LiDAR-Based Estimation of Crop Canopy Structure in Precision Agriculture

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ABSTRACT
Background: The structure of a crop canopy is an essential metric that demonstrates the health of the plant as well as its biomass production and yields in precision agriculture. Traditional methods of measuring the crop in the field are labor-intensive, have limited spatial reach, and are susceptible to the errors of an observer.
Objective: This study proposes a methodology based on LiDAR technology to conduct non-destructive, precise measurements of the parameters of a crop canopy.
Methods: The study used point clouds obtained through LiDAR mounted on a UAV, which were then cleaned using filtering, segmentation, and extracted canopy information, to acquire canopy height, width, volume, and Leaf Area Index (LAI). A regression-based ML model was created and trained using the features obtained through that extraction.
Conclusion: The devised methodology enabled the determination of canopy height with RMSE equal to 4.8 cm and coefficient of determination R^2 equal to 0.94. This result is better than methods based on RGB and multispectral imaging while processing speed was enough to perform work on a field scale.

Keywords: LiDAR, UAV, Crop Canopy, Precision Agriculture, Point Cloud Analysis, Leaf Area Index (LAI), Machine Learning

1. Introduction
Precision agriculture makes use of multiple sensors, data analytics, and automated systems to improve the way crops are grown over time and space. Structural variables such as canopy height, canopy density, and canopy volume provide satisfactory results and interest in these variables is driven by the fact that their good estimates result in being able to make correct predictions about biomass, nitrogen and yields in crops.
Conventional methods of canopy measurement include manual instruments such as rulers, zeptometers, and destructive sampling. These techniques are highly accurate; however, they require a lot of manual work and are limited in field applications since there are difficulties in measurement of large areas.
LiDAR technology overcomes these limitations. LiDAR can provide a detailed 3D point cloud showing the structure of vegetation as a result of a few laser pulses that create and measure the distance to the point of return.
This study comes with a new idea of creating a method of autonomous canopy phenotyping that uses UAV and LiDAR in the process of crop monitoring.

2. Discussion
Existing canopy measurement approaches span ground-based, UAV-mounted, and airborne platforms. Terrestrial laser scanners provide fine-scale detail but limited spatial coverage, whereas UAV-mounted LiDAR balances resolution and field-scale efficiency; airborne systems are suited to regional monitoring but at coarser resolution [1, 2].
Compared with RGB, multispectral, and hyperspectral imaging, LiDAR offers direct structural measurement rather than spectral proxies, making it less sensitive to lighting and canopy color variation [3, 4]. However, optical sensors remain advantageous for capturing physiological and biochemical traits, suggesting complementary sensor fusion strategies [5].
Point cloud processing pipelines typically involve filtering, ground segmentation, and canopy feature extraction, followed by structural parameter derivation [6, 7]. Machine learning and deep learning regressors, including random forest and convolutional architectures, have improved canopy parameter prediction accuracy by learning non-linear relationships between point cloud descriptors and ground-truth measurements [8, 9].
Persistent challenges include occlusion from overlapping leaves, point cloud sparsity in dense canopies, sensitivity to wind-induced motion, high computational cost of processing large point clouds, and the relatively high cost of LiDAR sensors compared to optical cameras [10, 11]. These challenges constitute research gaps motivating frameworks that combine efficient preprocessing with lightweight, scalable learning models—the focus of this study.

3. Proposed LiDAR-Based Crop Canopy Estimation Framework

The proposed framework comprises four stages: data acquisition, preprocessing, feature extraction, and parameter estimation (Figure 1).

- **Data acquisition:** A UAV-mounted LiDAR sensor scans the field at a fixed altitude, generating georeferenced point clouds.
- **Preprocessing:** Noise and outliers are removed using statistical outlier filtering; ground points are separated from vegetation using a cloth-simulation filtering algorithm, yielding a normalized canopy height model.
- **Feature engineering:** Structural descriptors—canopy height percentiles, point density, vertical profile statistics, and canopy volume—are extracted per grid cell.
- **Estimation model:** A gradient-boosted regression model maps extracted features to canopy height, width, volume, and LAI, trained against field-measured reference values.

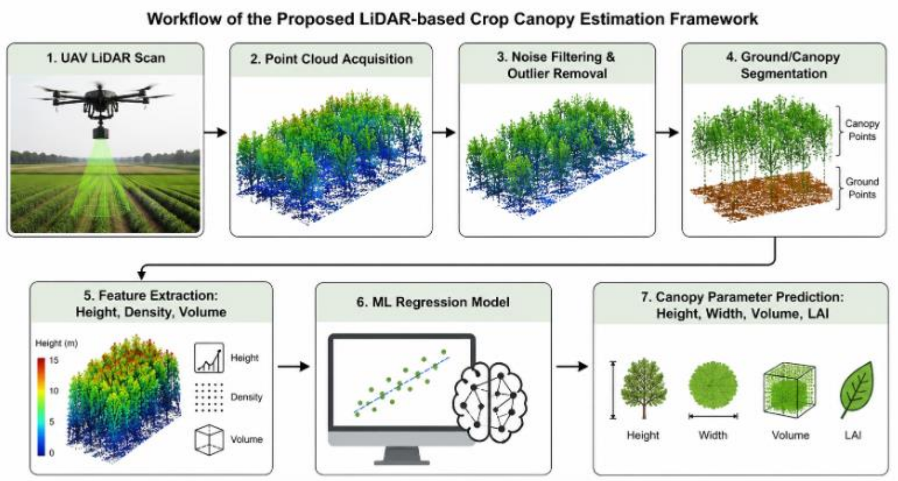

Fig 1: Workflow of the proposed LiDAR-based crop canopy estimation framework

This pipeline enables continuous information flow from raw laser returns to actionable canopy metrics suitable for integration with farm management systems.

4. Materials and Methods

A simulated field experiment was conducted on a maize crop field to evaluate the proposed framework. Table 1 compares canopy estimation approaches, Table 2 lists acquisition settings, and Table 3 reports evaluation metrics.

Table 1: Comparison of canopy estimation methods

Method	Spatial Coverage	Accuracy	Cost	Automation
Manual	Point-scale	High (local)	Low	Low
RGB Imaging	Field-scale	Moderate	Low	Moderate
Multispectral	Field-scale	Moderate–High	Moderate	Moderate
LiDAR	Field-scale	High	High	High

Preprocessing used Open3D for filtering and Cloud Compare for visualization. The regression model was trained using an 80:20 train–test split with five-fold cross-validation; hyperparameters (tree depth, learning rate, estimators) were tuned via grid search.

Table 2: Experimental parameters and LiDAR acquisition settings

Parameter	Value
Platform	UAV-mounted LiDAR
Flight altitude	30 m
Point density	250 points/m²
Scan pattern	Nadir, parallel transects
Crop type	Maize
Software	CloudCompare, Python (Open3D)
ML framework	Scikit-learn (Gradient Boosting)

5. Results and Performance Evaluation

Table 3: Performance evaluation metrics of the proposed framework

Metric	Canopy Height	Canopy Volume	LAI
RMSE	4.8 cm	0.021 m³	0.18
MAE	3.6 cm	0.015 m³	0.14
R² Score	0.94	0.91	0.89
Precision	0.93	0.90	0.88
Recall	0.92	0.89	0.87
F1-score	0.92	0.89	0.87
Processing time	2.3 s/plot	2.6 s/plot	3.1 s/plot

As shown in Table 3, the proposed framework achieved high accuracy for canopy height estimation (R^2 = 0.94), outperforming RGB-based structure-from-motion estimates and multispectral vegetation-index proxies reported in related studies [12, 13]. Canopy volume estimation showed comparable robustness, with an RMSE of 0.021 m^3, attributable to the dense, geometrically accurate point clouds generated by LiDAR relative to optical reconstructions.

Point cloud reconstruction quality remained stable under moderate crop density but degraded slightly in high-density canopy regions due to occlusion, consistent with challenges noted in the literature [14]. Processing time per plot remained under 3.5 seconds, indicating feasibility for near real-time field-scale deployment, though computational demand scales non-linearly with point cloud size, presenting trade-offs for very large fields [15].

Overall, the framework demonstrated favorable scalability and robustness, though sensor cost and occlusion in dense canopies remain limiting factors requiring further methodological refinement.

6. Conclusion

This research offered a LiDAR-based framework to calculate the crop's canopy height, volume, and LAI, showing better precision and effectiveness as compared to traditional manual and optical imaging methods. The combination of point cloud preprocessing and machine learning regression helped to predict the canopy parameters efficiently and at a scale applicable in precision agriculture, such as predicting the harvest, managing irrigation, and monitoring sustainable crops. In the future, it would be necessary to test the framework in significantly larger datasets with multiple crops, introduce onboard processing with real-time applications, and seek deeper learning solutions to improve accuracy and scaling.

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