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INDIVIDUAL TREE ABOVEGROUND CARBON STOCK ESTIMATION USING TERRESTRIAL LASER SCANNING (TLS)

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ABSTRACT

Methods for estimating aboveground biomass and carbon stock have been driven by advancements in remote sensing technology. This study is to assess the capability of Terrestrial Laser Scanning (TLS) in measuring individual trees to determine aboveground biomass and carbon stock. The method relies on allometric equations that have been improved by previous studies for urban trees with various species. A non-destructive laser-based approach for estimating aboveground biomass was introduced. Biomass for each tree was obtained using Terrestrial Laser Scanning (TLS) and compared with field data. The point cloud for this study was generated using the TOPCON GLS2000, with produce 103, 477, 813 points. This study involved 42 random samples of various tree to identify diameter at height (DBH). The study was conducted at University Teknologi Malaysia (UTM) campus, Johor Bahru. Measurements from both point cloud and field data provided estimates of Diameter at Breast Height (DBH) with a root mean square error (RMSE) of 0.038m with overestimation 0.004m. The difference between field and TLS measurements demonstrates a strong correlation with a correlation coefficient (r) of 0.982. In total, 135.736 tonne aboveground biomass was produced from 42 trees sample, while the total carbon stock was 67.868 tonne.

1. Introduction

Accurate measurements of carbon stocks are essential for sustainable forest management and for reducing greenhouse gas emissions that drive global climate change. The reliability of these measurements significantly impacts the scope and depth of carbon dynamics research. Estimating carbon stocks across different spatial scales requires the use of techniques specifically tailored to each scale requirement. These techniques can range from field inventories and TLS at individual tree level and plot level, airborne LiDARs, or radars at regional level and satellite remote sensing at national or global level (Singhal et al., 2021).

Urban trees help improve air quality by absorbing pollutants such as carbon dioxide, sulphur dioxide, and nitrogen dioxide, while releasing oxygen into the atmosphere. They also reduce the urban heat island effect by providing shade and lowering temperatures through evapotranspiration. Urban trees experience environmental and neighbourhood conditions distinct from those of their forest counterparts, often exhibiting greater adaptability and resilience but also facing increased mortality rates. (Tigges et al., 2017) and often faster growth rates (Pretzsch et al., 2017) and they tend to develop relatively large crowns and branches (MacFarlane & Kane, 2017). Thus, methods of evaluating tree structures and their ecological benefits designed for natural environments may not apply to urban areas (McHale et al., 2009). Consequently, extensive studies on ecosystem services provided by urban trees, such as carbon storage capabilities, are highly necessary.

Tree height, DBH and other forest structural attributes are fundamental data obtained from traditional tree resource surveys. These parameters play a critical role in assessing forest biomass, understanding the carbon cycle and carbon flow, and evaluating their implications for global climate change. With the development of remote sensing technology, especially the technology of Light Detection and Ranging (LiDAR), many research results have been obtained by using remotely sensed data to extract information on forest structure parameters (Liu et al., 2018).

Application of lidar to estimate biomass obtained it will be necessary for future research to develop new methods to resolve the shortcoming of single tree detection and segmentation for forest ecosystems with complex canopy or understory structures (e.g., broadleaf forests or natural forests with various ages)(Xu et al., 2021). Moreover, alternative methods are needed to detect tree location and field data collection to solve location shifting issues. Current methodologies of AGB estimation from UAV-LS point clouds still rely on allometric algorithms (Lu et al., 2020) therefore, automatic and direct extraction methods of individual tree AGB will be necessary.

In recent years, TLS has been increasingly applied to forest resource surveys, forest management and planning (Srinivasan et al., 2015:Moskal & Zheng, 2012) . Among a variety of forest structural parameters, DBH and tree height are the most important ones obtained in forest resource surveys. They can offer both the structural characteristics of individual trees and data on the sample plot level, which are crucial for studying forest carbon storage and estimating biomass. Several researchers have conducted studies on the efficient and accurate extraction of DBH, tree height, and other structural factors using TLS data. (Liu et al., 2018).

Forests represent the largest active carbon sinks on Earth, most research on above ground carbon storage has focused on these ecosystems (Zhang et al., 2015). However, urban forests and urban green spaces (UGS) have often been disregarded or at least have attracted less attention, in that their specific roles and impacts are still not clearly understood (Tigges et al., 2017). Urban vegetation can accumulate significant amounts of atmospheric carbon, which is especially important because urban areas are major carbon emitter.
Besides that, the conventional approach used in forest inventory involves a hands-on process of obtaining measurements using handheld equipment, with minimal or no use of computer

devices. These instruments commonly have a significant level of accuracy. The in-situ method of forest inventory is advantageous due to its ability to maintain reliability and consistency, as it only operates with a single forest definition. (Ramezani & Ramezani, 2021). However, the effectiveness of field tools ultimately relies on the competence and skill of the user, regardless of their perfection in design.

The involvement of many teams in forest inventory is likely to result in variability in the obtained data, which can significantly impact the consistency and dependability of the data, particularly over a long period (Paudel et al., 2021). This happens due to the skill issue which varies from one person to another, fatigue is also in question due to its labor-intensive task. Relating to the labor-intensive properties, it also consumes a lengthy amount of time when facing vast plots for sampling. While smaller plots to curb the extensive manpower usage may not be able to acknowledge the spatial variability within the plot.

Extraction of individual tree measurements from point cloud is the main part of overcoming the limitation of conventional approach for individual tree measurement. Since a single scan may result in millions of data points, the rapid data collection surpasses that of from the conventional method. Almost every individual tree measurement has its own algorithm that have a fast-processing time. Furthermore, individual tree measurements from point cloud offers a simple and quick solution such as the determination of tree height by simply computing the vertical distance between highest and lowest point cloud of the tree (Peng et al., 2021).Thus, the use of LiDAR point clouds decreases the likelihood of human intervention with great efficiency.

Measuring the forest's aboveground biomass with precision continues to be a challenge. It is possible to estimate above-ground biomass through destructive (harvest) or nondestructive means. Estimating biomass using the destructive method (i.e., cutting down trees and weighing their components) is highly accurate. However, it needs much time and labour, it is very expensive, sometimes it is illegal, it is not feasible for large-scale analysis, and often it is not environmentally friendly. To overcome, the limitations of the destructive approach, non-destructive approaches provide reliable estimates of tree volume or biomass without causing physical damage, thereby enabling the inclusion of larger sample sizes and the assessment of mature trees that would be logistically and financially prohibitive to harvest (Lee et al, 2025).

Therefore, this research is highly significant for scientific progress and practical applications in forestry and urban tree studies. The study attempts to overcome previous techniques of carbon stock assessment by utilizing TLS technology to obtain a higher degree of precision and accuracy. The ability to capture highly detailed three-dimensional information about individual trees provides a fine-scale spatial resolution, enabling a more thorough understanding of carbon distribution within forest ecosystems. Meanwhile, quantifying carbon storage in urban areas needs to be understood better to support urban landscape planning and management that is focused on ecosystem services. Understanding urban vegetation structure, function, and value can support planning and management decisions that will improve environmental quality.

Aims of this study is to generate high-density point cloud data through measurements obtained using TLS technology to capture detailed information on tree structure. This high-precision data will then be used to extract key parameters such as DBH, tree height, and canopy dimensions, which serve as primary inputs for calculating aboveground biomass and carbon stock. Through this approach, the study seeks to accurately estimate biomass and carbon stock at the individual tree level, thereby enhancing the understanding of carbon storage capacity of trees within the study area and contributing to climate change mitigation efforts.

This study was conducted within the UTM campus in Johor Bahru, located approximately 20 kilometres north of the state capital. The research area extends from the Sultan Ismail Mosque to the security station and the Faculty of Built Environment and Surveying (FABU) administrative and classroom buildings. The study area covers a small area due to the study focuses on the experimental aspect of tree measurement and from the measurement aboveground biomass and carbon stock can be determined The study area covers an area of around 10 acres of land. Most of the land of the study area land cover comprises of tree which is the appropriate land cover for the study. Trees that contain within the area have spaces at least 2 to 3 meters among each of the other trees which means that the density of trees are low. Height of trees that is being measured is below 20 meters and the lowest is about 7 meters in height. The study area starts of at the peak which is at the helipad area with the elevation of 40+ meters according to the GPS readings while the lowest part of the study area is about 20+ meters. Differencing in about 20 meters of elevation decline. Local species of trees can be found within the area.

2. Methodology

To achieve the research objectives, a systematic methodological framework was implemented, consisting of five main stages: Data Acquisition**,** Data Pre-processing**,** Data Validation**,** Aboveground Biomass Calculation**,** and Carbon Stock Estimation**.**

2.1 Data Acquisition

In this study, data collection is more focused on measuring the DBH of each tree. To assess data accuracy, the data from TLS will be compared with field measurements. Control Points and Ground control points (GCP) are established preferably before the data collection from Terrestrial Laser Scanner. The survey of GCP is crucial in terms of positioning. It facilitates georeferencing among the two datasets. With the presence of GPS data for the establishment of GCP, it also creates common points within the two domains of data. Giving access to the opportunity of integration by co-registration or fine registration. With higher amounts of GCP and accurate GPS measurements equate to higher accuracy and precision. The proposed method of GPS survey in establishing the GCP and CP is by using Real Time Kinematic (RTK) approach. The RTK records instantly as the record button is pressed, making it consume less time to record coordinates of many points.

Point cloud data acquisition was performed with GLS2000 from TOPCON. The extended field of view was 270° vertically and 360° horizontally and covered a maximum scanning area. The maximal accuracy was 3.1 mm at a distance of 10 m, and the data acquisition rate was 60 000 pixels/s. In this study, we used multi-scanning to get a good density of point clouds. TLS data were collected from 27 scan stations.

Figure 1. Data acquisition: a) Using Topcon TLS b) Tree in study area

The DBH measurement of the tree has been done using measuring tape and TLS method. DBH is the most frequently measured and utilized tree parameter and is considered to be the most important parameter in forestry. During field measurement, 42 trees those DBH more than 10 cm in study area was measured by tape. DBH Diameter at was measured at the 1.3 meters height from the base of the tree.

2.2 Data Pre-processing

The initial phase of data processing is pre-processing, which involves leveraging observational data obtained from TLS. During this stage, essential corrective measures, including noise removal and georeferencing, are implemented to guarantee the precise positioning of the point cloud data. At an early stage, it is important to determine the selection of the point cloud, considering that the point cloud data file is very large. The end goal for the data pre-processing is to have usable data for further analysis, storage, visualization, and manipulation.

For point cloud data in particular, Point Cloud Registration must be performed to assign each point cloud to the correct coordinate system. Since the TLS device does not inherently know its own location, without registration, each scan station will be placed at a single or uncorrelated coordinate. The registration process aligns all scan stations into a unified coordinate framework, resulting in a visually complete dataset.

Following registration, Elevation Correction is applied to adjust for height discrepancies caused by uneven terrain or instrument positioning. This step ensures that the point cloud accurately represents true ground elevation and tree height measurements.
Next**,** Noise Filtering and Point Cloud Classification are carried out to remove unwanted elements such as buildings, vehicles, or human activity from the dataset. This step also involves categorizing points into relevant classes to facilitate more accurate measurements and analysis.

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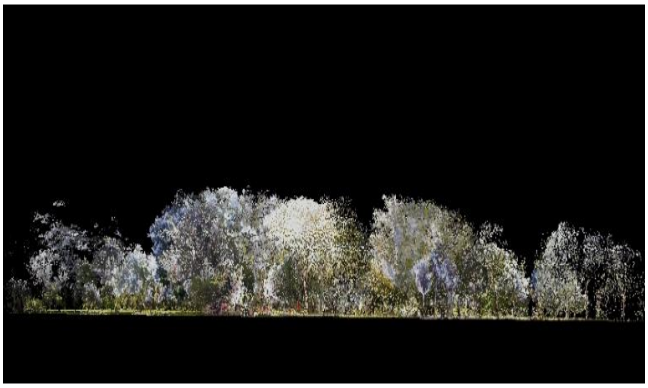
2.3 Data Validation

The post-processing stage is crucial in the study. This stage involves the ability to process data effectively. Among the methods involved in this study are ground point classification, point cloud normalization, point cloud segmentation, and accuracy assessment.

First, the ground points are needed to be classified as it is essential to construct a DEM. Ground point are classified by using the TIN densification algorithm proposed by (Zhao et al., 2016). The classification of the ground point starts with the identification of initial points or seed points where the classification starts. For point clouds that correspond with buildings, the maximum building size is needed to be identified. The lowest point will be taken as a seed. Next the TIN will be built from the initial point. The densification process will traverse through each unclassified point and will categorize each point to ground in accordance with the iteration distance and iteration angle. Thus, a hilly terrain should have a greater iteration angle than that of a flat terrain.

Point cloud normalization is a process used in TLS data processing to ensure that point cloud data is consistent and aligned with a common reference frame or coordinate system. This normalization step is essential for accurately comparing and integrating point cloud data acquired from different scan positions or at different times.

Before



After

Figure 2. Point cloud before and after normalization

Point cloud segmentation is the procedure in computer vision and 3D computer graphics of partitioning a three-dimensional point cloud, which is a collection of data points in space, into unique and meaningful parts. Each segment usually relates to a different item or area in the scene, which helps provide a better sense of the situation there. Point cloud segmentation tries to separate points from other objects or surfaces by elements like color, intensity, or closeness while keeping the points that belong to the same object or surface together. Advanced algorithms like deep learning-based methods and grouping techniques are used to correctly and quickly divide point clouds.

Once each of the individual points in the tree is separated into its different trees, they will be assigned random colours, similar to those seen in Figure 3. This random colouring technique may aid users in visually distinguishing each of the subsequent trees. Meanwhile, the unsegmented trees or shrubs will be excluded from the research and will be labelled as black or removed from the target point clouds by pruning. The purpose of the random colouring is to optimise the dataset by highlighting only the segmented trees.

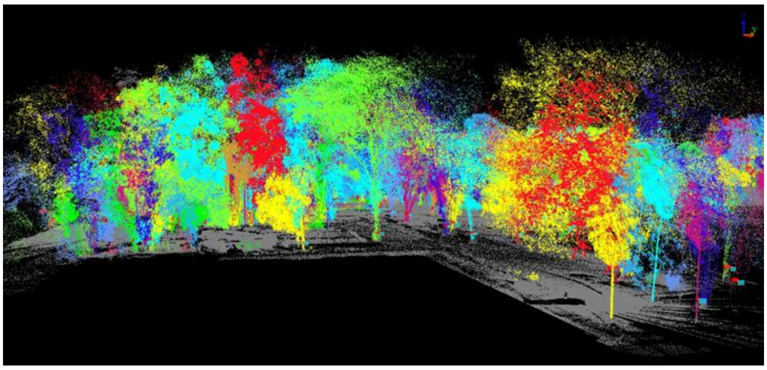


Figure 3. 3D view point cloud segmentation

Accuracy assessment seeks to provide a holistic evaluation to gauge the reliability of the processing result derived from the integrated point cloud dataset that is involved in the study. Accuracy assessment is pivotal in judging its credibility. It also prepares the data for further decision making for add-on knowledge value purposes.

A qualitative test has to be taken for the individual tree measurement results. This test as any other test which it will involve in the usage of reference data. Both the LiDAR derived, and the field measured derived tree measurements will undergo comparison. In this context, the test tools for the accuracy of the tree measurement includes the employment of Root Mean Square Error (RMSE), Normalized Root Mean Square Error (nRMSE), and Mean Absolute Error (MAE).

2.4 Aboveground Biomass Calculation

Calculating AGB for urban tree are different if compare to forest . In this study, we used (Ngo & Lum, 2018) allometric equation to calculate aboveground biomass. This equation for multi-species allometric equations from tropical forest sites. The deviation of each equation from data was calculated as:

$$\text{sum of squares} = (\ln(\text{predicted AGB}) - \ln(\text{measured AGB}))^2$$

Correction factors are often used when estimating urban tree biomass. (Ngo et al. 2013) applied this factor to the Chave et al. (2005) equation that was used to estimate AGB in a local rainforest. The best fit for the AGB-DBH relationship was:

$$\ln(\text{AGB}) = 2.511 \ln(\text{DBH}) - 2.413$$

2.5 Carbon Stock Estimation

Carbon stock was estimated using the above ground biomass (AGB) and the conversion factor (CF). Conversion factor that was used to calculate carbon stock both on biometric and model data was in the amount of 0.5 (Brown, 2002; C. Lin et al., 2016).

$$C = AGB * CF \text{ Where,}$$

C=carbon stock, ABG= above ground biomass, CF= conversion factor (0.5)

Total carbon (tonnes)= Total Biomass (tonnes) x 0.5

3. Results

Data analysis can be done once pre-processing stage was completed. Among the results to be discussed in this stage are point cloud density, aboveground biomass and carbon stock estimation.

3.1 Point Cloud Density

Point cloud density refers to the spatial distribution and density of points within the TLS dataset. Higher point cloud density provides more detailed and accurate representations of tree structures, allowing for precise measurements of individual trees and better estimation of aboveground biomass and carbon stock. Point cloud density can be influenced by factors such as scan resolution, scanning distance, and sensor specifications. Increasing point cloud density enhances the resolution of tree features and improves the accuracy of carbon stock estimation. Techniques for increasing point cloud density include adjusting scanning parameters, conducting multiple scans from different viewpoints, and utilizing advanced interpolation methods.

Studying the aboveground carbon stock of individual trees is an important task, particularly when utilising advanced technology such as Terrestrial Laser Scanning (TLS). Point cloud registration is the process of aligning and merging several scans of the same area, captured from different viewpoints, to create a cohesive and precise 3D representation. Figure 4. show the process to extracted density of point cloud.

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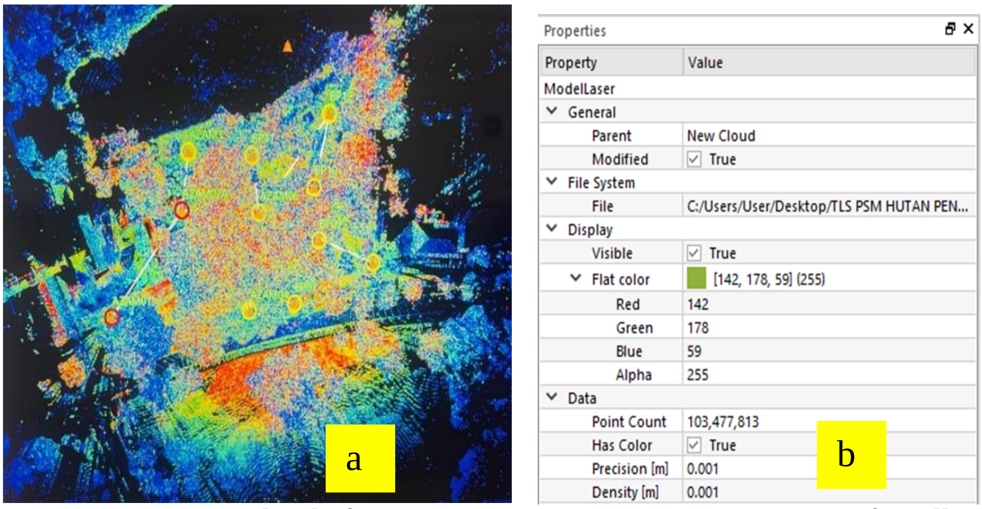

Figure 43. Point cloud after registration. a) TLS station appears after all scan views are combined b) Point cloud data properties

Data quality and density may vary depending on tree structure and noise sources such as understory vegetation density, mosses, etc. The total number of points and their distribution across the examined area determine the point cloud density in this study. In this study after the point cloud registration, the total point cloud was 103,477,813 points. After removing noise and cropping the area of study, the point cloud was reduced to 102,469,700 points. The purpose of cropping the area of study is for easier analysis that will focus on the study area only. All unrelated point clouds were removed using the software. By reducing the density of point clouds, data can be easily managed without involving large files.
Based on figure 4.2, Map density report show the scanned area covers an expanse of 41,693 square meters, giving geographical context to the point cloud data. Significantly, the pixel with the greatest point density recorded a remarkable 381,119 points per square meter, demonstrating a significant concentration of data in these areas. The data accuracy is determined by calculating the average point density throughout the whole region, which is 2,457.72 points per square meter. Using these density measures is essential for evaluating the accuracy and amount of information in the point cloud, which in turn affects its usefulness for other analyses.

3.2 Validation Individual Tree Measurement

The diameter at breast height (DBH) of each tree was measured at a height of 1.3 metres above the ground using the point cloud data. To test the accuracy of the data, 42 samples of tree was measured manually in the field using measurement tape and using TLS method. The correlation between the diameter at breast height (DBH) observed by field measurement and the DBH estimated manually by software was determined using linear regression analysis. A very good relationship was observed between manually measured by software and field measurement, it shows that indicating the effectiveness of TLS in DBH measurement.

The relationship between the field measurement and manually extracted DBH from the TLS point cloud showed a high R^2 value of 0.9821. The root mean square error (RMSE) between the field measurement diameter at breast height (DBH) and the manually recovered DBH from the TLS point cloud was 0.038 m while mean bias error (MBE) was 0.004m. The result showed that DBH measurement from the TLS point cloud had no different influence on the field measurement method since the linear regression line was close to the one-to-one line. An error in field measurement or a mistake in manually determining the diameter of a tree using software caused the overestimation of the DBH measurement. The mean absolute error (MAE) value was close to the RMSE, which is 0.029m, reflecting less extreme residual values that affect the error assessment. The results suggest that TLS is a potential technology that is useful for DBH estimation in individual tree measurements.

3.3 Aboveground Biomass Calculation.

Forest biomass estimation typically calculated based on allometric models that use DBH as input parameters. In this study, the biomass was calculated for individual trees derived from TLS point cloud data. The AGB was calculated with the allometric equation improved by (Ngo & Lum, 2018) for urban tree biomass for multi tree species. We also used a multi-scan approach for the retrieval of tree attributes and AGB/carbon stock estimation. AGB and Carbon stock was calculated using Arc GIS Pro by using this equation as shown in figure 4.5. The equation used for estimation was:

$$\ln (AGB) = 2.511 \ln (DBH) - 2.413$$

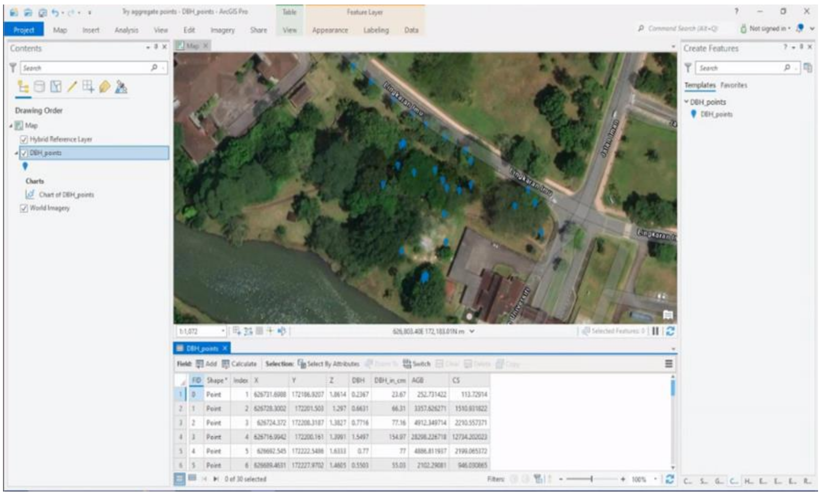

Figure 5. AGB and Carbon stock was calculated by equation using Arc GIS Pro

We used only the manually derived TLS based tree attributes to calculate AGB. Total AGB was 135.736 tonne for 42 samples of tree. The largest DBH, with a size of 154.970 cm, indicates a high biomass value, totalling 28.298 tonne. Meanwhile, the smallest DBH, with a size of 20.140 cm, shows an AGB value of 0.168 tonne. This shows that the DBH value has a strong influence on the biomass value.

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3.4 Carbon Stock Estimation

Carbon stock was estimated using the above ground biomass (AGB) and the conversion factor (CF). Conversion factor that was used to calculate carbon stock both on biometric and model data was in the amount of 0.5 (Brown, 2002; C. Lin et al., 2016).

$$C = AGB * CF$$ Where,

C=carbon stock, ABG= above ground biomass, CF= conversion factor

The estimated above ground biomass was multiplied by a conversion factor of 0.5 to estimate above ground carbon stock of the measured trees. Based on table 4.2, a total amount of 67.868 tonne of above ground carbon stock were obtained from 42 of individual trees with DBH between 20cm-160cm. High DBH values will indicate a lot of carbon storage. The highest carbon value is 14.149 tonne for DBH 154.97 cm, while the lowest carbon storage value is 0.084 tonne for 20.14cm DBH. It can be concluded that a large DBH value greatly affects the AGB and carbon stock estimation.

4. Discussion

This study confirms that Terrestrial Laser Scanning (TLS) can provide highly accurate Diameter at Breast Height (DBH) measurements, showing minimal bias and strong correlation with conventional methods. The ability of TLS to produce high-density point clouds enables precise 3D tree modelling, which enhances the calculation of Aboveground Biomass (AGB) and carbon stock.However, accuracy can be influenced by scan resolution, sensor specifications, data processing methods, and environmental factors. In urban areas, obstacles such as buildings, vehicles, and pedestrian activity require extensive data cleaning, while the limited availability of open source software and sample sizes restricts broader application.

Overall, TLS offers a non-destructive and efficient approach for urban tree inventory and carbon stock assessment. Integrating TLS with technologies such as UAV LiDAR, UAV photogrammetry, and deep learning algorithms could overcome current limitations, improve accuracy, and expand its role in urban forest management and climate change mitigation strategies.

5. Conclusion

This study successfully demonstrated that Terrestrial Laser Scanning (TLS) can provide highly accurate measurements of tree diameter at breast height (DBH), which is essential for estimating aboveground biomass and carbon stock. The comparison between field and TLS measurements revealed minimal discrepancies, with an MBE of 0.004 m, RMSE of 0.038 m, and R^2 of 0.982, indicating excellent agreement between the two methods. The TLS-generated 3D point clouds offered precise tree structure representations, enabling reliable calculations of

135.736 tonnes of aboveground biomass and 67.868 tonnes of carbon stock for 42 sampled trees. These results highlight the potential of TLS as a robust, efficient, and scalable approach for individual tree assessment in urban forestry, contributing to sustainable management practices and climate change mitigation. For future research, integrating additional tree parameters and species-specific analyses, as well as exploring alternative remote sensing techniques, could further enhance accuracy and applicability in diverse environmental contexts.

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