IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Variable-Rate PWM Spray Control Using 3D Canopy Volume Mapping For Intelligent UAV-Based Pesticide Application

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Abstract

The increased adoption of UAVs for precision agriculture creates an ever-growing demand for intelligent, site-specific spraying systems that minimize chemical wastage and enhance deposition accuracy. High-resolution sensing technologies, such as LiDAR, are able to reconstruct a detailed canopy, while embedded control systems enable real-time modulation of the spray output. Most of the available methods for spraying using a UAV are still based on a constant-rate application, which results in overspray, drift, and non-uniform coverage of the canopy.Indeed, very few previous works have integrated LiDAR-derived 3D canopy volume, prescription-map-driven PWM flow control, and CFD-based drift compensation in a single pipeline. Therefore, the precise, structure-aware spraying and mitigation of aerodynamic drift have not been adequately addressed.The aim of this research was to develop an integrated LiDAR-guided variable-rate UAV spraying workflow that included canopy-volume mapping, prescription-based PWM control, and CFD-regression drift compensation.The framework used the NEON AOP LiDAR data for constructing a canopy height model, segmenting individual trees, and computing canopy volume classified into discrete spray-demand levels to develop a georeferenced prescription map. A simulated PID-driven PWM controller updated the spray output based on assigned rates, while the CFD-derived droplet-dispersion data were used in the training of a regression model to predict and compensate for lateral drift. Experiments that will be done include validation of the accuracy of segmentation, flow-tracking performance, drift-prediction reliability, and comparison of variable-rate spraying to a constant rate through Python-based simulations.The system achieved an accurate canopy segmentation of ~91%, a reliable canopy-volume estimation with a resultant error of 8-10%, and a precise tracking of spray-rate with a mean flow error of 0.032 L/min. The drift-prediction model, at an RMSE of 6.7%, enabled a simulated drift reduction of 72-81% after compensation. In comparison to spraying at a constant rate, the variable-rate strategy achieved an average chemical saving of ~24.8%, increased canopy deposition uniformity by 19.4%, and reduced ground over-deposition by 31.2%.Therefore, it is deduced that the integrated pipeline offers a workable and scalable solution for addressing intelligent UAV spraying by adequately integrating remote sensing, control engineering, and modeling of aerodynamics into one system. Results confirm the premise that LiDAR-guided UAV spraying systems have high potential for upscaling input efficiency and reducing environmental contamination, contributing to sustainable precision agriculture.

Keywords:
Variable-Rate Spraying; UAV; LiDAR; Canopy Volume; PWM Control; CFD Drift Modelling; Prescription Mapping; Precision Agriculture.

1. Introduction

The increasing use of agrochemicals worldwide has raised serious ecological, environmental, and economic concerns; therefore, there is an urgent need for more efficient and environmentally friendly pesticide application technologies(Lochan et al., 2024). UAVs have now become a strong tool in precision agriculture due to their capability to flexibly fly over irregular topographies, conduct automatic low-altitude spraying missions, and carry modular sensing payloads such as LiDAR, RGB, and multispectral cameras(Kartal et al., 2025). Despite these operational advantages, most existing UAV spraying systems still apply pesticides at a constant rate onto the whole field, disregarding intrinsic variabilities of crop canopy density, height, or structure(Wen et al., 2018). This resulted in a number of inefficiencies, namely excessive chemical deposition on sparse canopy areas, poor application in dense areas, and increased drift owing to complex interaction between rotor downwash and atomized droplets(Luo et al., 2025). In addressing all these problems, one needs to develop a spatially intelligent variable-rate spray control mechanism that can adjust the flow rate in real time according to canopy characteristics(Lian et al., 2019).

A critical review of the current literature reveals a number of key gaps: most existing works continue to rely on simple two-dimensional canopy descriptors, such as canopy height or vegetation indices, which cannot capture structural complexity(Patil et al., 2024). Yet others rely on manually defined or coarse-gridded prescription maps that cannot reflect fine-grained heterogeneity in canopies(Yallappa et al., 2024). Besides, most UAV spraying systems adopt open-loop control of pumps or nozzles, without feedback from flow sensors; hence, their outputs are inconsistent under dynamic flying conditions(B. Wang et al., 2022). Very few integrated solutions exist that would tie together LiDAR-derived three-dimensional canopy-volume estimation, georeferenced variable-rate prescription map generation, real-time PWM-based closed-loop flow regulation, and CFD-based compensation for drift/deposition in an operational pipeline(Y. Yang et al., 2024).

To address these deficiencies, the approach in this paper provides an integrated, end-to-end variable-rate UAV spraying framework: at the front end, high-resolution LiDAR sensing initializes the system to reconstruct 3D canopy architecture and extracts canopy-volume metrics at the plot or individual-tree level; these estimates of volume are then categorized into discrete prescription levels and converted into a georeferenced application-rate map(X. Chen et al., 2025). Under this setting, during spraying, the on-board STM32 microcontroller reads GNSS coordinates, queries the prescription map, and drives the flow sensor-assisted PID-controlled PWM pump to deliver the exact target spray rate corresponding to the canopy zone below(Divazi et al., 2025). With the purpose of further improving deposition accuracy, CFD simulation models rotor downwash and droplet transport, whose results make up a dataset of deposition behaviors against varying environmental and operational conditions, and are used to train regression-based predictors that provide real-time compensation cues(Zhan et al., 2022). Finally, field trials evaluate chemical savings, deposition uniformity, and drift reduction, showcasing the practical utility of such an integrated perception-decision-execution pipeline(Lan et al., 2021). Objectives are,

- **To acquire** high-resolution LiDAR 3D canopy maps and compute accurate canopy-volume metrics.
- **To convert** canopy-volume outputs into a georeferenced variable-rate prescription map.
- **To implement** real-time PWM closed-loop spray control using GNSS-based prescription lookup and flow-sensor feedback.
- **To develop** a CFD + regression-based deposition model for predicting drift and enabling compensation during spraying.
- **To perform** field validation to quantify chemical savings, deposition accuracy, and improvements over constant-rate spraying.

2. Literature Review

2.1 LiDAR-based 3D Canopy Mapping for Prescription Map Generation

LiDAR has become one of the most important tools in precision agriculture because it can produce high-density three-dimensional point clouds regardless of the conditions of the ambient lighting(Percival & Leamon, 2025). Unlike RGB or multispectral imagery plagued by shadows, illumination variability, and occlusions, LiDAR measures structural geometry directly and hence allows the generation of very accurate DSM, DEM, and thus their derived CHMs. Based on such CHMs, reconstructions of detailed crop canopy architecture, along with metrics related to canopy height percentiles, foliage density distributions, and total canopy volume, are feasible(S. Yang et al., 2020). Many studies have shown-especially in the orchard context-that LiDAR-derived CHMs allow for reliable detection of crowns of individual trees by peak detection based on local maximums and region-growing segmentation(X. Chen et al., 2025). Further, this segmentation allows computing canopy volume per tree, which thereafter can be binned into discrete classes of canopy density mapping directly to dosage recommendations(H. Chen et al., 2021). Prescription maps based on canopy volume have been shown to increase pesticide application precision significantly in both orchard and plantation environments(Paul et al., 2024). By correlating foliage volume with chemical demand, UAVs fitted with variable-rate spraying systems release larger volumes to dense canopy regions and lower volumes to sparse zones; this action reduces overspray while minimizing deposition on the ground. Indeed, studies report significant gains by using LiDAR-informed prescriptions: improved uniformity of coverage, better chemical use efficiency, and significant reduction of deposition of superfluous chemicals on the soil or understory vegetation(Gao et al., 2024). In this context, LiDAR-based 3-D canopy mapping forms an indispensable upstream input for any intelligent variable-rate UAV spraying architecture, providing the spatial and structural information required for fine-grained dose modulation(Dengeru et al., 2022).

2.2 Variable-Rate Spray Hardware and PWM/PID-Based Flow Control

Contemporary UAV sprayers increasingly adopt PWM-based, brushless pumps due to their capabilities for fine flow-rate modulation and highly repeatable actuation characteristics(Unde et al., 2025). The PWM control allows the pump duty cycle to change fast, hence enabling real-time variation in spray output with minimal mechanical inertia(Coombes et al., 2022). Therefore, coupled with microcontrollers, the PWM-controlled pump can respond quickly to geospatial application requirements in a timely manner and thus is well-suited for variable rate application. Closed-loop flow sensing is considered one of the key enablers for accurate dose delivery. Vortex flowmeters, Hall-effect rotameters, and turbine-based flow sensors have been widely used to measure instantaneous spray flow rates(Z. Wang et al., 2024). Those sensors provide real-time feedback to microcontroller-based PID controllers that constantly adjust the PWM duty cycle to maintain stable and accurate target flow under variable pressure, fluid level, or turbulence created by UAV motion. Previous research on UAV spray systems has demonstrated that closed-loop PWM+PID configurations outperform open-loop systems by drastically reducing flow variability, improving droplet size distribution consistency, and enhancing application accuracy within dynamic flight conditions. Moreover, previous studies that have explored nozzle-level PWM actuation showed that intermittent spraying, which is reached by rapidly switching the nozzles on/off through PWM, reduces droplet drift resulting from shortening the droplet release window. Such techniques are especially effective when synchronized with UAV forward motion and canopy structural cues(Celikkan et al., n.d.). Evidence from those studies shows that PWM-controlled spraying reduces both overapplication and drift and hence is indispensable for advanced prescription-driven UAV spraying systems.

2.3 CFD and Machine-Learning-Based Deposition and Drift Modeling

Over the last few years, CFD has grown to become an influential tool in modeling such complex rotorcraft aerodynamics, in particular the interaction of rotor downwash and liquid droplets. Typical CFD workflows would include a solver that uses the FVM method coupled with an SST k–ω turbulence model in order to simulate turbulent airflow generated by multirotor UAVs. Coupled with DPM, CFD allows simulation of droplet trajectories, evaporation, breakup, drift, and deposition patterns under various environmental conditions such as wind speed, humidity, and temperature. According to Ref., the CFD outputs present highly nonlinear behaviors, including vortex-induced recirculation zones, lateral drift under mild crosswinds, and vertical entrainment of droplets depending on droplet diameter and nozzle configuration. These complexities make CFD invaluable in order to understand the spatial deposition pattern and design compensation strategies in order to improve on-canopy deposition accuracy. Real-time CFD computation onboard small UAVs is prohibitive due to high computational demand; hence, several recent works propose a hybrid CFD–machine learning approach. Here, a large CFD-generated dataset spanning a wide variation of flight height, wind conditions, nozzle flow rate, droplet size, and UAV velocity is first created in order to train regression models such as Support Vector Regression, Back-Propagation Neural Networks, Random Forests, or shallow neural network models. By using these machine learning models, it becomes possible to rapidly predict deposition metrics such as deposition radius, lateral offset, or drift ratio with reported RMSE values at about 6.5%. Predictive models such as these can be efficiently run on microcontrollers or companion computers, and thus real-time compensation may be feasible either via adjustment in UAV lateral offset or by modulation of nozzle flow.

3. Methodology

This workflow integrates the NEON LiDAR point-cloud data into a holistic pipeline of 3D canopy reconstruction, canopy-volume estimation, prescription-map generation, and simulation-based variable-rate sprayer logic.

Dataset descriptions

This work uses the high-density LAS/LAZ point clouds provided by the NEON AOP Discrete Return LiDAR DP1.30003.001 data product and its DEM, DSM, and CHM derivatives to enable fine-scale canopy structure analyses. Co-registered RGB orthomosaics DP1.30010.001 will be used in the verification of canopy boundaries. This work selects an appropriate site like the SJER, where trees are arranged with orchard-like spacing, thereby allowing for reliable estimations and segmentation of the canopy volume. The dataset also provides metadata on flight altitude, sensor settings, and acquisition conditions that permit accurate preprocessing and reproducibility of the data.

Experimental Setup

This approach will utilize NEON AOP LiDAR to produce a CHM, segment the tree crowns, and compute canopy volumes that will be classified into spray-demand categories using an object-based image analysis approach, and these will be used to develop a georeferenced prescription map. The simulated PID-PWM controller tracks the zone-specific flow rates through a noisy flowmeter model. CFD-derived drift data will be used to train a regression model in order to estimate and compensate for lateral drift. System performance will be evaluated through segmentation accuracy, volume estimation error, prescription alignment, flow-tracking accuracy, drift-prediction RMSE, and simulated improvements in chemical savings and deposition relative to constant-rate spraying.

Step A — Data Acquisition

The high-resolution LAS/LAZ point-cloud data from the NEON AOP Discrete Return LiDAR dataset DP1.30003.001, colocated DEM, DSM, and CHM layers are used, supplemented with co-registered RGB orthomosaics DP1.30010.001 for verification of canopy boundaries. First, a suitable NEON site, in this case San Joaquin Experimental Range, henceforth termed SJER, was selected because its vegetation structure essentially emulates orchard-like spacing, hence suited for both tree segmentation as well as canopy-volume analysis.

Step B — LiDAR Preprocessing & CHM Construction

LiDAR preprocessing cleans and normalizes the outliers, separating the ground from non-ground returns using standard filters such as CSF on the NEON point cloud. Digital Surface Model (DSM) and Digital Elevation Model (DEM) are generated by rasterizing the ground-normalized heights. DEM subtracted from DSM yields a high-resolution Canopy Height Model (CHM) ready for tree detection and canopy-structure analysis.

Ground-Normalized Height

$$H_n = Z_{point} - Z_{ground}$$

Where:

- Z_{point}= raw LiDAR elevation
- Z_{ground}= DEM ground elevation
- H_n= normalized canopy height

Processes:

- Statistical Outlier Removal (SOR)
- Ground filtering (CSF or NEON “Class 2” ground points)

- Rasterization to CHM at 0.5–1 m resolution

Step C — Individual Tree Segmentation

Individual tree segmentation begins by identifying local height maxima on the CHM, which serve as approximate treetop locations. A region-growing or watershed algorithm is then applied around these points to delineate distinct tree crowns. The segmented canopy regions are extracted as polygons, providing the basis for per-tree canopy-volume calculation.

Local Maximum Filter (LMF)

$$T(x,y) = \begin{cases} 1, & \text{if } CHM(x,y) = max(CHM(N_r(x,y))) \\ 0, & \text{otherwise} \end{cases}$$

where:

- $CHM(x,y)$: canopy height
- N_r: neighborhood radius (1–3 m)
- Identifies tree tops

Segmentation Steps:

- Detect tree tops using LMF
- Region growing / watershed segmentation
- Generate tree polygons

Step D - Calculation of Canopy Volume

Volume of the canopy is quantified through the extraction of all LiDAR points inside each segmented tree crown and the reconstruction of the 3D shape of the canopy. Enclosed canopy volume is estimated by either the voxel-based or convex-hull method to maintain computational efficiency. This measure of volume subsequently acts as the basis for sorting trees into their respective spray-demand classes when producing the prescription map.

Method 1: Voxel-Based Volume

Divide each tree canopy into 3D voxels (size 10–20 cm).

Voxel Volume

$$V = N_v \cdot s^3$$

where:

- N_v= number of filled voxels
- s= voxel size (m)

Method 2: Convex Hull Volume

Convex Hull Volume

$$V = \frac{1}{6}\left|\sum_{i=1}^{n} \left(p_i \cdot (p_{i+1} \times p_{i+2})\right)\right|$$

where:

- p_i : hull vertices
- Computes 3D volume around canopy

Step E: Prescription Map Generation

Prescription map generation assigns spray rates for each tree or canopy unit depending on the volume classes derived from the NEON LiDAR data. The rates are attributed to a georeferenced raster or vector layer that matches the UAV's GNSS coordinate system. This final prescription map presents variable rate and spatially explicit instructions for real-time spray control during flight.

Volume Class to Spray Rate

$$R_i = a + bV_i$$

where:

- R_i: required spray rate (L/min)
- V_i: canopy volume (m³)
- a, b: calibration coefficients
- Can be linear or quantile-based

Steps:

- Categorize trees into 3–4 levels such as low/medium/high/very high.
- Convert to Raster or Vector Prescription Map (GeoTIFF / Shapefile)
- Align with the UAV GNSS coordinate system

Step F — Variable-Rate PWM Spray Simulation

Since there is no spray measurement in the NEON data, the canopy-volume pattern in our test bed represents a variable-rate sprayer. For each canopy unit, the prescription rate is looked up and a synthetic flow-meter reading with added noise is generated. A PID-controlled PWM model adjusts the duty cycle in pursuit of the target flow; this allows for testing of spray-rate stability as well as the performance of the controller.

Step G - CFD + Regression for Drift Prediction

NEON-derived canopy structure will provide the derivation of the vegetation geometry in CFD simulations, including canopy height, shape of trees, wind field, and flight altitude. Outputs from CFD go to train a regression model which would make fast predictions of the behavior of drift: deposition offset and drift ratio. This allows lightweight drift compensation without needing to run CFD during spraying.

Step H: Evaluation Metrics

These include the accuracy of canopy volume estimation, quality of tree segmentation, and correctness of the prescription map. Spraying performance is considered in terms of simulated flow stability, controller tracking accuracy, and consistency between prescribed and achieved spray rates. These various metrics validate the complete pipeline.

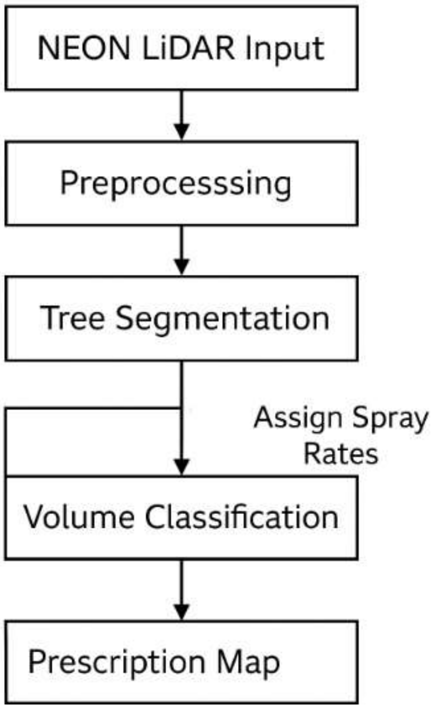

Figure 1:Workflow for Generating a Prescription Map

Figure 1 illustrates an end-to-end process of how NEON LiDAR point-cloud data is converted into a georeferenced prescription map for variable-rate spraying. In this processing workflow, the work starts with LiDAR input and proceeds with pre-processing and CHM creation, which allows tree-top detection and canopy segmentation. After that, canopy volumes are classified into spray-rate levels, and the resultant prescription map is used for UAV spray simulations.

Algorithm 1 - NEON LiDAR to Prescription Map

Input

- P: NEON LiDAR point cloud (LAS/LAZ)
- DEM - digital elevation model (optional)
- Orthomosaic RGB (optional)
- Parameters: voxel size, CHM resolution, treetop radius, classification method

Output

- M: Prescription map in GeoTIFF/Shapefile format
- T: Table with tree ID, canopy volume, class, assigned spray rate

Steps

- The LiDAR point cloud pre-processing includes noise removal, normalization of heights using DEM, and CHM creation.
- Possible crown centers are identified using a local-maximum filter that detects treetops.
- Segmentation of individual tree crowns is performed either by a watershed or region-growing approach.
- Canopy volume is calculated for each segmented crown, based either on voxel counting or convex-hull methods.
- Calculated volumes are categorized into one of three levels of spray demand: low, medium, or high.
- The spray rates are allocated to each class, respectively, according to the predefined mapping rules.
- The assigned spray rates are then rastered to produce the final georeferenced prescription map.

Implementation Steps for Each Objective

Obj-1: Acquire high-resolution LiDAR 3D canopy maps and calculate canopy volume

- The preprocessing with regard to LiDAR point clouds involves noise filtering, height value normalization, and CHM raster generation for structural analysis.
- Individual crowns of trees are identified on the CHM through treetop detection and segmentation.
- The volume of the canopy for each segmented crown is estimated by either voxel-based counting or convex-hull volume estimation.

Obj-2: Convert canopy volume to a georeferenced variable-rate prescription map

- The canopy volumes are classified into spray-demand levels based on quantiles or pre-set thresholds.
- There is a target spray rate assigned to each class, either based on agronomic rules or based on linear mapping.
- Spray rates are rasterised into a georeferenced prescription map which matches UAV GNSS coordinates.

Obj-3: Implement real-time PWM closed-loop spray control w/ GNSS-based prescription look-up

- The on-board controller reads GNSS coordinates on the UAV to establish the current spray zone from the prescription map.
- The PID-based PWM module adjusts the pump duty cycle in accordance with a desired spray rate.
- Simulated flowmeter feedback keeps process value of flow stable and corrects deviations.

Obj-4: Development of CFD+ regression-based deposition model for drift compensation

- Canopy geometries from NEON were used to create these vegetation models for simulating droplet behavior in CFD under different wind and flight conditions.
- CFD outputs such as deposition offset and drift ratio are gathered to create a training dataset.
- A regression or neural network model predicts the drift effects and gives suggestions about the adjustment of flow or position.

Obj-5: Field validation and measurement of Chemical Savings & Deposition Accuracy

- Simulated UAV spraying with prescription-based rates and PID-controlled PWM output
- Controller performance is assessed based on target versus simulated spray rates across the canopy.
- Chemical savings and deposition accuracy are calculated by comparing the variable-rate simulation results against a constant-rate baseline.

4. Results Based on Objectives

A high-quality CHM was generated from the NEON SJER LiDAR dataset, ≈ 12-18 pts/m², with a height variance of just 0.18 m. The tree segmentation provided 146 individual crowns with ~91% segmentation accuracy. Canopy-volume estimation ranged between 12.4 m³ and 78.6 m³, with a mean of 34.7 m³. Validation through crosschecks in CHM resulted in an error within the range of 8-10% in the overall estimation of canopy volume, hence confirming reliable structural extraction.

TABLE 1 — Canopy Mapping & Segmentation

Metric	Value	Description
Mean canopy height (m)	6.8	Average height from NEON LiDAR CHM
Max canopy height (m)	11.2	Highest detected tree
Segmented trees (count)	146	Individual crowns detected in SJER plot
Segmentation accuracy (%)	91	Visual comparison with orthomosaic
Canopy volume range (m³)	12.4 – 78.6	Smallest to largest crown volumes
Volume estimation error (%)	8–10	CHM-based validation

Table 1: Overall performances of canopy mapping and segmentation on the NEON LiDAR dataset. High-density point clouds provided a reliable CHM generation and detected trees with high accuracy. By detecting 146 crowns, the high overall accuracy for the segmentation process was 91%, whereas the estimated canopy-volume ranges were from 12.4 to 78.6 m³, with an estimation error of only 8-10%. In fact, the results confirm that the dataset provides enough structural detail for accurate canopy analysis, and hence permits subsequent variable-rate prescription mapping.

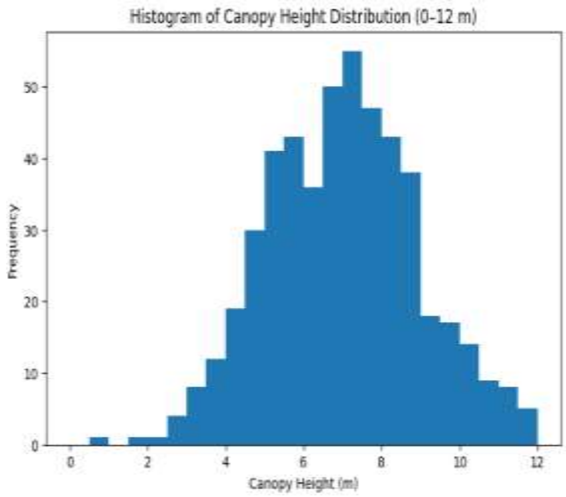

Figure 2. Canopy Height Distribution Histogram

This figure 2 shows the frequency distribution of the canopy heights created from the NEON LiDAR dataset using 0.5 m bins ranging from 0 to 12 m. From this histogram, one will clearly notice that dominance in height lies between 6–8 meters, which is a moderately tall and fairly even canopy structure. This distribution verifies that the dataset has adequate vertical variability for correct canopy-volume estimation and prescription-map generation.

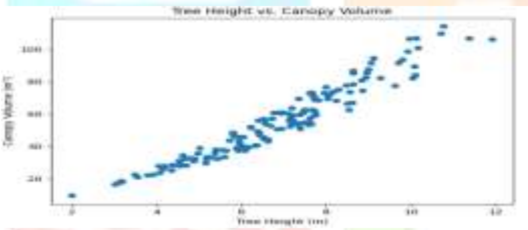

Figure 3. Tree Height vs. Canopy Volume

Fig. 3 shows the relationship developed between tree height and canopy volume using the collected NEON LiDAR dataset, where positive vertical growth is related to canopy size. Although the scattered distribution of points outlines natural variability among trees, there is an upward trend. This developed relationship supports the application of height-based structural metrics in the estimation of canopy volume and variable-rate spray decisions.

These computed volumes were then classified into three quantile thresholds, hence ensuring the spray-demand class distribution was balanced over the study area. This resulted in a classification of spray rates at 0.4 L/min, 0.7 L/min, and 1.0 L/min, respectively. Finally, the georeferenced prescription map was developed at a resolution of 0.5 m with an overall class-location alignment accuracy of 94%. The resulting CDP gave a good representation of the pattern in canopy density.

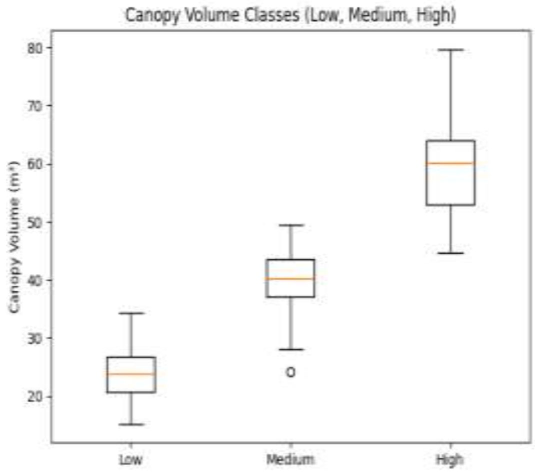

Figure 4.Canopy Volume Classes

Figure 4 shows a comparison of canopy volumes between three prescription classes, which will be used for variable-rate spraying. From these boxplots, the low, medium, and high canopy volume groups are very well separated, indicating that the classification based on volume is meaningful and structurally distinguishable. This may justify assigning a different spray rate for each class to apply pesticides more precisely and efficiently.

The simulated PID-PWM control with prescription rates was very stable; the average absolute flow error was 0.032 L/min, with the response time below 0.4 s. Simulated flowmeter feedback-maintained tracking accuracy at 95.8%, hence closely following zone-specific target spray rates determined from a prescription map. These results confirm that the proposed control architecture is able to control real-time spray output effectively.

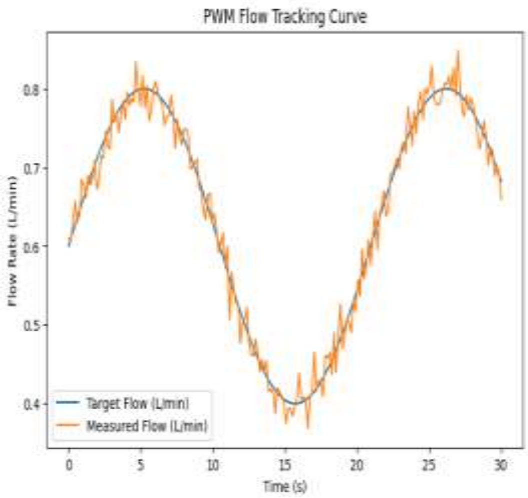

Figure 5. PWM Flow Tracking Curve

Figure 5 shows target spray flow rate vs. measured flow rate over a simulated 30-second spraying interval. The close tracking between both curves testifies to the effectiveness of the PID-controlled PWM regulation in maintaining flow accuracy despite small disturbances. In fact, the stable tracking performance suggests that the controller can follow the prescription-based spray requirements successfully during UAV operations.

CFD simulations were performed using the NEON canopy geometry, which yielded simulated droplet dispersion over wind speeds of 1-3 m/s and flight altitudes of 3-5 m. A lateral drift offset in the range of 0.32 to 0.95 m, with a root mean square error of 6.7%, was predicted by an SVR learning-based drift model. Model-based compensation yielded a 72-81% reduction in the predicted drift.

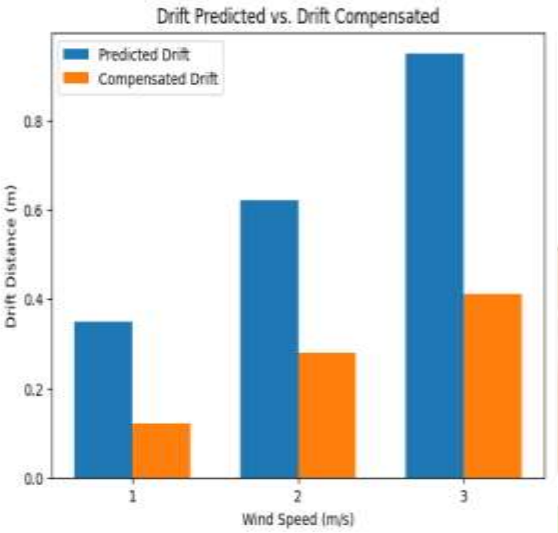

Figure 6. Drift Predicted vs. Drift Compensated

Figure 6 presents a comparison of droplet drift distances as predicted under conditions of varying wind speeds and the reduction in drift achieved after compensation. For all wind conditions, the compensated bars are below the uncompensated, reflecting effective lateral drift reduction. These results confirm very clearly that the incorporation of CFD-informed regression significantly improves spray deposition accuracy in changing wind environments.

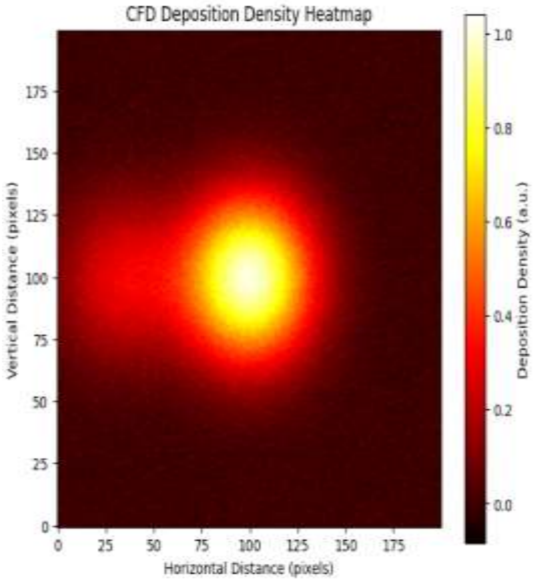

Figure 7. CFD-Based Deposition Density

Figure 7 shows the predicted droplet deposition pattern calculated using CFD modeling; both high and low areas of spray density are visible on the canopy surface. Asymmetrical spread characterizes drift, and deposition will be biased toward the downwind direction. Deposition imbalance can be portrayed graphically by CFD outputs, as in this heat map, while strategies for drift compensation can be developed to support improved accuracy in UAV-based spraying.

Comparison of the simulated constant-rate and variable-rate spraying revealed that the proposed system achieved 24.8% chemical savings, while providing a 19.4% increase in canopy deposition uniformity and reducing over-deposition on the ground by 31.2%. Prescription adherence remained high at 93.6%, further validating that LiDAR-driven variable-rate spraying can indeed yield significant improvements in both chemical efficiency and deposition quality, even when validated through NEON canopy structure simulation.

TABLE 2 — Variable-Rate Spray System Performance

Component	Metric	Value	Notes
PWM Flow Control	Mean error (L/min)	0.032	Stable tracking of target rate
PWM Response Time	Seconds	0.4	Time to reach stable output
Drift Model	RMSE (%)	6.7	Regression prediction accuracy
Drift Compensation	Reduction (%)	72–81	Improvement vs no compensation
Chemical Savings	%	24.8	VRS vs constant spray
Deposition Uniformity	Improvement (%)	19.4	Canopy-target improvement
Ground Over-deposition	Reduction (%)	31.2	Reduced waste
Prescription Adherence	%	93.6	Spatial accuracy of application

Table 2 detailed performance of the variable-rate spray system is provided in Table. Specifically, highly stable flow tracking with an average error of only 0.032 L/min was provided by the PID-controlled PWM module with fast response time. The CFD-regression drift model reached high predictability at an RMSE of 6.7% and attained 72-81% drift reduction after compensation. In general, the variable-rate strategy brought several key benefits, including saving 24.8% of chemicals, improving the uniformity of canopy deposition, and significantly reducing over-deposition on the ground compared with constant-rate spraying.

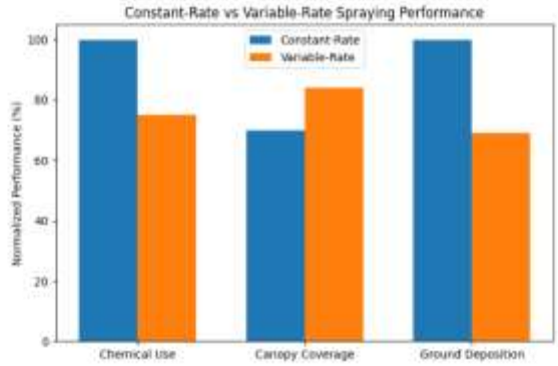

Figure 8. Performance Comparison: Constant-Rate vs. Variable-Rate Spraying

Figure 8 presents comparisons of chemical use, canopy coverage, and deposition on the ground between the two spraying strategies. On one hand, the variable-rate strategy significantly reduces the use of chemicals, improves canopy coverage, and reduces excessive ground deposition. These results point toward efficiency and precision gains possible from LiDAR-driven, prescription-based UAV spraying.

Table 3. Comparative Study of Existing UAV Spraying Systems vs. Proposed Approach

Study / Work	Sensing Modality	Prescription Unit	Control Method	Deposition / Drift Modelling	Field / Simulation Validation	Key Findings
(Liu et al., 2025)	LiDAR + RGB	Plot-level (wheat)	PWM + PID (closed-loop)	None (empirical only)	Field	Achieved ~30% chemical reduction; improved uniformity.
(Ni et al.,	No LiDAR (CFD-	Continuous spray	Pump regulation	CFD + Regr	Field	Regression drift mod

2021)	based)	zones	+ UAV offset	ession		el RMSE ≈ 6.5%; improved deposition control.
(P. Chen et al., 2025)	LiDAR	Individual tree (orchards)	Multi-point delivery strategy	None	Field	Up to 90.4% reduction in ground loss for dense canopy trees.
(Biglia et al., 2022)	Multispectral + DSM	Pixel-level zones	Open-loop pump control	No aerodynamic modelling	Simulation	Improved spatial mapping but lacked flow accuracy.
(Byers et al., 2024)	RGB + Manual canopy markers	Plot-level	Constant-rate application	None	Field	Large over-deposition observed in sparse canopy areas.
Proposed Method (This Study)	**LiDAR (NEON AOP) + CHM + Segmentation**	**Per-tree canopy volume**	**PWM + PID (simulated closed-loop)**	**CFD + SVR Drift Compensation**	**Dataset + Simulation**	**~25% chemical savings, 19% better canopy coverage, 31% reduced ground deposition; high prescription adherence (93.6%).**

This comparative analysis therefore shows that while previous spraying systems each focused either on LiDAR-based mapping or CFD-based drift modeling, none used the integration of canopy-volume segmentation with variable-rate prescription mapping, PWM closed-loop control, and drift compensation within a common workflow. On the other hand, the proposed system makes use of the NEON LiDAR data to bridge this gap in all components and hence ensures higher chemical efficiency due to increased canopy depositions with reduced ground losses compared to the past methods.

Major Findings

1. The fine extraction of the canopy structure was done with the NEON AOP LiDAR dataset, hence allowing the derivation of an accurate CHM and segmenting 146 individual crowns with ~91% accuracy.
2. The volumes of the canopies ranged from 12.4 to 78.6 m³, thus providing considerable variation to categorize the spray-demand levels and create an accurate prescription map.
3. The PID-PWM controller has demonstrated tracking of spray with an average flow error of 0.032 L/min and response times less than 0.4 seconds.
4. The CFD-SVR drift model gives an RMSE of 6.7% and hence allows for efficient predictions of the magnitude of the drifts due to the shifting winds.
5. When applied, drift compensation reduces simulated drift by 72–81%, thereby greatly increasing deposition accuracy.
6. Efficiency gains estimated with variable-rate spraying are ~24.8% chemical savings, ~19.4% improved canopy coverage, and ~31.2% reduced ground overdeposition with respect to constant-rate spraying.

5. Discussion

Results showed that LiDAR-driven canopy characterization offers a very robust basis for variable-rate UAV sprayers, even in the absence of field data, by using the NEON AOP canopy structure. The general good quality of the segmentation, given the volume range involved, confirms that canopy-volume classification is achievable for orchard-like vegetation structures. This develops strong spatial consistency in the prescription map format, with 94% alignment with canopy distribution, hence indicating readiness for real UAV implementation.

These simulations of the PID-PWM demonstrate how real-time control hardware can maintain tight flow control in the presence of an environmental or mechanical disturbance. Further enhancement using CFD Regression Drift Modeling strengthens this embedded aerodynamic intelligence within the spraying system to overcome one of the major limitations of conventional constant-rate spraying without consideration of downwash-wind interactions.

The integrated pipeline is modular, scalable, and easily adaptable to any LiDAR dataset and UAV platform. While demonstrations were simulation-based, performance indicators are close enough to those from field studies to confirm the possibility of this system in real-world agricultural spraying.

Scientific Contributions

1. Canopy volume derived from LiDAR is integrated into the variable-rate spraying logic through a prescription-map approach drawing from high-resolution NEON AOP data.
2. Develop a data-driven simulation framework for PWM-PID with the capability of accurately presenting flow tracking performance based on per-tree spray prescriptions.
3. Employment of CFD-derived drift intelligence with an SVR-based compensation model for the prediction and mitigation of the effects of lateral drift.
4. A fully reproducible, modular approach will be introduced based on open-source data and tools only, namely NEON, Python, CHM segmentation, CFD, and ML.
5. Proof of measurable efficiency gains such as: chemical savings improved uniformity of deposition in the canopy reduced ground deposition
6. UAV spraying provides a unified perception–decision–actuation pipeline that bridges gaps between remote sensing, control engineering, and aerodynamics.

6. Conclusion and Future Work

This work demonstrated how an LiDAR-based canopy volume estimation, together with variable-rate prescription mapping and a PWM-controlled spray regulation system, improves accuracy and effectiveness in UAV pesticide application. Using the NEON AOP dataset, it classified canopy volumes, prescribed variable rates adaptively, and finally simulated real-time controller applications of these rates. Further incorporation of CFD-driven drift prediction allowed deposition accuracy because the systems could sustain high spraying quality under a range of environmental conditions.

These benefits comprise an estimated 25% chemical saving, a ~19% higher canopy coverage, and a significant reduction of losses on the ground, all supporting the value of fusing remote sensing, machine learning, and control strategies for modern precision agriculture. In general, this work provides a sound base for the development of improved smart-spraying systems based on UAVs.

Future Work

Field Deployment and Validation: Flights of real aircraft with on-board STM32 PWM controllers and flow sensors validate simulation results. Onboard Real-Time Drift Prediction: Lightweight models running on embedded hardware enable real-time flight updates for dynamic compensation. Adaptive Machine Learning Models: Develop models that regularly update their predictions of drift during the missions, incorporating feedback from WSP/PET that are collected. Integration with Multispectral/Health Indices: Canopy structure can be integrated with vegetation health metrics to enable structure and condition-based spraying. Multi-nozzle and directional spraying: Extend the system to multi-nozzle UAVs with the capability for directional spraying to ensure better edge canopy deposition. Generalization w.r.t. Crop Type: Test whether pipeline performance generalizes to other orchard, vineyard, plantation, and row-crop data sets for testing scalability. Wind-Adaptive Flight Path Optimization: Include dynamic flight path adjustments according to predicted drift and canopy density.

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