Estimation of tree biomass using multisource remote sensing data

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Abstract

Forests serve as crucial carbon sinks, sequestering a significant portion of global terrestrial aboveground biomass and playing a crucial role in the carbon cycle. Similarly, urban greenery acts as a carbon sinks within urban areas, emphasizing the importance of accurately estimating biomass in both natural and urban environments for effective climate mitigation strategies. This paper proposes a method for extracting tree attributes, diameter at breast height (DBH) and height, utilizing point cloud data generated from LiDAR technology and Terrestrial Laser Scanning (TLS). Accurate calculations of trunk shape and radius were archived by extracting point cloud data in the trunk area for each tree. The paper compares the efficacy of UAV LiDAR (ULS) technology with TLS in the estimation of the DBH radius of the tree. This research highlights the potential of point cloud datasets in biomass estimation for urban greenery and dense forests, contributing to advancements in remote sensing technology for forest management and climate mitigation efforts.

1. Introduction

Forests contain about 80% of the global terrestrial aboveground biomass and play a key role in the global carbon cycle. Nearly 16% of the carbon emitted by fossil fuel CO2 emissions during the last two decades is sequestered annually by forest ecosystems. There is significant uncertainty about the magnitude and location of the forest carbon sink, mainly due to incomplete information about the spatial distribution of carbon stored in biomass. Improving knowledge of the density and spatial distribution of forest biomass is critically important for supporting future climate mitigation actions. (Guodong et al., 2015; Gazzea et al., 2022) Similar to forests, urban greenery and vegetation play a crucial role in the carbon cycle, serving as carbon sinks within urban areas. Hence, accurately estimating the biomass of urban greenery is equally imperative.

In 2005, was measured the amount of carbon stored and absorbed by trees in US cities to understand the role of urban forests in mitigating climate change. Data were gathered from 28 cities and 6 states to determine the average carbon content in areas covered by trees. That study utilized a combination of field data and model analyses from multiple cities. Data collection involved recording tree species stem diameter at 1.37 meters above the ground, tree and crown height, crown width, crown light exposure, and canopy condition. Gathering all this data was essential for the study. (David J. Nowak, Eric J. Greenfield, Robert E. Hoehn, Elizabeth Lapoint, 2013)

Remote sensing data, especially satellite images, are extensively utilized in calculating vegetation index, texture features, and Leaf Area Index, all of which are closely associated with aboveground biomass (AGB). (Zhang et al., 2020) Previous research had mostly relied on the analysis of satellite images and mapping techniques. In urban landscapes, big datasets are generated through street scanning, LiDAR technology, and photogrammetric imaging, all aimed at creating comprehensive 3D models of cities. These datasets hold significant potential, especially if they can be leveraged to extract valuable biomass information.

Models for the estimation of forest biomass at individual tree scales are based on the allometric relationship between the structure parameters (such as diameter at breast height (DBH) (Ledo, 2016) or both DBH and tree height (Zeng, 2017) and AGB. Additionally, the ratio of tree height and DBH, crown diameter, and crown height (Hofstad, 2005). Measuring forest biomass through field surveys over large regions is time and cost-consuming. In recent years, the application of remote sensing technology such as Terrestrial Laser Scanning (TLS), airborne LiDAR (ALS), and photogrammetry has been increasing in the measurement and extraction of forest parameters, characteristics, estimation of biomass and carbon stock and forest management (Lu et al, 2020), (Bazezew et al., 2018).

Laser scanning technology has become the primary choice for forest AGB estimation since the application of optical remote sensing has limitations due to signal saturation in dense canopies. In recent years, Both TLS and ALS have provided high accuracy for the estimation of basic tree parameters such as height, DBH, crown area, and individual tree position (Farraz et al., 2016; Pirotti et al., 2017; Raumonen P, 2013), (Cote, Fournier, & Egli, 2011). Different methodologies were used for the assessment of DBH from TLS data. Ye et al. (Ye, 2020) extract individual steam by using improved RANSAC cylinder fitting and robust least square ellipse algorithm to improve the accuracy of DBH estimation. Liu et al. (Liu, Wang, Dong, Chen, & Liu, 2018) used octree segmentation, connected component labeling, and Random Hough transform (RHT) to identify trunks and estimate DBH from TLS data while Zhang et al. (Zhang, et al., 2019) used a connected component segmentation algorithm for steam detection.

Although the TLS offers a unique advantage in measuring DBH, also TLS has several limitations including multiple-station scanning and registration which is time-consuming and labour-intensive, especially for large-scale regions and high hardware requirements. On another hand, ALS and unmanned aerial vehicles (UAV) offer fast acquisition, reduced data volume, and data collection over large regions. However, they use a top-to-bottom approach resulting in sparse point clouds

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under the crown which represent a great challenge for direct and accurate extraction of DBH.

In the context of this paper, the biomass of urban vegetation refers specifically to the weight of biomass associated with trees in urban green areas. Several methods exist to measure this biomass. A most common way is field measurements which involve measuring the diameter at the breast height of individual trees in the urban parks. This paper presents the concept of automatic extraction of these data using existing data in the form of point clouds generated by UAV photogrammetry, TLS, and/or LiDAR technology.

2. Materials and Methods

In this paper, extraction of diameter at breast height of individual trees using existing data in the form of point clouds is proposed

2.1 Study area

The study area used in this research is part of the Campus, University in Banja Luka. The City of Banja Luka is located in the northwest part of Bosnia and Herzegovina, on the Vrbas. According to the 2013 census, the total population of the city is approximately 186,000, and it has an area of 1239 km^2. The study area covers 1217 m^{2,} representing a part of the University Campus in Banja Luka and it is characterized by flat terrain. The research area is a surface that represents a smaller urban forest located on the green area of the campus characterized by irregularly distributed coniferous trees with height up to 22 m. The overview of the study area is presented in Figure 1.

Figure 1. Study area

2.2 Data acquisition

The fundamental dataset was a point cloud created using TLS and UVA LiDAR (ULS) technology. The survey of the study area was conducted in October 2023., to compare the results generated from the created point clouds.
ULS: The experimental data utilized in this research were collected by using DJI Matice 300 RTK UAV equipped with Zenmuse L1 sensor. Zenmuse L1 integrates a LIDAR module, high-accuracy IMU, and camera with 1-inch CMOS on a 3-axis stabilized gimble (DJI, n.d.). It supports 3 returns. The flight height was set to 60 m. The double gride flight pattern and 80% side overall were used. Additionally, the return mode was set to triple, the scanning mode to non-repetitive, the sampling rate to 160 kHz, and RGB coloring was on.

Characteristic	L1 sensor
Detection range	450 m (80% reflectivity) 190 m (10% reflectivity)
Accuracy	Horizontal: 10 cm (at 50 m) Vertical: 5 cm (at 50 m)
Scan Modes	Non-repetitive Reparative
Maximum Returns Supported	3

Table 1. Characteristics of Zenmuse L1

TLS data: Faro Focus M70 was used for conducting terrestrial datasets. It is a laser scanner for short-range applications. The integrated HDR camera provides a natural colour overlay to scan data that was captured. Dual-axis compensator, as an integrated sensor, performs a levelling of each scan with an accuracy of 19 arcsec valid within ±2°. Characteristics of Faro laser scanner are presented in Table 2. The entire scanned area was covered by seven strategically positioned recording stations across the study area. In the entirety of the scanned area, planar and spherical markers were distributed to ensure visibility from each scanning station forming the basis upon which point cloud registration is completed. Before scanning, a point distance of 7.3 mm was set, resulting in an 8-minute scan duration at each station. Afterward, the registration process generated a unique, photorealistic point cloud comprising more than 95 million points.

Characteristic	M70
Range	0.6-70 m
Unambiguity interval	614 m for up to 0.5 mil pts/sec
Range accuracy	± 3 mm
Integrated color camera	Yes

Table 1. Characteristics of Faro Focus M70 Lasser scanner

Reference data: To evaluate the performance of the canopy cover estimation from TLS and ULS, the reference data were generated by using flexible tape. The individual trees were identified and located based on field sketches and a high-resolution near-ground relief map.

3. Methodology

The methodology used in this paper consists of 3 phases: preprocessing, individual tree detection, and DBH and height calculation.

3.1 Preprocessing

The data collected by TLS were processed in Faro Scene software. The multiple scenes were registered by using manual registration and spherical targets. The maximum distance error was 0.5 mm. After, registration project point cloud was created and exported in .las format.
For processing of ULS data, the DJI Terra software was used. The point cloud density was set to high, while the project coordinate system was set to EPSG: 3908. After successful reconstruction, the 3D point cloud was exported in. las format. The exported point clouds were used for the creation of the Digital Terrain Model (DTM), Digital Surface Model (DSM), and Canopy Height Model (CHM) at 10 cm pixel resolution.

3.2 Individual tree detection

Individual trees were performed by using Python implementation of local maxima filter using a CHM. The local maxima filter finds the highest pixel in a moving window. In this case, a circular window with a diameter of 4 m was used. The circular window is used to determine whether the centre cell is higher than the surrounding cells. If multiple pixels have the same value, the center of mass of the pixel group is used as the highest point. Additionally, smoothing techniques and high thresholds were used to eliminate non-tree features. The local maxima represents the tree's top position. The height of the tree is determined by sampling the CHM value to the detected positions.

In this paper, the DBH and exact tree position are measured directly from the point cloud in three steps: (1) point selection, (2) parameter estimation (i.e. diameter and position), and (result validation). In the first step, a subset of the point cloud for each tree was created by using the detected tree top position and fixed radius of 1.5 m at breast height. The created box is vertically limited to 5 cm for TLS (between 1.275 and 1.325 m height above ground) and 50 cm for ULS (between 1.050 and 1.525 m above ground) due to lower point density. In that regions steams can be found without being interconnected to ground or low vegetation or by other steams or brunches. The box is used to slice steam along its height. Sections are projected into xy plain and then used for fitting circles and estimating the tree position and DBH.

Once the sections of each steams has been determined, the points are used for circle fitting by using Nonlinear Least Square algorithm (NLS). NLS is a mathematical optimisation method used to find the best-fit parameters of nonlinear function to a set of data points by minimizing sum of squared residuals (Gander, et al., 1994). The minimization problem was solve by using Levenberg-Marquardt algorithm (LMA), a hybrid method combining Gradient Descent and Gauss-Newton Method. Gradient Descent reduced sum of the squared errors by updating the coefficient in the steepest-descend direction while Gauss-Newton method is iterative procedure that reduce sum of squared errors by assuming that least squares function is locally quadratic in the coefficients, and finds the minimum of this quadratic (Gavin, 2019). Gauss-Newton will work well for problems where the initial guess is already near solution but method may not be globally convergent. However, the gradient descent ensure the global convergences a robustness of LMA.

LMA is fast, stabile method and has a high ability to reach proper values regardless how the starting point is remote.
In this study, the accuracy of the estimated DBH was evaluate by using the Root Mean Squared Error (RMSE) which is calculated using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

Where x_i and y_i are the values from the ith reference and estimated DBH.

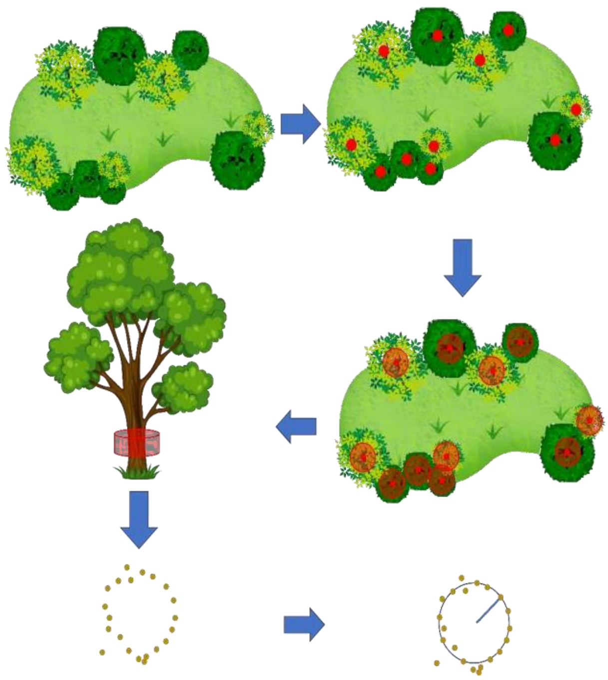


Figure 2. DBH estimation.

4. Results and discussion

In this paper, the compression of ULS and TLS for estimation of DBH and height of urban trees is presented.
Both techniques are widely employed in forest management. TLS offers high-resolution data providing accurate tree detection and characterization, including modeling of the 3D structures of trees (trunk, branches, and foliage), tree species classification, tree health assessment, etc. However, TLS systems are stationary require physical setup, and may have limitations in areas with steep slopes and dense vegetation. Due to the limited line of sight from the position of the scanner, both data capturing is time-consumed and usually spatially limited. On the other hand, the ULS provides broader coverage and captures data from different angles but the resolution is lower compared to TLS for objects on the ground, especially in case of dense vegetation (Figure 3 (b)). The distance between TLS and ULS point cloud was calculated using C2C distance tool in CloudCompare software (Figure 3 (c)). The mean absolute distance was 0.195 with a standard deviation of 0.076 m. The largest absolute distance was 1.26 m. However, the results indicate that 95% of points are within 0.30 m. Among axes, the lowest standard deviation is obtained for the Z axis (0.02), while the standard deviation for the X axis was 0.15 m.

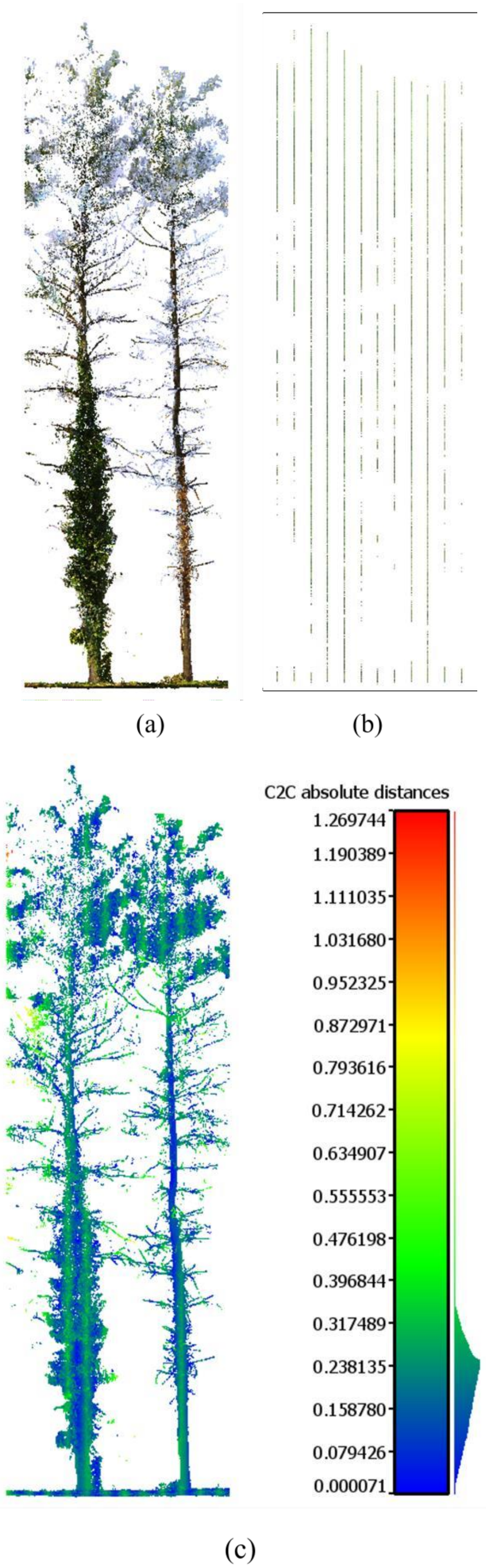
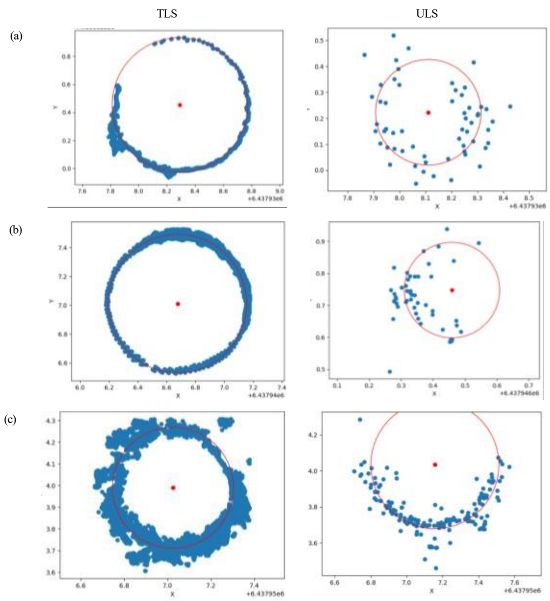


Figure 3.(a) TLS, (b) LiDAR, (c) cloud to cloud distance.

In the study area, the DBH ranged from 9 to 50 cm, with average value of 35 cm, while the tree height ranged from 6 to 22 m. The results of individual tree top detection are presented in Figure 3. The visual inspection (Figure 3.) shows that the algorithm was able to accurately detect the tree tops for both individual and group trees. However, in groups, some smaller trees are omitted. The RMSE of estimated tree top coordinates compared with TLS was 19.2 cm and 16.8 cm for X and Y coordinates respectively. The tree tops were used to determine tree height based on CHM. Although the local maxima, as a raster-based method, is well-known and widely used it should be noted that they allow only detection of trees in upper canopy state. Therefore, for more complex environments with high tree density or with steep slopes alternatives such as deep learning should be tested.

Figure 4. Detected tree tops for single and group trees.

The DBH is estimated by a circle fitting to a given point. The circle was fit to the projection of the point on a horizontal plane, i.e. only the X and Y coordinates were used in the fitting process. In comparison to field measurement, TLS and ULS data show reliable DBH estimates. The predicted accuracy of DBH was between 0.4 to 9 cm, with an RMSE of 2 cm. Figure 5, shows that ULS has much lower density and much noisier compared with TLS. Due to that, the lowest accuracy was obtained for the ULS dataset, which exhibited substantial data gaps and noise (Figure 5 (e), (f)). These artifacts are primarily attributed to the presence of ranches and leaf surrounding the tree trunk, which obstructed LiDAR returns and introduced inconsistency in point cloud (Figure 5 (c), (e)). While the maximum error reached 9 cm, corresponding to approximately 20 % of the estimated DBH, in certain case (Figure 5 (e)), the overall accuracy suggest that the LMA method remains effective for DBH estimation, though its performance may be influecend by data quality.



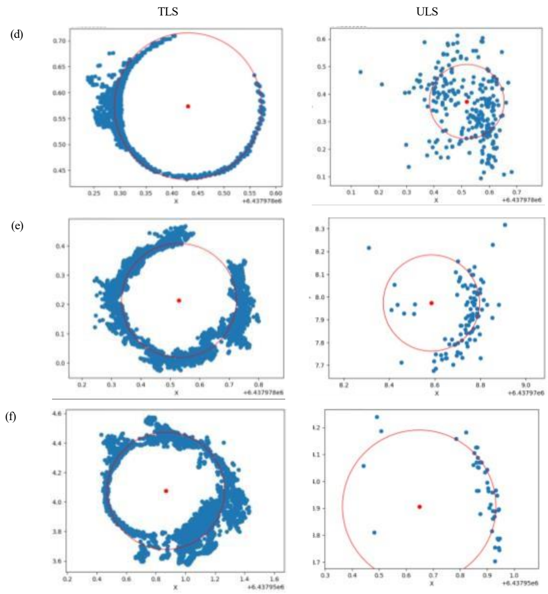


Figure 5. DBH estimation based on TLS and ULS data

5. Conclusion

In this paper, automatic procedure for extraction of diameter at breast height of individual trees and their height is proposed using existing data in the form of point clouds. The utilization of ULS and TLS to generate point clouds as input data enables precise measurements of tree attributes.

By using programming languages and integrated functions in programming language libraries like in Python, it is possible to very reliably detect the size of the tree, the structure of the crown, as well as the species of tree. This paper also highlights the extraction of the highest point of trees, showcasing advancements in tree attribute detection capabilities. In most cases, the highest point of trees represents the position of the trunk. Utilizing this data, trunk segments from the point cloud dataset were successfully extracted, enabling accurate calculation of trunk shape and radius.

Our analysis indicates that while ULS technology provides valuable data for tree attribute estimation, it falls slightly short of achieving optimal results for DBH compared to TLS. Although ULS offers lower resolution compared to TLS, it still provides sufficient detail for tree feature detection such as height and DBH. In order to increase point cloud density and accuracy in biomass estimation in urban areas it is recommended to capture data from multiple angles (such as a double-grid flight pattern). The accuracy of extracted characteristics for group trees shows that ULS has the potential to be used in dense forests however this should be feature analysed.

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