Urban Tree Height Assessment: A Case Study in Washington, D.C.

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1 Introduction

Urban tree canopy is crucial for environmental sustainability, human health, heat island effect mitigation (Locke et al., 2023; Tan et al., 2016; Ulmer et al., 2016), especially in densely populated cities like Washington, D.C. The D.C. government maintains a database of nearly 175,000 city-maintained trees. Even at a cost of just a few dollars per tree annually, the ongoing maintenance and expansion of this canopy require significant taxpayer funding. The city aims to achieve 40% tree coverage by 2032, as outlined by the D.C. Department of Energy and the Environment. Although the database includes extensive basic information about the trees, it lacks continuous and readily accessible data on canopy heights—an essential factor in various aspects of tree maintenance. In recent years, the operational use of Light Detection and Ranging (LiDAR) has become increasingly viable for measuring canopy heights and providing detailed information on canopy structures in urban environments. This study aimed to evaluate the effectiveness of LiDAR technology in detecting and estimating urban tree heights. The study focused on one city, Washington, DC, analyzing Ward 7 as a case study. The study aimed to answer the following research questions:

1. Can LiDAR effectively detect tree locations across a densely populated city?
2. Can LiDAR accurately estimate tree heights, and how does it compare to reference measurements?
3. Can LiDAR be used to estimate changes in tree height over time?

2 Methods and Materials

2.1 Study area

This study centers on Ward 7 in the D.C. area Figure 1, a region distinguished by its leafy streets, single-family homes, transit stations, and, most prominently, its extensive greenspace, as noted by D.C. government. Ward 7 is home to several historic Civil War fort sites that have been converted into parks, as well as green spaces such as Kenilworth Aquatic Gardens, Watts Branch Park, Anacostia River Park, and Kingman Island. Previous Tree Report Card 2021 stated that the percent area covered by tree canopy in Ward 7 is about 37%. However, as the population has grown, Ward 7 is now facing considerable vulnerability challenges related to safety, physical and social health. Effectively managing green infrastructure can help address these issues.

2.2 LiDAR

The airborne LiDAR data collected in 2015, 2020, 2022 were downloaded from the D.C data portal. The LiDAR datasets were captured over the Washington DC area in 2015 (April 1 and April 24),

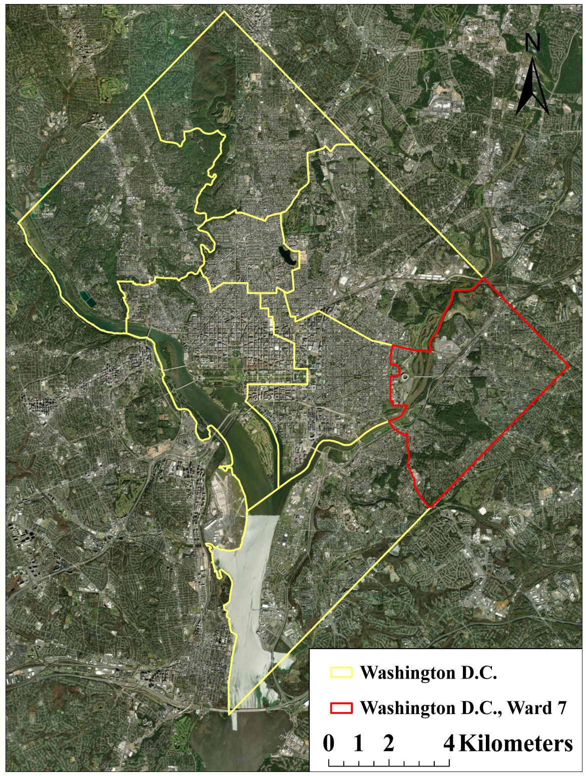


Figure 1: The study area of all Wards in Washington D.C. in yellow and Ward 7 in red

2020 (June 26, June 29, and June 30) and 2022 (January 24). However, because the 2022 data were collected during the leaf-on season, we decided to exclude 2022 from the analysis to ensure sufficient point density to generate CHMs (see LiDAR image for 2022 in Figure 2, right). The 2015 and 2020 LiDAR data were then preprocessed and converted into 1 m canopy height models (CHMs) through the following steps: (1) LiDAR point cloud normalization and filtering, (2) generation of 1 m CHMs, and (3) CHM projection, mosaicking, and clipping. A tree detection method was then applied to extract individual tree locations from the CHM data, using thresholds for a maximum crown size of 8 m and a maximum tree height of 2 m. The individual tree heights derived from LiDAR were compared against reference tree heights in Washington, D.C. All the analyses described were performed in R using the lidR package (Roussel et al., 2018).

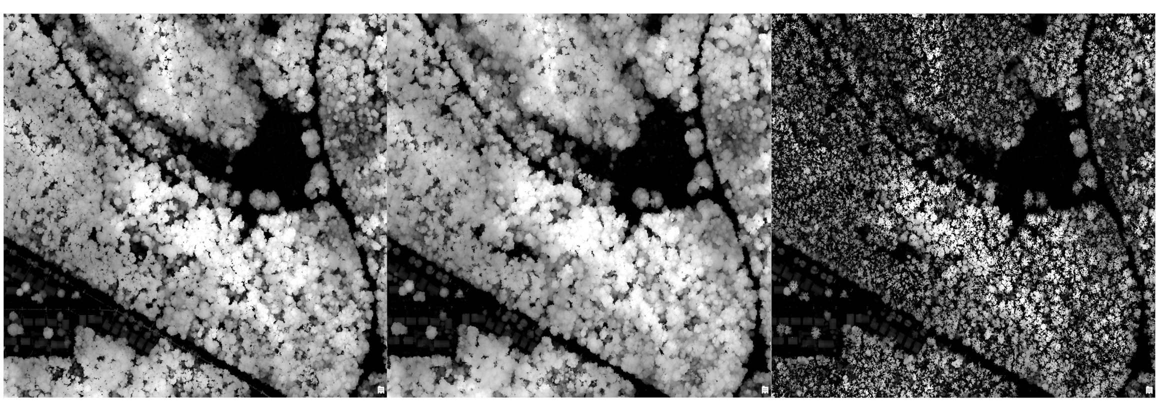
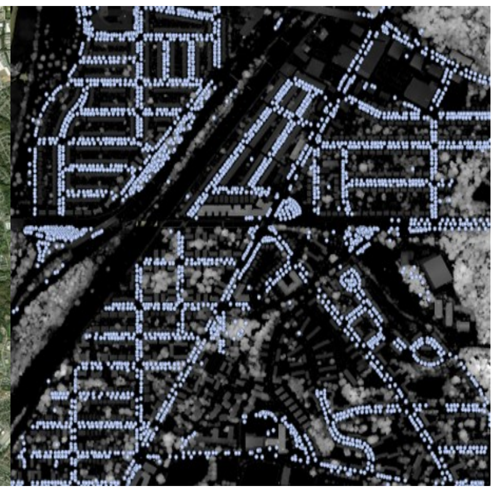


Figure 2: The airborne LiDAR-derived CHMs (left: 2015; mid: 2020; right: 2022)

2.3 Reference DC trees

The DC Trees dataset is a combination of trees and tree locations (latest survey date: 2023 summer) managed by Urban Forestry Division surveyors, and estimated trees heights based on an automated feature extraction process applied to 2022 LiDAR data. The individual tree locations in DC LiDAR datasets were classified into “known” and “estimated” (attribute: STATUS). Only 10% of the trees with STATUS = ”known” were identified as street trees within the blocks in DC, Ward 7 and were used as reference data in this study (Figure 3). The trees were measured by local arborists and updated annually to maintain precise information about individual trees in DC (current version: 2023 summer), such as tree height, diameter at breast height, etc. The estimated tree heights derived from 2022 LiDAR data were not used due to the very low point density that may result in misidentification of tree locations and inaccurate height estimates.

(a)



(b)

(c)

Figure 3: (a) Measured DC trees in DC. (b) Zoom-in of the DC trees along the streets in Ward 7, DC. (c) DC street trees (Flickr credit: Hari Menon).

2.4 Individual tree identification using airborne LiDAR-derived CHMs

The input data and processing workflow is given in Figure 5. As previously mentioned, we used the tree detection function to identify tree locations. This geographic information was stored in vector format and buffered to 3 meters to approximate tree crowns. Within each 3-meter buffer zone (Figure 4), we performed zonal statistics using CHMs and reference tree heights as inputs. All CHM pixels within the buffered zone were aggregated to determine the 98^{th} percentile height value. Zones with both valid aggregated CHM data and reference tree values were considered as matched data for further analysis. The percentage of matched data can be therefore calculated.

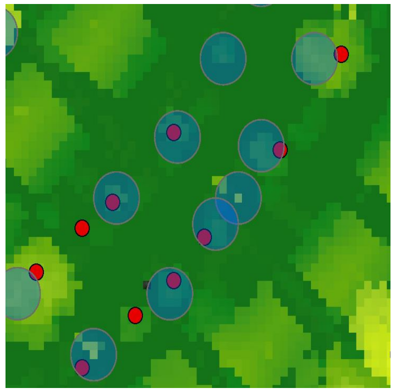


Figure 4: 3 m buffered zones of estimated tree locations (light blue circles) and reference DC tree locations (red dots) over LiDAR-derived CHM.

2.5 Comparison between reference tree heights and LiDAR-derived heights

To evaluate the performance of LiDAR in estimating tree heights, a 3-meter buffer was applied to all measured trees. The pixel values of the CHM within these 3-meter buffered zones were aggregated to determine the 98^{th} percentile height value. A statistical analysis was then performed to compare the 98^{th} percentile CHM heights with the reference tree heights (Figure 5).

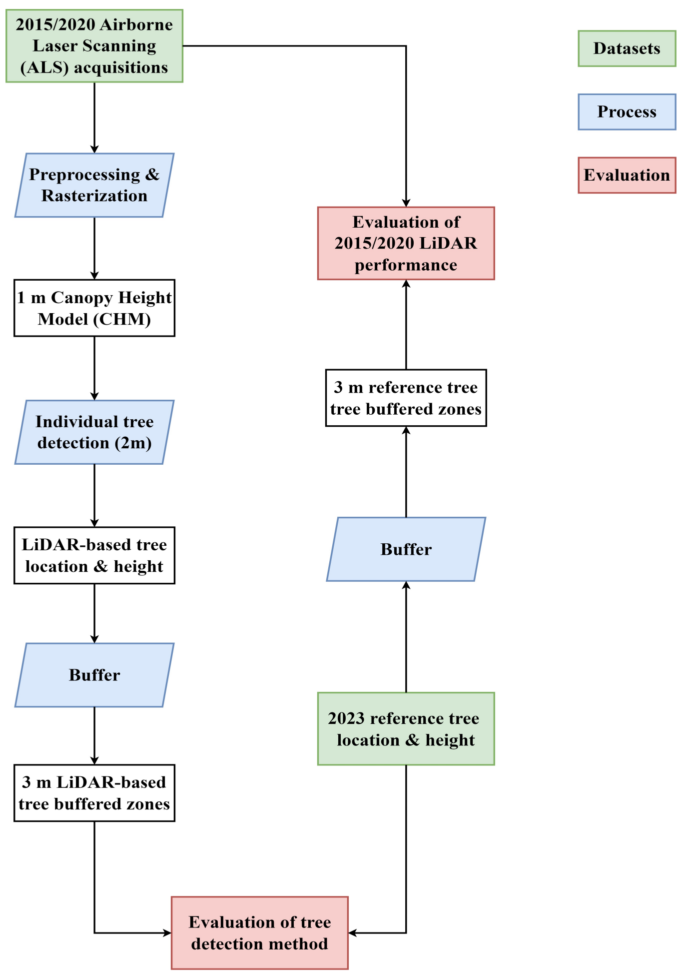


Figure 5: Workflow of LiDAR data processing and statistical analysis.

3 Results

3.1 Individual tree detection

The scatterplot demonstrated that LiDAR can accurately detect urban trees to a reasonable extent (Figure 6). Specifically, in Ward 7, LiDAR-based tree locations from 2015 and 2020 were compared to known trees in the 2023 dataset. The comparison revealed that 32% of the known trees were successfully detected in 2015, while 47.6% were detected in 2020. There is a strong relationship between 2020 LiDAR-based tree heights vs. 2023 reference heights, with an R^2 of 0.87. However, the 2015 data had a relatively lower R^2 (0.49) due to the longer time lag to 2023 compared to the 2020 data. Additionally, the bias observed in 2020 was considerably lower than that in 2015, indicating that 2020 LiDAR data performed better than the 2015 LiDAR data because it was collected relatively close to the time the 2023 reference data was collected (Figure 6).

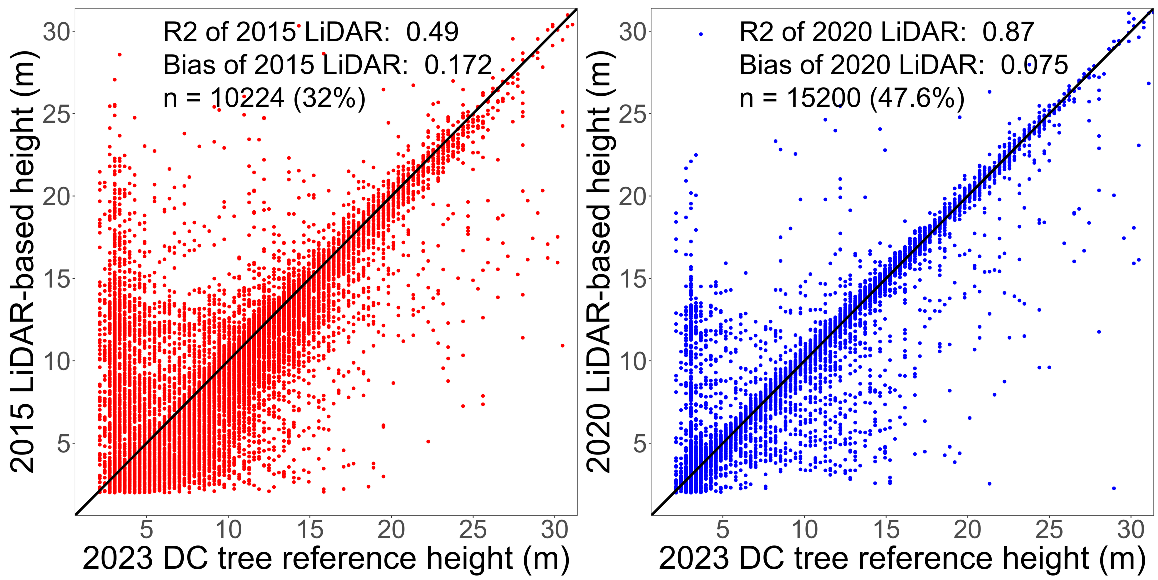


Figure 6: Scatterplots of LiDAR-based 98^{th} heights vs. reference tree heights (left: 2015 vs. 2023; right: 2020 vs. 2023) for all matched LiDAR-detected trees' 3 m buffered zones. 32% and 47.6% represent the percentage of matched data relative to the total data in 2015 and 2020, respectively.

3.2 LiDAR accuracy assessment

The accuracy of LiDAR in estimating tree heights was assessed by applying a 3-meter buffer around known DC trees and aggregating CHM pixels within each buffered zone to determine the 98^{th} percentile height. The analysis showed a strong correlation between LiDAR-derived heights and reference heights, with an R^2 value of approximately 0.8 for the 2020 data, indicating that LiDAR effectively captures tree height information. In contrast, the 2015 data exhibited a lower R^2 value of 0.46, likely due to the longer time lag compared to 2023. Similar to Figure 6, the bias of 2020 LiDAR data in Figure 7 is also smaller than that of 2015 data, which is mainly due to the phonological condition.

The group histogram plot (Figure 8) showed the relative height difference between 2023 reference heights and LiDAR-based heights. The relative height difference was calculated by dividing the difference between 2023 reference height and 2015/2020 98^{th} percentile height by the 2015/2020 98^{th} percentile height. The frequency of relative height differences in the 2023 vs. 2015 group is higher across all bins, ranging from -80% to 80%, compared to the 2023 vs. 2020 group. This indicates more variability in the relative height differences between 2023 and 2015 than between 2023 and 2020, likely due to more pronounced natural tree growth or tree management over the longer period.

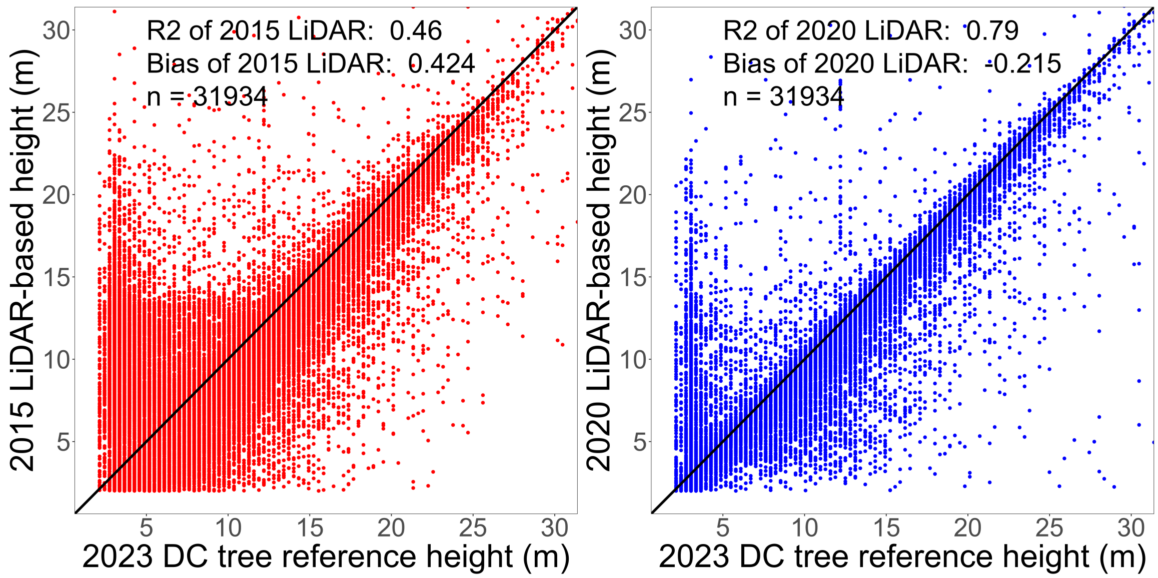


Figure 7: Scatterplots of LiDAR-based 98$^{\text{th}}$ heights vs. reference tree heights (left: 2015 vs. 2023; right: 2020 vs. 2023) for all trees' 3 m buffered zones in DC, Ward 7.

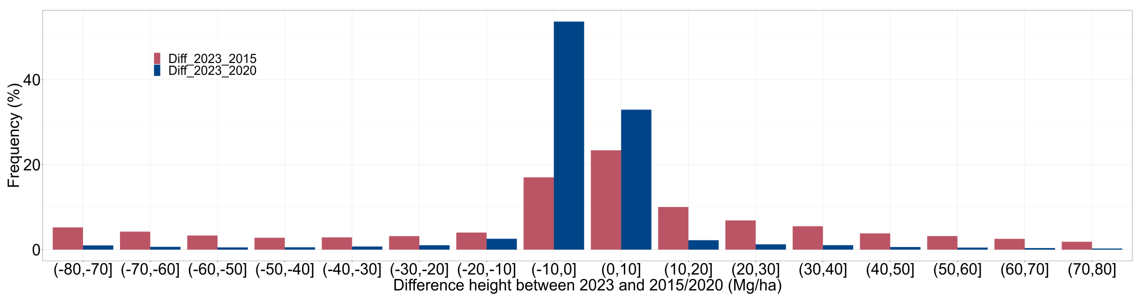


Figure 8: Histograms of relative height difference (%) between 2023 reference heights and 2015/2020 LiDAR-based percentile 98$^{\text{th}}$.

3.3 The Future of Urban Forestry in D.C.

The District of Columbia Urban Tree Canopy Plan suggests that an increase of 5% in canopy cover across the city could provide $4.2 million dollars annually in benefits to the city by improving air quality, reducing stormwater volumes, trapping greenhouse gasses, reducing the urban heat island effect, and increasing tourism and property values. Managing and monitoring a city's tree cover is essential for ensuring its sustainability. The findings of this study underscore the importance of continued investment in LiDAR technology and its integration into urban forestry management. As cities like Washington, D.C., strive to enhance their green spaces and tree canopy, the ability to accurately measure and monitor tree canopies will be crucial in achieving sustainability goals and improving human's quality of life. Moreover, the study suggests that LiDAR could play a significant role in broader environmental initiatives, such as biomass estimation, carbon sequestration, and environmental justice. As urban areas continue to grow and as they become more densely populated, the need for precise, data-driven approaches to managing natural resources will only become more critical. The use of LiDAR in urban tree canopy management offers a promising avenue for cities to enhance their green spaces, improve environmental quality, and ensure a healthier, more sustainable future for their residents.

4 Conclusion

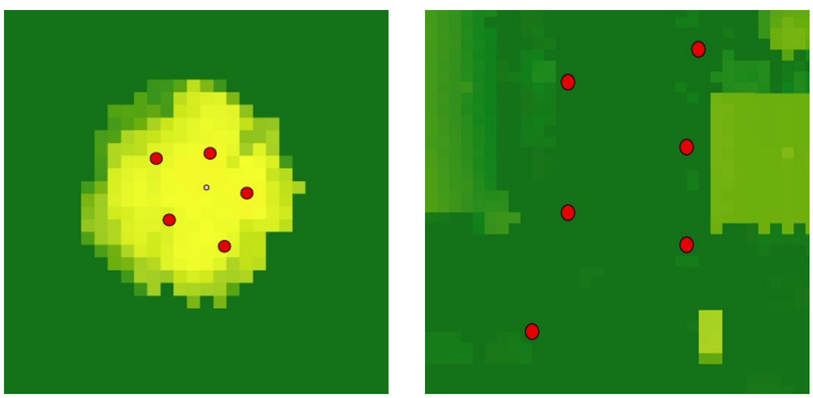
In this study, we applied a novel tree detection algorithm, assessed the performance of repeated LiDAR surveys in DC's Ward 7, and quantified the differences in tree height across various years. This research underscores the importance of continued development and refinement of LiDAR-based methods for urban tree assessment, particularly in improving the detection of individual tree locations and enhancing overall accuracy. In this research, we followed the methodology developed in previous studies (Li et al., 2023; Wessels et al., 2023). Here are the main findings and suggestions for future study:

1. The tree delineation method employed successfully detected 47% of these known trees above 2 m using 2020 LiDAR data, demonstrating the potential of LiDAR in urban tree detection. Based on previous experiment results, the methods can also be adjusted for mid (5 m) or high (8 m) trees as well, with comparable statistics compared to the current 2 m tree-finding settings.

2. The research suggests an inconsistency between the location of individual trees estimated by LiDAR 2022 and the LiDAR measurement (Figure 9a). For example, the DC tree database showed five points (five trees) over a single LiDAR detected tree, while our method only detected one point representing the individual tree location. This suggests an opportunity to refine the delineation method currently being used by Urban Forestry Division to more accurately represent the location and characteristics of individual trees.

3. The current LiDAR-derived CHMs failed to detect some very low trees, for example, in Figure 9b, the red dots indicate the locations of measured trees, while the gradient green color represents the overlaid 2020 CHM layer. This could be due to the limited penetration capability of LiDAR, potential instrument error, or changes in local tree management between 2020 and 2023.

4. The study suggests investigating the impact of trees on climate change and socio-environmental policies, particularly in the context of biomass estimation, carbon sequestration, and environmental justice.



(a) (b)

Figure 9: (a) Multiple tree locations detected by DC government in red dots and single tree location determined by the tree detection method proposed. (b) The CHM unable to detect local trees.

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