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AN AI INTEGRATED AUTOMATED TREE MAPPING AND CROWN METRICS ESTIMATION USING LIDAR DATA

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PROGRESS THROUGH KNOWLEDGE

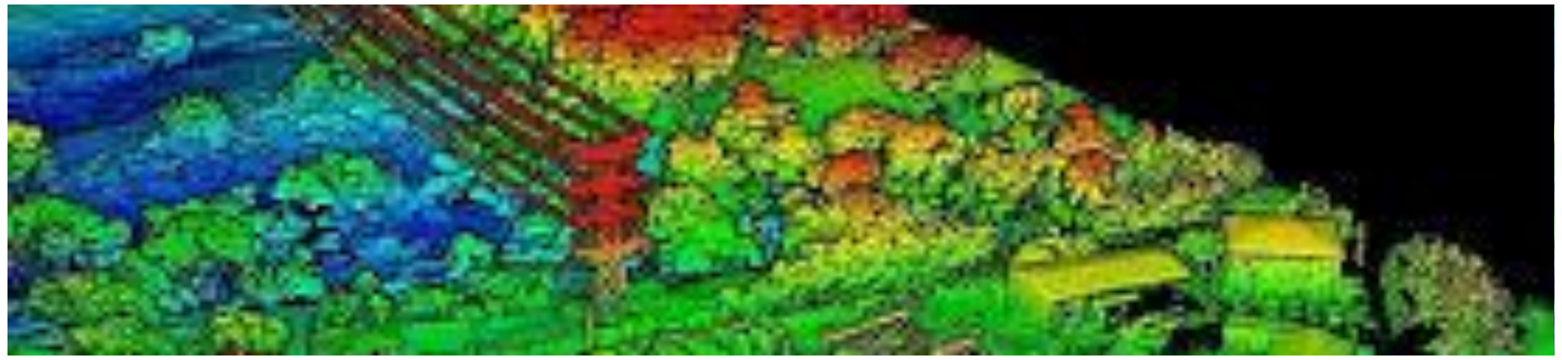
INTRODUCTION

- Urban green spaces are key for biodiversity, cooling, and air quality in cities.
- Tree mapping & species data are vital for urban forest planning and management.
- LiDAR offers precise 3D tree structure and crown volume data.
- Deep Learning enables automated tree detection, and volume estimation.
- Integration ensures high accuracy, scalability, and reduced manual effort for urban ecosystem monitoring.

NEED FOR STUDY

- India has rich indigenous tree diversity but lacks a centralized urban tree inventory.
- Urbanization and invasive species threaten native biodiversity.
- Kotturpuram Tree Park serves as a key site for conserving native species.
- Traditional surveys are time-consuming and miss structural details.
- LiDAR enables fast, accurate tree mapping, crown volume estimation, and structural analysis.
- LiDAR + Deep Learning offers automated, scalable solutions for conservation planning and urban biodiversity management.

OBJECTIVES

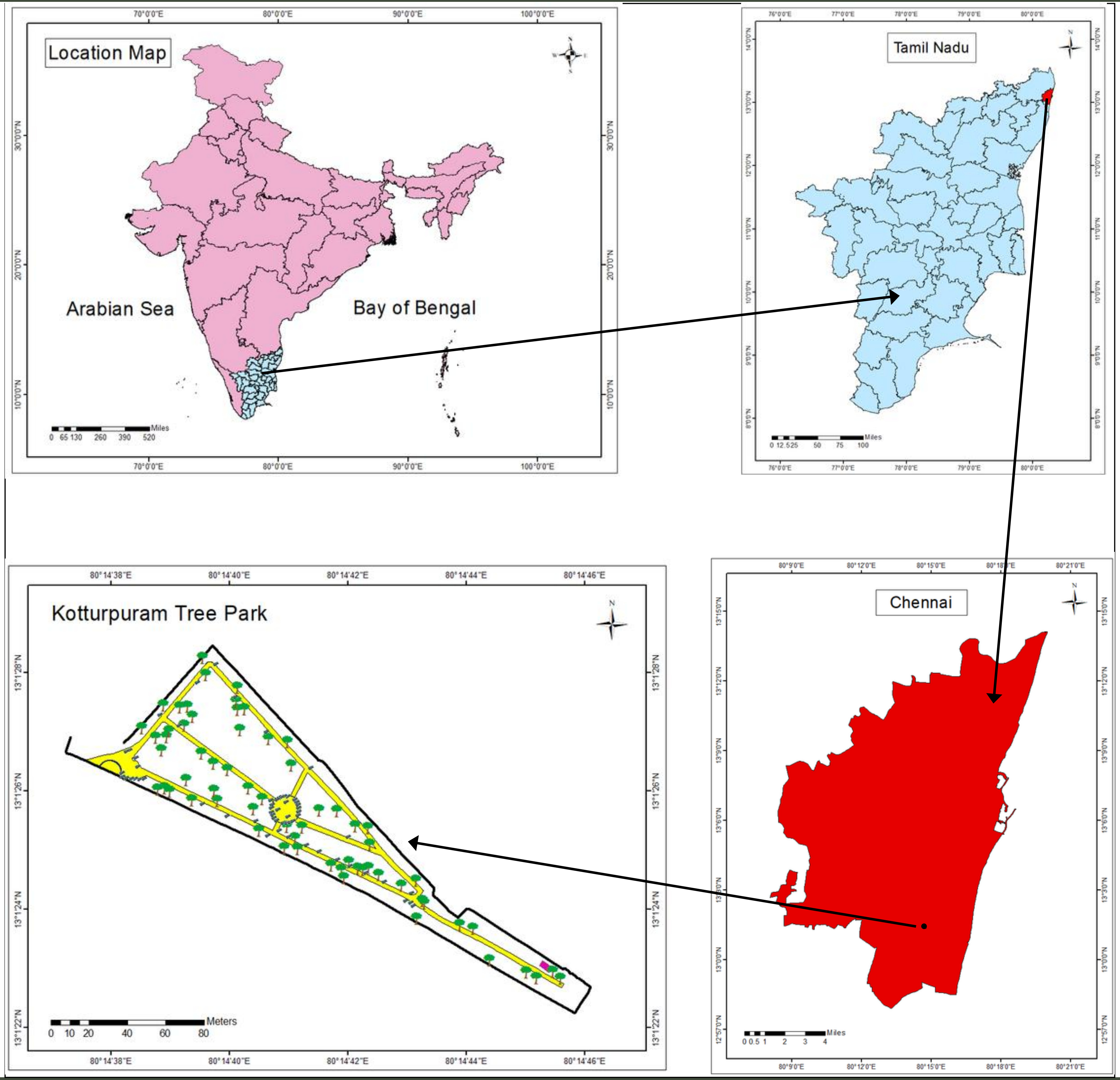


- To estimate accurate tree counting and crown width using lidar data in the study area.
- To develop a methodology to extract 3D structural information of trees from LiDAR point cloud data.
- To integrate a deep learning model for automated tree detection and crown delineation.
- To validate model accuracy using ground truth data to ensure reliability and scalability.
- To develop a user-friendly web interface for visualization and decision-making support.

STUDY AREA

"KOTTURPURAM URBAN FOREST"

- Situated at River View Road, Adyar House, Kotturpuram, Chennai, Tamil Nadu 600085
- Covers an area of approximately 4.2 acres
- Supports rich biodiversity, including birds, butterflies, moths, and other fauna-indicating a vibrant urban ecosystem
- Ideal for testing LiDAR-based inventory methods before scaling to larger forests.



DATA TO BE USED

- SLAM-based LiDAR data collected at Kotturpuram Tree Park.
- The dataset contains high-resolution 3D point clouds of trees and surrounding features.
- Visualization done in CloudCompare and Trimble Business Center.
- The current dataset covers trees along the survey pathway; future data collection will be undertaken if required.

LITERATURE REVIEW

- **Title**: "Deep Learning in Forest Structural Parameter Estimation Using Airborne LiDAR Data" Author :H. Liu et al.
- **Dataset Used:** Airborne LiDAR data (Rigel LMS-Q680i, ~9.6 pts/m^2) + 240 field plots (20×20 m) with DBH, height, crown, and stem density measurements.
- **Study Area:** Gaofeng Forest, Guangxi Province, Southern China.
- **Deep Learning Model:** Deep-RBN (a hybrid of Fully Connected Network + optimized Radial Basis Network).
- **Processing:** LiDAR point clouds → ground/non-ground separation → DTM normalization → extraction of height & density metrics → deep learning regression.
- **Accuracy Achieved:** R^2 = 0.67–0.86, rRMSE = 6.95%–20.34%, outperforming MLR and conventional FCN.
- **Impact**: Enables precise estimation of tree count, crown dimensions, and species classification with limited training data.
- **Application:** Supports sustainable forest management, large-scale forest inventory, and biodiversity monitoring.

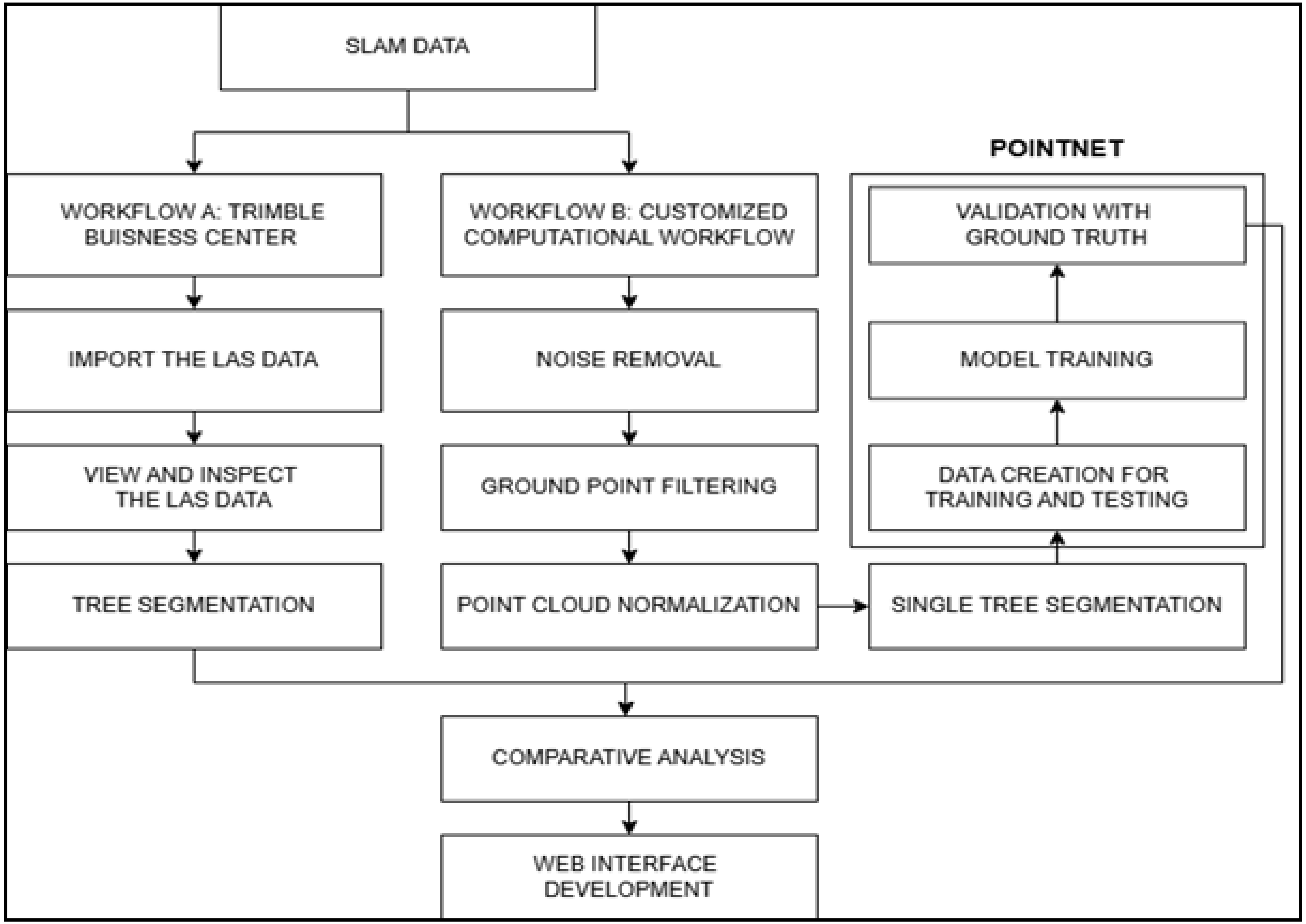
LITERATURE REVIEW

- **Title:** Individual Tree Crown Segmentation and Crown Width Extraction From a Heightmap Derived From Aerial Laser Scanning Data Using a Deep Learning Framework (Sun et al., 2022)
- **Goal:** Individual tree crown (ITC) segmentation and crown width extraction using LiDAR-derived heightmaps instead of RGB images.
- **Method:** Applied YOLO-v4 for crown detection; used GANs (WGAN, CycleGAN, SinGAN) to generate synthetic heightmap data for better training.
- **Study Areas:** Tested on tree nursery, forest landscape, and mixed plantation plots.
- **Detection Accuracy:** Achieved 83.6% recall and 81.4% precision for ITC segmentation.
- **Crown Width Estimation:** $R^2 \geq 79.9\%$, about 3.9% better than watershed-based methods.
- **Advantage:** Heightmap-only approach avoids lighting issues and texture noise in RGB imagery.

LITERATURE REVIEW

- **Title:** Automated forest inventory: Analysis of high-density airborne LiDAR point clouds with 3D deep learning (Xiang et al., 2024)
- **Goal:** To develop a fully automated pipeline for detailed tree-level forest inventories using high-density airborne LiDAR.
- **Method:** Introduced ForAINet, a novel 3D deep learning model performing semantic & instance segmentation directly on raw point clouds. Classified points into ground, vegetation, stem, and branches, followed by geometric algorithms to extract tree attributes.
- **Study Areas**: Applied across multiple forest types and countries using the FOR-Instance dataset.
- **Performance**: High accuracy with 85.1% F-score and 73.5% mean IoU, reliable for tree height and crown metrics, with some limitations for DBH and stem location.
- **Advantage**: Demonstrated scalability and generalization potential; with high-density LiDAR (≥75 pts/m^2), forest inventory can be achieved without manual intervention.

METHODOLOGY



WORKFLOW A: TRIMBLE BUSINESS CENTER

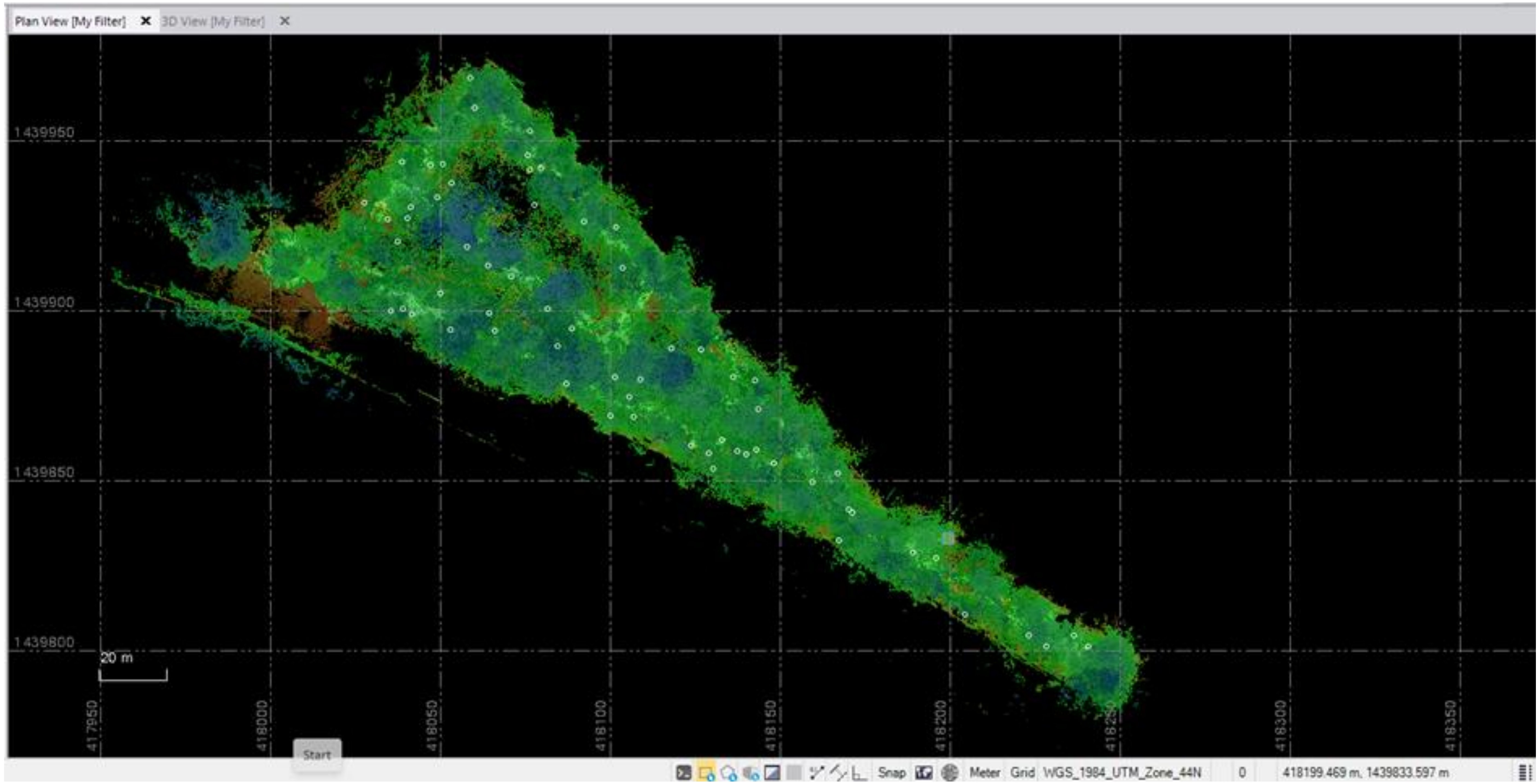
Import LAS Data - Bring in the .las file and set the right coordinate system to keep spatial accuracy.

Inspect Point Cloud - Open 3D view to check ground and canopy features, ensuring data quality.

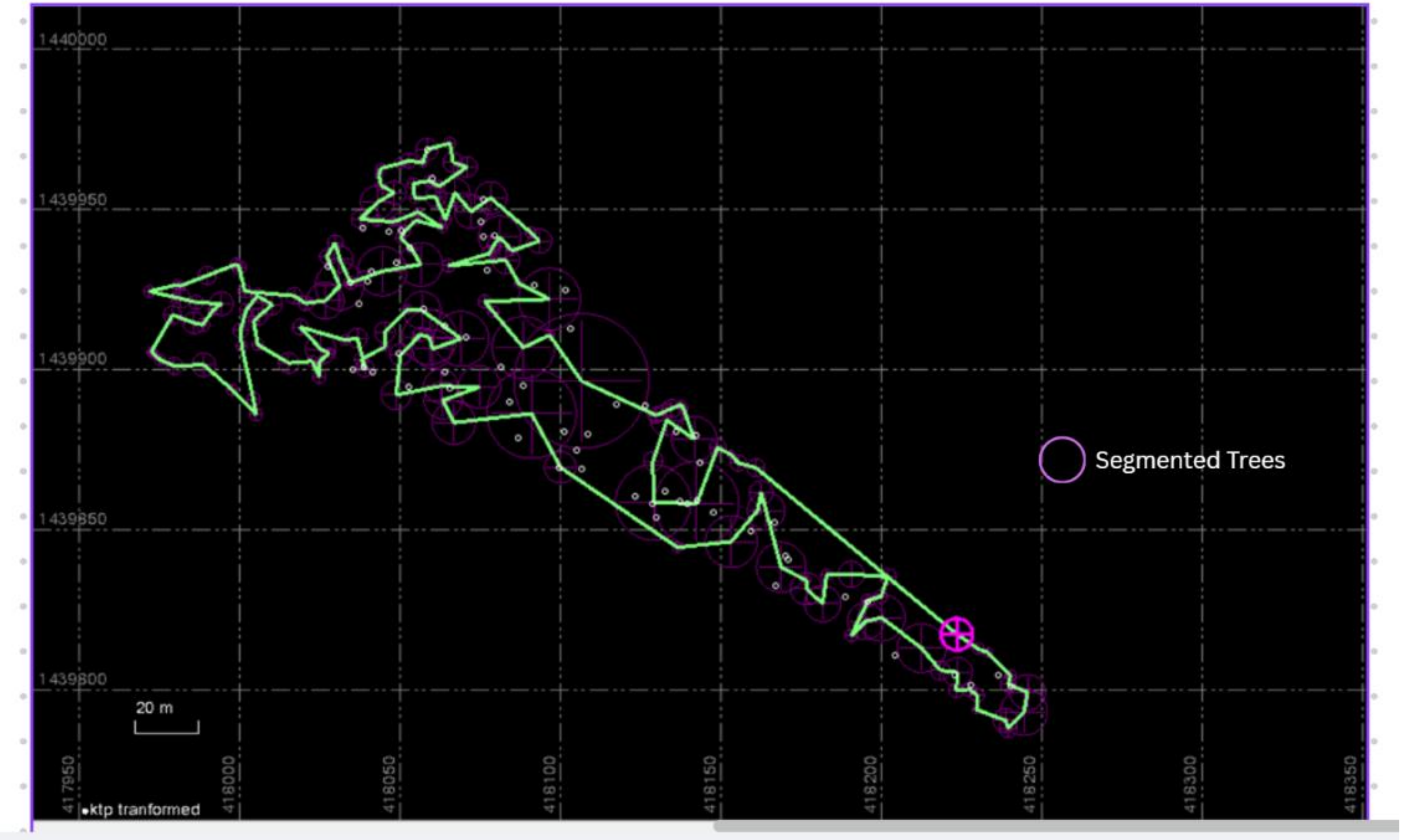
Classify Ground vs. Non-Ground - Separate terrain from trees/buildings using the classification tool.

Tree Segmentation - Trees are marked as circles centered on their trunks, and the circle's diameter represents the crown width..

LAS data in TBC



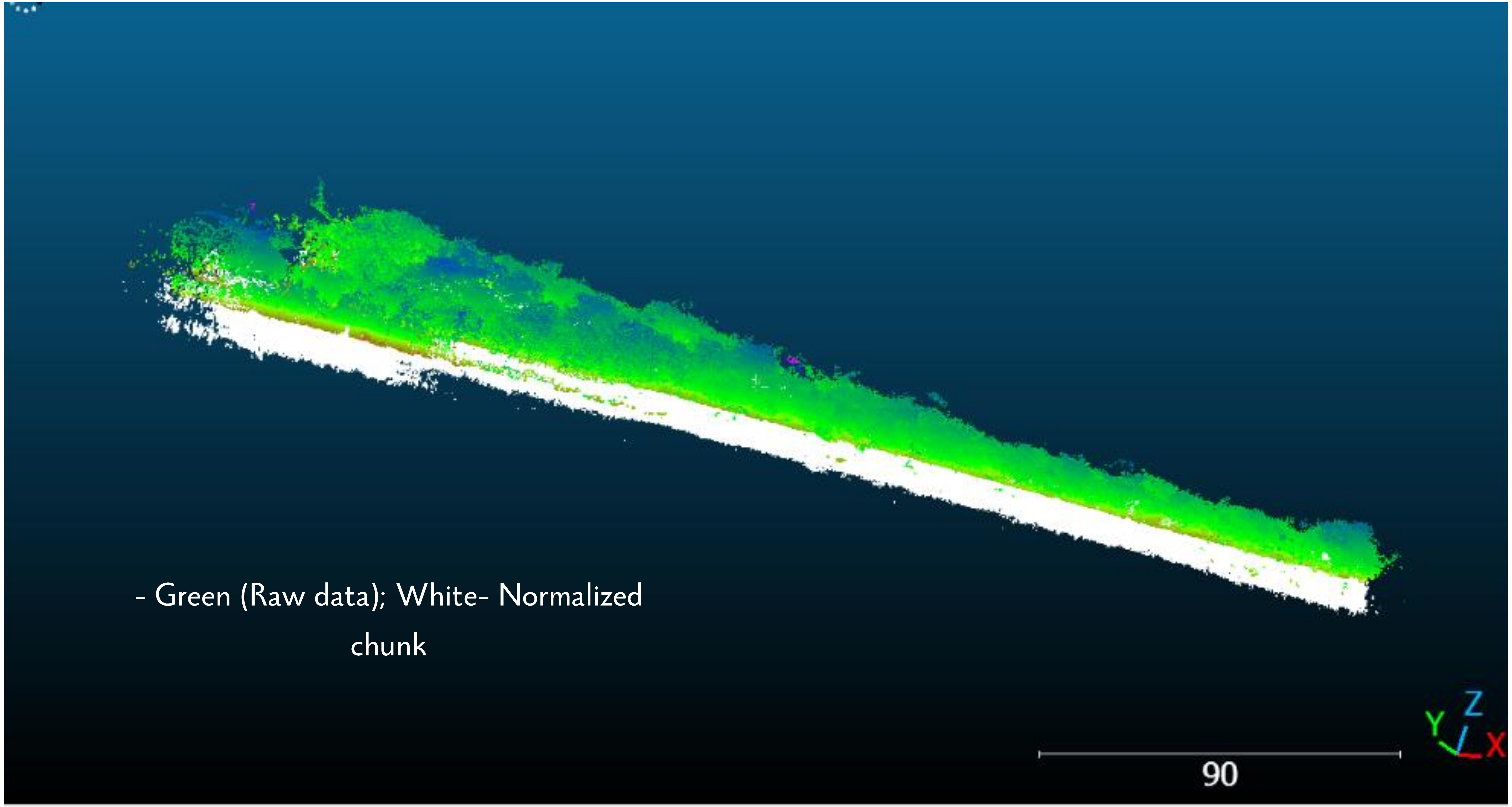
Tree Segmentation in TBC



WORKFLOW B: COMPUTATIONAL WORKFLOW

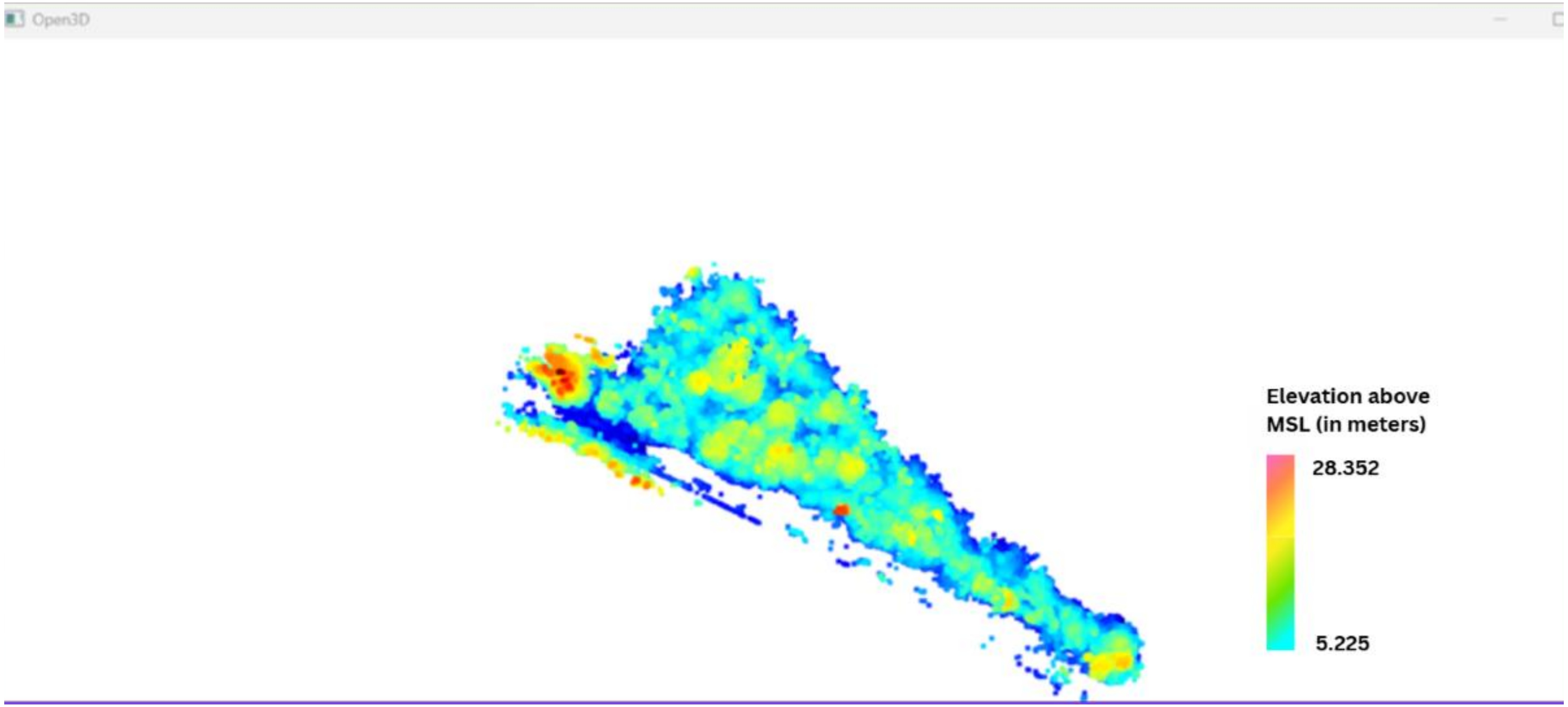
NOISE REMOVAL AND CHUNKING

- Raw LAS data is split into smaller chunks (36 chunks) and each chunk have the point cloud density of ~5million for easy handling.
- Statistical outlier removal (Open3D) removes stray points far from neighbors.
- Leaves only reliable points, ensuring a clean dataset for analysis.



Layers before and after normalization

LAS data visualized in open3D



GROUND POINT FILTERING

Method: Cell-based statistical filtering + KD-tree analysis

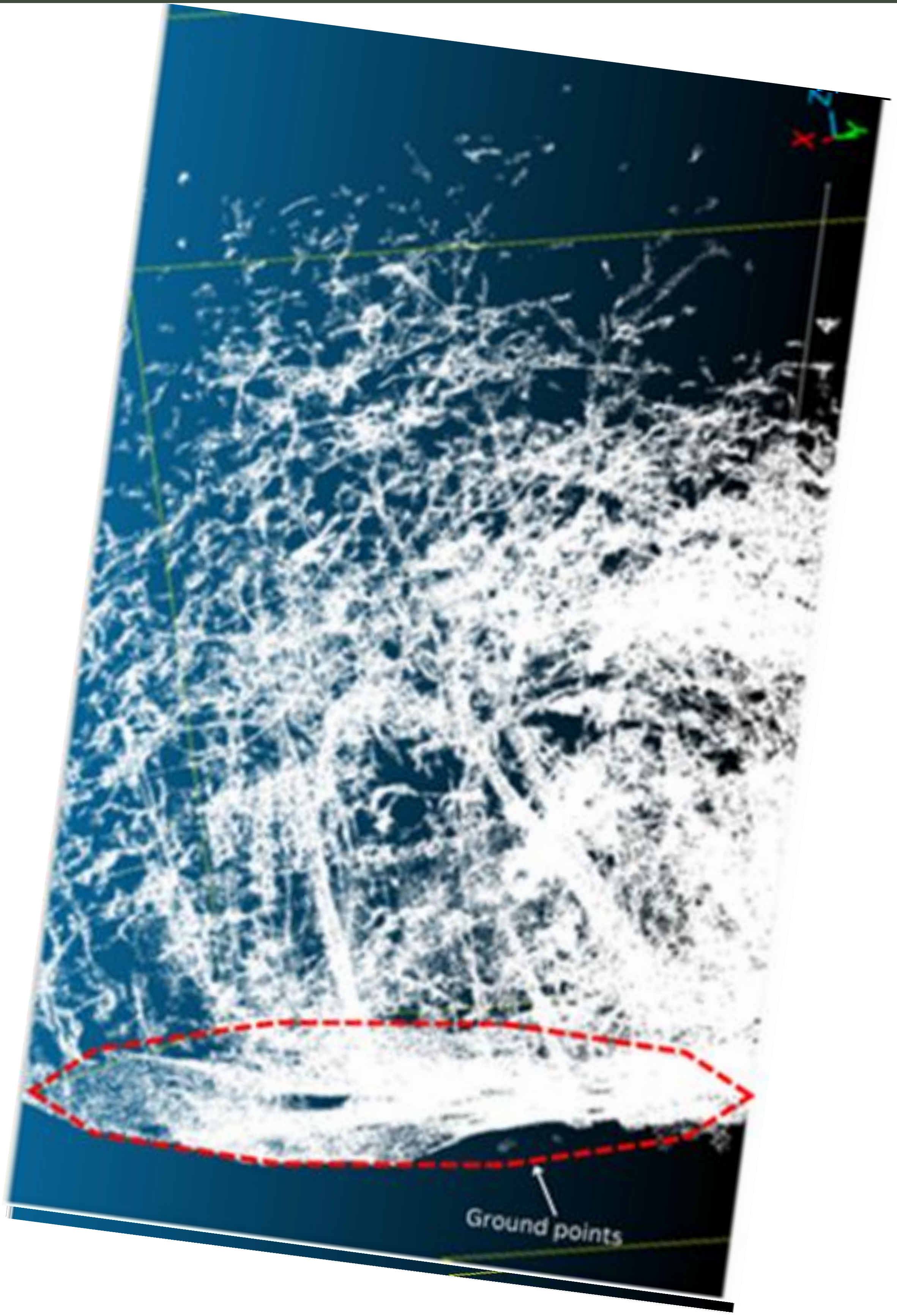
Process: Grid division → Local elevation thresholding → Density-based trunk preservation

Output: Separated ground/canopy PLY files

Key Feature: Preserves tree trunks while removing terrain

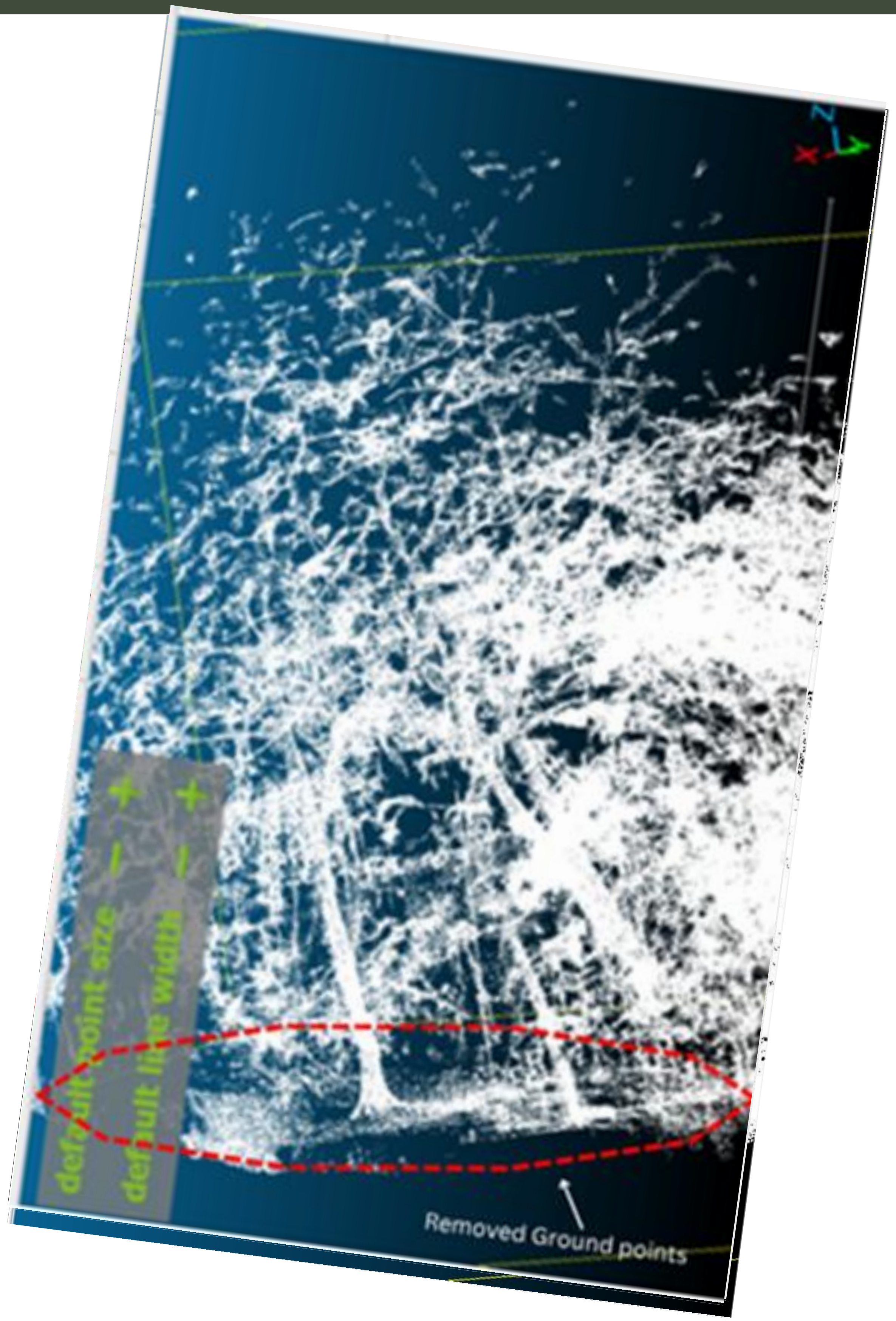
Before Ground Point Filtering

(visualised in CloudCompare)



After Ground Point Filtering

(visualised in CloudCompare)



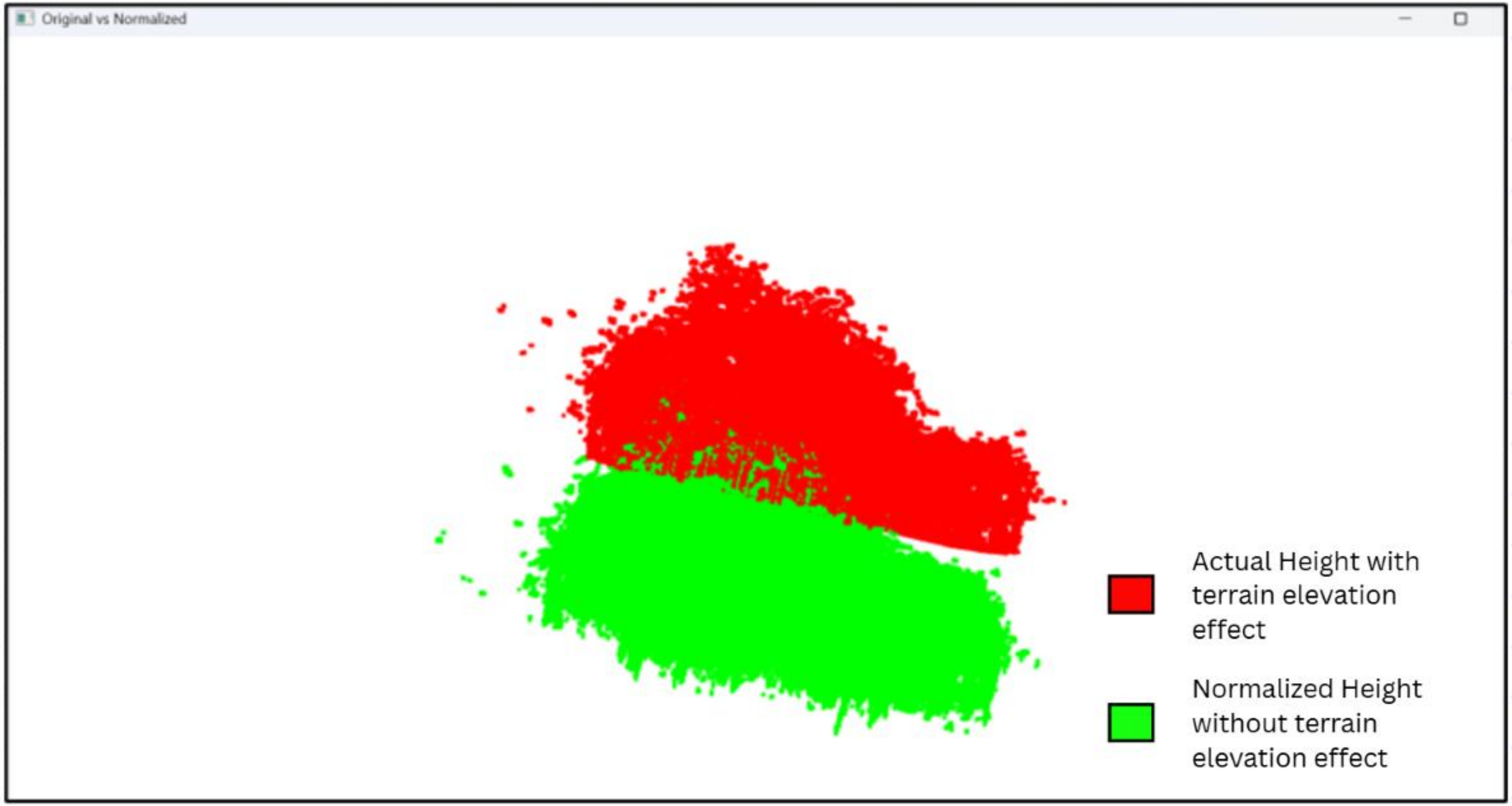
HEIGHT NORMALIZATION

Input: Ground points + Canopy points

Method: Ground surface interpolation (linear/nearest)

Process: Subtract ground elevation from canopy points

Purpose: Create height-above-ground values for CHM



(visualised in Open3d)

TREE SEGMENTATION

Method: Marker-controlled watershed algorithm

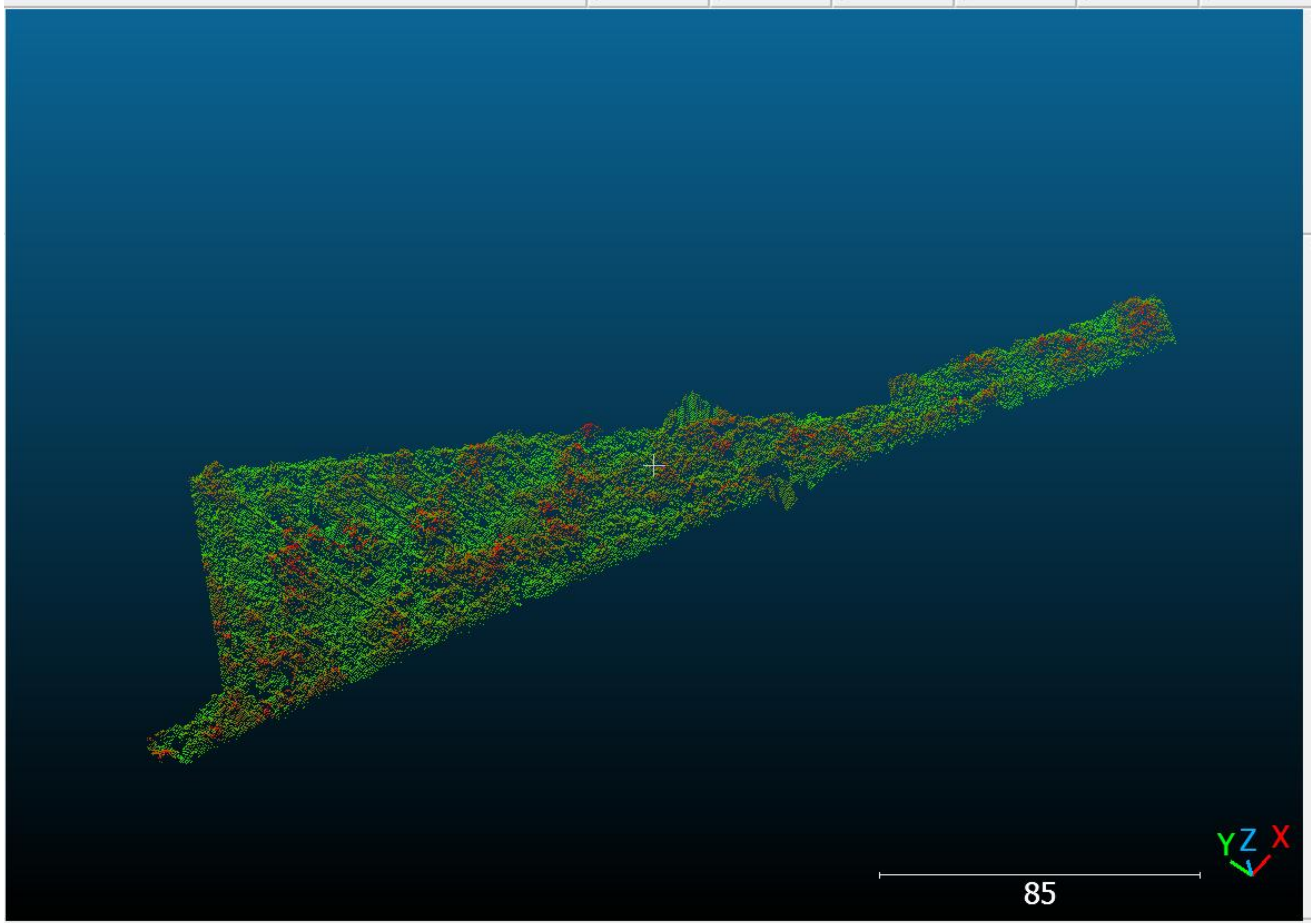
Process: Local maxima detection → Inverted basin flooding → Crown delineation

Output: CSV with tree metrics (ID, position, height, area, volume)

Advantage: Automated individual tree detection and quantification

Data Normalization (Coordinate Adjustment)

- Method: Coordinate transformation and scaling using Open3D
- Process: Reads raw canopy point clouds → Centers and scales coordinates → Normalizes the points and Generates CHM
- Output: Normalized ply files and CHM ply files
- Advantage: Ensures consistent scale and coordinate system across all tree datasets



Canopy Height Model (visualised in CloudCompare)

Sample CSV file generated from Tree Segmentation

FID	max_height	mean_heigh	area_m2	pixel_coun	volume_app	x_position	y_position	crown_radi	tree_id	chunk_name
0	9.813732172	6.279566039	35.5	142	74.30819813	418055.128	1439929.577	3.361547406	1	chunk_2
1	7.656896604	6.415235902	2.75	11	5.88063291	418055.128	1439891.577	0.93560258	2	chunk_2
2	6.727262815	4.140168093	116.75	467	161.1215416	418054.628	1439903.577	6.096120013	3	chunk_2
3	5.816295177	3.697204098	52.5	210	64.70107171	418054.128	1439951.077	4.087941906	4	chunk_2
4	5.207981406	3.53624323	34.75	139	40.96148408	418057.8537	1439914.098	3.325848545	3	chunk_3
5	5.09696679	4.083774063	6.5	26	8.848177137	418058.8537	1439956.098	1.438406848	4	chunk_3
6	10.42836798	6.99748347	30	120	69.9748347	418062.7775	1439936.556	3.090193616	1	chunk_4
7	7.844762615	6.116292046	8.25	33	16.81980313	418060.7775	1439896.556	1.620511204	3	chunk_4
8	5.866401989	2.96802218	47.75	191	47.2410197	418063.2775	1439958.056	3.898627587	5	chunk_4
9	5.644523164	5.02760056	21	84	35.19320392	418060.2775	1439909.056	2.585441473	6	chunk_4

Train - Test Split (Dataset Preparation)

- Method: Randomized 70/30 chunk-based division
- Process: Loads tree dataset CSV and normalized PLY → Extracts unique chunk names and tree metrics → Splits into train and test sets → Saves the separate PLYs and train, test CSVs
- Output: Structured folders containing training and testing point cloud data, along with the segmented trees
- Advantage: Provides organized, CRS-consistent (EPSG:32644) data for model development and validation

POINTNET Deep Learning Model

- Input: 2048 (x, y, z) points from each canopy point cloud chunks
- Shared MLP: 3 → 64 → 128 → 1024
- Max Pooling → Global 1024-D feature
- Fully Connected: 1024 → 512 → 256 → 7
- Output: Tree metrics (height, volume, crown radius, etc.)
- Loss: Mean Squared Error (MSE)

Key Features:

- Order and scale-invariant
- Works directly on raw 3D data
- Lightweight and efficient

POINTNET Deep Learning Model

Training Loss Percentage

From Ground Truth Verification:

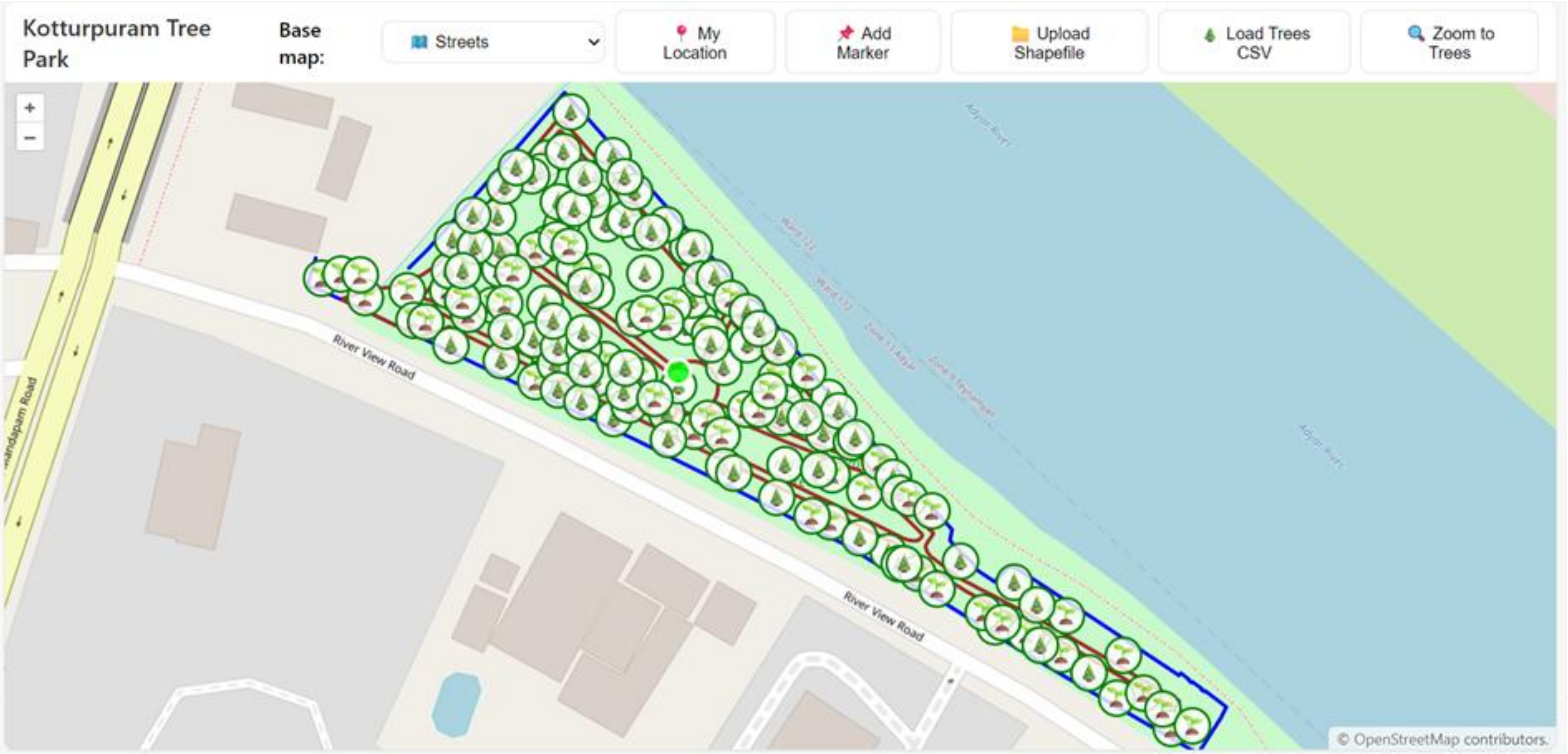
-TBC Results: 141 trees detected

-Proposed Method: 284 trees detected

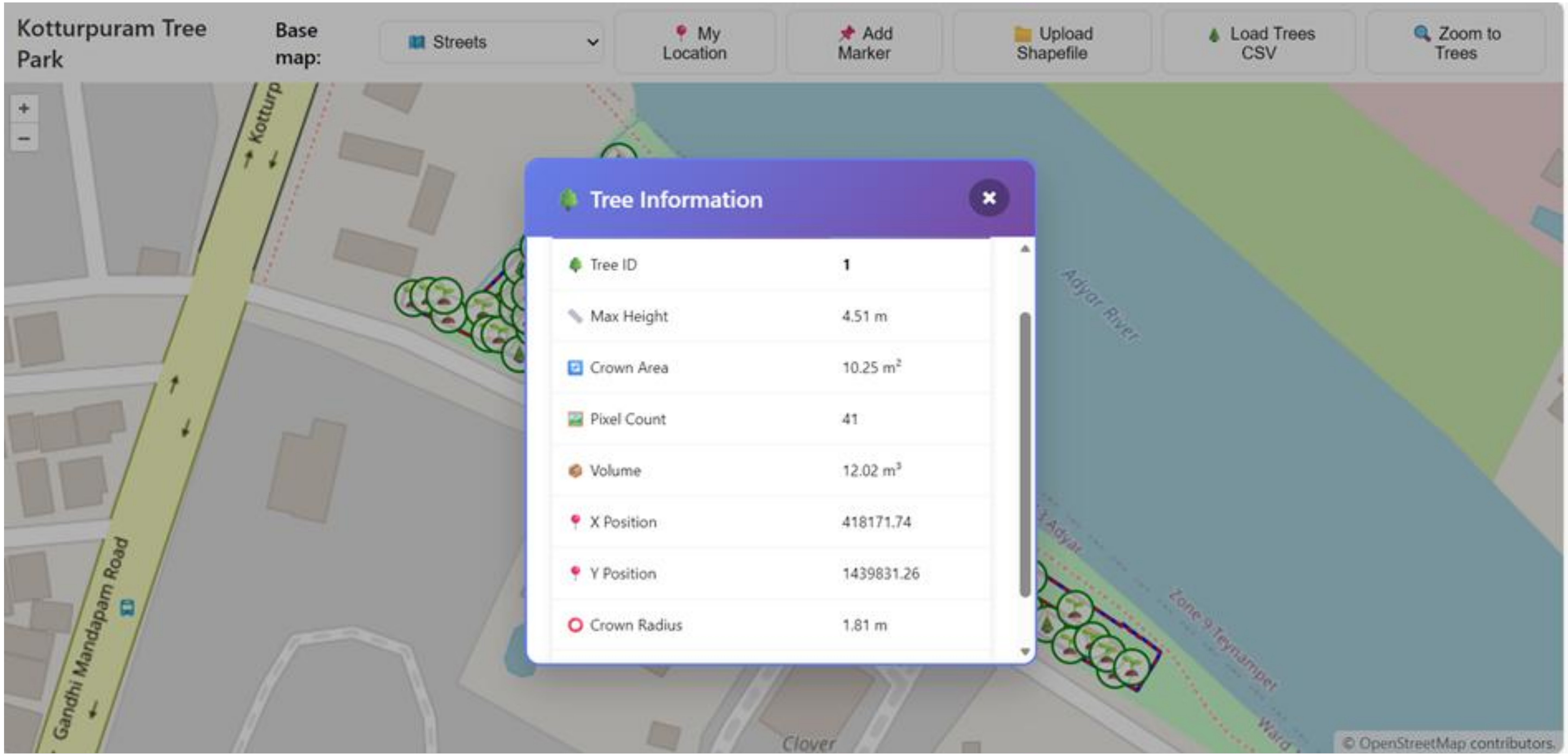
-Ground Truth (Field Survey): 302 trees recorded

-Accuracy Assessed: 94.04%

Web Interface



Web Interface



CONCLUSION

The workflow demonstrates that integrating LiDAR point cloud processing with deep learning models like PointNet enables accurate and scalable tree canopy analysis. PointNet's direct use of 3D point data supports precise tree detection, canopy delineation, and height estimation while avoiding manual feature extraction. With spatial chunking, height normalization, and CHM generation, the system efficiently handles large datasets and maintains high accuracy. The interactive web interface further improves accessibility and usability. Overall, the unified framework supports urban forest monitoring and ecosystem management, laying a strong foundation for future AI-driven environmental analysis tools.

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- Sun, Chenxin & Huang, Chengwei & Zhang, Huaiqing & Chen, Bangqian & An, Feng & Wang, Liwen & Ting, Yun. (2022). Individual Tree Crown Segmentation and Crown Width Extraction From a Heightmap Derived From Aerial Laser Scanning Data Using a Deep Learning Framework. Frontiers in Plant Science. 13. 914974. 10.3389/fpls.2022.914974.
- Li, L., Zhang, T., Jiang, Z., Yang, C. Y., Hwang, J. N., Oehmcke, S., & Igel, C. (2024). Tree Counting by Bridging 3D Point Clouds with Imagery. arXiv preprint arXiv:2403.01932.

THANK YOU