Building Green Decarbonization for Urban Digital Twin – Estimating Carbon Sequestration of Urban Trees by Allometric Equations using Blend Types of Point Cloud

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Abstract. The achievement of climate neutrality is a fundamental goal for cities in the next 30 years. In order to achieve this goal, this research focuses on a novel tree carbon sequestration utilizing point clouds. Using a multi-algorithm workflow, tree information is extracted to calculate carbon storage from airborne and mobile laser scanning data, using Helsinki as a test case. The study employs local maximum and seeded region growing algorithms to detect tree locations and crown extents from aerial point clouds. A Python script is generated using the DBSCAN algorithm to extract tree point clouds and trunk diameters. The established allometric equations are utilized to calculate the carbon sequestration of trees. The results are integrated into the digital platform, filling the gap in urban digital twins' carbon storage information. This innovative approach will contribute significantly to urban planning and decision-making for sustainable cities in the face of climate challenges.

Keywords: Urban tree, Carbon sequestration, Point cloud applications, Density-based clustering, Urban digital twin

1 Introduction

Turning climate and environmental challenges into opportunities to transform our current urban typologies into active agents for sustainable futures, supports the European Union’s aims to make Europe climate neutral by 2050 (EU, 2020). Global warming not only leads to environmental degradation and extreme climate (IPCC, 2018) but also triggers severe health problems for people (Robert et al., 2019). Nowadays over 74% of our global population is located in urbanized areas (UN, 2019). Urban areas contribute to 71% of total carbon emissions (Rosenzweig, 2010). The current implemented policies will lead to global warming of 3.1 to 3.7 degrees by the year 2100, which far exceeds the overall target of the Paris Agreement (Hannah et al., 2020). Therefore, the urban has the potential to play a more important role in solving climate and environmental challenges. The effectiveness of urban green for climate mitigation has been discussed and confirmed (IPCC, 2018). Carbon sequestration (CS) through vegetation is currently the most efficient way to achieve urban decarbonization, while there is a great deal of exaggeration and uncertainty about the amount of carbon sequestration obtained by current urban landscape projects today (Lefebvre et al., 2021).

2 Key Concepts

In the field of forestry, allometric equations are widely used to calculate the CS of trees, which rely on diameter at breast height (DBH) and tree height information (Yoon et al., 2013). Additionally, several studies have established correlations of tree CS with only tree height and canopy size, though this approach is considered less accurate (Dahal et al., 2022). Traditional methods often involve field surveys (Shadman et al., 2022) or urban inventory (Neto & Sarmento, 2019) for CS assessment. Nowadays with the increasing application of Light Detection and Ranging (LiDAR) technology in urban settings, various studies have explored the use of point clouds for carbon storage assessment. Point cloud data finds widespread applications in urban studies, including object recognition (Fang et al., 2022), visual assessment (Qi et al., 2022; Tang et al., 2023), and urban environment simulation (Urech et al., 2022; Yao & Fricker, 2021). Its advantages, rapid information acquisition and cost-efficiency, lead to numerous research endeavors aimed at using LiDAR to evaluate the CS of urban trees.

According to the acquisition methods, point cloud data can be broadly categorized as aerial-based LiDAR primarily capturing canopy layer information, and ground-based LiDAR containing vegetation details closer to the ground. Aerial-based LiDAR, including airborne laser scanning (ALS) and unmanned aerial vehicle (UAV), estimating CS through tree height and crown diameter. Crown delineation is often achieved using algorithms such as watershed segmentation (Münzinger et al., 2022). Lin et al. (2022) utilized UAV to calculate the above-ground biomass (AGB) of trees based on height and crown diameter. Yu et al. (2023) employed UAV data to fuzzily estimate the CS of an area based on tree canopy volume. For lacking tree trunk information, aerial-based LiDAR serves as an alternative computation method when ground-based LiDAR data is unavailable. Ground-based LiDAR methods, including mobile laser scanning (MLS) and terrestrial laser scanning (TLS), involve point cloud clustering and segmentation to obtain tree height and trunk information. Researchers have developed their clustering algorithms for different focuses. Luo et al. (2021) employed the deep pointwise direction-based method to cluster trees via point direction aggregation from MLS data. Velasco and Chen

(2019) used Plantscan3D software combined with manual segmentation from TLS data to perform allometric equations for precise AGB calculation. Kukenbrink et al. (2021) utilized multiple algorithms for AGB analysis from TLS data. Zhao et al. (2018) divided MLS data into grids, performed planarization, and extract tree information for CS evaluation. But this method overlooked trees with lower height or smaller crown sizes. Montoya et al. (2021) developed software to extract trunk information using a Euclidean clustering algorithm based on TLS point cloud normal, while this software was not accurately depicting the tree canopy. Point cloud clustering methods are based on density, spatial distance, and normal of the points. Due to the complexity of urban environments, most clustering methods necessitate a significant amount of manual data preparation work.

Urban Digital Twin (UDT) establishes links with real cities or physical counterparts to improve the understanding of the complex phenomena of cities as well as the understanding and analysis of urban changes and operations (Nochta et al., 2020). For this reason, UDT is considered as enabling technology that promotes situational awareness of urban management and provides real-time urban information models. As a core function of the UDT, environmental simulation and scenario prediction has been investigated in recent years such as flood event (White et al., 2021), traffic flow (Dembski et al., 2020), and carbon emission analysis (Park & Yang, 2020). The emergence of UDT signifies the potential to address climate-related challenges through systematic urban planning. Towards urban climate mitigation, cities need to incorporate trees into digitalization processes. This is essential not only for the development of UDT but also for long-term environmental sustainability.

This study aims to measure the CS of trees in urban areas and support decision-making in carbon neutrality and UDTs. CS is calculated based on tree trunk diameter and absolute height, using ALS data for tree height extraction and MLS data for trunk diameter extraction. In the Nordic urban environment, trees are often intertwined with other urban facilities, making it challenging to accurately cluster tree point clouds using conventional methods. To address this issue, a Python script is developed to extract tree point clouds and trunk diameters from MLS data based on point cloud density. Compared to other methods, our approach narrows down the clustering scope via other segmentation algorithm and clusters each scope via a loop command. Then reintegrate trees into a unified whole, which significantly reduces the time-intensive manual data preparation work. Due to the lack of local data, the established allometric equations from existing studies are imported to calculate tree carbon sequestration. Compared to methods employed by other researchers, our approach offers precise tree extraction, and the extracted point cloud information can be integrated into a digital twin platform for more intuitive public display.

3 Methodology

3.1 Pilot area and data

A pilot area in the city of Helsinki, Finland (60.2°N and 24.94°E) is selected. The pilot area is located in the southwest of Helsinki called Jätkäsaari with an area of around 150 * 150 m2 (Fig.1).

Figure 1. Aerial image of the pilot area in Helsinki.

The existing ALS point clouds of the City of Helsinki serves for identifying tree heights. Collected in 2021, the LiDAR point clouds owned a point density at a nadir of 40 points/m² and were gathered from a flight height of 380 m above the ground. The effective opening angle was 40 degrees, and the coverage between lines was 50% (https://hri.fi/data/en_GB/dataset/helsingin-laserkeilausaineistot). The orthophotographs of the City of Helsinki is imported to operate crown delineation. The used orthophotograph was captured in June 2021 with a resolution of 5 cm/pixel (https://hri.fi/data/en_GB/dataset/helsingin-ortoilmakuvat). The resolution is downscaled to 10cm/pixel for more efficient data management. The MLS data provided by "© 2022 Cyclomedia" is used in order to collect tree trunk information. The point cloud was collected in September 2022 using the Cyclomedia DCR10 sensor. The data was originally captured in the scope of Forum Virium Helsinki's project "Mobility Lab Helsinki" (https://mobilitylab.hel.fi/). Mounted on a vehicle, the sensor was equipped with five different directions 100 Mpx cameras capturing point cloud with 1500 ppsm density, 10 cm position accuracy, and 0.1º orientation accuracy. Finally, the tree inventory derived from the Helsinki urban tree database (https://hri.fi/data/en_GB/dataset/helsingin-kaupungin-puurekisteri) is used for validation and get the species information for CS calculation. The data contains locations, species (group), and size categories.

3.2 Method

The Figure 2 presents the methodology using blend types of point clouds to estimate the CS of trees. In this study, the ALS dataset's first output canopy height model (CHM), is used to generate treetops with height information. The orthophoto processed by a random forest classifier is involved in this step to operate misclassified filtration. Based on the detected treetops, the seeded region growing (SRG) algorithm is utilized to delineate tree crowns. The generated tree crown is utilized to crop the MLS point cloud. Then the DBSCAN algorithm clusters trees and the script acquires DBH from 1.3 - 1.4m of tree trunks. Finally, the established allometric equations compute the CS of each tree and link the information with the tree point cloud.

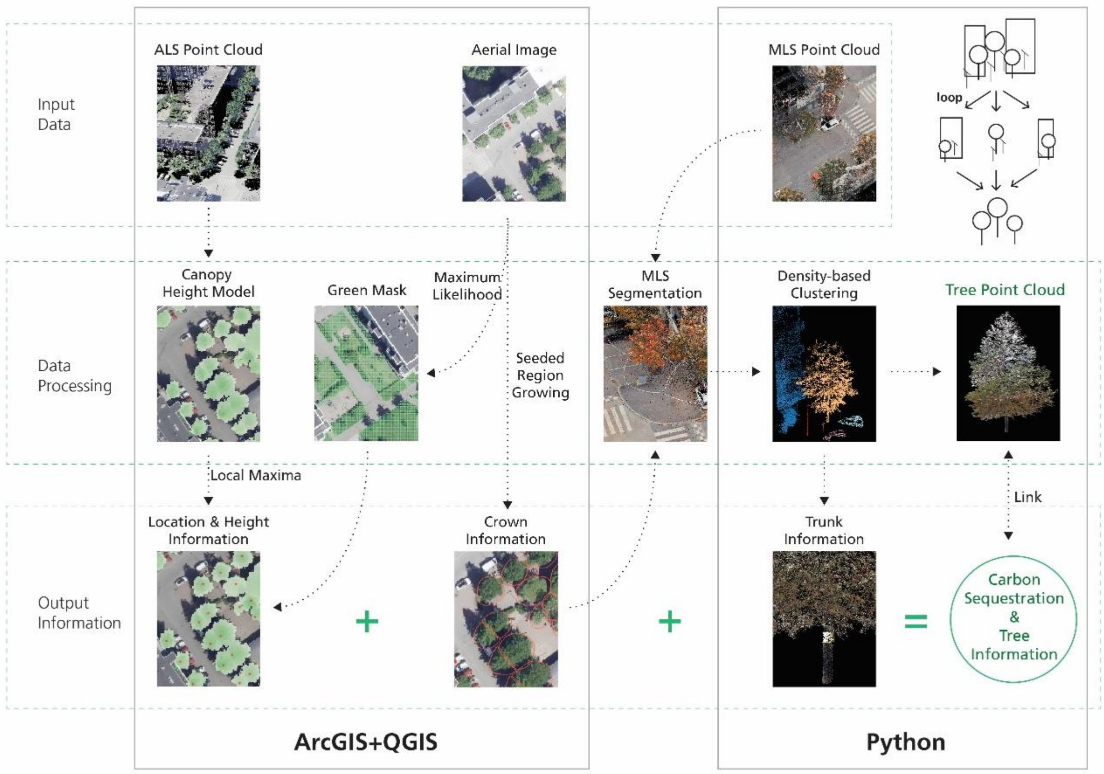

Figure 2. The diagram displays the detailed steps using ALS, MLS point cloud, and Orthophoto to calculate CS and output a single tree point cloud. The top layer is input data and the bottom layer illustrates how CS is computed.

First, the Local Maxima (LM) algorithm (Coomes et al., 2017) is implemented to detect the highest value of the neighboring pixel in the CHM model as treetops. Due to the complexity of the urban environment, many infrastructure elements such as building roofs and lambs are incorrectly classified as ‘high vegetation’ in the ALS dataset. Therefore, the maximum likelihood estimation helps to extract the green area in the orthophoto as a mask layer to filter out the misclassified tops. With the detected treetops, the SRG algorithm (Ma et al., 2020) then delineates the tree crowns based on the orthophoto and CHM model. The SRG algorithm can be described as follows, with the notations ‘f’ representing pixel value, ‘r’ denoting pixel location, and ‘σ’ representing the spatial variance of color (Bechtel et al., 2008). Starting with the seed pixels (s), adjacent pixels (p) with similar values to each seed point coalesce into clusters. The similarity (α) indicates the correlation between the value of connected pixels and the value represented by the corresponding seed. Higher similarity is achieved when the color and spatial distance of adjacent pixels to the seed pixel are closer (weights can be adjusted by changing variance 'σ'). The similarity threshold can be fine-tuned to achieve optimal results in different environments.

$$\text{Similarity } \alpha = \exp\left(-\frac{1}{2}\left(\frac{(fp - fs)(fp - fs)}{\sigma 1} + \frac{(rp - rs)(rp - rs)}{\sigma 2}\right)\right) \quad (1)$$

Second, the MLS dataset is cropped from tree crown extents and separately exported for clustering. A Python script is developed that utilizes the Open3D (Zhou et al., 2018) and Laspy (https://github.com/laspy/laspy) libraries to perform a loop of the DBSCAN algorithm (Ester et al., 1996) on the cropped MLS datasets. The script removes non-tree objects based on the point cloud density after clustering. It exports the cluster of point cloud trees and extracts DBH information of tree trunks. The DBH in our study is measured from the range of 1.3m to 1.4m of the tree trunk. Due to the limitations of incompletely capturing when mobile laser scanning tree trunks, the maximum recorded diameter determines the DBH value of each tree (Fig.3).

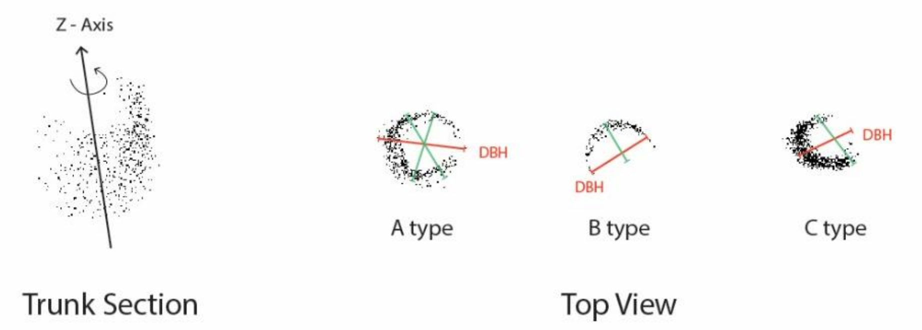

Figure 3. The diagram displays how the DBH is measured from the point cloud. the largest diameter (red line) is picked as the DBH of the tree.

Third, the established allometric equations compute the volume of each tree species (Table 1). The allometric equations are established by other researchers mentioned in Table 1. For tree species without developed allometric equations at the genus level, a general calculation method proposed by McPherson et al. (2016) was adopt for CS calculation.

Table 1. Allometric equations were used to compute AGB (kg) for each tree species based on DBH (cm) and tree height (m). References are listed at the end of each line.

Tree Species (Group)	**Allometric Equation**	**Similar Species**	**Reference**
Acer	AGB = 0.041225*DBH$^{0.922}$ *H$^{2.222}$	Acer buergerianum	(Yoon et al., 2013)
Salix	AGB = 1.5976 + 0.0371*DBH^{2}*H	Salix nigra	(Dahal et al., 2022)
Tilia	AGB = 0.1193969*DBH$^{1.951853}$*H$^{0.664255}$	general calculation	(McPherson et al., 2016)
Ulmus	AGB = 0.1193969*DBH$^{1.951853}$*H$^{0.664255}$	general calculation	(McPherson et al., 2016)

Based on the calculated ABG, the following formulas are used to calculate the stored carbon weight. CF, the carbon factor, is generally 50% of the tree's total volume (Penman et al., 2003).

$$\text{aboveground carbon storage (AGC)} = AGB * CF \tag{2}$$

4 Results

The extracted trees were compared with the Helsinki tree database in our study area. The database recorded a total of 56 trees, out of which 54 were trees successfully extracted along with the respective point clouds. Regarding morphological information, height information was recorded for all extracted trees, while DBH information was obtained for 49 trees. 4 trees failed to get separated from urban objects by the clustering algorithm, resulting in DBH values that were significantly unrealistic (> 2m). Additionally, 1 tree lacked DBH information because the MLS data did not scan the tree trunk. Further details can be found in the limitations in Section 5. Due to the data acquisition characteristics of MLS, many recorded tree trunk point clouds were incomplete. In this research, the maximum diameter represents the DBH, which might lead to larger DBH values compared to actual measurements. Although the Helsinki tree database contains information on DBH, the data is quite dated and reported in 10-cm intervals, making it unsuitable for validation. Table 2 summarizes the evaluation with an F1 score within the study area.

Table 2. The diagram displays the accuracies of collected tree information. Matched means both location and DBH get extracted, Commission means the extracted trees without DBH information, and Omission means the missed tree in the pilot site.

Total	Matched	Commission	Omission	Recall	Precision	F1-Score
56	49	5	2	0.96	0.91	0.93

Due to the lack of allometric equations in Nordic countries, we referred to equations developed by other researchers to compute the CS of trees. The 49 trees collected in the area stored a total of 8022.5kg of carbon, with an average of 163.7kg in each tree. The tree species Acer stored the least carbon, with 10.2kg, corresponding to a height of 5.89m and a DBH of 11.7cm. The most carbon-sequestrated tree was Tilia, with 416.85 kg, corresponding to a height of 10.77m and DBH of 41.5cm. The information difference between 4 species in the pilot area is summarized as a statistical analysis (Fig. 4). Among them, Ulmus had the highest average CS, while Acer has significantly lower CS compared to the other three species. Assuming the referenced allometric equations are correct, it is evident that Acer stores less carbon per unit height/DBH than the other three species. This indicates that Acer, despite being a common urban tree species, is not ideal for decarbonization. While the tree age can be estimated based on its height and DBH, the growth of trees follows a curve-like pattern, making it difficult to predict the annual carbon captured by the trees. Additionally, the patterns of height and DBH for different species in this area were summarized based on the collected information. For dense forests, where MLS makes it challenging to obtain trunk information, the use of this relationship allows for the estimation of tree DBH based on height, enabling the calculation of AGC weight.

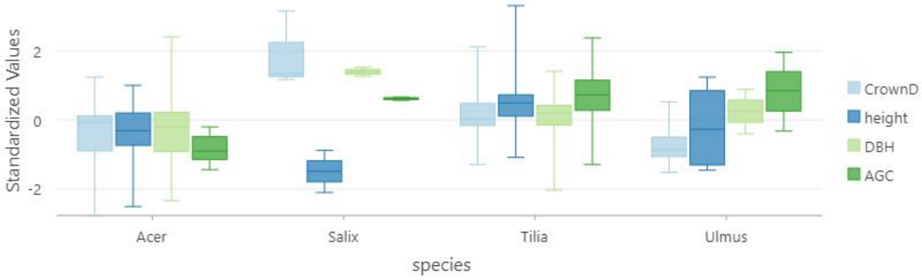

Figure 4. The diagram summarizes the collected information (Crown diameter, Height, DBH, and AGC) and distributes by species name. Due to the different units for the above information, we standardized the y-axis to reflect the variations of different vegetation types within the area.

5 Discussion

Cities should play a more vital role in addressing climate and environmental issues. This research has established a comprehensive tree CS measurement for urban areas. clustering and segmentation algorithms were employed on various point cloud data to extract tree height and DBH, then used allometric equations to calculate the AGC weight. Compared to studies that utilize a single feature for calculation, our approach is more rigorous. The collected information from the experimental area is associated with corresponding tree point cloud data and integrated into the digital platform (Fig.5), addressing the current lack of carbon storage information in UDTs. Stakeholders, including governors and the public, can intuitively evaluate the carbon reduction value of trees. And this information system allows for the target selection of tree species with higher CS capacity for landscape design in local conditions. Furthermore, with the ease of LiDAR data collection, cities can maintain long-term updates on trees and dynamically assess the changes in carbon capture by comparing growth from different years.

Figure 5. The diagram displays the linkage between the point cloud and collected information. Using ArcGIS Pro as an example, the figure demonstrates the feasibility of applying it in UDTs for better-informing decision-making on carbon reduction.

Figure 6 illustrates the limitations of the current method. While the density-based clustering algorithm excludes most of the urban objects in the scene, especially in urban situations where objects are closely integrated with trees, the developed algorithm may recognize them as a single entity. Using color differences as a solution may filter out many tress points with similar colors, especially for the limitations of color assignment to point clouds collected by ground-based LiDAR. Additionally, the discussed method has limited adaptability to dense forest areas. In the selected pilot area, in which 8 trees are closely crowded, 6 trees could be identified with 5 extracted DBH information. This is partly due to the unsuitability of MLS for scanning dense forests. The applicability of this method to dense forest areas needs validation through TLS data. As an alternative, the DBH can be estimated based on height to estimate tree CS in forest regions.

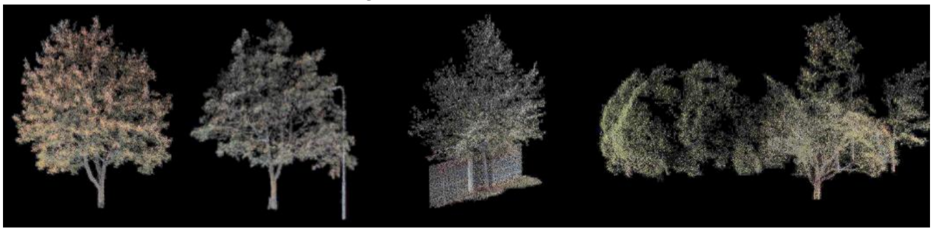

Figure 6. From left to right: the normally extracted tree point cloud, trees extracted together with utility poles, mixed extraction with fences causing DBH extraction issues, and some tree trunks not captured by MLS in densely populated tree areas.

The proposed method is expected to yield similar results for most Nordic cities, whereas the effectiveness has not been tested for other countries. Optimizing can be discussed from data acquisition and algorithm improvement. Since tree trunks have higher reflectance compared to leaves, ideally, trees without leaves should be easier to cluster. Additionally, collecting on overcast days can mitigate shadow issues and provide better data. In our next step, we plan to explore measuring the variation in CS data for Helsinki trees over different years to enhance the carbon-neutral modeling capabilities of UDTs. Also, Data collection and clustering will be extended to dense forests. Given their characteristics, the study plans to cluster with bottom-up logistics, starting with trunk clustering and then segmenting the upper crowns.

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