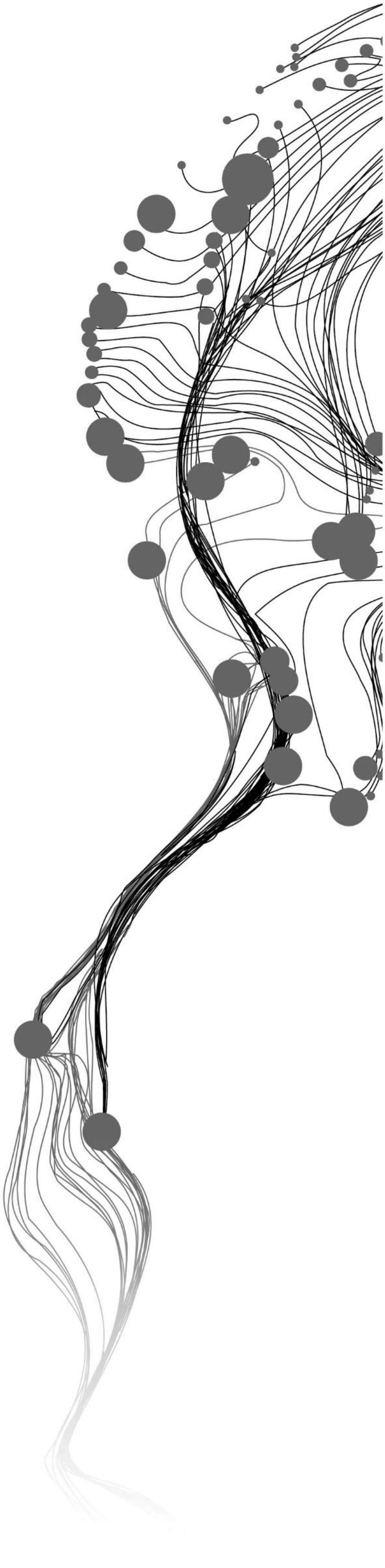

Generating Tree Crown Volumes using 3D Modelling

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Summery

This study explores the use of 3D modeling techniques to estimate tree crown volumes in urban areas, with a focus on the city of Nijmegen, Netherlands. The study was part of the internship project at ANG, a consultancy firm aiming to enhance its geospatial data products by incorporating tree crown volume measurements. Using high-resolution LiDAR datasets (AHN4 and Kavel_10), the study employed a methodology that included pre-processing, tree segmentation, and crown volume calculation using an ellipsoidal model. The results demonstrated that accurate tree crown volumes could be generated, which were then mapped to provide spatial insights into urban greenery. However, the validation was done on small subset. Therefore, generalization of this requires broader experimentation. The findings underscore the potential of 3D modeling in urban tree management and offer recommendations for improving data quality and expanding the analysis. The internship contributed significantly to my professional development by bridging theoretical knowledge and practical application in geospatial analysis.

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1. INTRODUCTION

1.1. Background

Urban green spaces are particularly trees within city environments, offer ecosystem services that improve environmental conditions and the quality of life for its residents (Niemelä et al., 2010). The benefits include aesthetic and cultural values, increased biodiversity, mitigation of the urban heat island effects, carbon sequestration, air pollutant reduction, and storm water runoff (Pretzsch et al., 2015). Trees are claiming a bigger role in nature policy for municipalities (Chishaleshale et al., 2015). Effective urban tree planning and management for enhanced ecosystem services requires better insights on tree growth behaviors (Geller & Thomas, 2013). Tree crown contributes significantly to physiological and ecological functions such as photosynthesis, respiration, and transpiration that are essential for the tree's growth, health, and reproduction (Zhu et al., 2021). To better assess the impact of trees in urban areas, crown volume is preferred over crown area. ANG is a Netherlands-based consultancy firm that collaborates with local governments, including provinces, municipalities, and water boards. ANG specializes in leveraging geospatial data products to address social and environmental challenges. The firm's GeoAI team offers a range of geospatial data services aimed at supporting climate adaptation and managing rising construction permit fees. Among the services provided are geospatial products that map green space percentages and canopy cover at the neighbourhood level. To further enhance their offerings and support the National Tree Standard, ANG is now exploring the provision of 3D crown volume measurements.

1.2. Literature review and Problem Analysis

The Trees Standards Institute works to ensure the quality of trees in public spaces, recognizing their role in creating a healthy living environment. Trees offer numerous benefits, both visible and invisible. Despite their importance, there has been no standardized method to determine how much greenery, specifically in the form of tree canopy volume, is necessary for maintaining a healthy living environment.

Municipalities, districts, and neighbourhoods face challenges in determining the appropriate level of greenery required (Aronson et al., 2017). Key questions include: how much tree canopy volume is needed for an area to be considered sufficiently green? Which trees should be prioritized during urban redesigns? How many trees should be planted to ensure climate resilience after infrastructure renovations? Moreover, there is a need to varify if the 'green' designs of new neighbourhoods will achieve to meet their intended environmental benefits.

The National Tree Standard has been developed to address these issues, providing a benchmark for the required tree canopy volume in different areas. This standard aims to guide municipalities in achieving adequate greenery, essential for a healthy living environment. However, many areas currently have inadequate tree canopy volumes, posing a significant greening challenge (Norminstituut Bomen, 2024).

Despite this progress, there remains a need for robust methods to measure tree canopy volume accurately. Remote sensing techniques offer a promising solution for assessing tree canopy volume over large areas accurately and efficiently. By leveraging these technologies, municipalities can better plan, monitor, and enhance urban green spaces, ensuring they meet the standards necessary for a healthy living environment.

Thus, the central problem is the development and implementation of remote sensing techniques to measure tree canopy volume timely and accurately. This internship project intends to develop a robust remote sensing data-based method to estimate trees canopy volume for urban areas.

A thorough literature review was conducted to explore and evaluate the existing data and methodologies for estimating tree canopy volume. The literature review is summarized in Table 1.

Table 1 Overview of Methods and Data Types Used for Tree Crown Volume Modeling, Highlighting Their Advantages, Disadvantages, and Key References

Method	**Data Type Used**	**Advantages**	**Disadvantages**	**Cited Papers**
PointNet for point-wise classification, Watershed segmentation for tree segmentation, Slicing method for 3D modeling	Aerial LiDAR point cloud data from the AHN (Actueel Hoogtebestand Nederland) dataset	High accuracy (average 92%), efficient for large-scale deployment, relatively low resource consumption	Misclassification of objects similar to trees (e.g., trucks), difficulty in segmenting densely packed trees, noise generated by outliers in Mean Shift segmentation	Knippers et al.,2021
PointNet deep learning network, Watershed segmentation	LiDAR point clouds	High accuracy (95%), scalable for large areas, efficient for processing	Sensitive to outliers, computational complexity in high-density areas	Münzinger et al.,2022
Field Measurement	Crown length, crown base height, crown diameter, crown radius, crown projected area, crown shape	Direct measurement, straightforward	Labour intensive, time-consuming	Drake et al., 2002; Pretzsch et al., 2015; Hauglin et al., 2013
Terrestrial Photography	Horizontal and vertical photographs	Permanent records, useful for urban areas	Quality dependent on processing and conditions	Winn et al., 2010; Miranda-Fuentes et al.,2015; Phattaralerphong and Sinoquet, 2005
Aerial Photography	Vertical aerial photographs	Rapid data collection, large area coverage	Limited sub-crown structure info, resolution challenges	Mäkinen et al., 2006; Lee et al., 2016; Zarco-Tejada et al., 2014
LiDAR - Airborne Laser Scanning (ALS)	3D point clouds	Detailed canopy structure, comprehensive data	Occlusion effect, underestimation of lower layers	Vauhkonen et al., 2014;
LiDAR - Terrestrial Laser Scanning (TLS)	3D point clouds	Accurate field data, detailed lower crown	Multiple scans needed, device relocations	Barbeito et al., 2017;

Method	Data Type Used	Advantages	Disadvantages	Cited Papers
LiDAR - Mobile Laser Scanning (MLS)	3D point clouds	Rapid and flexible data acquisition	Low measurement range, divergence issues	Yan et al., 2019;
Simple Geometric Shape Approximation	Crown width, crown diameter, crown length	Easy to implement, less data required	Ignores crown cavities, subjective shape choice	Estornell et al., 2018;
Computational Geometry - Convex Hull	3D point clouds	Simple and versatile, sound predictions	Higher values than other methods, basic approximation	Lin et al., 2017
Computational Geometry - Alpha Shape	3D point clouds	Detailed approximation, adjustable parameter	Requires optimal parameter, challenging to define	Xiao et al., 2016
Computational Geometry - Wrapping Surface	3D points on crown boundary	Efficient for irregular crowns	Density affects accuracy, complex processing	Yan et al., 2019;
Voxelization	Voxelized 3D point clouds	Captures irregular shapes, excludes empty space	Scale-dependent, sensitive to voxel size	Lecigne et al., 2018;

Based on the literature review, it is evident that LiDAR data is the mostly used data for estimating 3D tree crown volume, with terrestrial LiDAR offering higher accuracy. However, terrestrial LiDAR is limited in its spatial coverage, making it less suitable for large-scale applications. As a result, airborne LiDAR (ALS) has emerged as the preferred option due to its broader spatial coverage while still maintaining a good balance between accuracy and efficiency. In the Netherlands, two types of ALS data are available: the Actueel Hoogtebestand Nederland (AHN) dataset and Commercial datasets. The AHN dataset is freely available through Publieke Dienstverlening Op de Kaart (PDOK) and therefore, a widely accessible resource for various applications. On the other hand, commercial ALS datasets, which may offer different specifications and higher resolutions, are sold by organizations such as Kavel10. A part of this internship objective is also to understand the suitability and efficiency of these two datasets.

1.3. Objectives

- Extract and detect trees from point cloud of AHN4 and Commercial dataset
- Measure tree biophysical parameters and tree crown volume
- Produce map of tree crown volume per square meters for urban area.

2. STUDY AREA AND DATA

2.1. Study area

The pilot study area is in the municipality of Nijmegen of the southwest Netherlands (Figure 1). The municipality is located between 51°50'51"N and 05°51'45"E. Nijmegen, integrates urban greenery with nature. Native trees like English oak, European beech, and Rose of Sharon enhance the city's beauty and play vital roles in supporting biodiversity and improving air quality. The average elevation is 29m.

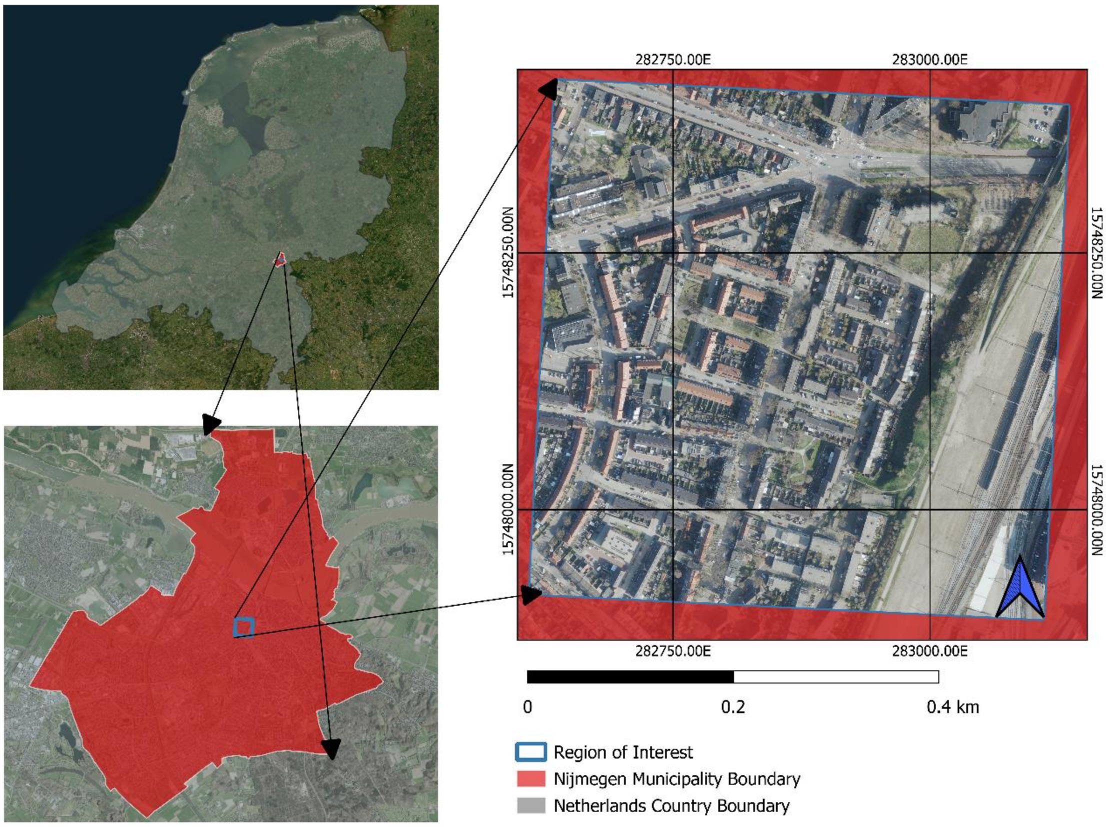

Figure 1 (a) Location of the Nijmegen within the Netherlands (b) geographical position of region of interest in Nijmegen municipality (c) RGB image of the region of interest

2.2. Datasets

LiDAR: For the purpose of this internship, LiDAR data was acquired from two sources: AHN4 and the Kavel_10 ALS dataset. Two data sources have varying characteristics in terms of point numbers, spacing, acquisition date, scanning angels and even in temporal resolution. The key attributes of point clouds are reported in the Table 2.

Table 2 Key features of LiDAR datasets

Feature	***AHN 4***	***Kavel_10***
Number of points	5294234	18967372
Point density (points per m²)	21.18	75.87
RGB	Available	Not available
NIR	Available	Not available
Class Numbers	4	6
Acquisition Date	2021	Unknown

Test dataset: In the absence of field measurements, a small dataset was created for validation. The biophysical parameters of these trees—such as treetops, tree diameter, tree height, and crown height—were manually measured using CloudCompare from the point cloud data of the LiDAR datasets. Due time constraints and computational limitation larger validation dataset was not possible to create.

3. APPROACH AND METHODOLOGY

The crown volume estimation procedure includes four main steps: (1) Pre-processing and reclassification (2) individual tree segmentation (3) individual tree crown diameter and crown height calculation, and (4) tree crown volume calculation and generate volume per square meters map.

3.1. Pre-processing and reclassification

The preprocessing steps primarily involved noise removal and spatial filtering. Both datasets underwent spatial outlier removal to eliminate noise, as described by Ujvári et al. (2023). Specifically, the number of points and the standard deviation for mean distance were set to 50 and 2, respectively. These parameters were chosen through a trial-and-error process, guided by visual inspection. However, reclassification was carried out for both datasets as the tree class was not properly classified. The AHN data has mixed tree class with ground class and labelled as unclassified class (Figure 2 a). The trees were reclassified from ground class using CSF plugin in cloudCompare (Sarıtaş, & Kaplan, 2023). The trees were assigned as class 5. However, cars and bushes were also included in the tree class. To remove this, further filtering was carried out. The tree filtering includes calculation of geometric features such omni -variance, anisotropy, linearity, PCA1 etc. from point clouds. Using value extraction tool, the trees were further filtered using these geometric features

In contrast, the Kavel10 LiDAR data were severely misclassified, with cars and even parts of buildings being categorized as trees (Figure 2 (b)). To make this data suitable for tree detection and crown volume estimation, major classes such as trees, buildings, and ground had to be reclassified. Due to the extensive size of the point cloud, this process is both time-consuming and computationally expensive and falls outside the scope of the internship. However, a small subset of the area was cropped and reclassified using the Canupo plugin (Iglhaut, 2016). This reclassification required labeled point clouds for each class to train the algorithm, for which the masking tool was utilized. Beyond reclassification, the filtering processes applied to the AHN4 dataset were also replicated for the tree detection in the Kavel10 data. Finally, both datasets were normalized and subsequently downsampled by a ratio of 0.3. The normalization process removed the terrain effect, ensuring that the z-values represented the height of each point relative to the terrain. Downsampling was conducted for computational efficiency.

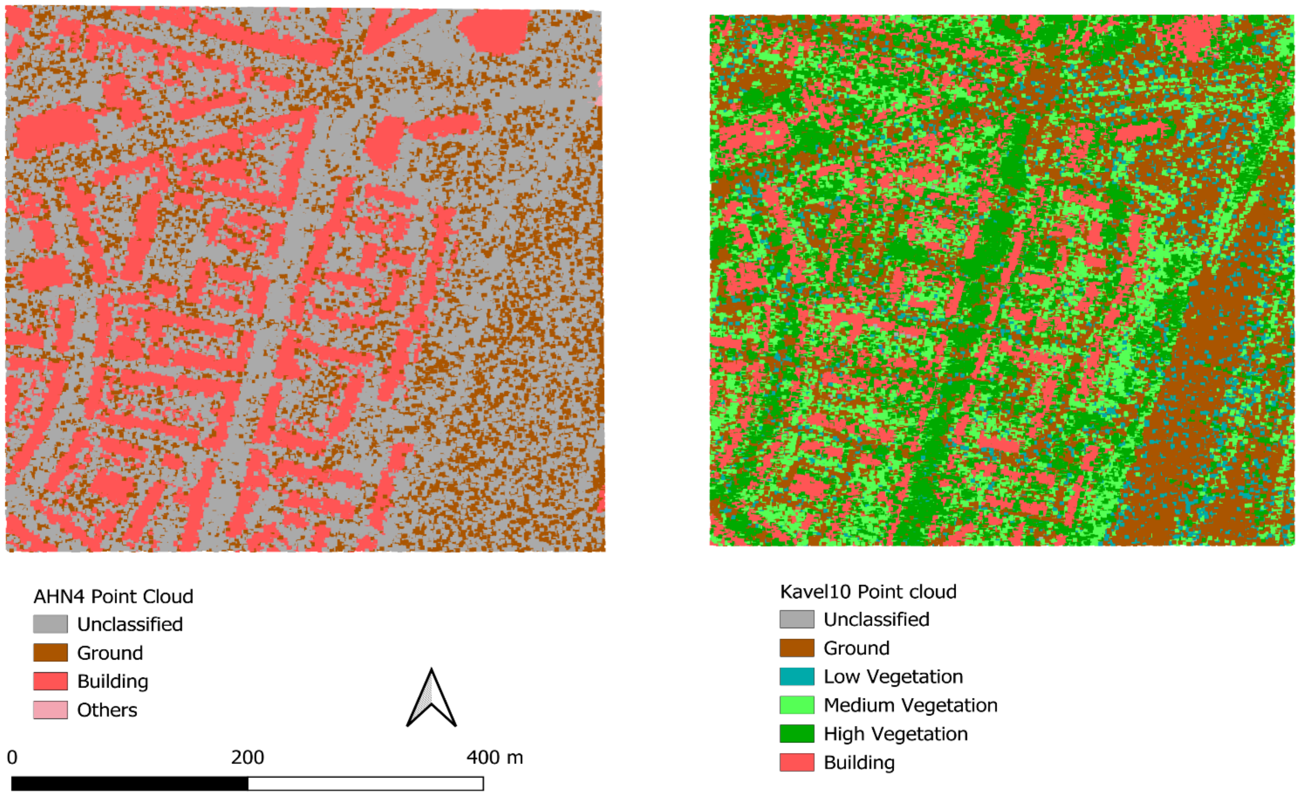

Figure 2 (a) AHN4 data ground and trees in same class (b)Kavel10 data yellow tree labels over and around the buildings class for Kavel10

3.2. individual tree segmentation

The methods used for tree detection are based on the internship project of Jorges Nofulla (2023). Although the project method involves detection of tree trunk. Therefore, the methodology and parameters were modified for the purpose of these study. The methodology involved two primary approaches for individual tree delineation. First, a KD-tree algorithm was used to cluster tree points based on their 3D proximity. The first approach identified tree trunks by calculating point density within these clusters, while the second approach refined the clusters using parametric analysis to evaluate tree characteristics like height and diameter, thereby delineating the entire tree. Both methods aimed to efficiently and accurately segment individual trees.

3.3. Individual tree crown diameter and crown height calculation

After the tree segmentation procedure, tree location was recorded as the treetop location, and tree height was derived as the above ground height of treetop. The tree diameter was estimated using convex hull on X and Y axis point clouds of each segmented trees. The tree base height estimation was challenging yet important parameter to estimate tree crown volume. The crown base height (CBH) was estimated using a methodology by Luo et al. (2018), which involves fitting a spline curve to percentile rankings and analyzing the first and second derivatives to identify inflection points. The CBH is determined at the inflection point with the maximum first derivative and a percentile rank below 0.5, making it applicable for measuring CBH in mixed-species vegetation stands.

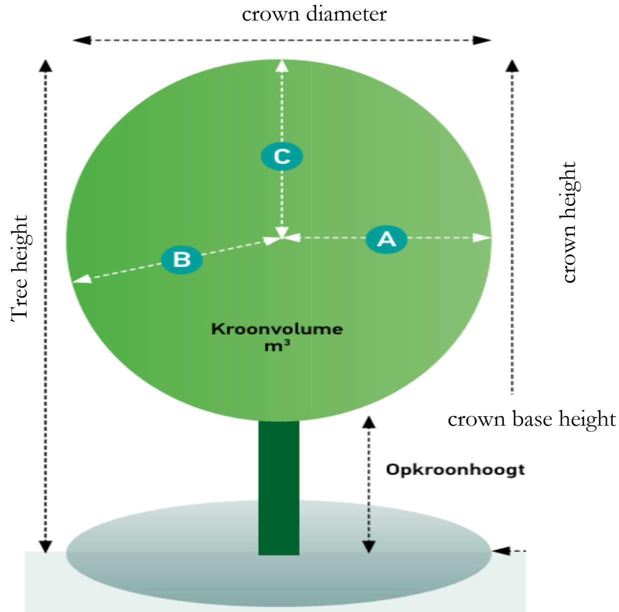

Figure 3 Tree crown volume measurement from tree biophysical parameters (source: Norminstituut Bomen brochure,2024)

After that tree crown height was estimated by subtracting tree height from tree base height. As set by the Trees Standards Institute (NORMINSTITUUT BOMEN), the ellipsoidal crown volume was estimated using following formula for all types of species.

$$\text{Tree crown volume} = 4/3\ \pi\ (\text{crown diameter})\ \text{X}\ (\text{crown height}/2) \quad (1)$$

Lastly, a shapefile with pointing the treetops with measured tree features attributes were created. Which later used for crown volume map production.

3.4. Tree crown volume calculation and generate crown volume per square meters map

This step involved extraction of building footprints from the point cloud. After classification, the building points are isolated, and a Point to Raster conversion is applied to create a raster surface. The raster is then processed using the Raster to Polygon tool, which generated building footprints as polygon features. These polygons were further refined by regularizing to ensure accurate representation of the building outlines. The through overlaying of tree points with the building footprints the final map were produced.

4. RESULTS

4.1. Filtering & Reclassification :

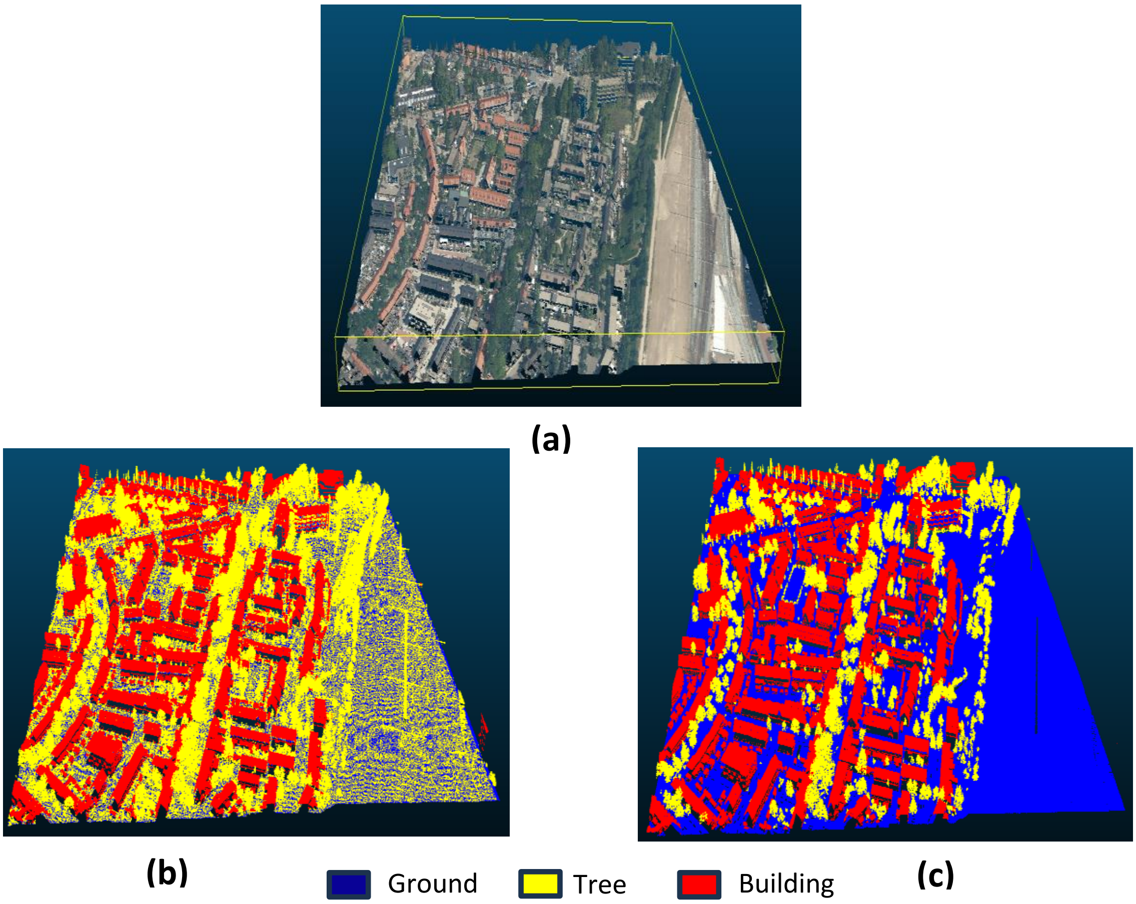

Figure 4 AHN4 (a) RGB (b) Raw data (c) Reclassified point cloud

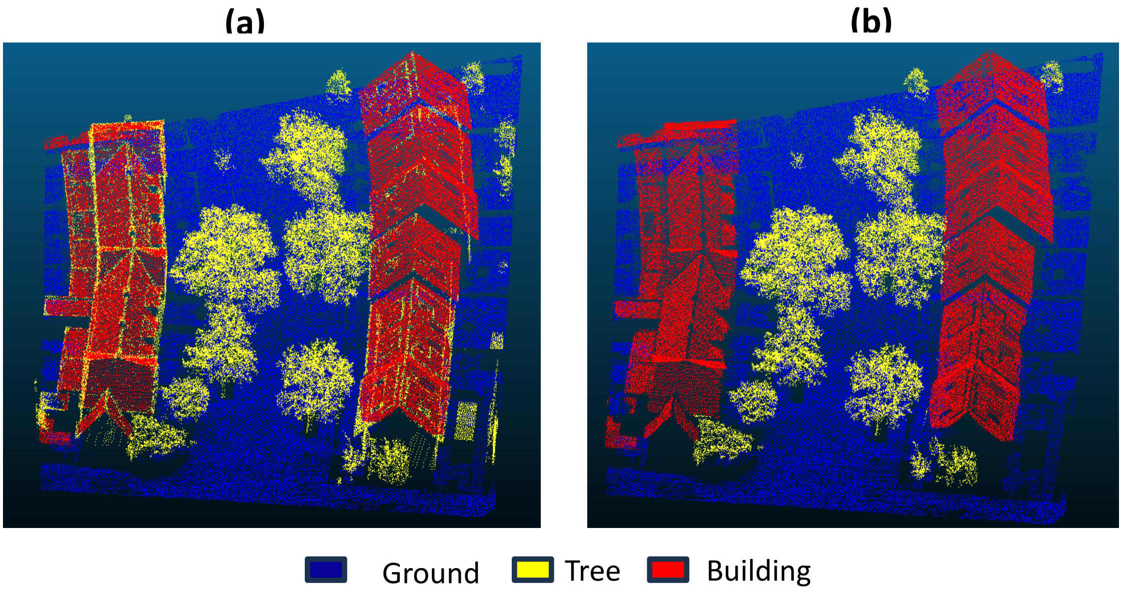

Figure 5 Kavel10 (a) Raw data (b) Reclassified point cloud

Figure 4 & 5 illustrates the reclassification result of AHN4 and Kavel10 LiDAR point clouds. The images clearly indicated that the point clouds were appropriately pre-processed and can be utilized for further segmentation and tree detection. However, during the preprocessing small trees or portion of the trees were filtered out. This is because the reclassification is sensitive to the parameter of classifiers

4.2. Tree detection

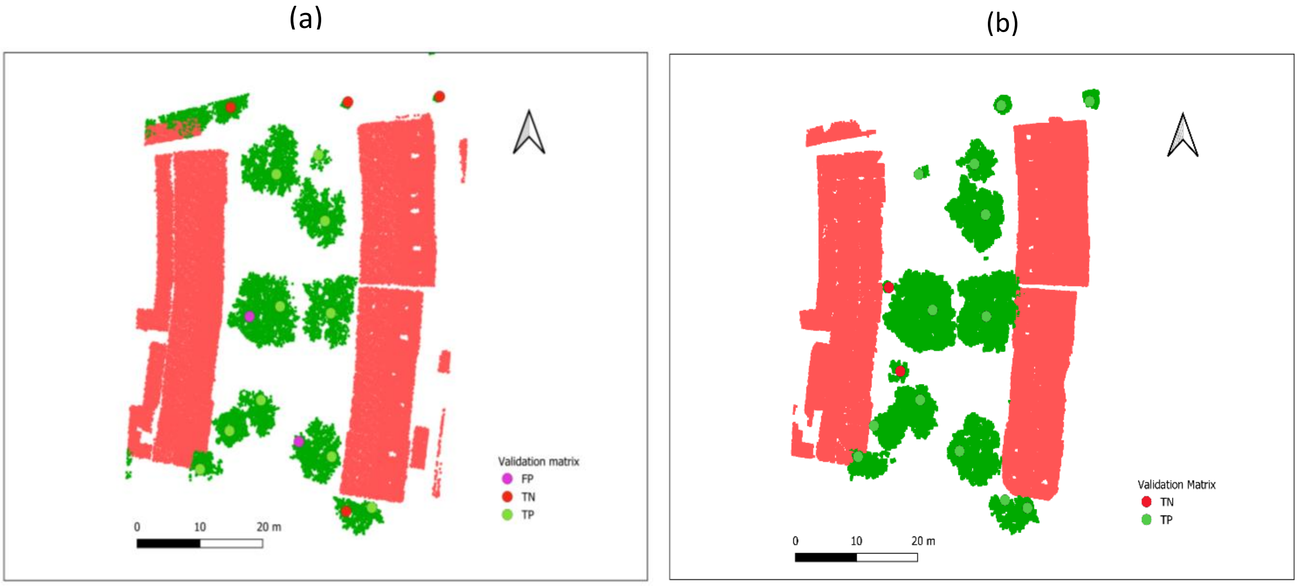

Figure 6 Tree detection validation matrix (a) AHN4, (b) Kavel10

Figure 6 demonstrated a tree detection accuracy for in small subset of the study area. As previously mentioned, the temporal resolution of AHN4 and Kavel10 are different. Furthermore, the canopy and tree sizes are different from each other. Although it is not ideal to compare such dataset, we only compare the tree detection accuracy and avoided comparing other tree features. The performance metrics (Table 3) derived from confusion matrix (appendix 1) indicated that the Kavel10 model outperforms AHN4 across all evaluated criteria. Kavel10 has perfect precision (1.00), meaning all its positive predictions are correct, and a high recall (0.87), effectively identifying most true positives. Its F1 Score of 0.93 reflects a strong balance between precision and recall. In contrast, AHN4 has lower precision (0.83), recall (0.67), and F1 Score (0.74), making it less accurate and reliable overall.

Table 3 Confusion matrix for detected trees from AHN4 and Kavel10

	AHN4	Kavel10
Precision	0.83	1.00
Recall	0.67	0.87
F1 Score	0.74	0.93

4.3. Tree crown volume measurement and map

In the validation of tree crown volume estimation, we compared measurements from different datasets against a manually detected test dataset (see Appendix 2). The results showed that the Kavel10 dataset, which recorded a crown volume of 12.31 m^3, provided more accurate measurements than the AHN dataset, which had a root mean square error (RMSE) of 16.94 m^3. Although it was not possible to generate a crown volume map for the Kavel10 dataset, a crown volume map was produced for the AHN4 dataset, as illustrated in Figure 7. Figure 7 demonstrates that the region of interest in Nijmegen contained targeted greenery with a crown volume exceeding 0.6 m^3 per m^2, in accordance with the Norminstituut Bomen standard. The figure also showed less greenery near the yard, parking lot and alley, this could be attributed to the fact that we excluded the bushes and small trees during the data pre and post processing.

Figure 7 Tree crown volume map of region of interest

5. DISCUSSION

Both datasets used for tree crown volume detection have their pros and cons. The AHN4 dataset is freely available but lacks yearly data. Its point density sometimes results in small, sparse clusters from trees. Additionally, the AHN4 dataset may have been overlapped with RGB and NIR images of different temporal resolutions or misaligned, causing power lines to share the same near-infrared (NIR) values as trees, and some trees to have RGB values similar to the ground. Due to these issues, even though AHN4 possesses certain valuable attributes, it cannot be reliably used for tree filtering.

On the other hand, the Kavel10 dataset has a high point density and provides detailed classification for low, medium, and high trees, with data available yearly. However, it is highly misclassified and noisy, making it computationally expensive to reclassify using machine learning algorithms. During this internship, we experimented with various rule-based classification approaches, such as classification by height, extracting buildings, and buffering around building footprints, but none yielded sufficient classification output for tree detection. Moreover, commercial datasets like Kavel10 are often economically expensive. However, as our study demonstrates, once correctly classified, the Kavel10 dataset can achieve better accuracy in tree detection, with even trunks clearly visible.

Notably, comparing two datasets with different temporal resolutions and without ground truth data is not ideal. Temporal resolution differences can lead to variations in data granularity, which may impact the performance metrics like precision and recall. Without ground truth data, it's challenging to accurately assess the true positives, false positives, and false negatives, making the comparison potentially misleading. Therefore, any conclusions drawn from such a comparison should be interpreted with caution.

This study primarily focused on previously established methodologies that have achieved good accuracy for similar or even more complex sites (Nofulla, 2023; Luo et al., 2018). During the segmentation of trees using Nofulla's methodology, it was observed that large trees in the AHN4 dataset were often segmented into two or more trees, whereas they were correctly segmented in the commercial dataset. This issue is likely due to the parameters being highly sensitive to point density. Additionally, the difference in segmentation results could be attributed to the size of the point cloud, as AHN4 was segmented across the entire region of interest, while Kavel10 was only segmented for a small subset of the region.
Furthermore, a major drawback of this study is the lack of field measurements for result validation. The validation points were chosen with certain preferences, such as selecting a subset where trees are easily visually detectable and crown base height can be measured. As a result, the study lacks an evaluation of performance in overlapping complex tree sites.

6. CONCLUSION AND RECOMMENDATIONS:

The results indicate that this methodology could be integrated for tree crown volume estimation using both nationally available and commercial datasets. However, it is crucial to consider the trade-offs associated with different datasets before applying this method on a large scale. A more detailed analysis using advanced methodologies and across complex sites is also needed before scaling up to a national level. Additionally, any potential misclassification issues with commercial data should be reported, including the reclassification accuracy, to ensure the reliability of the results.

While point cloud data can offer better accuracy in measuring crown base height, it is complex, computationally intensive, and requires expertise in point cloud data analysis. Therefore, one recommendation is to experiment with LiDAR 2D Digital Surface Models (DSM) and Digital Terrain Models (DTM) to detect and measure crown diameter and tree height. Crown base height or crown volume could then be estimated using ellipsoidal ratio techniques, as described by Lim (2007).

7. INTERNSHIP REFLECTION REPORT

This part of the report offers an overview of the non-technical experiences during my internship at ANG from June to August 2024. It will concisely outline the theoretical knowledge, technical skills, professional development, and personal growth I achieved throughout this time.

7.1. Theoretical aspects:

- Developing an understanding of urban green space concepts, including their importance, the relationship with relevant policies, and the roles of those responsible for their maintenance and monitoring.
- Gaining insights into the geospatial industry, including market trends and competitors in the field.

- Gaining familiarity with existing data sources and methodologies for measuring tree crown volume.
- Learned to how to conduct systematic literature review thus acquiring theoretical knowledge on the measurement's techniques of tree crown volume.
- Grasping the basic concepts of 3D point clouds.
- Learning how to preprocess point cloud data.
- Understanding the classification of LiDAR point clouds through machine learning models.

7.2. Practical aspects:

- Hands on experience on handling point 3D cloud data and commercial data
- Utilizing CloudCompare and ArcGIS Pro to filter and preprocess large point cloud datasets.
- Employing Python scripting to detect individual trees within point cloud data.
- Leveraging GitHub repositories to reproduce and explore the work of the scientific community.
- Understanding the pros and cons of using public and commercial data.
- Comparing model estimations with existing municipal data to enhance understanding.
- Learn to manage and organize large dataset.
- Interpreting and drawing conclusions from the data and plots.

7.3. Professional aspects:

- Maintaining consistent communication with both internship supervisors and the technical supervisor regarding deliverables, progress, and methodologies.
- Presenting bi-weekly progress to the team members of ANG
- Two-weekly meetings that helped sustain workflow and overall progress.
- Enhancing my communication skills, time management, and analytical abilities.
- Gaining insights into the managerial aspects of an organization.
- I enhanced my problem-solving skills and became more effective at applying theoretical concepts to practical projects.

7.4. Objectives achieved during the internship

- Submitting all deliverables on time.
- Conducting comprehensive literature review
- Detecting trees, measuring biophysical parameters, specifically tree crown volume with good accuracy
- Generating crown volume map per square meter map for neighbourhood of Nijmegen

7.5. Self-reflection and realization

From my very first day at the office, I was warmly welcomed by all my colleagues, making me feel like a true part of the team, not just an intern. During the introductory meetings, as I discussed my internship goals, I quickly realized how connected everyone was. It felt like a puzzle—if I missed talking to someone or didn't communicate well, I wouldn't get the full picture. This experience also helped me improve my communication skills.

Additionally, I participated in the fortnight GeoAI team meetings, where I gained insights into the progress of ongoing projects and learned about the technical aspects involved. These meetings were open, allowing everyone to share their views, suggest ideas, or comment on the work being done. I was thrilled to have the opportunity to brainstorm and contribute to real-world, application-based projects.

While I had access to everyone in the office for technical support, I worked closely with my technical advisor, who guided me in conceptualizing and developing methodologies. I also learned a lot about Python scripting from one of my colleagues. I was fortunate to have two very supportive internship supervisors. Since I was balancing both my thesis write-up and internship tasks, one of my supervisors recognized the challenge and allowed me to work only two days a week for the first four weeks. This flexibility was crucial in helping me successfully complete my thesis. Furthermore, my host supervisor provided me with the opportunity to engage in discussions with other stakeholders involved in the projects. For instance, I was able to communicate directly with raw data providers and clients, giving me valuable experience in handling real-world interactions and understanding the broader context of the projects.

Overall, this internship significantly enhanced both my soft and technical skills. I improved in areas such as communication, collaboration, presentation, time management, and professional interaction. Additionally, I gained expertise in scripting and machine learning. The experience contributed to my personal and professional growth, helping me develop a well-rounded skill set.

I would like to express my sincere gratitude to my team. Throughout this time, I felt consistently supported by my colleagues, which made a significant difference in my overall experience. Their encouragement and assistance played a crucial role in my growth and success during the internship.

7.6. Recommendation

I highly recommend ANG to ITC students for internships, as the unique office environment fosters both personal and professional growth. However, I suggest that ANG consider hiring experts in 3D modelling. Without such expertise, it can be challenging for interns to work independently. This addition is particularly important given ANG's plans to expand their Geo services into 3D applications.

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8. APPENDIX

Appendix 1:

Table 1 Tree detection confusion matrix for AHN4

Predicted		Actual	
		POSITIVE	NEGATIVE
	POSITIVE	10	2
	NEGATIVE	5	0

Table 2 Tree detection confusion matrix for Kavel10

Predicted		Actual	
		POSITIVE	NEGATIVE
	POSITIVE	13	0
	NEGATIVE	2	0

Appendix2:

Table 3 Tree crown volume matrix for AHN4

TRUE (m3)	AHN4 (m3)
0	21
26	22.4
75	89.8
0	19
185	149
138	159
146	138
160	175
95	102.35
105	122.27
75	77.25
140	145.12

Table 4 Tree crown volume matrix for Kavel10

TRUE (m3)	KAVEL10(m3)
3	3.5
8	7.06
22	18.15
17	18.39
36	35.09
58	54.09
45	61.05
175	180.97
180.5	188.07
270	234.36
233	245.25
250	254