StormSeg: Segmenting Storm-Damaged Trees From Point Cloud Data

Aishwarya Dhaigude, Aryaman Sinha, Parthav Shah, Suraj Iyer
Indiana University Bloomington
{adhaigude, sinhaary, ps47, suraiyer}@iu.edu

***Abstract*—Storm-induced forest damage creates major challenges for recovery and management, especially where large-scale assessment tools are lacking. Manual field surveys are slow, labor-intensive, and often inconsistent. This project presents a modular pipeline for segmenting and classifying storm-damaged trees from airborne laser scanning (ALS) point cloud data. Building on top of FSCT, we combine semantic segmentation with additional processing steps such as resolution enhancement and height-based filtering to separate upright trees from fallen debris. Visual evaluation suggests the pipeline can capture key structural features of storm-affected forests, offering a foundation for automated post-disaster analysis.**

***Index Terms*—3D Point cloud segmentation, Storm damage assessment, Airborne laser scanning (ALS), Forest Structural Complexity Tool (FSCT), Semantic segmentation, Coarse woody debris (CWD).**

Project Repository: StormSeg

Relevant Files: Sharepoint

I. Introduction

The increasing frequency and intensity of storms have created serious challenges for forest ecosystems, often leading to complex and varied patterns of tree damage. Accurate post-storm assessment is essential for effective ecological recovery, forest management, and disaster mitigation planning. However, traditional manual surveys are time-consuming, labor-intensive, and susceptible to human error.

This project focuses on investigating existing methods for tree segmentation and developing a pipeline to segment and classify storm-damaged trees using ALS point cloud data collected from a state park in the United States. Unlike previous work in this area, our dataset features a wide range of tree conditions, including upright trees, fully fallen trees (with or without visible root bowls), and partially uprooted trees leaning at various angles.

To address this challenge, we propose to study and evaluate established tree segmentation models — such as FSCT (Krisanski et al.) and TreeLearn (Henrich et al., 2024) — in terms of their effectiveness at identifying the unique structural patterns of storm-affected trees. Our broader aim is to develop a flexible, modular pipeline that adapts to varying data resolutions and tree orientations, paving the way for more scalable and generalizable approaches to post-disaster forest monitoring.

II. Background and Related Work

We came across several methods that have been developed for segmenting and analyzing individual trees from 3D point cloud data. These methods vary in complexity, assumptions, and suitability depending on forest structure and data resolution.

Shendryk et al. (2016) proposed a bottom-up method tailored for broadleaf forests, which are often too complex for traditional top-down approaches. Their method detected tree trunks using conditional Euclidean distance clustering on full-waveform ALS data and then segmented the tree crowns using a graph-based random walk seeded from those trunks. The study highlighted the limitations of canopy height model (CHM)-based methods in dense or irregular canopies and emphasized the need for bottom-up, data-driven approaches in such environments.

Burt et al. (2018) introduced treeseg, an open-source tool built to automatically extract individual trees from large LiDAR point clouds. Their method combines Euclidean clustering, region growing, and cylinder fitting without relying on strict tree shape rules. While treeseg performed well in open-canopy forests, its accuracy declined in structurally complex environments, where overlapping crowns and dense vegetation led to challenges in fully separating individual trees.

Krisanski et al. (2021) introduces FSCT, a fully automated tool that extracts tree-level measurements from complex forest point clouds. The pipeline starts with semantic segmentation using a PointNet++ model to classify points into terrain, stems, vegetation, and coarse woody debris. It then fits cylinders to stem segments before grouping them into individual trees based on orientation and spatial continuity. This bottom-up process is well-suited to occluded and dense environments, making it effective for high-resolution TLS, MLS, and close-range photogrammetry data.

More recently, Henrich et al. (2024) introduced TreeLearn, a deep learning-based pipeline that segments individual trees from ground-based LiDAR point clouds using a 3D U-Net. TreeLearn predicts both tree and base locations at the point level, followed by clustering to form instances. Unlike rule-based tools, TreeLearn learns from annotated data and generalizes well across varied forest types when fine-tuned. It showed strong performance in benchmark tests and was particularly effective in segmenting upright trees in high-resolution TLS data.

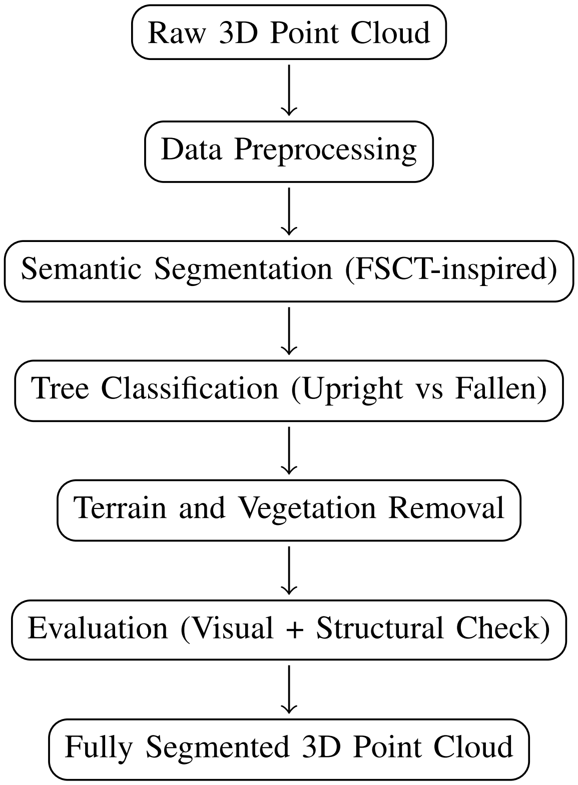

Fig. 1. Workflow of the storm-damaged forest point cloud segmentation pipeline.

III. Methods

A. Data Collection

The dataset used in this study consists of Airborne Laser Scanning (ALS) point cloud data collected over a state park in the United States following a major storm event. The data captures a range of tree conditions, including upright standing trees, fallen trees (both with and without exposed root bowls), and leaning or partially uprooted trees.

The dataset comprises nine individual plots, each representing a distinct spatial region within the storm-affected forest. Each plot maintains high spatial fidelity, providing an accurate three-dimensional representation of tree structures, ground surfaces, and storm-induced damage features such as canopy gaps and pit-and-mound topography. No explicit classification labels (e.g., tree vs. ground vs. debris) were provided, requiring the use of unsupervised and semi-supervised processing approaches.

The ALS data was acquired from a top-down aerial perspective, facilitating visualization of large-scale forest structural changes. The dataset was provided by Dr. Brian Yanites, Associate Professor in the Department of Earth and Atmospheric Sciences at Indiana University Bloomington, and offered a valuable opportunity to investigate the real-world impacts of storms on forest structure.

B. Data Preprocessing

The raw point cloud data was notably sparser than typically required for direct application of deep learning-based segmentation models. As a result, resolution enhancement was performed as a necessary preliminary step.

1) Resolution Augmentation: To increase point density and enable effective segmentation, we developed a custom augmentation procedure:

- **Point Duplication and Shifting:** The original points were duplicated and shifted by a margin of 0.025 m.
- **Crowding Control:** Points closer than 0.01 meters were merged or truncated to maintain a natural spatial distribution.
- **Iterative Enhancement:** The process was repeated 3–4 times, approximately doubling the original resolution while keeping noise minimal.

2) Denoising and Ground Removal: After augmentation:

- Denoising was applied to remove isolated outlier points.
- A Digital Terrain Model (DTM) was generated by identifying low-elevation points.
- Ground points were subsequently removed to focus on above-ground structures, such as trees and coarse woody debris.

C. Semantic Segmentation

To classify the point cloud into meaningful structural components, we adapted the semantic segmentation model developed in the Forest Structural Complexity Tool (FSCT). FSCT's model is based on PointNet++, a deep neural network architecture designed for directly processing 3D point sets without requiring intermediate gridding or meshing.

The FSCT segmentation pipeline involves several key steps:

1) Preprocessing for Segmentation: Before feeding the data into the neural network, the point cloud was preprocessed through:

- **Tiling:** The dataset was divided into overlapping cubic tiles of fixed dimensions to ensure manageable input sizes for the model while preserving spatial context. This also reduced memory usage during inference.
- **Voxelization and Feature Normalization:** Each tile underwent voxelization to aggregate local neighborhood information. Given the lower density of our ALS dataset compared to FSCT's original TLS training data, we reduced voxel sizes to better preserve fine-scale structures such as thin fallen branches and small leaning stems.
- **Height Normalization:** Points were normalized relative to the local ground elevation (derived from the DTM) to provide the model with consistent vertical references across plots.

2) Network Architecture and Class Labels: The PointNet++ model architecture hierarchically learns local and global features through a series of Set Abstraction and Feature Propagation layers. The adapted model classified points into four semantic categories:

- Terrain (ground points),

- Vegetation (canopy and understory foliage),
- Coarse Woody Debris (CWD) (fallen stems, branches, and woody material),
- Stems (vertical tree trunks and large branches).

Although full model retraining was outside the project scope, hyperparameters for inference—such as minimum points per tile, voxel resolution, and neighbor search radius—were tuned to accommodate the sparser and noisier nature of the augmented dataset.

D. Tree Classification

Following segmentation, a two-stage classification strategy was employed:

1) Separation of Upright and Fallen Trees: Height above the DTM served as the primary criterion. Points exhibiting consistent vertical structure were classified as upright trees, while horizontally oriented points near ground level were flagged as fallen trees.

Some misclassifications between fallen woody material and dense understory vegetation was observed during this stage, likely due to similarities in geometric structure and point density. This limitation was further evaluated during visual assessment.

2) Assignment to Individual Trees: For upright trees, we applied a Euclidean distance-based clustering approach, inspired by DBSCAN principles. Clusters were formed based on:

- A fixed radius search (analogous to DBSCAN's ε-neighborhood),
- A minimum number of points per cluster to filter noise.

E. Evaluation Strategy

Given the absence of ground-truth classification labels, evaluation was conducted qualitatively through visual inspection.

Processed outputs were compared directly against the raw point cloud to assess:

- The accuracy of upright tree identification and fallen tree detection,
- The coherence of individual tree instances after clustering,
- The consistency of terrain and vegetation segmentation relative to expected forest structures.

To ensure that structural realism was maintained, the predicted semantic classes and upright/fallen classifications were superimposed onto the original unprocessed point cloud. This enabled verification that the spatial arrangement, relative positioning, and morphology of trees and debris remained intact after segmentation.

Systematic errors were also monitored during evaluation. Notably, some confusion between coarse woody debris and vegetation classes was observed, likely due to the similarity between fallen branches and dense understory vegetation.

This issue was partially addressed through additional post-processing heuristics, which are discussed further in Section 4. Despite these challenges, visual assessment confirmed that the segmentation and classification pipeline provided a robust framework for distinguishing standing trees, fallen debris, and ground features within the storm-damaged plots.

IV. Results

A. Semantic Segmentation Outcomes

The adapted FSCT-inspired semantic segmentation model was applied across all nine storm-damaged plots. Figures **??** and **??** show the original ALS point cloud input and the corresponding segmented output.

In the segmented visualization:

- **Red points** represent **upright tree stems**,
- **Green points** represent **vegetation**,
- **Blue points** represent **terrain (ground surface)**,
- **Yellow points** represent **coarse woody debris (CWD)**.

Upright stems were consistently identified as coherent vertical structures. Terrain mapping was clean and continuous based on DTM generation. Vegetation layers were largely well classified.

However, challenges persisted for fallen debris: - Many fragmented CWD structures were misclassified as vegetation, - Only 2 out of the 9 plots achieved optimal segmentation performance, - Dense understory regions increased confusion rates.

B. Tree Classification and Post-Processing Results

Following semantic segmentation, a two-stage classification and filtering process was used to identify upright and fallen trees.

Figures **??** and **??** show the TIF orthophoto input and the isolated fallen trees output.

In the two optimally processed plots:

- Upright trees were accurately separated into coherent instances,
- Fallen tree trunks were distinctly extracted with minimal confusion.

In the other plots: - Fragmented debris fields, - Sparse point density, - Partially uprooted leaning trees
increased misclassification rates.

C. Structural Integrity Assessment

To validate the outputs, segmented and classified point clouds were superimposed onto the original ALS data.

Visual inspection confirmed that the global structure—tree spacing, canopy gaps, ground depressions—was generally preserved, particularly in the two optimally processed plots. Minor artifacts appeared mainly in dense vegetation regions, but in general the pipeline maintained spatial fidelity under various disturbance conditions.

V. Discussion

This project marked our first experience working with 3D point cloud data. It was fascinating to engage with spatial datasets that closely resembled natural environments. The richness and realism of the ALS point clouds provided a unique and immersive perspective on forest ecosystems and storm-induced damage patterns.

The primary research objective was to develop a pipeline capable of automatically segmenting and classifying storm-damaged trees using ALS-derived point cloud data. The results showed that upright standing trees could be segmented robustly across certain plots. However, due to the absence of ground-truth annotations, the evaluation relied entirely on visual inspection rather than empirical metrics, leaving the research question partially addressed.

Segmentation of fallen trees and coarse woody debris (CWD) presented significant challenges. Many fallen stems and fragmented debris were misclassified into the vegetation class due to structural similarities in shape and density. To mitigate this, a post-processing strategy was employed that involved:

- Separating terrain points and upright tree stems,
- Retaining vegetation points and misclassified fallen material,
- Applying height-above-DTM filtering to suppress low-lying shrubs and noise,
- Generating top-view projections of the filtered points,
- Visually comparing these projections with the original TIF orthophotos.

This approach effectively highlighted the major fallen tree structures and cross-sectional patterns within the storm-damaged plots. While visual comparisons confirmed that key spatial features were captured, the absence of labeled datasets prevented formal quantitative validation through metrics such as precision, recall, or F1-score.

Several limitations influenced the overall performance. The sparse nature of the ALS point clouds, particularly in regions of dense understory or heavy fragmentation, constrained segmentation accuracy and detail. Additionally, the dataset's coverage was limited to nine localized plots, restricting the generalizability of results across the entire storm-affected area.

Despite these challenges, the proposed pipeline demonstrated that robust segmentation of upright trees is achievable through a combination of deep learning-based segmentation and targeted post-processing. Addressing fallen debris classification in complex environments without ground-truth labels remains an important area for future research.

VI. Conclusion

Through adapting existing segmentation frameworks and designing custom post-processing strategies, we were able to reliably segment upright trees and partially isolate fallen tree structures from complex, sparse 3D datasets.

While our results were evaluated qualitatively due to the lack of ground-truth labels, the ability to recover key spatial patterns highlights the potential of automated point cloud analysis for forest disturbance assessment. Such capabilities could significantly benefit ecological research, forest management, and disaster response by reducing tedious on-site surveys.

Looking ahead, a key next step is to create annotated subsets of the dataset, which would allow us to begin experimenting with training and fine-tuning segmentation models directly on storm-affected data. Along with that, we want to work towards developing a model that work with low-resolution data, possibly using images to provide rough tree location hints.

In addition, we are exploring the use of geometric algorithms such as convex hull construction to further refine object detection. By fitting convex hulls around clustered fallen tree points or debris fields, it may be possible to better distinguish large fallen trunks from low vegetation or fragmented material, improving the accuracy of fallen object classification. Convex hull-based shape descriptors could also help capture the cross-sectional outlines of fallen stems, providing an additional structural cue beyond height filtering alone.

Acknowledgments

We would like to sincerely thank Professor David Crandall for his guidance and support throughout the course. We are also grateful to Mr. Vibhas Vats and the teaching assistants for their assistance during various stages of the project.

We especially thank Mr. Saugat Adhikari for proposing the project idea that inspired our work. We also acknowledge Dr. Brian Yanites for providing the ALS point cloud dataset used in this study.

Finally, we would like to thank our fellow classmates in B657 for their valuable discussions, idea sharing, and constructive feedback that helped shape the direction of the project.

References

[1] Shendryk, Yuri & Broich, Mark & Tulbure, Mirela & Alexandrov, Sergey. (2015). Bottom-up delineation of individual trees from full-waveform airborne laser scans in a structurally complex eucalypt forest. Remote Sensing of Environment. 173. 69-83. 10.1016/j.rse.2015.11.008.

[2] Ruizhongtai Qi, Charles & Yi, Li & Su, Hao & Guibas, Leonidas. (2017). PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space. 10.48550/arXiv.1706.02413.

[3] Burt, Andrew & Disney, M. & Calders, Kim. (2018). Extracting individual trees from lidar point clouds using treeseg. Methods in Ecology and Evolution. 10. 10.1111/2041-210X.13121.

[4] Krisanski, Sean & Taskhiri, Mohammad Sadegh & Gonzalez, Susana & Herries, David & Muneri, Allie & Gurung, Mohan & Montgomery, James & Turner, Paul. (2021). Forest Structural Complexity Tool—An Open Source, Fully-Automated Tool for Measuring Forest Point Clouds. Remote Sensing. 13. 4677. 10.3390/rs13224677.

[5] Krisanski, Sean & Taskhiri, Mohammad Sadegh & Gonzalez, Susana & Herries, David & Turner, Paul. (2021). Sensor Agnostic Semantic Segmentation of Structurally Diverse and Complex Forest Point Clouds Using Deep Learning. Remote Sensing. 12. 1413. 10.3390/rs13081413.

[6] Henrich, Jonathan & Delden, Jan & Seidel, Dominik & Kneib, Thomas & Ecker, Alexander. (2024). TreeLearn: A deep learning method for segmenting individual trees from ground-based LiDAR forest point clouds. Ecological Informatics. 84. 102888. 10.1016/j.ecoinf.2024.102888.