1]. There is also a lack of generalized 3D vegetation volume assessment standards [2]. The 3D structural characteristics of green space plants are significantly different from those of urban gray infrastructure, and appropriate methods are needed to represent the spatial morphological characteristics and growth changes of green plants [3]. Urban green space involves different scales, from regional and urban to neighborhood, which make it essential to establish digital model representations of green space tailored to the monitoring and evaluation needs of these different scales [4]. This paper reviews methods of 3D urban green space modeling and illustrates several cases to discuss 3D urban green space modeling methods at different scales to explore their feasibility for a range of practical needs.

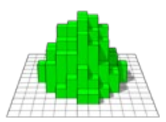
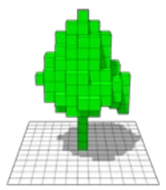
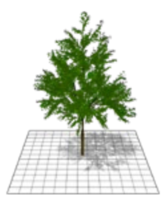
2. REPRESENTATION METHODS FOR 3D URBAN GREEN SPACES

Based on different scales and modeling approaches, green space models can include various types, such as 2D surfaces, simple geometric models, triangular mesh, spatial voxel models, and generative models.

2.1 The 2.5D model

The 2.5D model utilizes indicators with a vertical dimension, which can be divided into two types: one expressed through the leaf area index (LAI), and the other represented by the spatial volume occupied by the stems and leaves of plants. With the widespread application of remote sensing, using remote sensing imagery to estimate the LAI has become a common method for rapid 3D vegetation volume calculation. Various open datasets based on satellite-borne LiDAR can be used for vegetation volume measurements at the regional scale, such as the GLAS system on the ICESat-1 satellite, the ATLAS system on ICESat-2, and the GEDI and MOLI systems deployed on the

Table 1: Methodology framework adopted for different scales
Table 2: Case study performed at different scales
►►**Table 3:** Indicators and formulas for calculating 3D vegetation volume

Illustrations	Modeling methods	Applicable Scale	Features and applications
	2.5D model	Regional scale	2.5D models can be obtained from vegetation height datasets. It provides a basic distribution of green space across different regions. The limitation is that with only 1 vertical indicator, it cannot reflect complicated 3D spatial distribution.
	Spatial voxel model	Community scale	Voxel models can be built from LiDAR scanners and generated by sampling algorithms. They are adaptable to different kind of scales and can be used to express 3D distribution in a normalized data structure.
	Generative model	Project scale	Generative algorithm models can simulate plant growth and environmental interactions, which makes them suitable for visualization and biological analysis. The modeling of each species will require specified study to obtain an accurate result.

Scale	Site	Methods
Regional scale	413 cities in mainland China	Different indicators for the measurements of 2.5D green space were proposed and an automated calculation process was established based on the GEDI global canopy height data.
Community scale	Sixth Middle School Campus, Hengyang, China	An automated voxelization method was established from the airborne LiDAR data, which could be used for further spatial analysis.
Project scale	Dormitory area of Xiangyang Academy, Xiangyang, China	Different L-system tree species were modeled with on-site collected data to predict plant growth and calculate the LAI and LAD values.

International Space Station. A research group combined an annual time series of Landsat imagery with high-density airborne LiDAR data to capture the 3D structure of forests, describing the changes, scale, and persistence of the impacts of Amazon rainforest degradation on aboveground carbon density (ACD) and canopy structure [5]. The 2.5D model contains only one variable in the vertical space which cannot reflect the vertical complexity.

2.2 Spatial voxel model

A voxel represents a unit cubic grid in 3D space. Unlike the triangle mesh model, a voxel model can simplify complex geometry and express the internal structure of a plant, which is suitable for spatial analysis, such as leaf area density (LAD) estimation (Figure 1) [6, 7]. A handheld laser scanner can be used to obtain a 3D point cloud of a single tree and convert it to a voxel model to analyze the LAD [8]. Hosoi et al. used 3D point cloud data to construct a 3D voxel vegetation model to calculate 3D vegetation volume [6]. The waveform LiDAR data has been used to establish a green space voxel model in the Cranfield Triangle area of London, UK, and visualized by GIS and Minecraft [9]. However, voxel modeling techniques are not yet widely used because there is no standardized modeling process, and the point cloud classification process tends to be time-consuming and requires intense work.

2.3 Generative model

Generative algorithms can be used for plant modeling by simulating the plant growth process (Figure 2). The L-system algorithm was proposed by Swedish biologist Lindenmayer and has been widely adopted in plant modeling and visualization [10, 11, 12,13]. With the development of Open L-system algorithm, the interactions between plants and

Indicators	Formulas	Explanation
3D vegetation volume per unit in built-up area	$\lambda_I = \frac{V_{G1}+V_{G2}+V_{G3}+V_{XG}}{A_{c1}}$	λ_I: 3D vegetation volume per unit in built-up area (m^3/m^2)
		V_{G1}: Total vegetation volume of urban parks (m^3)
		V_{G2}: Total vegetation volume of protective green space (m^3)
		V_{G3}: Total vegetation volume of green space in public squares (m^3)
		V_{XG}: Total vegetation volume of affiliated green space (m^3)
		A_{c1}: Built-up area of the city (m^2)
3D vegetation volume per capita in built-up area	$V_{Gm} = \frac{V_{G1}+V_{G2}+V_{G3}+V_{XG}}{N_p}$	V_{Gm}: 3D vegetation volume per capita in built-up area (m^3/pp)
		V_{G1}: Total vegetation volume of urban parks (m^3)
		V_{G2}: Total vegetation volume of protective green space (m^3)
		V_{G3}: Total vegetation volume of green space in public squares (m^3)
		V_{XG}: Total vegetation volume of affiliated green space (m^3)
		N_p: Population of built-up area (person)
3D urban park vegetation volume per capita in built-up area	$V_{G1m} = \frac{V_{G1}}{N_p}$	V_{G1m}: 3D urban park vegetation volume per capita in built-up area (m^3/pp)
		V_{G1}: Total vegetation volume of urban parks (m^3)
		N_p: Population of built-up area (person)
3D vegetation volume per unit city proper area	$\lambda_L = \frac{V_{G1}+V_{G2}+V_{G3}+V_{XG}+V_{EG}}{A_c}$	λ_L: 3D vegetation volume per unit city proper area (m^3/m^2)
		V_{G1}: Total vegetation volume of urban parks (m^3)
		V_{G2}: Total vegetation volume of protective green space (m^3)
		V_{G3}: Total vegetation volume of green space in public squares (m^3)
		V_{XG}: Total vegetation volume of affiliated green space (m3)
		V_{EG}: Total vegetation volume of suburban green space (m^3)
		A_c: City proper area (m^2)

*City built-up area is the existing development land of the city.
*City proper area is the area contained within city limits, including the development land and non-development land.

the surrounding environment were simulated [14] and the 3D trees generated by L-system were utilized to analyze the forest structure [15]. Obtaining accurate generative models usually requires a long period of on-site data collection and is often used at neighborhood-scale sites.

2.4 Comparison of different modeling methods

The 2.5D model, spatial voxel model and generative model are sufficiently flexible and adjustable to meet the different demands of green space modeling. A comparison of the models is shown in Table 1.

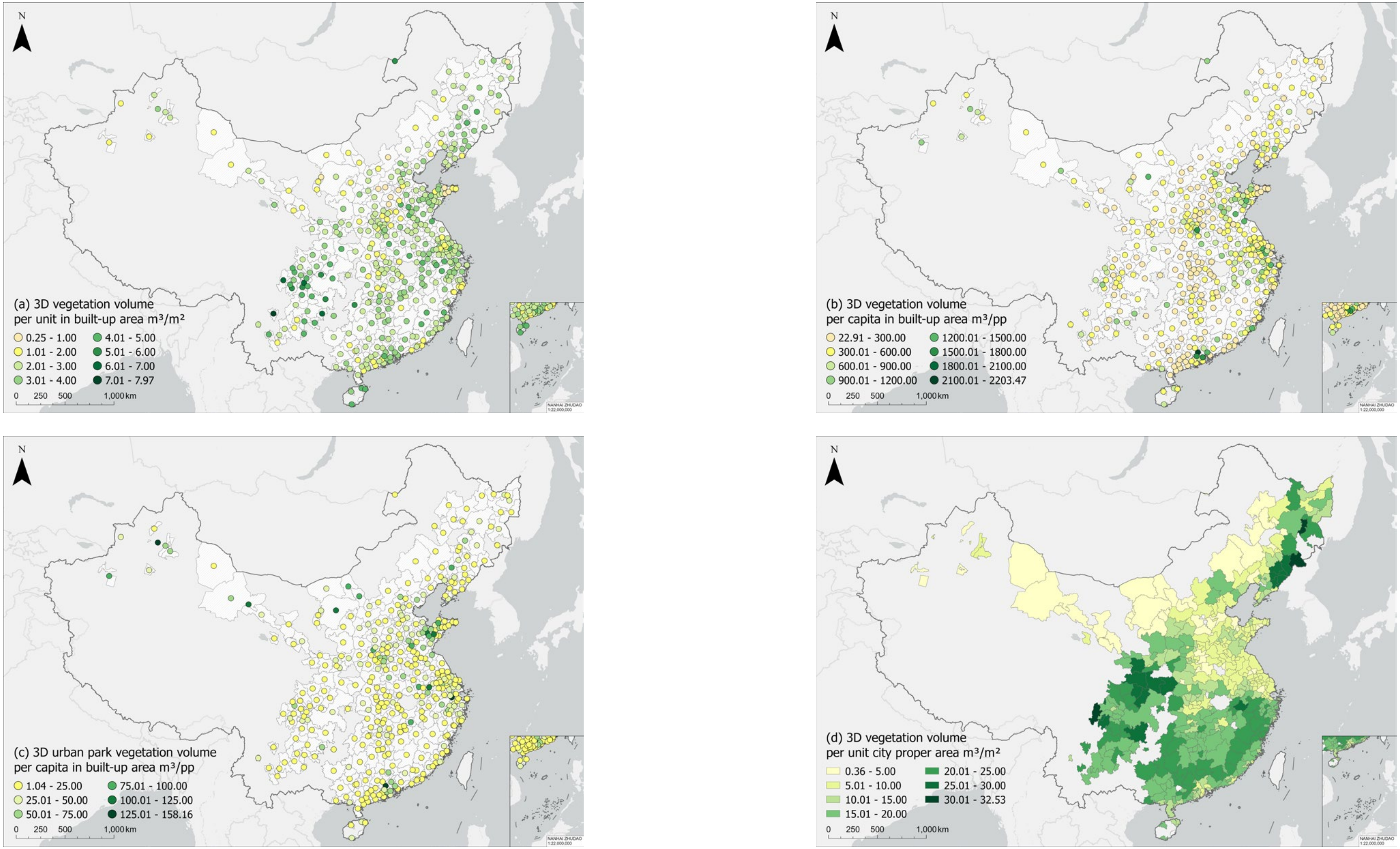
3. URBAN GREEN SPACES 3D MODELING CASE STUDY

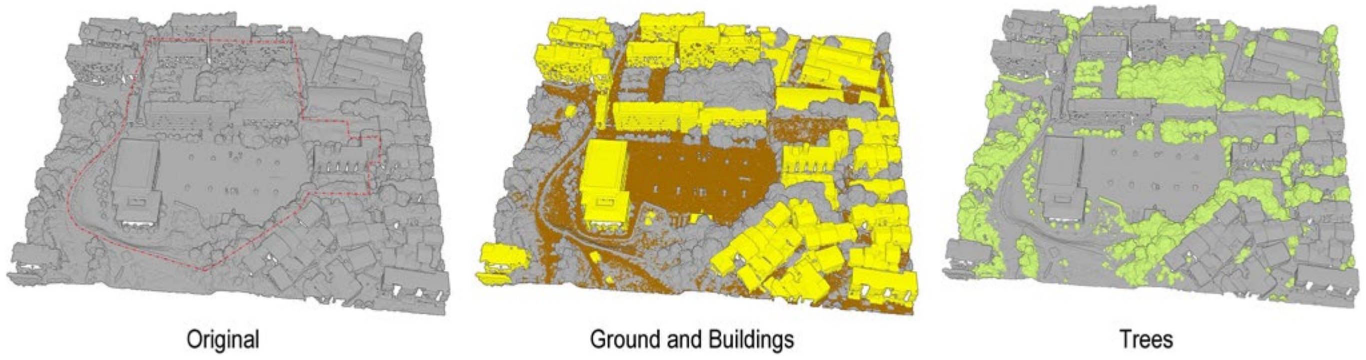
Although existing 3D modeling approaches for green spaces have been applied in related studies, there is a lack of unified modeling standards and automated processes. Based on open datasets and on-site collected data, we established several automated green space modeling and assessment methods at three different scales using semantic segmentation and node-based programming tools, including ArcGIS Model Builder and Houdini (Table 2). The study explored the visualization and assessment methods for 3D green spaces and examined three applications across different scales to achieve a generalized and automated process for 3D green space model construction and analysis.

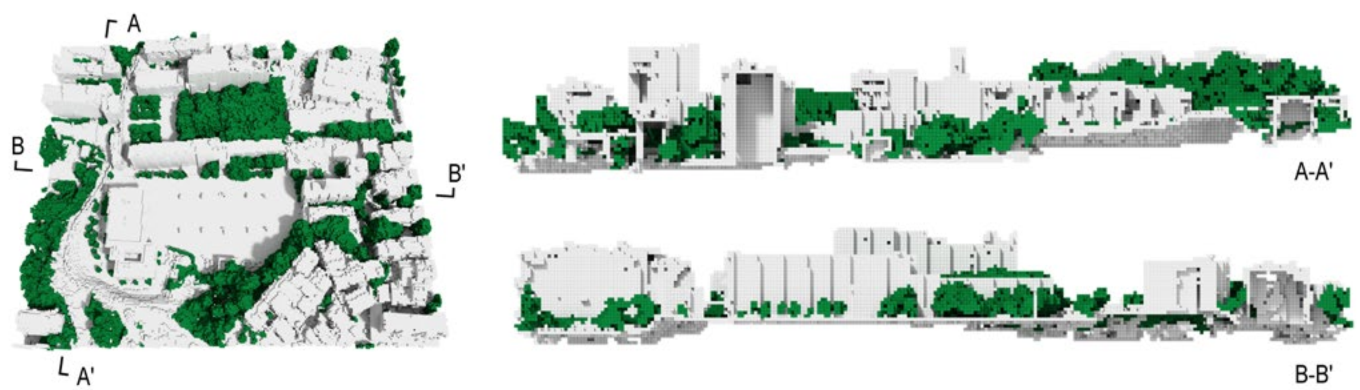
3.1 Regional scale

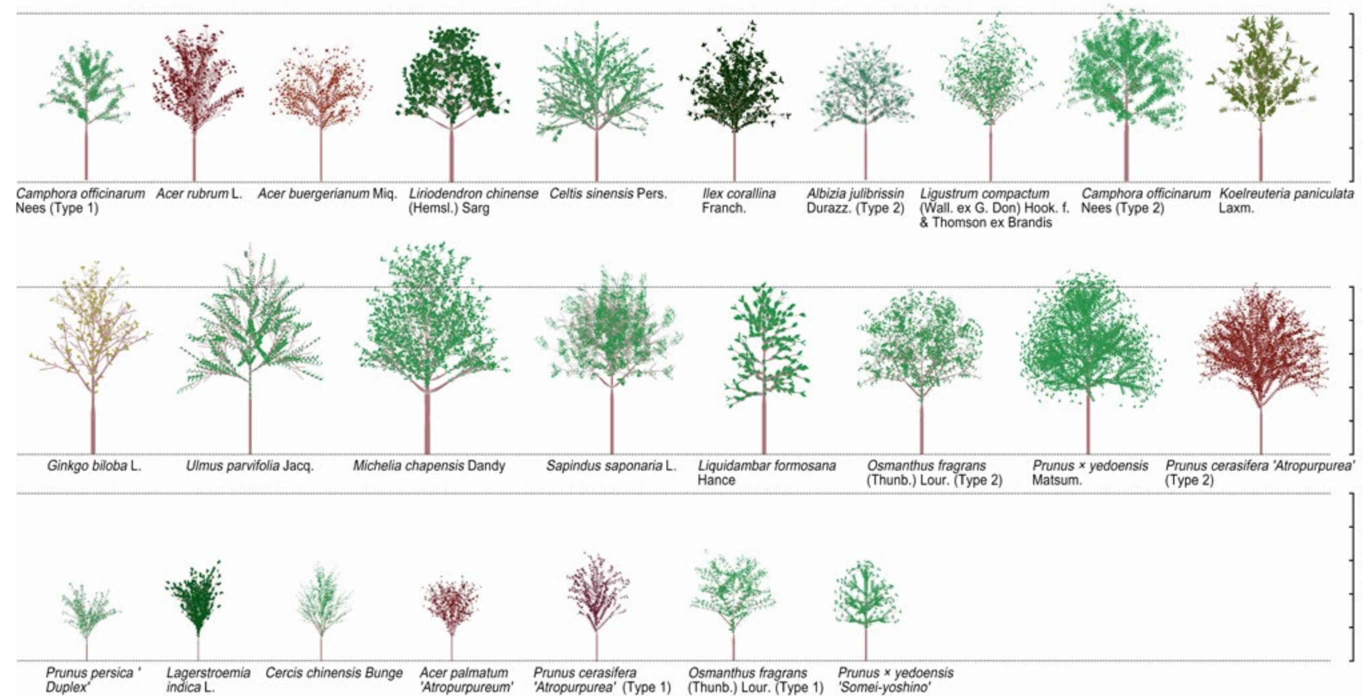
Photogrammetry provides a fast and standardized method to acquire 3D spatial data. By referring to the 2D indicators commonly used in China (green space rate in built-up area, green space area per capita in built-up area, urban

Figure 3: 3D indicators for green spaces across cities, 2.5D model based calculation for 413 cities in mainland China with populations exceeding 150,000. (a) 3D vegetation volume per unit in built-up area; (b) 3D vegetation volume per capita in built-up area; (c) 3D urban park vegetation volume per capita in built-up area; (d) 3D vegetation volume per unit city proper area









◂◂**Figure 4:** Semantic segmentation results of the point cloud
◂◂**Figure 5:** Section views of the voxel model
Figure 6: L-system algorithm model for different tree species

park area per capita in built-up area, and green space rate in city proper area) [16], the definitions and calculation methods of four 3D urban green space assessment indicators were proposed, including 3D vegetation volume per unit in built-up area, 3D vegetation volume per capita in built-up area, 3D urban park vegetation volume per capita in built-up area, and 3D vegetation volume per unit city proper area based on 2.5D volumetric data from LiDAR-derived canopy height datasets (Table 3). An automated calculation method was also constructed based on ArcGIS Pro Model Builder.

To test the usability of 2.5D green space modeling representation and metrics at the regional scale across different cities, the case study focused on 413 cities in mainland China with populations exceeding 150,000. The canopy height dataset was extracted from the 2020 global 10m resolution canopy height data based on the Global Ecosystem Dynamics Investigation (GEDI) and Sentinel-2 imagery [17]. The land cover data were extracted from the ESA 2020 global 10m land cover dataset. The administrative boundaries for each city were obtained from the National Geographical Information Center of China, while the population data were collected from statistical yearbooks and bulletins. The urban park boundary data was obtained from the OpenStreetMap. Due to the incomplete park boundary vector data in some cities, the park green space-related indicators were calculated in 264 cities. Based on the ArcGIS model builder, an automated calculation process was established to calculate each city's 2D and 3D indicators (Figure 3).

3.2 Community scale

Voxel modeling usually requires a lot of manual work. In this case study, an automatic modeling method based on PointCNN for semantic segmentation and voxel model generation was proposed to visualize and quantify the 3D vegetation.

The case study was conducted on the Sixth Middle School Campus in Hengyang City, Hunan Province, China. The campus covers an area of about 32,000 m² with a building footprint area of 4,000 m². We used a DJI L1 drone to obtain the LiDAR data. The PointCNN model was used for automated point cloud semantic segmentation and modeling. The model was trained on the airborne LiDAR dataset published by the UK Environment Agency, achieving a precision of 0.975 and a 0.971 F1-score [18]. The semantically segmented point cloud data were categorized into four classes: trees, buildings, ground, and others (Figure 4). The segmentation results contained some minor errors in specific areas, such as misclassifying a basketball hoop as trees, which required further manual correction. A resampling algorithm was employed to convert the classified point cloud data into a 1 m-interval evenly spaced point cloud model. Subsequently, the point cloud was voxelized into a 3D model with 1m×1m×1m voxels for visualization (Figure 5).

3.3 Project scale

We took the green space around the dormitory area of Xiangyang Academy as a case study. The modeling of the tree branches was based on the morphological characteristics of each tree with three primary variables (tree height, crown width, and height below branches) and multiple secondary variables (uniaxial branching or synaxial branching, branch angle, etc.). The twigs were modeled by collected on-site tree samples. Based on the planting design drawings and on-site collected data, 24 parametric plant growth models were constructed using the L-system algorithm tools in Houdini to generate the 3D site model (Figure 6).

Due to the differences in plant growth and morphological characteristics, this study combined growth data from the i-Tree database and allometric equations in related studies to determine the geometric features of each tree species in different growing stages [19]. By adjusting the iterations of the L-system, models of different growing stages were then generated (Figure 7).

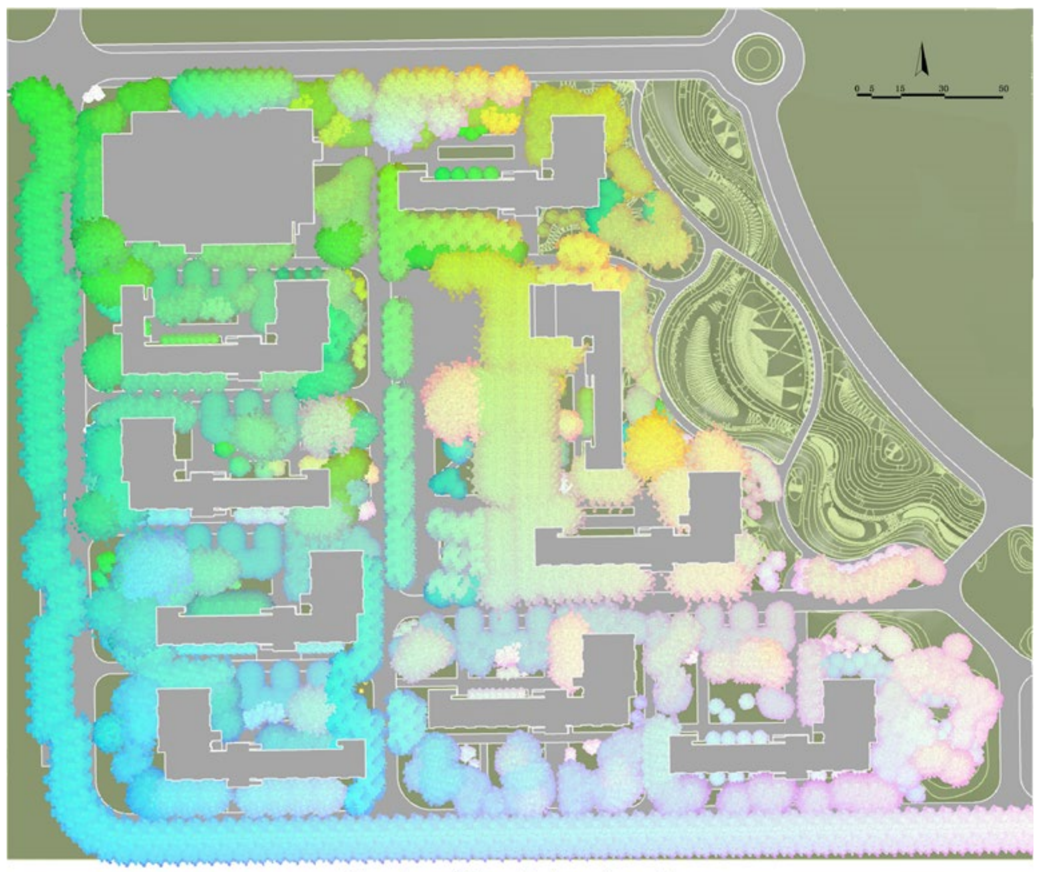
4. RESULTS AND DISCUSSION

4.1 Regional-scale 2.5D modeling

Based on the GEDI open data, different 3D indicators were calculated for each city. The results showed that in the built-up areas of the 413 cities, the average value of 3D vegetation volume per unit area is 2.80 m³/m² and 458.15 m³ per capita. The average value of 3D vegetation volume per unit city proper area is 12.89 m³/m².

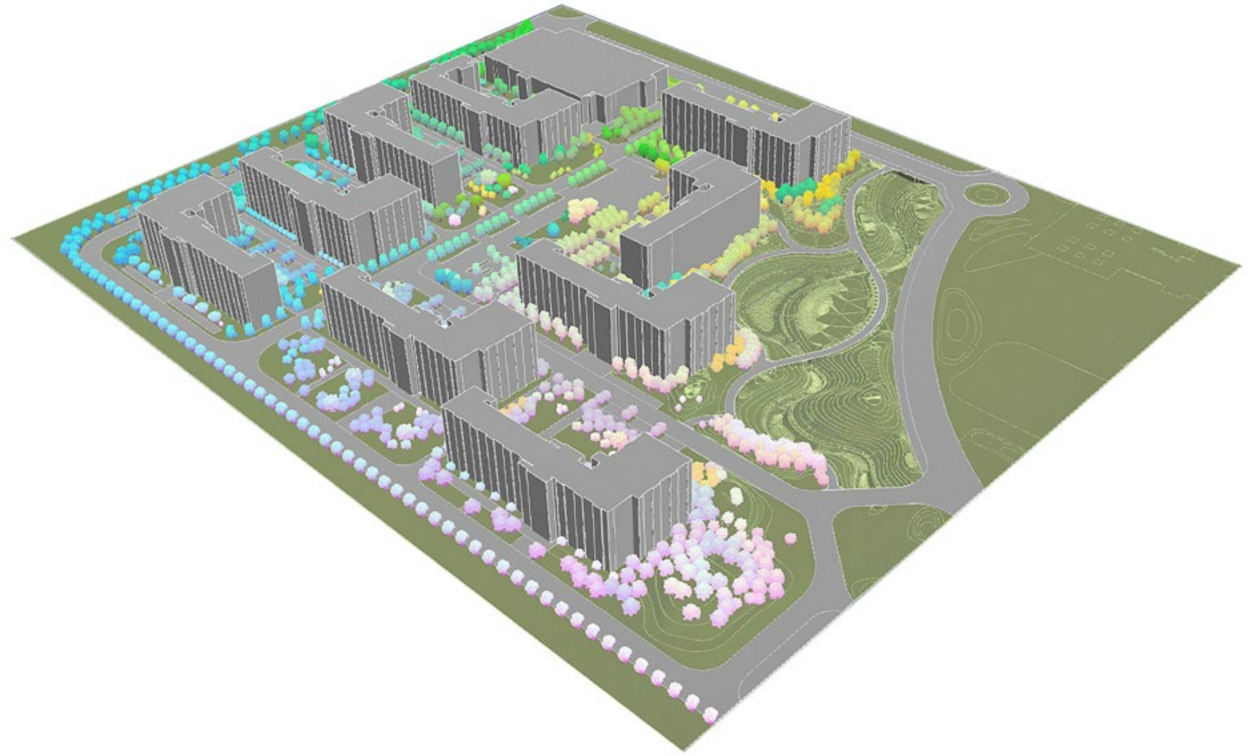
Regarding spatial distribution, the 3D vegetation volume per unit in built-up area in cities in the Southwest, Northeast and East areas was generally higher than that in the Northwest, North and Central areas. 264 cities had a mean 3D urban park vegetation volume of 25.21 m³

Plan view of the site in early-stage

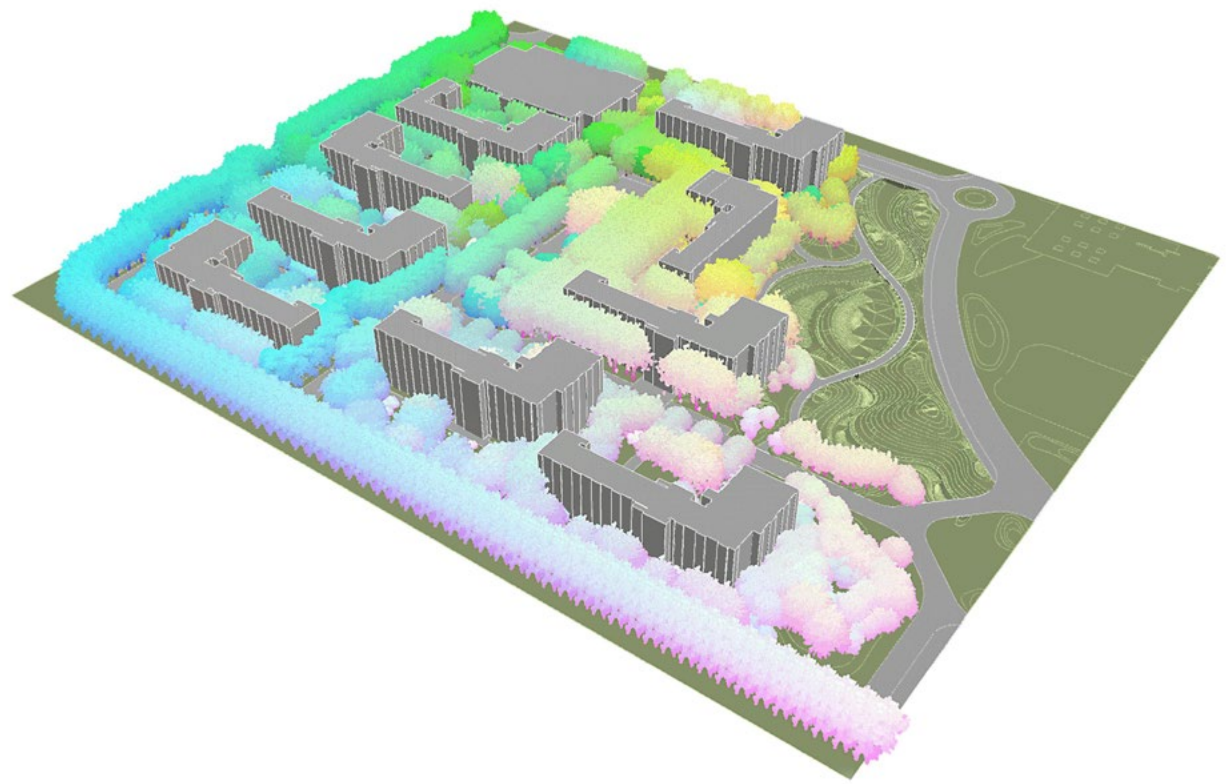


Plan view of the site in mature-stage

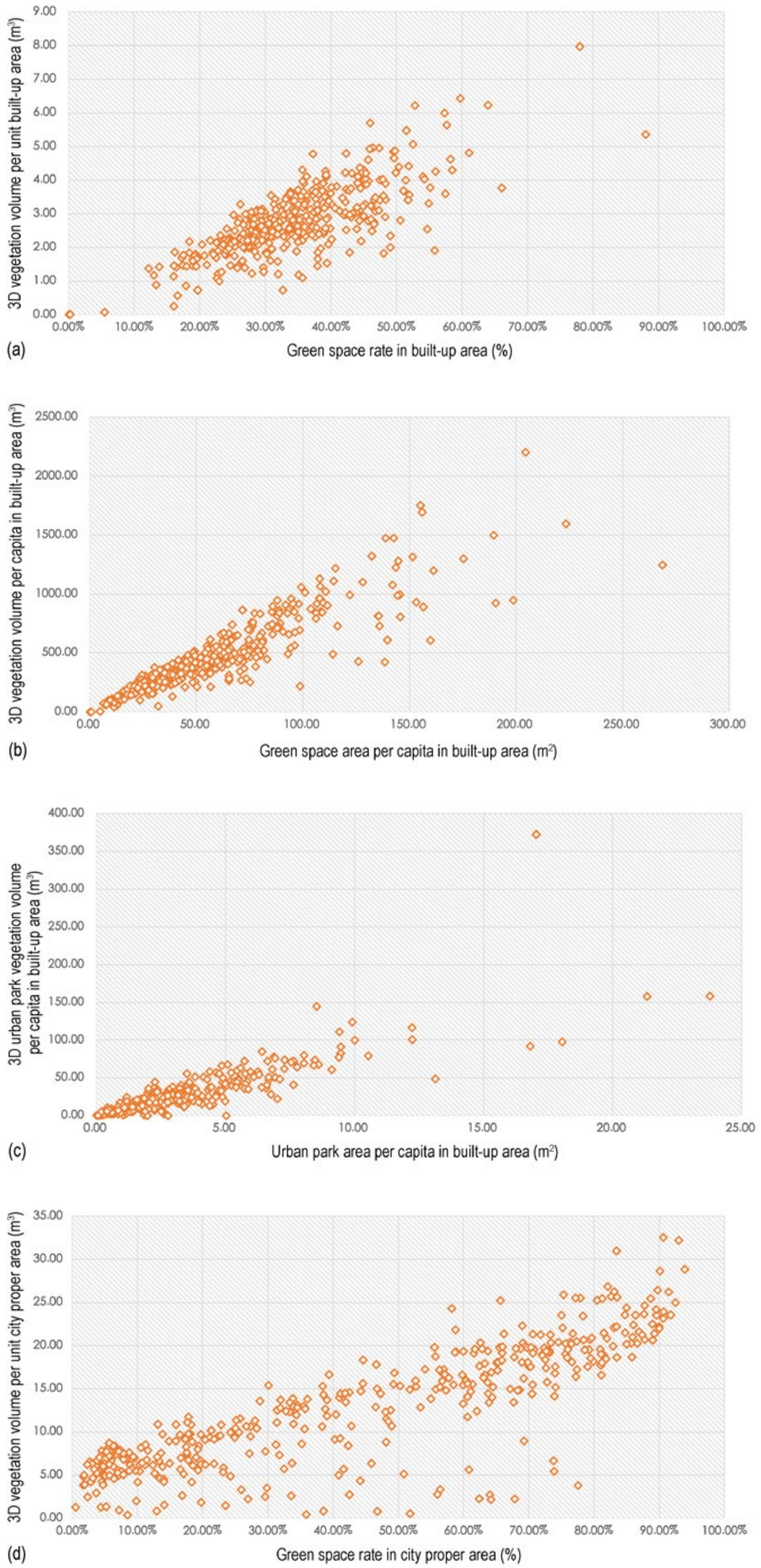
Figure 7: Parametric plant models of the site

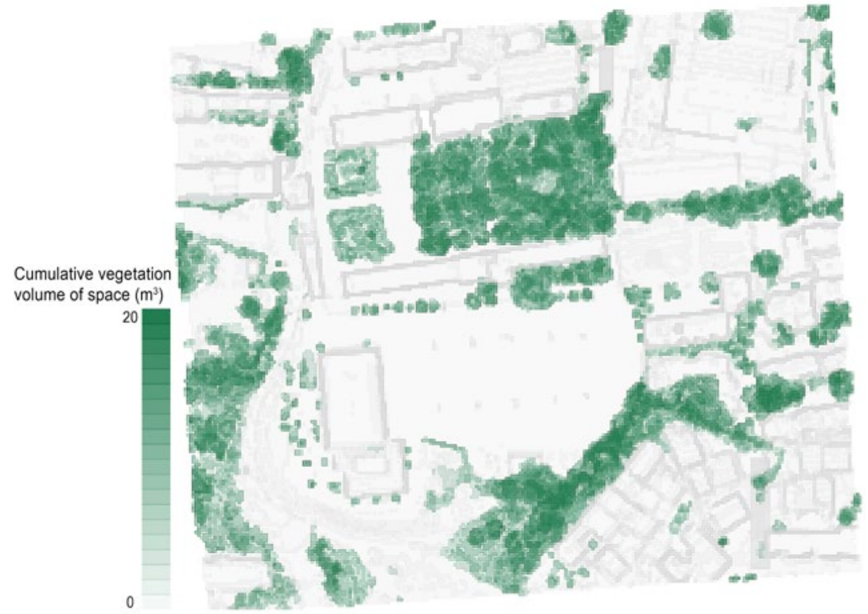


Bird-eye view of the site in early-stage



Bird-eye view of the site in mature-stage





◂◂ **Figure 8:** Differences between the values of 2D and 3D green space indicators in each city. (a) Differences between 3D vegetation volume per unit built-up area and green space rate in built-up area; (b) Differences between 3D vegetation volume per capita and green space area per capita in built-up area; (c) Differences between 3D urban park vegetation volume per capita and urban park area per capita in built-up area; (d) Differences between 3D vegetation volume per unit city proper area and green space rate in city proper area
Figure 9: The cumulative vegetation volume per voxel grid in vertical space
▾▾ **Figure 10:** Models with different voxel sizes

per capita. The evaluation results of the 3D vegetation volume indicators differed from those of the 2D indicators (Figure 8), which shows that the 3D vegetation volume indicators can be used to supplement the 2D indicators to describe urban green space.

To simplify the calculation process, the 3D volume of vegetation space in this study was calculated using the crown height, and the under-crown spaces were not excluded, resulting in higher values than LiDAR scan-based studies, which will need further refinement. This method can also be used for vegetation studies at the neighborhood and project scales. The 3D indicators can be widely applied in urban green space planning and management. Unlike 2D indicators, the 3D vegetation volume can change with plant growth, which makes it suitable for monitoring and evaluating the long-term dynamics of urban green spaces.

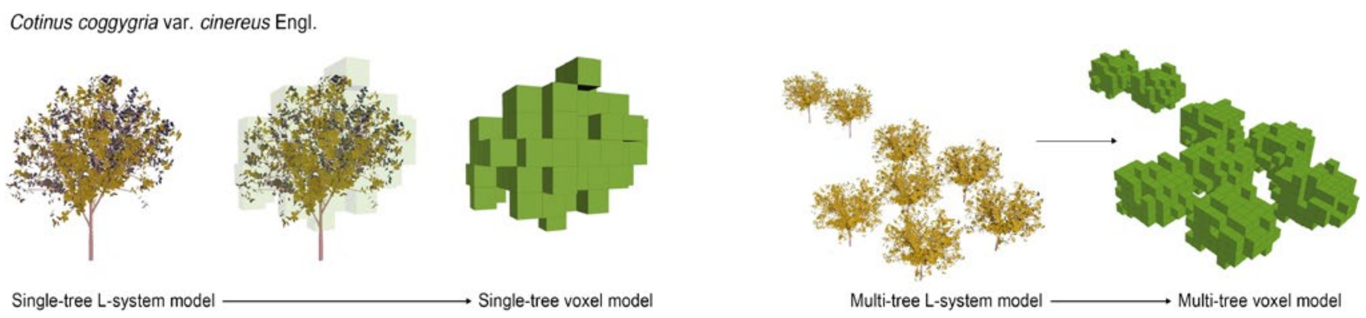
4.2 Community-scale voxel modeling

The results indicated that the total vegetation volume in the campus area was 61,192 m³, accounting for 37.28% of the total campus buildings and vegetation volume. The green space in front of the North Academic Building was rich in vegetation types and had the largest 3D vegetation volume proportion (68.37%). The cumulative vegetation volume of the site can be seen in Figure 9.

The voxel model can visually represent the 3D spatial distribution of the plants and their surroundings. Moreover, with adjustable voxel sizes (Figure 10), the model can be adapted to different precisions and various scales, from regional to neighborhood.

In terms of 3D voxel modeling, this study proposed a method for isolating green space from airborne LiDAR data by semantic segmentation to generate a voxel model. The current semantic segmentation results of neural

Figure 11: Converting from the L-system model to the voxel model



networks such as PointCNN are not yet reliably accurate enough, and some types need to be adjusted manually. The voxel model can express the vertical structure of the green space and can be applied to a wide range of scales with adjustable voxel size. It can also be used to analyze spatial positions with other urban elements. Based on the voxel models, it is also possible to extend the commonly used 2D spatial metrics indices to 3D to reflect landscape vertical changes.

4.3 Project-scale L-system modeling

Comparative analysis showed that the 3D vegetation volume of the site at the early stage was 13,497 m³ (12.25 m³ per unit area); the 3D vegetation volume at the mature plant stage can reach up to 215,097 m³ (195.00 m³ per unit area).

To analyze the vegetation volume, the generated model was then converted into a voxel model in Houdini (Figure 11). Based on the statistics of the geometric elements within each voxel, the LAD of each voxel can be obtained and stacked to construct a voxelized LAD model, which can be used for further analysis in microclimate simulation tools such as ENVI-met.

In terms of L-system modeling, the study constructed a plant model and predicted the different plant growth stages based on allometric equations and field-collected data by using Houdini. There were some approximations and simplifications in the construction of generative models for the details of leaf morphology and branching structure of tree species, and the correlation characteristics between iterative branching and the growth cycle of different plants need to be further fitted and studied. Compared to triangular mesh models, the generated models are based on the natural branching rules with dynamically adjustable parameters, which can be used to construct a dynamic digital twin model for the entire life cycle of plant communities.

5. CONCLUSIONS

Due to the structural complexity and cross-scale existence of green space, modeling it in 3D requires different methods to achieve a balance between ease of use and accuracy for various needs. At the regional scale, 2.5D vegetation evaluation indicators could provide a quick and easy-to-use tool for estimating green space volume distribution. At the community and site scales, voxel and generative modeling for plants can provide a more precise 3D spatial representation. The rapidly evolving deep learning and parametric modeling techniques could also provide tools to establish standardized and automated evaluation methods. The base of urban green space planning and management could transform from 2D-based documents to various 3D representations of green space for densely populated urban areas. Additionally, different green space 3D models can be interconnected with various digital information modeling and ecosystem service evaluation tools for predictive analysis. ⦿

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