Deriving Tree Stem Profile and Volume Using a Close-Range Remote Sensing and Machine Learning Approach

Basam Dahy [1], Dag Björnberg [2,3], Shafiullah Soomro [2], Johan E. S. Fransson [1]

[1] Department of Forestry and Wood Technology, Linnaeus University, Sweden – bassam.saeed@lnu.se, johan.fransson@lnu.se
[2] Department of Computer Science and Media Technology, Linnaeus University, Sweden – dag.bjornberg@lnu.se, shafiullah.soomro@lnu.se
[3] Softwerk AB, Sweden – dag.bjornberg@softwerk.se

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Abstract

Accurate estimation of tree volume is essential for precision forestry and sustainable forest management. Traditional forest inventory methods rely on manual measurements of tree height and diameter, which are time-consuming and costly to conduct over large areas, and difficult to perform efficiently in dense forest stands. This study presents a data-driven approach for estimating tree volume from partial tree stem profiles derived from high-resolution datasets. While the study relies on harvester production data (Sweden) and field-measured tree stem profiles (Brazil), the framework is designed to support the estimation of tree volume from close-range remote sensing techniques, such as terrestrial photogrammetry using handheld cameras. Three modelling approaches were evaluated, including two machine learning models (XGBoost and Random Forest) using partial tree stem profile measurements as predictors, and one baseline model (XGBoost) using diameter at breast height and tree height as predictors. The models were developed using two independent datasets: harvester production data of Norway spruce (*Picea abies* (L.) H. Karst.) from Sweden and field-measured tree stem profiles of Slash pine (*Pinus elliottii* Engelm.) and Loblolly pine (*Pinus taeda* L.) plantations from Brazil. The results show that tree volume can be predicted with reasonable accuracy using partial tree stem profiles, although models incorporating tree height achieved the lowest prediction errors. The findings demonstrate that partial tree stem profiles provide valuable structural information for machine learning-based tree volume estimation. This framework supports the future integration of close-range remote sensing techniques into modern forest inventory systems.

1. Introduction

Quantifying tree volume is a cornerstone of forest resource assessment, carbon stock estimation, and ecosystem modelling. Conventional forest inventories rely on *in situ* measurements of diameter at breast height (DBH) and tree height, combined through empirical allometric equations (Brown, 1997; Picard et al., 2012). While these approaches are well established, they are constrained by the need for manual data collection, limited spatial coverage, and sensitivity to measurement error, especially in heterogeneous or inaccessible forest conditions. The growing availability of remote sensing (RS) techniques now offers new opportunities to automate forest structure estimation while maintaining or improving accuracy. Thus, it is recommended to develop new allometric equations that are integrable with RS variables and rely more directly on RS techniques to estimate volume, biomass, and carbon stock (Jucker et al., 2017; Dahy et al., 2020). For example, close-range terrestrial photogrammetry was evaluated for tree architecture reconstruction in mixed forest species, showing promising results albeit with higher error margins for complex stem geometry (Šleglová et al., 2025). A rapid increase in ultra-high-density UAV-LiDAR now allows individual tree attributes (height, diameter, volume) to be derived directly with relative RMSEs under 20% in plantation forests (Watt et al., 2025). Together, these developments support an accelerating shift from plot-based forest inventories toward tree-level inventories, where RS-derived structural metrics can directly replace or complement traditional field measurements. Extending the principles of remote sensing even further, close-range remote sensing techniques now offer enhanced flexibility through terrestrial platforms. Recent developments in close-range remote sensing and AI-driven photogrammetry have transformed how forest structural data can be acquired (Marzulli et al., 2020; Song et al., 2023; Kulicki et al., 2024; Magnuson et al., 2024; Hristova et al., 2025). Using smartphones or handheld cameras, terrestrial photogrammetry enables high-resolution 3D reconstruction of tree stems from overlapping images or video frames, effectively digitizing the forest scene (Figure 1). Combined with computer vision and machine learning (ML) algorithms, these data can be processed to extract quantitative variables such as tree stem profiles, taper curves, and ultimately, tree height, and volume.

The objective of this study is to develop and evaluate machine learning models for the estimation of tree volume using detailed partial tree stem profile data. The proposed framework is expected to support tree volume estimation from close-range remote sensing techniques, such as terrestrial photogrammetry using GoPro video data. Using extensive datasets from Sweden and Brazil, where prior research established strong relationships between multi-height stem diameters and tree volume, this work

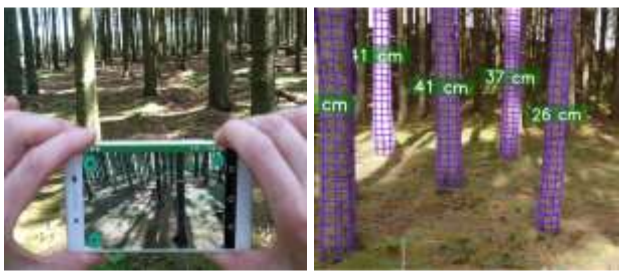

Figure 1. Example of high-resolution 3D reconstruction of the lower part of tree stems from terrestrial photogrammetry. Purple wireframe cylinders represent automated stem detection, with the estimated diameter at breast height for each detected stem.

supports the use of RS-extracted stem metrics to bypass manual measurements and serve as inputs to ML models, effectively linking field allometry with 3D computer vision in a framework suitable for future remote sensing integration. The approach supports the development of scalable, multi-sensor forest inventory systems in line with ongoing research within AI, photogrammetry, and 3D modelling for precision forestry.

In the present study, stem profile data are obtained from existing high-quality sources, including harvester production records and detailed field measurements. These datasets provide reliable structural information for developing and evaluating the ML models. Close-range remote sensing techniques, such as GoPro-based terrestrial photogrammetry, are not part of the current data acquisition but are envisaged to utilize the proposed framework for tree volume estimation.

2. Data and Study Areas

This study combines machine learning and empirical forest datasets from Sweden and Brazil to develop and evaluate algorithms for estimating tree-level volume from stem profiles derived from the lower part of the tree stem. The algorithms are based on machine-acquired harvester production (hpr) data from Sweden and field-measured stem profiles from Brazilian plantations. Each dataset supports independent model training and cross-validation.

The Swedish dataset consists of 30,000 stem profiles of Norway spruce (*Picea abies* (L.) H. Karst.) measured at 0.10 m intervals and collected from the county of Skåne, in southern Sweden. The stem profiles were measured by the harvester and stored in hpr files, consequently, the very top of the trees were not included. Because stand information was not available, stands were delineated using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm using a radius of 40 m and a minimum of 300 data points within each stand (Ester et al., 1996). Although this is not a perfect clustering algorithm, it separates the data into disjoint clusters allowing for independent validation. The volume of each tree was estimated from the hpr data using species-specific allometric volume functions. This high-resolution dataset provides a reliable foundation for training and validating AI algorithms that infer full-stem volume from partial profiles. The number of trees and tree volume distributions for each stand are shown in Figure 2.

The analysis of the Brazilian dataset includes tree-level measurements from multiple farms and focuses on two dominant species: Slash pine (*Pinus elliottii* Engelm.) (n = 398) and Loblolly pine (*Pinus taeda* L.) (n = 657). Species with in-sufficient samples were excluded to ensure robust model performance. After filtering, the dataset contains observations from 28 farms, each including detailed stem profile measure-ments at fixed heights of 0.1 m, 0.5 m, 1.0 m, 2.0 m, 3.0 m, 4.0 m and upwards for every meter until a defined threshold, along with tree height, age, and other site-specific attributes such as soil information and thinning history. The tree volume was calculated using Smalian’s formula, which estimates the volume of a segment based on the average of cross-sectional areas at both ends multiplied by the segment length. Stems were divided into sections according to the fixed-height diameter measurements, and the total tree volume was computed by summing all segment volumes. Diameters were measured in centimeters and converted to meters prior to calculating volume; the final tree volumes are, therefore, expressed in cubic meters (Husch et al., 2003). The number of trees and the tree volume distributions for each farm are shown in Figure 3.

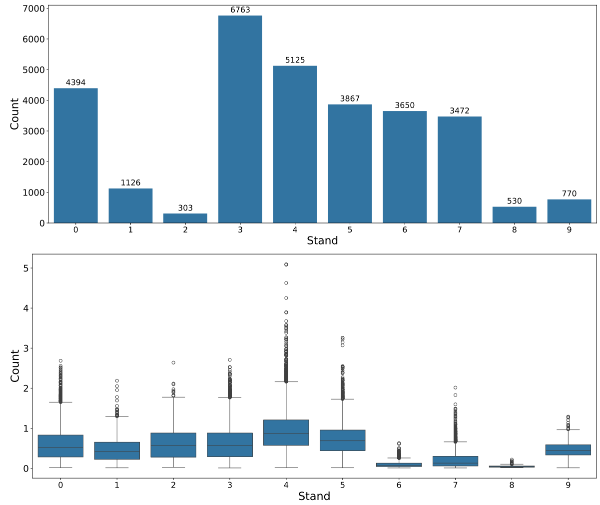

Figure 2. Number of trees and tree volume distributions for each stand in the Swedish dataset.

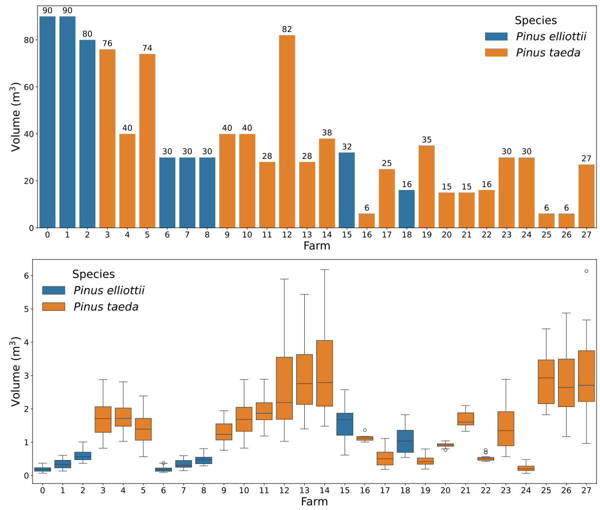

Figure 3. Number of trees and tree volume distributions for each farm in the Brazilian dataset.

3. Methods

For both datasets, we compared three different approaches: (i) Extreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) using DBH and tree height as predictor variables, (ii) XGBoost using all available stem profile measurements between 0 m and 4.0 m as predictors, and (iii) Random Forest (Breiman, 2001) using all available stem profile measurements between 0 m and 4.0 m as predictors. For all approaches species was included as a predictor for the Brazilian dataset.

The rationale for model (i) was to establish a baseline model that incorporates tree height, serving as a reasonable proxy for traditional DBH–height (and species)-based allometric volume functions. Although this study focuses on using partial tree stem profile and not the total tree height, the baseline model serves as a useful point of reference for evaluating the performance of the partial-profile models. Models (ii) and (iii) represent a realistic scenario where detailed partial tree stem profiles are available, for example derived from smartphone- or GoPro-based measure-ments. In the remainder of this paper, baseline model (i) is referred to as Baseline, model (ii) as XGBoost, and model (iii) as Random Forest.

3.1 Swedish Dataset Workflow

For all stem profiles, a partial tree stem profile was used as model input. This profile was measured at 0.10 m intervals from 0 m (the cut) up to 4.0 m, providing 41 distinct diameter values.

Because actual total tree height measurements were unavailable in the Swedish dataset, the variable *tree height without top* was included as an explanatory variable in the baseline model. The missing top section accounts for only a small proportion of the total tree volume, making this variable a reasonable proxy for total tree height.

Model evaluation was performed at stand level using the ten stands. The relative RMSE (rRMSE) was computed at tree level for each stand, and the percentage difference was calculated at stand level by comparing total predicted and observed volumes.

3.2 Brazilian Dataset Workflow

For the Brazilian dataset, the inputs consisted of six stem profile diameters measured at 0.1 m, 0.5 m, 1.3 m, 2.0 m, 3.0 m, and 4.0 m along the stem.

Similarly to the Swedish dataset, the relative RMSE was computed at tree level for each farm, and the percentage difference was calculated at farm level by comparing total predicted and observed volumes.

4. Results

4.1 Tree Volume Estimation from the Swedish Dataset

The performance of the different models applied to the Swedish dataset is summarized in Table 1. The baseline model achieved the best performance, with an average rRMSE of 12.49% and a stand-level percentage difference of 2.13%.

When only the partial tree stem profile (0–4.0 m) was used as input, the prediction accuracy decreased. The XGBoost model produced an rRMSE of 19.95%, while the Random Forest model resulted in an rRMSE of 19.21%. The corresponding stand-level percentage differences were 7.16% and 6.71%, respectively.

These results indicate that incorporating total tree height together with DBH provides stronger predictive power for tree volume estimation in the Swedish dataset. Nevertheless, the partial tree stem profile models still achieved reasonable performance, demonstrating the potential of using lower-stem geometric information derived from close-range terrestrial photogrammetry. The tree-level prediction performance of the models is illustrated in Figure 4, which shows scatter plots of predicted versus observed tree volumes for the Baseline, XGBoost, and Random Forest models.

Model	rRMSE (%)	Stand-level percentage difference (%)
Baseline	12.49	2.13
XGBoost	19.95	7.16
Random Forest	19.21	6.71

Table 1. Comparison of rRMSE values and stand-level percentage differences for the models applied to the Swedish dataset.

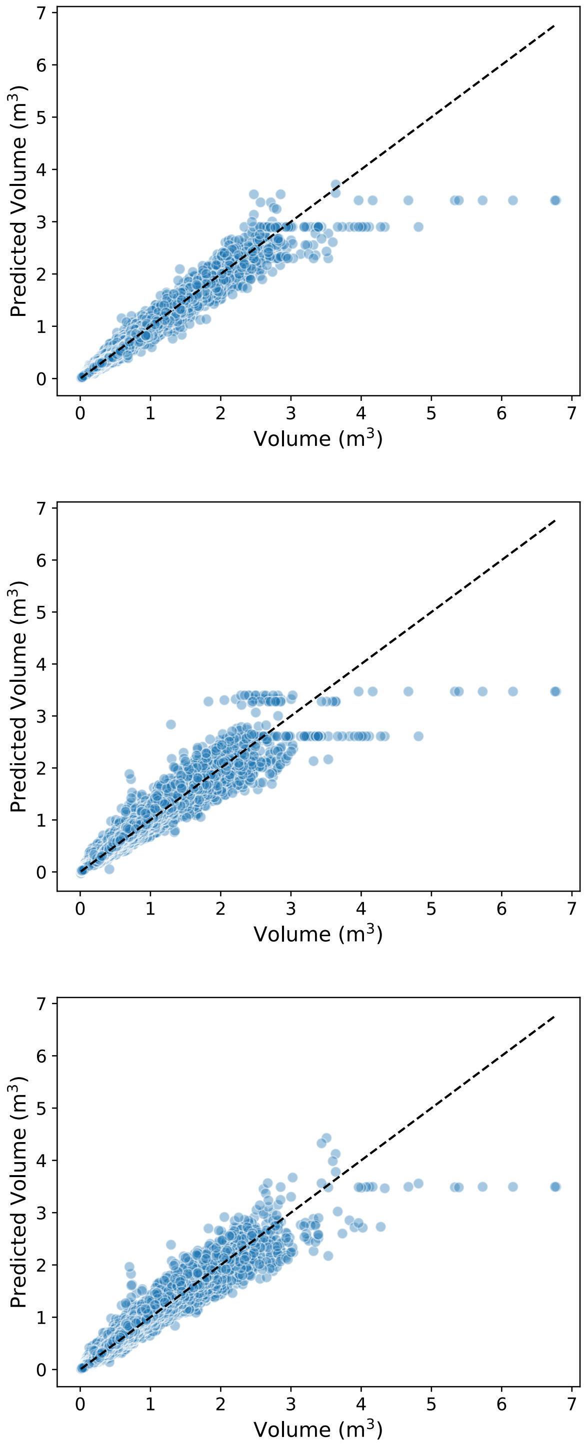

Figure 4. Scatter plots of predicted versus observed tree volumes for the Baseline (top), XGBoost (middle), and Random Forest (bottom) models applied to the Swedish dataset.

4.2 Tree Volume Estimation from the Brazilian Dataset

For the Brazilian dataset, model performance was evaluated separately for the two species *Pinus elliottii* and *Pinus taeda*. The results are summarized in Tables 2a and 2b.

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(a) *Pinus elliottii*

Model	rRMSE (%)	Farm-level percentage difference (%)
Baseline	11.26	4.47
XGBoost	17.82	9.64
Random Forest	16.25	8.16

(b) *Pinus taeda*

Model	rRMSE (%)	Farm-level percentage difference (%)
Baseline	20.92	12.77
XGBoost	22.69	14.27
Random Forest	21.56	14.02

Table 2. Comparison of rRMSE values and farm-level percentage differences for the models applied to the Brazilian dataset: (a) *Pinus elliottii* and (b) *Pinus taeda*.

For *Pinus elliottii*, the baseline model achieved an rRMSE of 11.26%, while the XGBoost and Random Forest models produced rRMSE values of 17.82% and 16.25%, respectively.

For *Pinus taeda*, prediction errors were higher across all models, with rRMSE values of 20.92% for the baseline model, 22.69% for XGBoost, and 21.56% for Random Forest.

These differences likely reflect structural variability between the two species, as *Pinus taeda* typically exhibits greater variability in tree height and stem form compared to *Pinus elliottii*. The corresponding scatter plots of predicted versus observed tree volumes are shown in Figure 5.

4.3 Cross-Dataset Comparison

A comparison of the results from the Swedish and Brazilian datasets highlights differences in model performance across forest ecosystems. In both datasets, the baseline model consistently produced the lowest prediction errors, indicating that including total tree height remains an important predictor of tree volume.

The partial-profile models based on XGBoost and Random Forest produced higher prediction errors, but still achieved reasonable predictive performance using only lower stem profile information. This result is encouraging because tree volume using partial tree stem profiles can then be estimated efficiently using close-range terrestrial photogrammetry from video streams acquired with smartphones or GoPro cameras.

The results also indicate that prediction errors tend to increase when stem-form variability is higher, as observed in the Brazilian dataset for *Pinus taeda*. This highlights the importance of structural variability when transferring machine learning models across different forest ecosystems.

5. Discussion

The results demonstrate that tree volume can be predicted with reasonable accuracy using partial tree stem geometry derived from close-range terrestrial photogrammetry. Across both datasets, however, the baseline model, which incorporates DBH and total tree height, consistently achieved the lowest prediction errors. This highlights the importance of tree height as a strong predictor of tree volume in operational forest inventory applications.

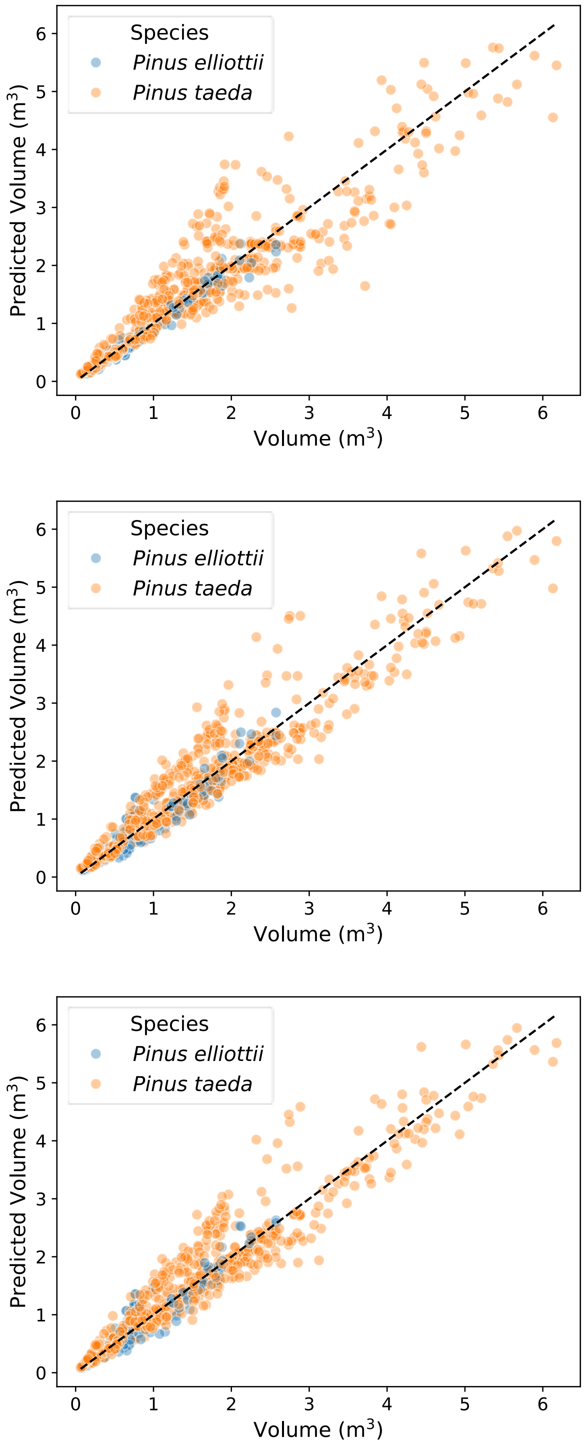

Figure 5. Scatter plots of predicted versus observed tree volumes for the Baseline (top), XGBoost (middle), and Random Forest (bottom) models applied to the Brazilian dataset.

Nevertheless, the models relying only on partial tree stem profiles produced reasonable prediction accuracy. These models use geometric information extracted from the lower part of the stem (0–4.0 m), which can potentially be obtained using video streams acquired with smartphones or GoPro cameras. Compared to traditional field measurements requiring manual DBH and tree height measurements, this approach significantly reduces fieldwork effort. Consequently, a practical trade-off exists between prediction accuracy and data acquisition efficiency. One limitation of the proposed approach is that only the lower part of the stem is directly observed, while the upper stem remains unmeasured. This can introduce uncertainty when predicting total tree volume. Future improvements could, therefore, include explicit modelling of the unobserved upper stem using taper equations or synthetic reconstruction techniques. Such approaches may help better align the training labels with the partial-profile inputs and reduce prediction noise.

Differences in prediction accuracy were also observed between species and datasets. In the Brazilian dataset, prediction errors were generally higher for *Pinus taeda* compared to *Pinus elliottii*, likely due to greater variability in tree height and stem form within *Pinus taeda* plantations. Similarly, differences between the Swedish and Brazilian datasets highlight structural contrasts between boreal and subtropical plantation forests, which can influence model performance.

In the experiments conducted here, the Random Forest model performed slightly better than XGBoost when applied to lower stem profile inputs. Both models, however, showed tendencies toward poor extrapolation, particularly in the Swedish dataset. Tree-based ensemble models are known to perform well for interpolation within the range of the training data, but may produce unreliable predictions for observations outside that range. When applying such models operationally, it is therefore important to ensure that the training data sufficiently represent the variability of the target forest conditions.

When scaling the modelling framework to regional or national forest inventories, however, this limitation may become less critical. In such applications, most predictions occur within the range of forest conditions represented in the training data, making interpolation the primary objective.

In the present study the partial tree stem profiles were not directly derived from close-range remote sensing data. Instead, high-quality reference datasets were used to develop and evaluate the modelling framework. Future work will focus on integrating terrestrial photogrammetry (e.g., GoPro-based acquisition) to estimate tree volume under operational conditions and assess the full end-to-end performance of the proposed approach.

Finally, incorporating additional explanatory variables may further improve model performance. Site-specific variables such as stand age, geographic location, elevation, or soil characteristics may capture environmental factors influencing tree growth and could enhance model generalization when sufficient training data are available.

6. Conclusions

This study demonstrates that tree volume can be estimated with reasonable accuracy using partial tree stem profiles derived from high-resolution datasets. While models incorporating total tree height achieved the lowest prediction errors, machine learning models based solely on lower stem profile geometry also provided promising results.

The findings highlight the potential of partial tree stem profiles as an alternative source of structural information for tree volume estimation, reducing reliance on traditional field measurements. The proposed modelling framework is flexible and can be integrated with emerging close-range remote sensing techniques, such as terrestrial photogrammetry, to enable efficient and scalable forest inventory solutions.

Future work will focus on evaluating the approach using stem profiles derived directly from image-based 3D reconstruction and assessing its applicability to estimate tree volume under operational field conditions.

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