

A comparative evaluation of UAV-LiDAR and deep learning for delineating tree crowns and conducting spectral analysis in walnut orchards

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Abstract

Accurate individual tree crown delineation is fundamental for reliable tree-level orchard analysis. This study compared three crown delineation methods in two Hungarian walnut orchards: manual digitization (reference), an automated 3D LiDAR point cloud-based geometric approach (FLAI), and a Deep Learning (DL) Mask R-CNN instance segmentation model utilizing RGB orthomosaics. While structural delineation relied exclusively on LiDAR and RGB data, UAV multispectral imagery was strictly reserved for the post-delineation extraction of spectral statistics. Geometric performance was evaluated using spatial descriptors, Intersection over Union (IoU), and size-based error analysis. Accuracy depended heavily on tree size and planting pattern; DL performed well in dense canopies (IoU: 0.65) but struggled with small crowns, whereas FLAI was highly accurate (IoU: 0.76) and consistent across all sizes. Despite geometric discrepancies, tree-level spectral statistics (CI_{re}, NDRE, PRI) extracted from automated polygons showed no statistically significant differences from the manual reference. Thus, while segmentation methods affect geometric fidelity, they do not significantly influence derived spectral health indicators, validating both automated workflows for operational monitoring.

Keywords: UAV Remote Sensing, LiDAR, Deep Learning, Precision Agriculture, Walnut (*Juglans regia*).

Introduction

For high-value crops like walnuts (*Juglans regia*) to be managed effectively in precision agriculture, individual tree health monitoring is crucial (Weng et al., 2024; Zhang et al., 2025). In contrast to broad-acre farming, orchard management necessitates the exact isolation of individual tree crowns (ITC) to extract biological traits (Diószegi et al., 2024; Jurado et al., 2020b). Although manual delineation is still the most accurate method, it is time-consuming and not scalable. As a result, automated solutions utilizing Deep Learning (DL) and UAV-based LiDAR have become more popular (Goodbody, n.d.). There is still a significant gap in the validation of these techniques, though. The majority of research does not evaluate how segmentation errors spread into the spectral data used for decision-making; instead, it concentrates on geometric accuracy, or how well a polygon matches the shape of a tree (Jurado et al., 2020a). Does an automated model drastically alter vegetation indices like NDRE or PRI if it splits one tree (over-segmentation) or merges two trees (under-segmentation)? In order to fill this gap, this study compares three delineation techniques: (1) manual reference, (2) the FLAI LiDAR-based algorithm, and (3) the ArcGIS Pretrained Deep Learning model. This study examines whether the geometric trade-offs involved in automated segmentation introduce statistically significant bias into tree-level spectral measurements in two walnut orchards in Hungary (Tárnok and Vereb).

Data and Methods

Study Areas and Data Acquisition

The research was conducted in two Hungarian walnut orchards, Vereb (2.4 ha) and Tárnok (4.2 ha), chosen to illustrate differing canopy densities. All field campaigns and remote sensing data acquisition for these sites were completed on the same day to ensure strict temporal consistency. The first orchard in Vereb is an intensive commercial orchard utilizing rigorous irrigation and chemical protection. The second one in Tárnok is a genetic archive owned by the HUALS Fruit Growing Research Center; this site contains diverse cultivars with varying management levels (including untreated controls), offering a higher probability of observing heterogeneous disease responses (Fig. 1). A DJI Matrice M210 UAS with a 10-band MicaSense RedEdge-MX Dual system and a DJI Matrice M350 RTK UAS with a Zenmuse L2 LiDAR sensor were used to collect data. At height of 25 m above ground level (AGL), multispectral surveys were done. The ground sample distance (GSD) was 1.7 cm/pixel. The UAV LiDAR campaigns collected data from both nadir and oblique angles while flying at a height of 39.59 m. This resulted in a high-resolution point cloud with an average density of 1,843 points/m². The RGB and multispectral imagery, acquired via the DJI Matrice M210 with the MicaSense RedEdge-MX Dual system, was processed and orthorectified using Pix4Dmapper (v4.5.6). At the same time, the LiDAR point cloud, captured via the DJI Matrice M350 RTK equipped with a Zenmuse L2 sensor, was processed using DJI Terra (v5.0.1). To ensure precise spatial alignment between the optical and structural outputs, Tárnok workflow was anchored by a shared network of 8 well-spatially distributed Ground Control Points (GCPs) measured with a GNSS rover. By combining these GCPs with the M350's onboard RTK positioning, both the photogrammetric and LiDAR datasets were tied to the exact same ground-truth coordinate system, guaranteeing sub-pixel co-registration prior to data extraction.

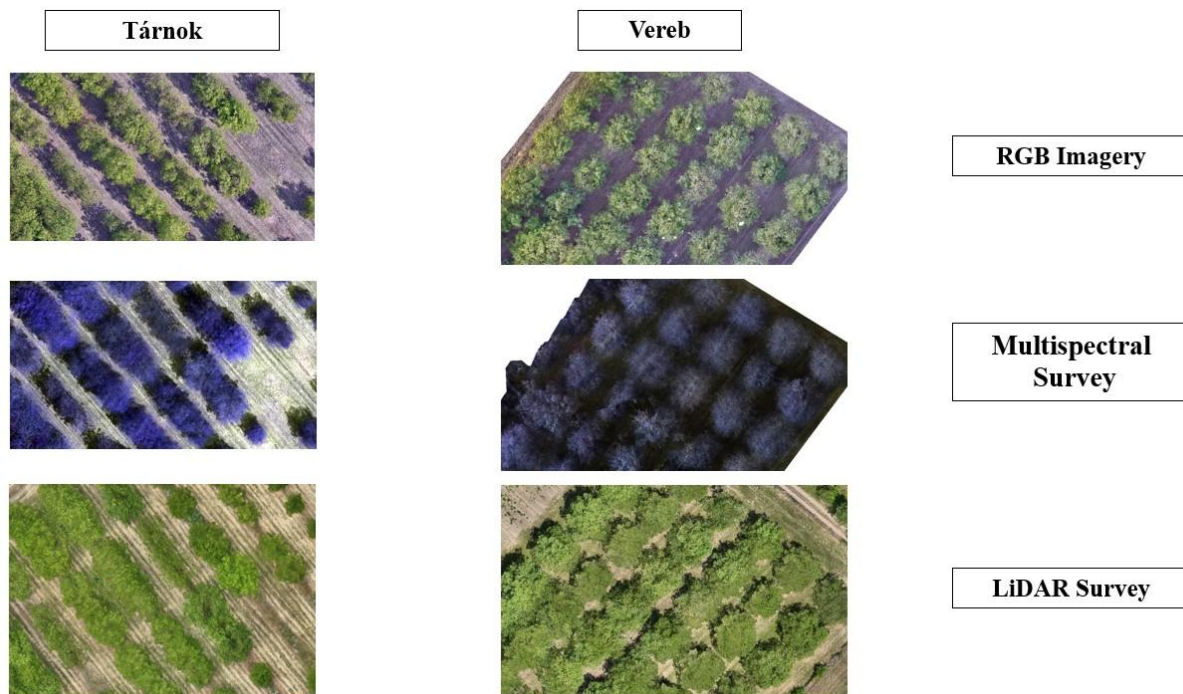


Figure 1. Overview of the different surveys conducted in both case study areas; note that only a portion of the total study areas is presented.

Models for Crown Delineation

Three methods were tested:

1. **Manual Delineation (Reference):** In total, 55 and 59 expert-digitized tree crown polygons, delineated at a map scale of 1:150, were used as reference ground truth data for Tárnok and Vereb, respectively. This manual delineation process took 2 months to complete for Tárnok and 1.5 months for Vereb.
2. **LiDAR-based Delineation (FLAI):** An automated, geometric tree crown delineation approach executed via the FLAI platform (FLAI, 2025). This algorithm segments individual tree crowns by analyzing the 3D spatial distribution and full vertical structure of the classified LiDAR point cloud, separating distinct canopy features based on geometric morphology rather than optical reflectance.
3. **Deep Learning (DL):** Automated individual tree crown delineation was performed using a Mask R-CNN instance segmentation architecture. The model was executed within ArcGIS Pro (v3.5) to extract distinct crown boundaries directly from the high-resolution RGB orthomosaics (Fig. 2) (ESRI, 2023).

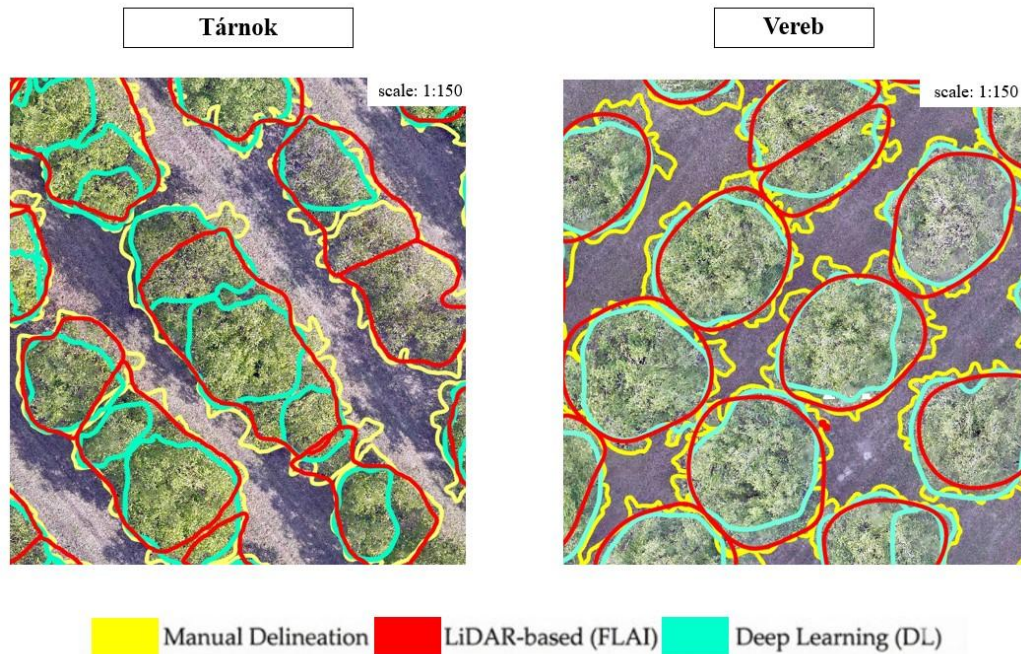


Figure 2. Three crown delineation methods used in two study areas.

Evaluation of Performance

We used Intersection over Union (IoU) (Wu et al., 2020) and segmentation error indices (Over-segmentation and Under-segmentation) to see how accurate the shapes were. We also used Kruskal-Wallis tests to look at how crown size affected items by putting trees into small, medium, and big groups and looking at the IoU distribution (Fig. 3). Finally, the grouped boxplots were used to see if there was any bias in the tree-level spectral statistics (mean Cl_{re} , NDRE, and PRI).

Choosing and Extracting the Spectral Index

We selected three spectral indices because they are highly sensitive to physiological variations in dense walnut canopies. We chose Normalized Difference Red-Edge (NDRE) and Chlorophyll Red-Edge (Cl_{re}) because they both use the red-edge band. This stops signal saturation in thick, mature walnut canopies, where traditional indices (like NDVI) often stop working (Pokovai et al., 2025). We also used the Photochemical Reflectance Index (PRI) to measure how plants photosynthesize effectively and how much water stress they faced (Berger et al., 2022). This is very important for managing irrigation in high-value nut crops.

Results

Geometric Performance at the Site

Geometric validation indicated that the structural configuration of the orchard had a significant impact on the model's performance. The ArcGIS DL model demonstrated slightly higher accuracy in Tárnok, with a Mean IoU of 0.65 ± 0.21 , compared to the LiDAR-based model, which had a Mean IoU of 0.64 ± 0.21 . Although the differences between the two models were notable, the LiDAR method exhibited substantial issues with under-segmentation (0.85), resulting in the merging of closely situated trees in this denser orchard. Conversely, the LiDAR-based (FLAI) model performed more effectively and exhibited greater stability in Vereb, characterized by a low standard deviation of 0.08 and a high Mean IoU of 0.76. In contrast, the DL model was less reliable, with an IoU of 0.69 ± 0.17 , and some detections were not processed at all, as indicated by a minimum IoU close to 0.07 (Table 1).

Table 1. The geometric comparison of delineation models based on (manually drawn) ground truth data

Study Area	Delineation Model	Mean_IoU	IoU_SD	Over_segmentation (Percentage)	Under_segmentation (Percentage)
Tárnok	FLAI	0.64	0.21	59.25%	84.61%
Tárnok	DL	0.65	0.21	41.51%	40.07%
Vereb	FLAI	0.76	0.08	52.55%	45.33%
Vereb	DL	0.69	0.17	35.59%	39.51%

The effect of crown size on segmentation accuracy

To assess the robustness of each model, segmentation accuracy, measured by Intersection over Union (IoU), was evaluated across three crown size categories: small, medium, and large. The study demonstrated that tree size and the delineation of crown shapes by the models significantly influenced each other. The LiDAR-based FLAI model exhibited considerable stability, as there was no statistically significant difference in IoU across tree size classes in either the Tárnok ($p=0.62$) or Vereb ($p=0.30$) orchards. This indicates that the LiDAR algorithm, which relies on the vertical structure of the canopy, performs effectively for both small saplings and large, mature crowns. Conversely, the Deep Learning (DL) model exhibited performance biases dependent on size. In the structured Vereb orchard, the DL model performed significantly worse on small trees (mean IoU= 0.58) compared to large trees (mean IoU= 0.79, $p < 0.001$), likely due to the indistinctness of small features in the orthomosaic. In the dense Tárnok orchard, however, the DL model's accuracy

decreased for large trees (mean IoU 0.56), indicating a tendency to under-segment (merge) large, overlapping canopies (Fig. 3).

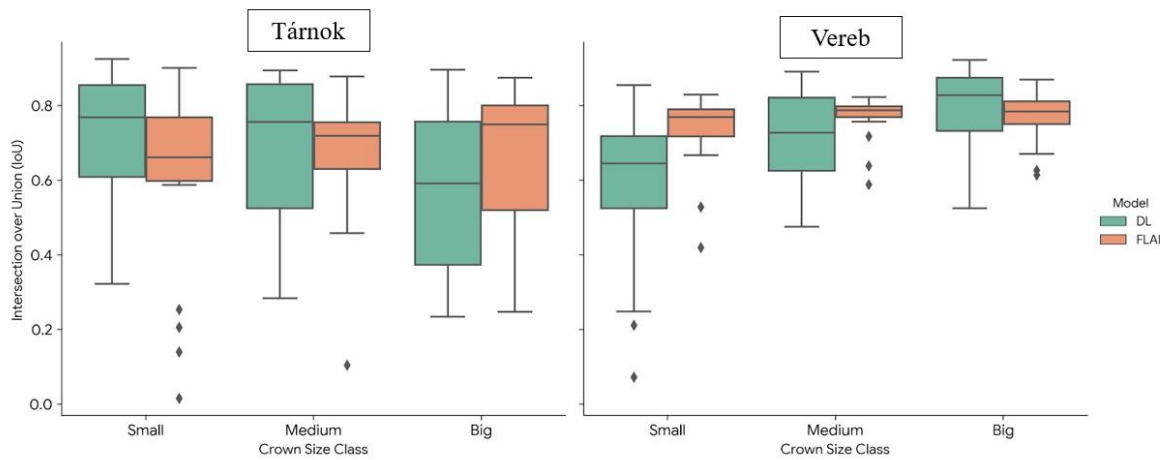


Figure 3. Impact of crown size on segmentation accuracy (IoU)

Effect on Spectral Indices

Despite variations in shape and size that influenced the results, the spectral integrity remained stable. The distribution analysis of CI_{re} , NDRE, and PRI indicated no statistically significant differences among the Manual, FLAI, and DL datasets. The interquartile ranges for all three indices exhibited substantial overlap, suggesting that even significant errors, such as FLAI's merging in Tárnok or DL's failure with small trees, did not consistently impact the health data (Fig. 4).

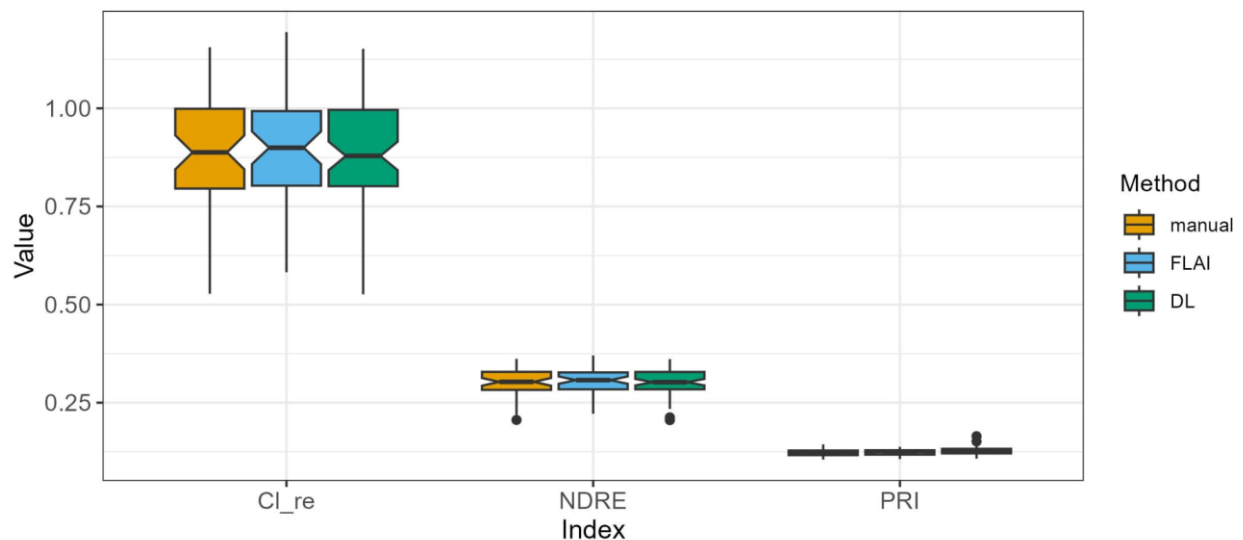


Figure 4. The effect of tree delineation method on spectral indices

Conclusion

This study demonstrates that the optimal method for delineating a crown is contingent upon the orchard environment. LiDAR-based (FLAI) algorithms work best in orchards with trees of all sizes

that are well-organized (Vereb). Deep Learning (ArcGIS) models work best in dense canopies (Tárnok), but they are very sensitive to tree size. On the other hand, these geometric differences don't affect how useful the data can be for farming. Since neither automated method added much bias to the derived spectral indices, we can say that both workflows are safe to use. The finding lets orchard managers put less cost and speed up processing without lowering the quality of their spectral health monitoring.

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