

Review

Advances in Drift Mitigation and Integrated Precision Spraying Technologies

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Abstract

Agricultural spraying has evolved from conventional passive drift mitigation toward active, intelligent precision management. This review synthesizes advancements in agricultural precision spraying, evaluating both established passive drift-reduction techniques and emerging active application systems. The analysis emphasizes three core technological pillars: multi-sensor target perception, real-time variable-rate decision modeling, and high-frequency actuation mechanisms. The findings indicate that integrating these distinct mechanisms into a unified “perception–decision–execution” architecture offers a means of balancing the trade-off between drift reduction and canopy coverage. By transitioning from broadcast applications to targeted delivery, this synergistic approach may contribute to improving pesticide utilization, minimizing off-target environmental contamination, and enhancing the biological efficacy of crop protection. Overall, this technical progression may facilitate the translation of precision spraying technologies from controlled laboratory validation to broader field implementation.

Keywords: precision spraying; drift control; variable-rate application; sensor fusion; PWM control; multi-technology synergy

1. Introduction

A substantial fraction of applied pesticide volume is lost during transit. These losses contribute to soil and aquatic contamination. For sensitive crops, off-target herbicide exposure may result in significant yield losses. Spraying technology has followed a distinct evolutionary trajectory, shifting from passive drift suppression to active precision delivery.

Mechanistically, spray drift is categorized into two distinct forms: particle drift and vapor drift [1]. Particle drift involves the physical displacement of droplets away from the target area driven by wind currents, a trajectory governed by the complex interplay of droplet evaporation, gravitational sedimentation, and turbulent diffusion [2,3]. Conversely, vapor drift occurs when pesticide molecules volatilize and subsequently migrate through the gaseous phase [4,5]. Droplets smaller than 100 µm in diameter often contribute disproportionately to off-target drift. Among the variables affecting spray drift, droplet size is considered a major influencing factor [6,7]. Moreover, when ambient wind speeds exceed 5 m/s, the drift propensity of droplets under 200 µm increases substantially [8]. Ultimately, spray drift is rarely driven by an isolated variable. Rather, it manifests from the intricate coupling of environmental conditions (e.g., wind velocity and direction, temperature, and



Academic Editor: José Miguel Molina Martínez

Received: 30 June 2026

Revised: 16 July 2026

Accepted: 20 July 2026

Published: 24 July 2026

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relative humidity), equipment parameters (nozzle architecture, operating pressure, and boom height), and the physicochemical properties of the spray solution (such as surface tension, viscosity, and emulsion structure) [9–11].

Spraying technology has followed a distinct evolutionary trajectory over the past few decades, with the core research objective gradually shifting from passive drift suppression to active precision delivery, as documented in multiple comprehensive reviews [12,13].

Early research predominantly focused on mitigating drift risks by coarsening droplet size spectra, a strategy rooted in the well-established correlation between droplet diameter and off-target displacement [14]. To underpin these investigations, standardized droplet characterization methodologies—including laser diffraction, phase Doppler particle analysis (PDPA), shadowgraph, and liquid immersion techniques—have been systematically validated and compared, establishing a unified measurement framework for nozzle performance evaluation [15]. Air-induction nozzles exemplify this passive mitigation approach, and their internal Venturi air-entrainment mechanism and resulting droplet size distributions have been extensively characterized across laboratory and bench-scale test platforms [16–18]. Subsequent studies have further extended performance validation to emerging application scenarios, quantifying drift potential and coverage uniformity of air-induction nozzles when mounted on agricultural drones, revealing distinct aerodynamic behaviors compared to ground-based boom sprayers [19,20]. Other passive mitigation strategies, such as shielded boom configurations and anti-drift curtain devices tailored for strip intercropping systems, have also been developed and validated, offering complementary drift reduction effects alongside nozzle optimization [21]. Design factors such as Venturi geometry, orifice area, and operating pressure have been demonstrated to exert pronounced effects on both droplet size spectra and drift reduction efficacy, providing a theoretical basis for targeted nozzle structural optimization [22].

However, although coarse droplets generated by air-induction nozzles can reduce drift risk, they may also reduce canopy penetration and abaxial leaf coverage under certain canopy and operating conditions [23,24]. This fundamental trade-off between drift reduction and target coverage is further amplified when adjuvants are incorporated: although polymeric and oil-based adjuvants can modulate atomization dynamics and droplet deposition behavior on leaf surfaces, their efficacy is highly contingent on formulation compatibility, shear degradation resistance, and field operating conditions [25,26].

The limitations of standalone passive technologies contributed to a gradual shift in research emphasis from drift prevention toward more targeted liquid delivery. Driven by advances in sensing and automatic control technologies, novel precision application modalities—including electrostatic spraying, whose charge formation modes and droplet charging mechanisms have been systematically classified in established theoretical frameworks [27,28], real-time orchard variable-rate sprayers, and UAV-based targeted spraying systems—have been investigated as alternatives to conventional broadcast application [29,30]. PWM variable-rate nozzles have been characterized in terms of droplet size distribution, velocity, spray angle, and flow rate under a range of duty-cycle and adjuvant conditions [31–33]. Consequently, spray application is increasingly considered a systems engineering problem involving target perception, dynamic decision-making, and precision actuation.

Reliable drift evaluation provides an important basis for technological optimization, regulatory assessment, and verification of the biological efficacy and deposition consistency of emerging application systems [34]. Field trials accurately capture drift behavior under real-world operational conditions, enabling simultaneous measurement of canopy deposition, off-target ground loss, and airborne drift across full crop phenological stages; however, they are heavily constrained by limited controllability over meteorological condi-

tions, high labor and material costs, and poor experimental repeatability [35]. Wind tunnel testing provides a widely used standardized platform for comparing nozzle types, adjuvant formulations, and drift-reduction devices under controlled environmental conditions. Nevertheless, it struggles to fully replicate the intricacies of field turbulence structures and dynamic canopy interactions, limiting its ability to predict actual field performance directly.

Alternatively, CFD simulations have become widely used in agricultural spray research because they provide detailed flow-field information under controlled numerical conditions [36–38]. CFD methods have been applied to a wide spectrum of scenarios, including optimizing the aerodynamic performance of mechanical spray shields, modeling internal flow fields of irrigation and spray components, designing air-assisted and air-curtain spray systems, and optimizing agricultural machinery structures through fluid–solid coupling analysis [39–42]. For instance, the two-stage CFD model developed by Cui et al. (2024) achieved a coefficient of determination of 0.8684 between predicted and measured airflow velocities, alongside a normalized mean absolute error of 17.2%, indicating a moderate agreement between the predicted and measured airflow velocities under the evaluated conditions [43]. Beyond drift assessment, CFD has also been leveraged to guide structural optimization of variable-rate spray equipment and orchard-specific application systems, bridging the gap between fundamental mechanism research and engineering implementation.

Several studies support the complementary roles of these three methodologies: wind tunnels provide standardized comparative data, field trials evaluate performance under practical operating conditions, and CFD simulations help interpret the underlying flow mechanisms [44,45]. Combining these approaches may improve the reliability and comprehensiveness of performance evaluation and facilitate the iterative development of precision spraying technologies.

This review systematically maps the evolutionary trajectory of agricultural precision spraying technologies from “passive mitigation” to “active precision.” Section 2 synthesizes passive drift reduction techniques. Section 3 shifts the focus toward active precision spraying technologies. Section 4 explores multi-technology synergy and system integration. Finally, Section 5 projects future developments, highlighting intelligent upgrades, platform diversification, and addressing existing technical constraints.

Although several reviews have summarized developments in agricultural spraying platforms and drift-mitigation technologies, a synthesis gap remains regarding the mechanical integration and operational interactions between passive and active approaches. Previous reviews have often discussed passive interventions and active precision configurations in separate sections or analytical frameworks.

Compared with previous general reviews, this review makes three main contributions. First, it examines the interactions and operational boundaries between passive drift mitigation and active precision spraying within a unified “perception–decision–execution” framework. Second, it discusses the fluidic and aerodynamic interactions arising from combinations of complementary technologies, including physical shielding with low-drift nozzles and air assistance with electrostatic charging. Third, it evaluates practical engineering constraints, including pipeline pressure oscillations associated with PWM switching, spatiotemporal misalignment between sensors and actuators, and the sensitivity of machine-vision models to variations in natural illumination.

To ensure methodological transparency, this review adopted a semi-systematic literature review approach rather than a fully systematic review framework. Literature searches were conducted on 15 June 2026, using the Web of Science Core Collection, Scopus and Google Scholar, covering studies published primarily between 2000 and 2026. The search strategy was developed using the following Boolean expression: (“precision spraying”

OR “variable-rate application”) AND (“spray drift” OR “drift mitigation”) AND (“sensor fusion” OR “LiDAR” OR “PWM control”).

The retrieved studies were screened through a multi-stage selection process, including title and abstract screening, full-text evaluation, and relevance assessment. Studies were excluded when they lacked quantitative experimental validation, were outside the scope of precision spraying technologies, or were not peer-reviewed publications. A total of 285 records were identified. After 70 duplicates were removed, 215 records underwent title and abstract screening. Of these, 98 were excluded, leaving 117 articles for full-text assessment. Following the exclusion of 56 articles, 61 studies were included in the core technical synthesis.

A PRISMA-style flow diagram (Figure 1) is provided to summarize the identification and selection process. It should be noted that the 61 core studies were selected for the structured comparative synthesis, while additional references cited throughout the manuscript were used to provide theoretical background, historical development, and complementary explanations of specific technologies. Several foundational studies published before 2000 were retained only as contextual references because of their significant contributions to the underlying principles of spraying technology.

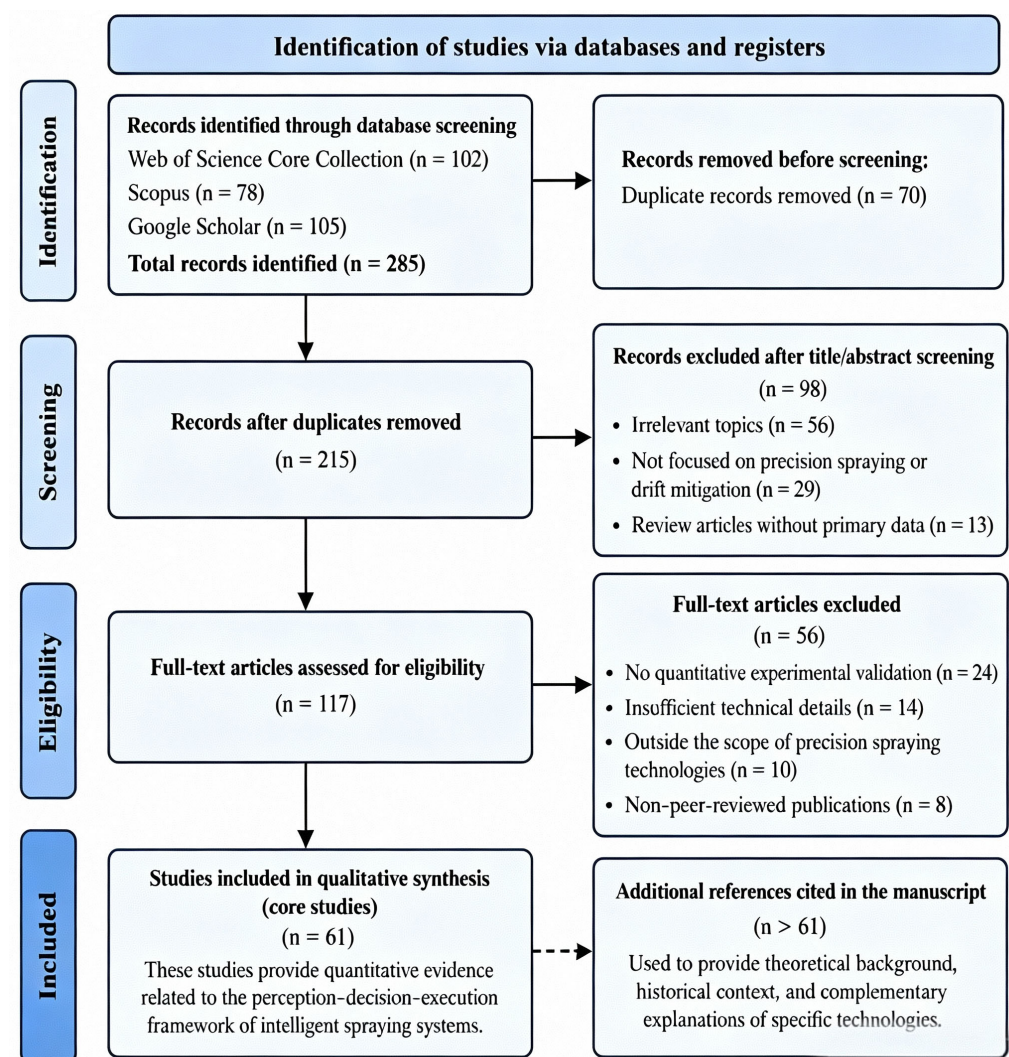


Figure 1. Literature identification and selection process adapted from the PRISMA framework.

2. Passive Drift Mitigation Technologies

2.1. Droplet Size Regulation: Design Principles and Performance Trade-Offs of Low-Drift Nozzles

Droplet size distribution is one of the main factors influencing spray drift because droplet diameter affects aerodynamic behavior, settling velocity, and atmospheric residence time [46]. Wind-tunnel experiments and field studies have consistently shown that changes in droplet size distribution are associated with variations in off-target losses [47,48]. Droplets smaller than 100 μm are frequently identified as major contributors to spray drift. Accordingly, some studies have proposed 200 μm as a practical threshold for evaluating drift-prone droplets, with droplets below this size accounting for more than 70% of the total drift mass under specific field conditions [49,50]. Further analyses have reported a significant negative correlation between the driftable spray fraction and volume median diameter, although the strength of this relationship may vary with crop canopy characteristics and meteorological conditions [51,52]. When wind speed exceeds 5 m/s, droplets smaller than 200 μm generally exhibit greater drift potential than coarser droplets [53]. Wind speed is therefore an important meteorological factor affecting the influence of droplet size on drift. At wind speeds below 3 m/s, the effect of droplet size may be relatively limited, whereas at speeds above 5 m/s, enhanced turbulent transport can substantially increase the horizontal displacement of fine droplets [54]. Temperature and relative humidity can further modify droplet diameter through evaporation. Under low-humidity conditions, fine droplets may continue to decrease in size during transport, thereby increasing their susceptibility to drift [55,56]. Consequently, coarsening the droplet spectrum through nozzle design has become a widely used approach to passive drift mitigation. Compared with post-atomization measures such as adjuvant application and physical shielding, nozzle optimization can reduce the formation of fine droplets during the initial atomization process. Its relatively low cost, operational simplicity, and compatibility with existing spraying equipment have contributed to its broad application in plant-protection spraying systems.

Air-induction nozzles incorporate an internal Venturi restriction to entrain ambient air into the liquid stream. As a representative type of low-drift nozzle, their atomization and drift-reduction mechanisms have been investigated using numerical simulations, flow-field measurements, and high-speed imaging [57,58]. Venturi geometry—including the contraction angle, throat diameter, diffuser length, and outlet-orifice dimensions—can influence the local pressure distribution, air-entrainment rate, and resulting spray characteristics, and is therefore an important consideration in nozzle design. As the pressurized liquid passes through the Venturi throat, its velocity increases while the local static pressure decreases. When the pressure falls below atmospheric pressure, ambient air is drawn into the liquid through lateral inlets, forming a gas–liquid two-phase flow [59]. High-speed imaging studies have shown that the entrained-air volume may initially increase and subsequently decrease with increasing operating pressure, with the response also depending on orifice size.

The entrained air is dispersed within the liquid stream as microbubbles, which modifies liquid-sheet and ligament breakup relative to conventional hydraulic nozzles. Bubble expansion and gas–liquid interactions can promote the formation of larger droplets containing internal air inclusions. Under the evaluated conditions, this atomization behavior is generally associated with an increase in volume median diameter and a reduction in the proportion of droplets smaller than 100 μm , thereby lowering the fraction of droplets that are particularly susceptible to drift. Previous studies have generally shown that air-induction nozzles produce coarser droplet spectra than conventional flat-fan nozzles [57]. Comparative evaluations of different nozzle types have similarly indicated that, under comparable operating-pressure and nominal-flow-rate conditions, air-induction nozzles tend to increase the volume median diameter and reduce the proportion of fine droplets

susceptible to drift. However, the magnitude of these effects varies with nozzle geometry, operating pressure, formulation properties, and measurement conditions.

In an orchard study, Derksen et al. (2007) compared three nozzle configurations: a fine-spectrum D3-25 disc-core nozzle ($Dv_{50} = 125\text{--}155\text{ }\mu\text{m}$), a medium-spectrum D4-25 disc-core nozzle ($Dv_{50} = 210\text{--}225\text{ }\mu\text{m}$), and a TD02 air-induction nozzle ($Dv_{50} = 253\text{ }\mu\text{m}$) [60]. The experiment was conducted in a mature apple orchard using ground polyester-line collectors and high-volume airborne samplers to quantify ground deposition and airborne drift at several downwind distances. The sampling procedure was based on standardized field drift-test methods. Ground deposition associated with the TD02 nozzle was significantly lower than that of the D4-25 nozzle over the 8–32 m sampling range. At distances of 8, 16, and 32 m, ground drift deposition from the TD02 nozzle was reduced by 67.8%, 85.5%, and 92.4%, respectively, relative to the D4-25 nozzle, with the differences reported as statistically significant ($p < 0.05$). These results indicate that the coarser droplet spectrum generated by the TD02 nozzle was associated with lower near-field drift under the tested orchard conditions.

Droplet settling behavior depends on the balance between gravitational force and aerodynamic drag. An increase in Dv_{50} generally favors a higher settling velocity and a shorter atmospheric residence time. For air-filled droplets, however, this effect may be partly moderated by their lower effective density relative to droplets composed entirely of liquid [61]. Therefore, the reduced atmospheric residence time observed for air-induction sprays is more appropriately interpreted as the combined result of increased droplet size and altered droplet density, rather than as a consequence of air entrainment alone.

The mechanisms underlying drift reduction by air-induction (AI) nozzles remain an active area of investigation, particularly with respect to the relative contributions of air entrainment and nozzle geometry. Early studies commonly associated drift reduction with the formation of air-filled droplets. However, comparative experiments by Guler et al. (2007) showed that sealing the air inlets did not produce statistically significant changes in spray characteristics when AI nozzles with comparable exit-orifice areas were evaluated [62]. These results indicate that exit-orifice geometry may have a substantial influence on droplet formation by reducing liquid exit velocity and promoting the production of coarser droplets. Air entrainment may provide an additional contribution by modifying droplet internal structure and aerodynamic properties. Such changes could affect droplet deformation, fragmentation, and retention following canopy impact, although their direct contribution to airborne drift reduction has not yet been fully resolved.

Derksen et al. (2007) reported adaxial leaf coverages of 59% and 56% for the D3-25 nozzle at canopy heights of 2.0 and 3.0 m, respectively, compared with 54% and 49% for the TD02 air-induction nozzle [60]. Although adaxial coverage was numerically higher with the D3-25 nozzle, the differences between the two nozzle types were not statistically significant at either canopy height. In contrast, abaxial coverage was significantly greater with the D3-25 nozzle, reaching 13% compared with 6% at 2.0 m and 18% compared with 9% at 3.0 m. Relative to the D3-25 nozzle, the TD02 nozzle was therefore associated with reductions in abaxial coverage of 53.8% and 50.0% at canopy heights of 2.0 and 3.0 m, respectively. These results indicate a potential trade-off between drift mitigation and deposition on the abaxial leaf surface. The agronomic relevance of this trade-off depends on the location and biological characteristics of the target organism, particularly when pests or pathogens are concentrated on the underside of leaves. Table 1 provides a detailed comparison of droplet-size characteristics and drift-deposition profiles for the three nozzle configurations.

Table 1. Comparison of droplet size and drift deposition among the three evaluated nozzles.

Nozzle Type	D _{v50} (μm)	Leaf Surface Covered (2.0 m/3.0 m)	Covered on the Back of the Leaf (2.0 m/3.0 m)	Airborne Drift Deposition at 8 m (Relative Value)
D3-25	125–155	59%/56%	13%/18%	—
D4-25	210–225	57%/47%	10%/10%	Approximately threefold that of TD02 at most sampled elevations
TD02	253	54%/49%	6%/9%	1 (Baseline)

Doruchowski et al. (2017) conducted a four-year field study in an apple orchard to compare the biological efficacy of coarse-spectrum air-induction (AI) nozzles with that of conventional fine-spectrum hollow-cone nozzles at application volumes of 250, 500, and 750 L/ha [57]. Under relatively low disease pressure, the two nozzle configurations provided comparable control of apple scab. Under the higher infection pressure observed in 2010 and 2013, however, the fine-spectrum spray provided better control of powdery mildew than the coarse-spectrum AI spray. For exposed foliar pests, including aphids and spider mites, no statistically significant differences were detected between nozzle types across the evaluated application volumes. In contrast, effective control of concealed pests, such as the apple blossom weevil, and wax-protected species, such as the woolly apple aphid, was achieved only at the highest application volume of 750 L/ha, which produced near-runoff canopy coverage.

These results indicate that nozzle selection should be adapted to the biological target and application conditions rather than based on a single performance criterion. The suitability of coarse-droplet drift-mitigation strategies depend on several interacting factors, including the location and biological characteristics of the target organism, disease or pest pressure, canopy structure, application volume, and the mode of action of the agrochemical, particularly whether it is contact or systemic.

A comparison of drift-reduction approaches applied during atomization further illustrates the balance between limiting off-target movement and maintaining target deposition. AI nozzles may reduce near-field drift by producing coarser droplet spectra and decreasing the proportion of drift-prone fine droplets. Their relatively simple mechanical structures also allow them to be incorporated into conventional boom-sprayer systems with limited modification. However, the production of coarser droplets may alter deposition patterns. Under the reported experimental conditions, AI nozzles were associated with reductions of approximately 50.0–53.8% in abaxial leaf coverage relative to conventional fine-spectrum nozzles.

Polymeric and other chemical adjuvants provide an alternative means of modifying spray formation by altering properties such as dynamic surface tension and extensional viscosity without requiring changes to nozzle geometry. These additives may improve droplet-size distribution and foliar spreading at relatively moderate operational cost. Their performance, however, can depend on formulation composition, operating conditions, and mechanical stability. In particular, some long-chain polymers may undergo shear degradation during continuous pumping and tank recirculation, reducing their rheological effect over time. Consequently, adjuvant-based drift mitigation may exhibit greater variability during operation than nozzle-based structural modification.

2.2. Physicochemical Property Regulation: Adjuvant and Formulation Engineering

While nozzle design establishes the initial droplet size distribution, the physicochemical properties of the spray liquid also influence the atomization process. Hilz and Vermeer (2013) identified shear viscosity, extensional viscosity, dynamic surface tension,

and structural heterogeneity within spray formulations as important factors affecting spray formation [63]. Among these properties, rheological modification through the use of adjuvants has received considerable attention because it allows droplet breakup to be adjusted without requiring changes to the spraying hardware.

Polymeric adjuvants are widely investigated as drift-reduction additives [64]. Their effects, however, cannot be explained solely by changes in shear viscosity. Many agricultural polymers exhibit shear-thinning behavior, whereby their apparent viscosity decreases under the high shear rates encountered within spray nozzles [65]. Extensional viscosity may therefore play a more prominent role during liquid-sheet stretching and ligament breakup. During extension, polymer chains generate elastic stresses that can delay fragmentation and favor the formation of larger droplets. The extent of this effect depends on factors such as polymer molecular weight, chain rigidity, and concentration, which influence the onset and magnitude of extensional thickening.

Despite their potential to reduce drift, the field performance of polymer-based adjuvants can be affected by several practical constraints. Polymer molecules may undergo mechanical degradation during pumping, recirculation, and delivery, which can reduce their rheological effectiveness relative to that observed under laboratory conditions. In addition, adjuvant performance depends on interactions with pesticide formulations and operating parameters. Active ingredients and formulation components, including emulsifiers and dispersants, may alter the physicochemical properties of the spray liquid and thereby influence droplet formation, deposition behavior, and biological efficacy [66]. Consequently, results obtained for a specific spray mixture may not be directly transferable to other pesticide formulations or application conditions.

The evaluation of adjuvants should therefore extend beyond changes in droplet size distribution alone. Modifications to the droplet spectrum may also affect canopy penetration, retention, spreading, and target coverage. Future research could focus on developing predictive relationships among formulation properties, atomization behavior, and field performance. Integrating physicochemical characterization with spray measurements and field validation may support the more reliable incorporation of adjuvant technologies into precision spraying systems.

2.3. Physical Shielding and Air Assistance

While nozzle design and adjuvant formulation primarily affect the droplet-generation stage, physical shielding and air assistance act mainly during droplet transport. These approaches rely on different mechanisms: shielding reduces the exposure of the spray plume to ambient airflow through physical interception, whereas air assistance modifies droplet trajectories by introducing a directed airflow toward the target [67].

A two-year field study compared drift from shielded and open-boom sprayers across four droplet-size categories. Within a downwind distance of 2–31 m, the shielded sprayer reduced drift by up to 86% for fine sprays and 56% for medium sprays. At distances of 43–104 m, drift was approximately 50% lower with the shielded configuration than with the open boom under the evaluated conditions, with relatively limited variation among droplet-size categories. Vieira et al. (2022) further reported that a shielded application using AIXR nozzles without an adjuvant produced an area under the drift curve of 31.5, which was comparable to the value of 27.7 obtained with an open-boom application using TTI nozzles and a drift-reducing adjuvant [67]. This similarity was observed despite the difference in initial droplet size, with $Dv50$ values of 447.5 and 985 μm , respectively. These results suggest that physical shielding may partly compensate for differences in droplet-size distribution under certain operating conditions.

The performance of shielding systems, however, depends on their structural configuration. Sidahmed et al. (2004) conducted wind-tunnel experiments at an air velocity of 6.2 m/s using 8001 and 8003 nozzles operated at pressures of 138, 276, and 414 kPa [68]. The reported drift reductions were 61% for symmetrical three-foil shields, 55% for symmetrical two-foil shields, and 48% for unidirectional two-foil shields. The greater reduction associated with the three-foil design was attributed to the combined effects of mechanical interception, directed airflow, and air-curtain formation. By comparison, the unidirectional two-foil configuration produced a less effective air-curtain effect during downwind operation. Ozkan et al. (1997) similarly evaluated nine shield configurations and reported drift reductions ranging from 13% to 59%, depending on the design [69].

Despite their potential aerodynamic benefits, shielding systems also present operational limitations. Full-boom enclosures may restrict nozzle visibility and reduce accessibility for inspection, adjustment, and maintenance [70]. In addition, pesticide residues deposited on the shield surface may create a risk of phytotoxicity if the structure contacts sensitive crops during operation [71]. These practical constraints may affect field usability and user acceptance and should therefore be considered alongside drift-reduction performance. A comparison of the reported drift-reduction efficiencies of different shield configurations is provided in Table 2.

Table 2. Comparison of drift reduction efficiencies across diverse physical shield configurations.

Shield Configuration	Reported Reduction in Drift or Deposition-Distance Metric (%)	Aerodynamic & Structural Mechanism	Source Attribution
Symmetrical Triple-Foil Enclosure	61%	Combines mechanical interception, direct forced airflow routing, and a multi-layer air curtain effect.	Sidahmed et al. [68]
Symmetrical Double-Foil Shield	55%	Designed to provide direct air assistance during both upwind and downwind travel.	Sidahmed et al. [68]
Unidirectional Double-Foil Shield	48%	More effective during upwind travel, when the induced airflow forms an air curtain; less effective during downwind travel because this air-curtain effect is weakened or absent.	Sidahmed et al. [68]
Best-performing double-foil shield configuration	59%	Maximized aerodynamic enclosure geometry tailored for flat-fan nozzle spray patterns.	Ozkan et al. [69]
Least-effective shield configuration	13%	Least effective among the evaluated shield configurations under the reported wind-tunnel conditions.	Ozkan et al. [69]

Air-assisted spraying employs a different approach to modifying droplet transport [72]. Wolff and Watson (1986) developed an air-assisted row-crop sprayer in which air outlets were positioned adjacent to conventional hydraulic nozzles to direct the spray plume toward the target zone [73]. In field trials, combining the air-carrier unit with a shield increased whole-plant deposition by 100% in maize and 234% in soybean. Abaxial leaf deposition increased by 900% in maize and 400% in soybean under the tested conditions. These results suggest that the directed airflow altered droplet trajectories and may also have promoted leaf movement or modified the aerodynamic conditions governing droplet interception by leaf surfaces.

The air-curtain delivery system used a high-aspect-ratio tangential, or cross-flow, fan to generate a planar air jet with an initial exit velocity of approximately 65 km/h. Although a jet at this velocity would be expected to operate under turbulent flow conditions,

the term “non-turbulent” used in earlier empirical descriptions appears to refer to the relatively coherent, low-divergence structure of the linear jet rather than to a strictly laminar flow regime. Compared with the more dispersive, three-dimensional flow fields produced by conventional axial or centrifugal fan systems, a cross-flow fan can generate a more rectilinear air curtain. This flow structure may reduce early mixing with ambient crosswinds and allow the directed airflow to retain part of its momentum as it penetrates the crop canopy.

The performance of air-assisted spraying nevertheless depends on the configuration of the airflow system and its interaction with canopy structure. In vineyard trials with a tunnel sprayer, Pergher et al. (2013) found that air-outlet angles of $20^\circ/20^\circ$ increased the variability of abaxial deposition and produced uneven coverage between adjacent rows [74]. Reconfiguring the outlet angles to $0^\circ/30^\circ$ improved deposition uniformity. These results indicate that spray deposition is influenced not only by airflow velocity but also by airflow direction and canopy geometry. Changes in airflow velocity can affect both leaf inclination and the airflow field surrounding the leaf, thereby altering droplet interception and deposition. Figure 2 illustrates the corresponding leaf-surface pressure distributions under different airflow velocities.

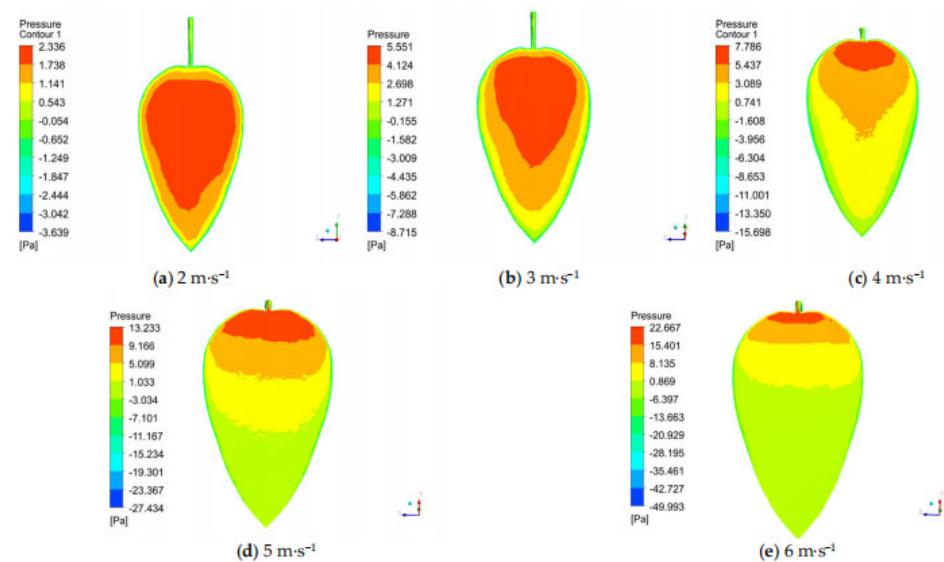


Figure 2. Leaf surface pressure distribution under different airflow velocities [75].

Air-assisted spraying systems operating in open environments can be influenced by ambient crosswinds. Using a two-stage computational fluid dynamics (CFD) model, Cui et al. (2024) examined how lateral wind affects airflow and droplet transport in air-assisted spraying [43]. Under zero-crosswind conditions, the auxiliary airflow directed droplets toward the target canopy. When a lateral wind was introduced, the downward airflow was deflected, which reduced canopy penetration and increased the off-target displacement of droplets. These results indicate that ambient wind conditions can alter the intended transport pathway of air-assisted sprays and thereby affect both deposition performance and drift risk.

Mechanical shielding and forced air assistance therefore exhibit different performance characteristics. Physical shields primarily reduce spray drift through mechanical interception and have been reported to decrease downwind drift by approximately 48–86% under specific operating conditions. However, shielding does not actively promote droplet penetration into dense canopies and may provide limited improvement in abaxial leaf deposition. In addition, pesticide residues accumulated on shield surfaces may create a risk of phytotoxicity if the shields contact sensitive crops during operation. By contrast, forced

air assistance can increase canopy penetration and abaxial deposition by directing droplets into the canopy and inducing leaf movement. Its performance, however, is sensitive to local airflow conditions, because ambient crosswinds may deflect the assisted airflow and increase off-target droplet transport.

Overall, these findings suggest that standalone air-assistance systems may exhibit variable performance under complex field microclimates. Combining air assistance with physical shielding may therefore provide a complementary approach to improving airflow stability, canopy deposition, and drift control, although the effectiveness of such integration should be evaluated under a range of canopy structures and environmental conditions.

2.4. Recycling Tunnel Spraying Systems

Tunnel sprayers combine drift mitigation and spray-liquid recovery of drift mitigation and fluid recycling into a unified architecture [76,77]. By establishing a semi-enclosed physical barrier encompassing both flanks of the target canopy, these systems can reduce off-target dispersion. Concurrently, they actively intercept and recirculate the non-deposited spray fraction for continuous reuse.

A tunnel sprayer equipped with external axial fans, providing an airflow rate of 2.23 m³/s per row, and lamellar separation plates was evaluated under vineyard conditions. At both late flowering (BBCH 69) and early ripening (BBCH 81), mean foliar deposition obtained with the tunnel sprayer did not differ significantly from that achieved with a conventional air-blast sprayer. Although the tunnel system operated at a lower volumetric airflow rate than the conventional sprayer (2.23 versus 3.49 m³/s), it produced comparable canopy penetration under the tested conditions. This performance was attributed to the higher inter-row air velocity generated within the confined tunnel (10.5 versus 6.4 m/s) and the shorter nozzle-to-canopy distance (0.4 versus 0.8 m). Initial trials nevertheless showed considerable variability in abaxial leaf deposition. This variation was associated with the symmetrical 20°/20° orientation of the front and rear air outlets, which caused airflow deflection within the tunnel. Reconfiguring the outlet angles to an asymmetrical 0°/30° arrangement improved deposition uniformity in the subsequent trial.

Spray-liquid recovery is an important performance indicator for recycling tunnel sprayers. Pergher et al. (2013) reported that the recovered proportion decreased from 50.1% at late flowering (BBCH 69) to 34.0% at early ripening (BBCH 81), while foliar deposition increased from 35.2% to 53.6% over the same period [74]. These results suggest a seasonal relationship between canopy development and liquid recovery. As leaf area and canopy density increase, a greater proportion of the applied spray is intercepted by the foliage, leaving a smaller fraction available for collection and recirculation. In a dwarf apple orchard, Jamar et al. (2010) compared a tunnel sprayer with a conventional axial-fan sprayer using hollow-cone nozzles (ATR, Dv50 ≈ 78 µm) and air-induction cone nozzles (TVI, Dv50 ≈ 507 µm) [78]. The recirculation system reduced pesticide use by 28% with the ATR nozzles and by 32% with the TVI nozzles. Singh et al. (2026) subsequently applied response surface methodology to optimize tunnel-sprayer operating parameters [79]. For a canopy with an LAI of 1.6, the parameter combination identified as optimal within the evaluated range consisted of a forward speed of 0.69 m/s, an air velocity of 15 m/s, and an operating pressure of 0.75 MPa. Under these conditions, the reported foliar deposition was 3.14×10^{-2} µg/cm², while the application volume was reduced by 38.56%.

Tunnel sprayers also present several operational constraints. Studies using TVI air-induction nozzles have reported significantly lower deposition at the canopy apex than that obtained with conventional sprayers [80–83]. The trajectories of coarse droplets may be altered by the curved airflow pathways within the tunnel, indicating that some tunnel configurations may be less compatible with coarse-droplet spray spectra. Mostade et al.

(2010) similarly reported lower deposition uniformity than that achieved with axial-fan sprayers in apple orchards with canopy heights of 2.80 and 3.25 m [78]. These differences were associated with mismatches between tunnel dimensions and tree height, together with non-optimal air-outlet configurations. Subsequent structural adjustments, including a tunnel-opening width of 1100 mm, nozzle spacing of 350 mm, and fin spacing of 41 mm, increased the reported recovery rate to 38.80%. This finding indicates that tunnel geometry and airflow configuration can substantially influence liquid recovery and deposition performance. Nevertheless, relatively high initial costs and limited maneuverability during headland turns may restrict the adoption of tunnel sprayers, particularly in small- and medium-scale orchards. Table 3 summarizes the reported recovery rates and deposition characteristics of the evaluated tunnel-sprayer systems.

Table 3. Empirical liquid recovery rates and foliar deposition profiles for recycling tunnel sprayers.

Crop/Target Canopy	Phenological Stage (BBCH)	Volumetric Recycling Rate (%)	Absolute Foliar Deposition (μg/cm ²)	Target Leaf Area Index (LAI)	Source Reference
Vineyard Canopy	Late Flowering (BBCH 69)	50.1%	—	0.62	Pergher et al. (2013) [74]
Vineyard Canopy	Early Maturity (BBCH 81)	34.0%	—	1.66	Pergher et al. (2013) [74]
Dwarf Apple Orchard	Main Growth Phase (ATR Nozzle)	28.0%	—	—	Jamar et al. (2010) [78]
Dwarf Apple Orchard	Main Growth Phase (TVI Nozzle)	32.0%	—	—	Jamar et al. (2010) [78]
Optimized Orchard System	Full Canopy Development	38.56%	3.14 × 10 ^{−2}	1.60	Singh et al. (2026) [79]

Recycling tunnel sprayers integrate drift mitigation with the recovery and recirculation of non-deposited spray liquid. By partially enclosing both sides of the canopy, these systems can reduce off-target dispersion and maintain relatively high air velocities within the confined inter-row space [84,85]. Their practical application, however, may be limited by relatively high initial investment and reduced maneuverability during headland turns, particularly in small-scale orchards with restricted operating space. Liquid recovery also varies with canopy development. Reported recovery rates decreased from 50.1% at late flowering to 34.0% at early ripening as increasing leaf area and canopy density intercepted a greater proportion of the applied spray. These findings indicate that recovery efficiency tends to decline as canopy volume and leaf area increase.

3. Active Precision Spraying Technologies

3.1. Target Perception: Sensor Technologies and Multi-Source Fusion the Foundational Step in Variable-Rate Application (VRA) Is Spatially Defining the Target—Determining Exactly “Where to Spray”

The primary objective of the perception stage is to convert information on crop architecture, biological stress distribution, and ambient environmental conditions into signals that can support spraying decisions. Over the past two decades, sensing technologies used in variable-rate application (VRA) systems have progressed from ultrasonic and infrared devices to LiDAR, machine vision, and multi-sensor fusion approaches [86]. Despite these advances, a persistent challenge is the acquisition of sufficiently accurate and timely target information under variable field conditions.

Ultrasonic sensors were among the earliest sensing technologies incorporated into VRA systems. They estimate target distance by emitting acoustic waves, receiving the reflected signals, and calculating the corresponding time of flight. Their relatively low cost and limited sensitivity to dust and illumination variation make them suitable for basic canopy detection. Jeon et al. (2011) evaluated a commercial ultrasonic sensor and reported acceptable performance under low-temperature, dusty, and windy conditions, although detection accuracy was influenced by target geometry [87]. Irregular canopy surfaces can produce multipath reflections and increase ranging errors. The application of filtering algorithms reduced the root mean square error from 0.101 to 0.064 m, but residual errors remained because signal-processing methods could not fully compensate for the physical effects of irregular reflection. Similar observations have been reported in pistachio orchards, where randomly oriented leaves produced diffuse reflections and reduced ranging consistency. An eight-channel ultrasonic array decreased tracking errors by an average of 35%; however, variability in single-scan angular measurements remained relatively high, and multi-frame averaging was required to stabilize the output [88,89]. These findings indicate that ultrasonic sensors are generally more suitable for estimating target proximity or canopy presence than for reconstructing detailed canopy morphology. They are therefore often used as supplementary sensors in systems requiring higher spatial resolution.

Infrared sensors have followed a similar development pathway. Their rapid response and relatively low cost have supported their use in binary target detection and canopy-gap identification in orchards [90]. One autonomous target-aligned sprayer achieved a maximum detection range of 10 m and a minimum detectable gap of 0.3 m. However, detection performance depended on the reflectance characteristics of the target, and complex canopy structures or changing illumination conditions could increase the frequency of false detections. In another study, an infrared sensor detected green foliage at distances of up to 0.65 m with a reported recognition rate of 100% at travel speeds below 1.5 m/s. The effective detection range varied with target color, reaching 0.70 m for white, 0.26 m for gray, and 0.14 m for black surfaces. Although this sensitivity may be acceptable in relatively uniform green canopies, performance may decline in the presence of senescent leaves, exposed soil, deep shadows, or other surfaces with contrasting reflectance properties.

The introduction of Light Detection and Ranging (LiDAR) has improved the spatial characterization of crop canopies. LiDAR systems emit laser pulses and measure their return times to generate two- or three-dimensional point-cloud data. Chen et al. (2012) used an LMS291 scanner to develop a VRA system capable of mapping four canopy geometries at travel speeds of 0.89–1.78 m/s, although detection accuracy decreased as operating speed increased [91]. A UTM-30LX sensor was evaluated for profiling complex objects and produced coefficients of variation of 6.1%, 8.6%, and 5.3% along the X, Y, and Z axes, respectively, over a measurement range of 0.58–2.94 m. Errors along the Z axis increased at longer distances. An LMS511 scanner was also used to estimate the cross-sectional volumes of different geometries, with maximum relative errors of 3.3% for rectangular prisms, 7.9% for triangular prisms, and 9.4% for cylinders. These results suggest that LiDAR measurements are generally more accurate for regular geometries, whereas increasing structural complexity can reduce volumetric-estimation accuracy.

In greenhouse experiments using a UST-10LX sensor, measurement precision along the X axis decreased with increasing target distance. In contrast, target color and surface texture had relatively little influence on LiDAR measurements, distinguishing its operating characteristics from those of optical imaging systems. More recently, maize plants were reconstructed using an R-Fans-16 three-dimensional LiDAR. Plant-height prediction errors remained below 10%, and leaf-area estimates achieved an R^2 greater than 0.9 under the evaluated conditions. During dynamic scanning, however, higher travel speeds reduced

point-cloud density and lowered the accuracy of leaf-area prediction in complex canopies, with the minimum reported R^2 decreasing to 0.74. Figure 3 illustrates the extraction of aerial point-cloud data obtained with the vertically oriented LiDAR system.

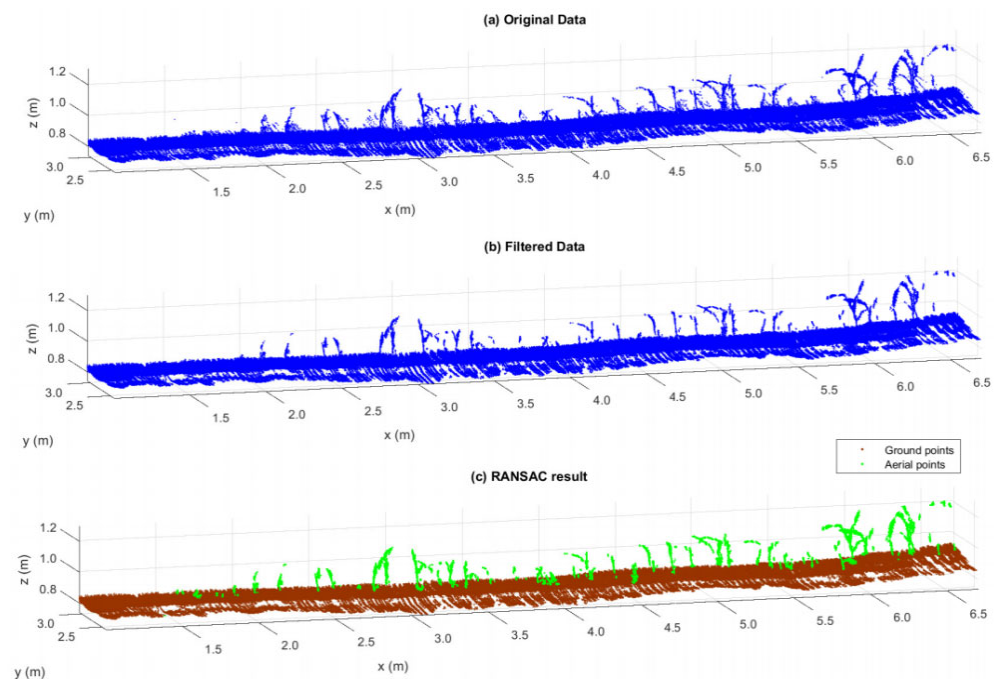


Figure 3. (a) Original point cloud; (b) filtered point cloud; and (c) RANSAC results during aerial cloud extraction for the vertical LiDAR's orientation when going at path 1 and row 2 [92].

Although LiDAR can provide high-precision spatial measurements, its performance is influenced by operating distance, target geometry, scanning configuration, and vehicle speed. Under less favorable conditions, reduced point-cloud density and uncertainty in boundary extraction may increase measurement errors. In addition, LiDAR primarily provides geometric information, such as plant height, canopy width, and canopy volume, and does not directly characterize pest or disease severity. This capability is generally sufficient for canopy-volume-based variable-rate application (VRA), but applications requiring spray adjustment according to biological stress intensity typically require complementary optical, spectral, or thermal sensing methods [93–95].

Machine vision can supplement LiDAR by capturing optical characteristics such as color, texture, and morphology, which can support the detection of disease lesions, weeds, and pest-related symptoms. Esau et al. (2018) developed a site-specific weed-spraying system for wild blueberry fields, although target discrimination became more difficult in mixed vegetation canopies and required additional texture-based analysis [96]. In an olive-orchard VRA system, the reported activation and deactivation delays were 0.55 and 0.85 s, respectively. At higher travel speeds, such delays may increase the spatial offset between target detection and spray actuation. A machine-vision system for detecting rice blast lesions required approximately 800 ms for image processing at a travel speed of 0.25 m/s. However, its dependence on a green background to reduce illumination interference limited its direct applicability under field conditions. A monocular-vision system for estimating citrus leaf-wall area achieved a reported error of 0.5% with a response time of 40 ms [97]. Nevertheless, monocular imaging does not directly provide depth information and therefore has limited capacity for reconstructing complete three-dimensional canopy structures. Overall, the field performance of machine-vision systems is affected by illumi-

nation variability, background complexity, image-processing latency, and vehicle motion, all of which may reduce recognition and actuation accuracy during high-speed operation.

Multi-sensor fusion provides one approach to addressing the limitations of individual sensing modalities. Dharrao et al. (2025) combined RGB, multispectral, and thermal infrared imaging for pest and disease detection on grape leaves [98]. The standalone RGB model achieved an accuracy of 93.41%, whereas the multimodal fusion model achieved 96.05% under the evaluated conditions. However, thermal measurements were influenced by ambient temperature, while the high dimensionality of multispectral data introduced feature redundancy and, in some cases, contributed to misclassification associated with confidence-threshold settings. In another system, industrial cameras were combined with ultrasonic sensors for target detection in open-field vegetables, reducing targeting errors. Nevertheless, camera performance remained sensitive to complex illumination and high-speed movement, while the relatively low update frequency of ultrasonic measurements introduced delays during rapid operation. LiDAR has also been integrated with binocular vision for orchard VRA. The reported two-dimensional reconstruction error of the LiDAR system was $0.633\% \pm 0.0276\%$, while the leaf-wall area estimated using binocular vision differed from the LiDAR reference by 1.525% [99,100]. These results indicate that sensor fusion can improve perception performance by combining complementary geometric and optical information, although issues related to sensor synchronization, environmental sensitivity, computational demand, and data redundancy still require consideration. Table 4 summarizes the reported performance characteristics of sensing technologies used in variable-rate spraying systems.

Table 4. Performance comparison of different sensors in variable-rate spraying perception.

Sensor Type	Environmental Robustness	Response Latency	Typical Relative System Cost	Typical Field Applicability
Ultrasound	High (immune to illumination, moderate dust)	Moderate; multi-frame averaging may increase processing delay	Low	Coarse canopy volume estimation for low-speed VRA in orchards
Infrared	Medium (susceptible to sunlight and target color)	Low	Low	Binary presence/absence detection (e.g., gap detection)
LiDAR	High robustness to illumination; performance may be affected by motion distortion, scan geometry, rain, and dense dust	Moderate to high, depending on point-cloud density and processing hardware	High	3D canopy structure mapping for precise volumetric VRA
Machine vision	Medium–low under uncontrolled natural illumination; improved with illumination compensation and model adaptation	Moderate to high, depending on model complexity and computing hardware	Medium	Disease/pest detection, weed identification in controlled lighting

Although multi-sensor fusion can improve perception performance by combining complementary information from different sensing modalities, it also introduces additional implementation challenges. LiDAR, cameras, and ultrasonic sensors generate data in different formats, sampling frequencies, and spatial reference frames: LiDAR produces point clouds, cameras provide pixel-based images, and ultrasonic sensors typically return

distance measurements. Integrating these heterogeneous data streams therefore requires accurate spatial calibration, temporal synchronization, and data registration [101–103]. In dynamic field operations, these procedures must also be completed within limited processing times to maintain timely target detection and spray actuation.

Jiao et al. (2024) identified three main challenges associated with multi-sensor fusion algorithms: heterogeneity among sensor data, the balance between computational complexity and real-time processing capability, and dependence on expert-defined features and the quality of annotated datasets [104]. These factors can affect model accuracy, computational efficiency, and transferability across crops and operating environments. Multi-sensor fusion therefore represents a promising approach for precision spraying, but its transition from controlled experiments to reliable field deployment requires further improvements in sensor calibration, synchronization, computational efficiency, data quality, and system-level robustness.

3.2. Variable-Rate Decision-Making: Application Volume Modeling

While the perception stage characterizes the spatial and morphological properties of the target, the decision-making module determines the appropriate application rate. Spray volume should be adjusted not only according to canopy geometry but also in relation to the severity of the biological threat, the physicochemical properties of the agrochemical formulation, and prevailing meteorological conditions [105,106]. The control workflow of the variable-rate spraying system is illustrated in Figure 4.

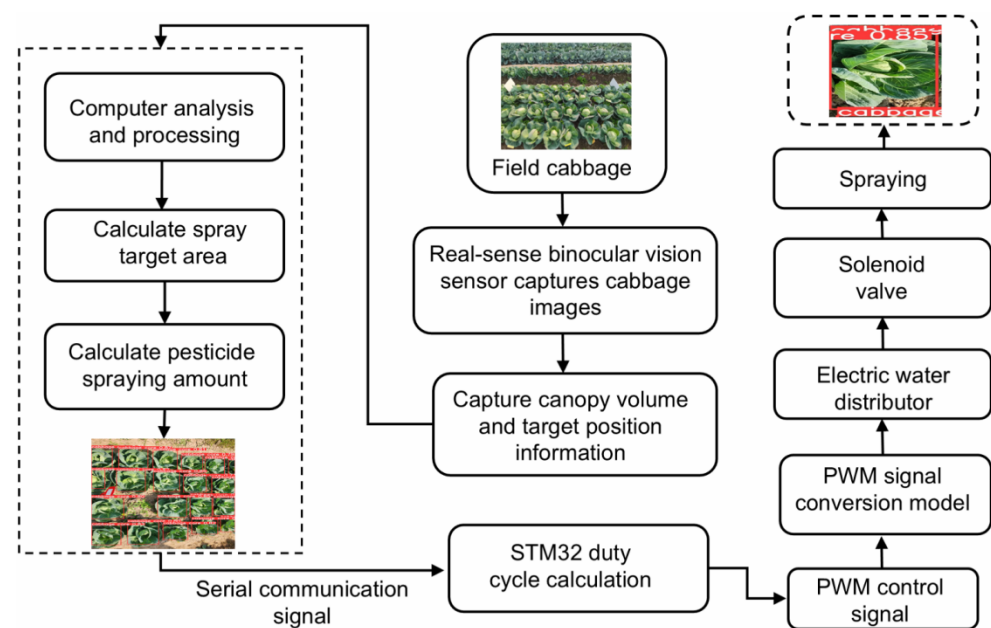


Figure 4. Variable rate spray system control flowchart [107].

Early spray-volume models were based primarily on ground area and applied a fixed volume per unit area without accounting for crop morphology. Although straightforward to implement, this approach may be less suitable for three-dimensional crops such as orchards because trees of different sizes receive the same nominal application volume, resulting in lower deposition per unit leaf area in larger canopies. The Tree Row Volume (TRV) model proposed by Sutton (1984) addressed this limitation by adjusting application volume according to canopy volume and was subsequently adopted in orchard and vineyard spraying [102]. However, the TRV approach generally assumes a relatively uniform distribution of foliage within the canopy. In practice, leaf density often varies spatially, with denser foliage near the canopy exterior and lower density in the interior. Consequently,

canopies with similar external volumes may differ substantially in total leaf area. Vineyard experiments conducted by Pergher et al. (2013) illustrated this limitation: when the Leaf Area Index (LAI) increased from 0.62 at late flowering to 1.66 at early ripening, deposition per unit leaf area decreased by approximately 43.1% [74]. This result indicates that, under a constant application rate, canopy expansion can reduce the amount of spray deposited per unit leaf area.

Adjusting spray volume according to LAI or Leaf Area Density (LAD) may provide a more direct representation of canopy characteristics, but obtaining these parameters in real time remains technically challenging. Point measurements from optical instruments may not adequately capture field-scale spatial variability, while real-time LAD estimation often requires intensive processing of three-dimensional point-cloud data. Such computational demands can exceed the capacity of onboard processors, particularly during high-speed field operations [108,109].

From a broader decision-support perspective, Gil (2011) developed a vineyard application model that estimated spray efficiency by integrating crop characteristics, pesticide properties, equipment parameters, and environmental conditions [110]. Under the evaluated conditions, the method reduced conventional application volume by approximately 39.9%. Its implementation, however, required accurate input data for variables such as LAI and canopy volume, and some efficiency factors were derived from empirical weighting procedures. Llorens et al. (2010) proposed a variable-rate approach in which nozzle flow was adjusted in real time according to canopy width, canopy height, and forward speed [111]. Across three grape varieties and several phenological stages, the system reduced pesticide use by an average of 58% while achieving deposition and recovery performance comparable to, or in some cases greater than, that of conventional spraying. Nevertheless, because leaf density and LAI were not explicitly included, the model may be less adaptable to canopies with substantial internal structural variability. In addition, when canopy volume was very small, minimum operating-pressure requirements caused the actual application coefficient to deviate from the calculated value, resulting in localized over-application.

Gil et al. (2011) subsequently developed DOSAVINA, a decision-support system that estimated application volume by integrating canopy characteristics, equipment parameters, environmental conditions, and pest-related information [110]. Field evaluations showed reductions of 39.9% in total application volume and 53% in active ingredient use, while deposition uniformity improved and control of powdery mildew and *Botrytis cinerea* remained comparable to that achieved with conventional high-volume treatments. However, DOSAVINA depended on pre-established crop-parameter databases and did not explicitly account for interactions among multiple agrochemical formulations. In dense canopies, conventional applications also produced higher recovery rates than DOSAVINA-guided treatments under the reported test conditions.

More data-driven approaches have also been investigated. Gao et al. (2012, 2013) incorporated fuzzy neural networks into variable-rate decision-making using crop area, target distance, and pest severity as input variables [112]. After 191 training iterations, the model reached a target error of 0.001 and showed lower decision errors on the test dataset than a conventional fuzzy-control model. However, pest severity was still determined manually, and validation was limited to laboratory simulations. More generally, increasing model complexity does not necessarily lead to improved field applicability. The performance of intelligent decision models depends strongly on the quality and timeliness of their input data, while variables such as LAI, pest severity, and local meteorological conditions remain difficult to measure accurately and continuously during field operation.

Jiao et al. (2025) identified several recurring limitations of current application-volume models, including dependence on offline databases or manual data entry, simplified as-

sumptions, limited incorporation of environmental variables, and restricted transferability across crops and canopy types [113]. They proposed the development of dynamic, multi-factor models that incorporate real-time wind speed, temperature, humidity, and other relevant variables, with machine-learning methods used to support adaptive parameter matching. The practical performance of such models will nevertheless depend on whether the perception system can provide sufficiently accurate, timely, and stable input data under field conditions.

3.3. Precision Execution: Control Strategies and Component Reliability

Once the decision model determines the target application volume, the execution system converts the calculated command into a corresponding fluid output. The accuracy and response time of this conversion influence the overall performance of variable-rate application (VRA), particularly during dynamic field operation.

Pulse-width modulation (PWM) is widely used for flow regulation in VRA systems. In a PWM-controlled system, solenoid valves switch at a fixed frequency, and the average flow rate is adjusted by varying the proportion of each cycle during which the valve remains open, referred to as the duty cycle. Qiao et al. (2024) evaluated PWM control in a maize VRA system and reported that flow rate generally increased linearly with duty cycle, although nonlinear responses were observed at low duty cycles [114]. These results indicate that system-specific calibration is required to establish an accurate relationship between duty cycle and flow rate, particularly within the lower operating range.

Differences may also arise between performance measured under laboratory conditions and that achieved during field operation. Jiao et al. (2025) noted that intelligent optimization algorithms can provide precise dynamic regulation in controlled experiments, whereas many field systems continue to rely on conventional proportional–integral–derivative (PID) controllers and standard solenoid valves [113]. Under field conditions, control accuracy may be affected by sensor interference, mechanical and hydraulic response delays, and limited onboard computing capacity. Consequently, field control errors are often greater than those reported in laboratory evaluations.

High-frequency actuation of solenoid valves is an important factor affecting the long-term performance of PWM-based spraying systems. Repeated switching can generate mechanical impacts on the valve spool and seat, which may gradually alter the opening and closing characteristics of the actuator. Over extended operating periods, such wear can cause deviations from the initially calibrated relationship between duty cycle and flow rate. Solenoid valves also exhibit a finite mechanical response time, typically on the order of tens of milliseconds. Although this delay may have a limited effect at low travel speeds, it can produce a measurable spatial offset between target detection and spray actuation at higher vehicle speeds. Under these conditions, the nozzle may move beyond the intended application position before the spray command is fully executed [115–117]. Open-loop time-proportional control provides a relatively simple method for regulating spray output through duty-cycle adjustment [118]. However, in the absence of feedback, the system cannot compensate automatically for pressure fluctuations, actuator deviations, or other operational disturbances. Its performance therefore depends on relatively stable hydraulic and mechanical conditions, which may restrict its reliability during prolonged or variable field operation.

Pressure fluctuations within the hydraulic circuit represent another important consideration in PWM-controlled spraying. Because fluid delivery is intermittent, valve opening and closing generate transient pressure waves in the pipeline. These oscillations can affect both volumetric flow rate and the atomization process at the nozzle orifice. Studies have shown that droplet-size distributions generated under pulsating pressure may differ from

those produced under steady-pressure conditions [119–121]. Such changes can influence drift potential, deposition uniformity, and target coverage, indicating an interaction between flow-control dynamics and spray atomization. To improve system performance, Jiao et al. (2025) suggested further investigation of solenoid-valve geometry and actuator design, with the aim of reducing response time and improving durability under continuous high-frequency operation [113].

4. Multi-Technology Synergy and System Integration

4.1. Combinatorial Strategies and Synergistic Effects of Drift Mitigation Technologies

The preceding sections examined passive drift-mitigation approaches, including low-drift nozzles, adjuvant formulation, and physical shielding, together with active technologies such as air assistance and electrostatic spraying. When applied independently, each approach is associated with specific limitations. Coarse-droplet nozzles may reduce canopy coverage, adjuvant performance can be affected by shear degradation, the effectiveness of shielding may vary with downwind distance, air-assisted spraying depends on airflow and environmental conditions, and the charge-to-mass ratio in electrostatic systems may vary nonlinearly with applied voltage [122–124]. These constraints have motivated increasing interest in combining complementary mechanisms to improve overall spraying performance.

Ozkan et al. (1997) evaluated nine shield configurations used in combination with low-drift nozzles under wind-tunnel conditions [69]. Without shielding, the tested low-drift nozzles reduced drift by 20–67%, whereas combining them with a two-foil shield produced a reported drift reduction of 59%. These results suggest that shielding may reduce variability in drift-control performance among nozzle types rather than simply adding a fixed reduction to the effect of the nozzle. Sidahmed et al. (2004) further reported drift reductions of 61% for symmetrical three-foil shields and 48% for unidirectional two-foil shields [68]. This comparison indicates that shield geometry can substantially influence aerodynamic performance and should be considered together with nozzle characteristics when designing integrated drift-mitigation systems [125–127].

Vieira et al. (2022) compared shielded and open-boom sprayers using AIXR, ULD, and TTI nozzles, both with and without drift-reducing adjuvants [67]. A shielded application using an AIXR nozzle without an adjuvant produced an area under the drift curve of 31.5, compared with 27.7 for an open-boom application using a TTI nozzle with an adjuvant. These similar drift indices were obtained despite substantial differences in initial droplet size, with $Dv50$ values of 447.5 μm for the AIXR nozzle and 985 μm for the TTI nozzle. Under the evaluated conditions, this result suggests that combining physical shielding with a moderately coarse spray may provide drift control comparable to that achieved using an ultra-coarse spray and an adjuvant. Such a combination may also help maintain greater foliar coverage than approaches based solely on very large droplets [128,129]. The value of integrated strategies therefore lies not only in cumulative drift reduction but also in the possibility of balancing drift mitigation with target deposition.

The combination of air assistance and electrostatic spraying represents another potential complementary strategy. Air assistance uses directed airflow to transport droplets into the canopy and promote leaf movement, whereas electrostatic charging increases droplet attraction to plant surfaces through Coulombic forces. Ou et al. (2025) developed an air-assisted electrostatic nozzle based on transverse-jet atomization [130]. Vineyard experiments showed that electrostatic charging increased abaxial leaf deposition under several operating conditions. During unilateral spraying, improvements in abaxial deposition were observed at distances of 0.90 and 1.20 m, although deep-canopy penetration decreased. During bilateral spraying at a distance of 0.60 m, the electrostatic treatment produced

statistically significant improvements in foliar coverage, droplet density, and deposition uniformity [131–134]. These findings indicate that the performance of combined air-assisted and electrostatic systems depends on operating distance, spraying configuration, airflow intensity, and charging parameters. Although airflow can promote inward transport, excessive or premature electrostatic attraction may increase deposition on the outer canopy and reduce the number of droplets reaching deeper layers. Appropriate coordination between aerodynamic transport and electrostatic attraction is therefore required.

Available evidence suggests that integrated approaches can improve performance relative to individual technologies under certain conditions, although the magnitude of the benefit depends on system configuration and operating environment. Synergistic performance is more likely when one mechanism compensates for a specific limitation of another, rather than when their effects are assumed to be linearly additive. Evaluation of these systems should therefore include not only drift reduction but also foliar coverage, canopy penetration, deposition uniformity, energy demand, operational stability, and application efficiency.

Overall, comparisons between passive and active technologies indicate that individual systems rarely optimize all performance objectives simultaneously. Passive approaches, such as air-induction nozzles and physical shields, generally offer relatively simple mechanical structures and moderate implementation costs, but they may reduce abaxial coverage or restrict nozzle visibility and accessibility. Active systems, including PWM-based variable-rate spraying, enable real-time regulation of application volume but require additional sensors, processors, and control components. Their long-term field performance may also be affected by valve wear and transient pressure fluctuations that modify flow rate and atomization behavior. Further development of integrated systems could therefore focus on dynamically coordinating airflow, droplet characteristics, and liquid output according to real-time measurements of canopy density and environmental conditions.

4.2. Integrated Perception-Decision-Execution System Architecture

A variable-rate application (VRA) system generally comprises three interdependent modules: the perception module acquires spatial and morphological information about the target, the decision-making module determines the corresponding application rate, and the execution module regulates the actual fluid output. Although the technical challenges associated with each module were discussed in Section 3, this section focuses on the engineering requirements for integrating them into a coordinated architecture capable of reliable field operation.

Qiao et al. (2024) developed an intelligent VRA system integrating three-dimensional LiDAR with pulse-width modulation (PWM) control and mounted the system on a lightweight, high-clearance, self-propelled sprayer [114]. The decision algorithm converted canopy-height information extracted from LiDAR point clouds into PWM duty-cycle commands for real-time flow regulation [135]. Field experiments showed that plant height estimated by LiDAR had a relative error of less than 10%, enabling the system to adjust spray output in response to local variations in crop morphology. Under variable-rate operation, droplet penetration across the upper, middle, and lower canopy layers followed the expected decreasing pattern from the upper to the lower layer and was comparable to that obtained with conventional uniform-rate spraying [136]. These results indicate that the integrated system reduced agrochemical use while maintaining a similar canopy deposition pattern under the evaluated field conditions, thereby demonstrating the potential of a closed-loop “perception–decision–execution” architecture for precision spraying [137,138]. The overall structure of the variable-rate spraying system is illustrated in Figure 5.

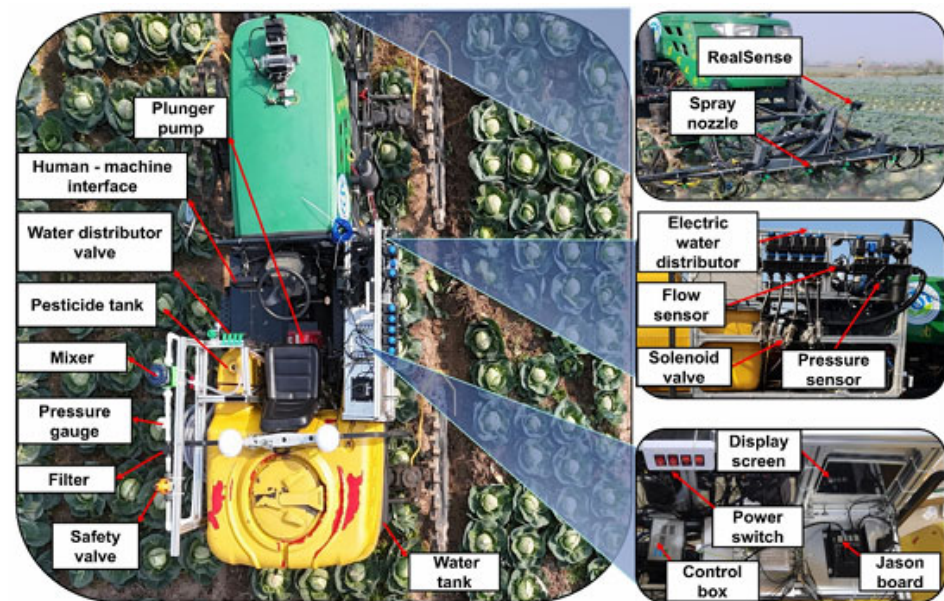


Figure 5. Overall structure of the variable-rate spraying system [107].

At the engineering level, integrated variable-rate application systems face several practical challenges. The first concerns synchronization between the sensor leads distance and total system latency. When LiDAR is mounted at the front of the vehicle, a time delay occurs between target detection and mechanical actuation, during which the sprayer continues to move forward. If this delay is not adequately compensated, the spray may be applied at a position offset from the intended target. Qiao et al. (2024) addressed this issue using a decision model based on point-cloud thresholds; however, the accuracy of spatial compensation remained dependent on the coordination of vehicle speed, sensor scanning frequency, data-processing time, and actuator response [114].

A second challenge is the implementation of decision algorithms on resource-limited onboard platforms. Three-dimensional point-cloud data require substantial storage and computational capacity, whereas embedded processors used on agricultural vehicles often have limited processing resources. Reducing computational demand while maintaining acceptable prediction accuracy is therefore an important requirement for real-time deployment. A third challenge involves actuator response and hydraulic stability. High-frequency switching of PWM solenoid valves can generate transient pressure fluctuations within the pipeline, which may affect flow regulation and nozzle atomization [139,140]. Although these effects may be less apparent in controlled laboratory experiments, they can accumulate during continuous field operation and contribute to system-level performance variation.

Many integrated VRA systems are still at the prototype or experimental stage. Their transition to broader field application requires improvements in both economic feasibility and operational reliability. The combined cost of high-resolution sensors, controllers, onboard processors, and precision solenoid valves generally results in a higher initial investment than that required for conventional spraying equipment. In addition, field conditions such as mechanical vibration, temperature variation, dust, moisture, and agro-chemical exposure may reduce the service life and measurement stability of electronic and hydraulic components [141–143]. Addressing these cost, durability, synchronization, and control challenges will therefore be important for the wider adoption of integrated precision spraying systems.

4.3. Multi-Objective Optimization of System Parameters

Variable-rate application (VRA) systems involve multiple and potentially competing objectives, including increasing target deposition while reducing spray drift, improving response speed while maintaining control accuracy, and reducing application volume without compromising biological efficacy. Because these objectives cannot always be optimized simultaneously, system design generally requires a balance among competing performance criteria, which can be represented by solutions along a Pareto frontier [144,145]. Parameter optimization is therefore an important step in improving the efficiency and operational performance of VRA systems.

Response Surface Methodology (RSM) is widely used for offline parameter optimization. It employs statistically designed experiments to establish regression relationships between operational variables and system responses and is particularly suitable for problems involving a limited number of factors and relatively smooth response surfaces [146]. Singh et al. (2025) applied RSM to optimize the structural parameters of a tunnel sprayer by evaluating the effects of nozzle spacing, nozzle angle, tunnel-opening width, and fin spacing on spray deposition and liquid recovery [79]. The parameter combination identified as optimal within the investigated range consisted of a nozzle spacing of 350 mm, a nozzle angle of 42.5° , a tunnel-opening width of 1100 mm, and a fin spacing of 41 mm. Under these conditions, spray deposition reached $2.75 \times 10^{-2} \mu\text{g}/\text{cm}^2$, and the liquid-recovery rate was 38.80%. In a related study, Singh et al. (2025) used RSM to optimize VRA operating parameters. At a moderate Leaf Area Index, the selected configuration produced a deposition of $3.14 \times 10^{-2} \mu\text{g}/\text{cm}^2$ while reducing the application volume by 38.56% [77].

RSM offers standardized experimental procedures and relatively interpretable regression models. However, its practical efficiency may decrease as the number of factors and interaction terms increases. Its predictive performance may also be limited when the system response is strongly nonlinear or contains complex relationships that cannot be adequately represented by low-order polynomial models.

Hybrid Particle Swarm Optimization–Artificial Neural Network (PSO–ANN) methods provide an alternative approach for high-dimensional and nonlinear optimization problems. In this framework, the ANN is used to model the relationships between input parameters and target responses, while PSO searches the resulting parameter space for a near-optimal solution [147]. Singh et al. (2025) applied this approach to the structural optimization of a tunnel sprayer and reported that the PSO–ANN model provided greater predictive accuracy than the RSM model under the evaluated conditions [77]. Statistical indicators, including the coefficient of determination (R^2), root mean square error (RMSE), and ratio of performance to deviation, were used to assess the predictive performance of the hybrid model.

The two approaches differ primarily in their modeling and optimization procedures. RSM develops explicit regression equations based on structured experimental designs, whereas PSO–ANN relies on data-driven neural-network modeling combined with heuristic parameter-space exploration. RSM generally offers greater interpretability and lower computational demand when relatively few variables are considered. By contrast, PSO–ANN may be more suitable for representing complex nonlinear interactions, provided that sufficient high-quality training data are available. The comparative characteristics and reported performance of the two approaches are summarized in Table 5 [148].

Deep learning-based methods have improved the detection and segmentation of spray deposits in complex images through automated feature learning [149,150]. Several studies have reported better performance than conventional image-processing methods, particularly in situations involving droplet overlap, uneven illumination, and background interference. However, model accuracy remains dependent on the representativeness and

annotation quality of the training data, and performance may decline when models are transferred across crops, imaging systems, or environmental conditions. In addition, most deep learning approaches primarily extract image-level features, whereas the estimation of physical quantities, such as deposited spray mass or volume, often requires empirical calibration, supplementary measurements, or additional modeling assumptions. These methods are therefore well suited to image-based recognition, segmentation, and feature extraction, but their use for direct quantitative estimation and reliable engineering implementation may require integration with sensor measurements, calibration procedures, and physics-based models.

Table 5. Performance comparison between RSM and PSO-ANN optimization methodologies.

Optimization Method	Optimized Parameters	Optimization Results	Quantitative Prediction Accuracy Metrics
RSM	Nozzle spacing, nozzle angle, tunnel opening, fin spacing	Spray deposition: $2.75 \times 10^{-2} \mu\text{g}/\text{cm}^2$; liquid-recovery rate: 38.80%	Not explicitly reported
RSM	Forward speed, airspeed, working pressure (LAI = 1.6)	Spray deposition: $3.14 \times 10^{-2} \mu\text{g}/\text{cm}^2$; application-volume reduction: 38.56%	Not explicitly reported
PSO-ANN	Tunnel Sprayer Structure Parameters	Close to the RSM optimization results	ANN prediction model: $R^2 = 0.972$

The application of multi-objective optimization in spraying systems remains relatively limited. Many existing studies combine multiple performance criteria into a single weighted objective function. Although this approach simplifies model formulation and computation, the results can be sensitive to the selected weights and may not fully represent the range of trade-offs among competing objectives. Future research could therefore place greater emphasis on Pareto-based optimization and systematic comparison of alternative solutions involving target deposition, spray drift, biological efficacy, energy consumption, and economic cost. Such analyses may provide a more transparent basis for selecting operating parameters according to specific agronomic and engineering requirements.

5. Future Perspectives and Conclusions

5.1. Intelligent Upgrades: Real-Time AI Decision-Making and Digital Twins

Although deep learning has shown potential for weed recognition and pest or disease diagnosis, its transfer from controlled laboratory settings to field applications remains challenging. As noted by Jiao et al. (2025), many current models depend on offline databases or manually supplied inputs. Limited incorporation of dynamic environmental variables can reduce model adaptability under variable field conditions and restrict transferability across crops and production environments [113]. In addition, the availability of high-quality annotated datasets, requirements for model interpretability, and the limited computational capacity of edge devices can constrain the practical deployment of AI-based systems.

Digital twin technology represents a possible approach to addressing some of these limitations. By constructing a virtual representation of the spraying process, different combinations of operating parameters can be evaluated through simulation before field implementation, thereby supporting parameter selection and decision-making. The Smart Droplets project has explored the integration of artificial intelligence, digital twins, and autonomous robotic spraying to enable adaptive spray regulation and reduce off-target losses. For UAV-based crop-protection systems, the integration of digital twins with multi-

source information fusion has also been proposed as a potential development direction. However, practical field implementation will depend on improvements in crop-growth and spray-process models, real-time acquisition of environmental data, model validation under diverse operating conditions, and the availability of sufficient onboard or edge-computing resources.

5.2. Platform Diversification: Differentiated Evolution of Ground Machinery and UAVs

Self-propelled ground boom sprayers are widely used as platforms for variable-rate application (VRA). Their relatively high payload capacities and large working widths make them suitable for broad-acre crop production. However, their mobility may be limited in complex environments, including hilly orchards, paddy fields, and areas with restricted field access, which can reduce their applicability in these settings.

UAV-based spraying provides an alternative platform for operations in terrain that is difficult for ground machinery to access. In related studies, multispectral UAV imagery has been used to generate georeferenced three-dimensional orchard canopy prescription maps, which were subsequently applied to guide variable-rate spraying. This offline prescription-map approach can reduce the need for each sprayer to carry high-cost onboard sensing equipment and may therefore lower overall system cost and computational demand. Nevertheless, the integration of VRA technologies into aerial platforms remains constrained by limited payload capacity, flight endurance, and sensitivity to ambient crosswinds.

Ground-based and aerial platforms may therefore follow different development pathways. Ground sprayers are likely to accommodate more comprehensive onboard sensing, decision-making, and actuation systems, supporting closed-loop “perception–decision–execution” control. By contrast, UAV platforms may place greater emphasis on lightweight sensors, simplified onboard processing, and variable-rate operation guided by externally generated or cloud-based prescription maps.

5.3. Key Technical Challenges: Sensor Anti-Interference, Model Generalization, and Execution Reliability

A review of the existing literature identifies three recurring technological challenges that may limit the broader adoption of precision spraying systems. The first concerns the accuracy and stability of target perception under dynamic field conditions. At higher operating speeds, LiDAR point-cloud density may decrease, machine-vision performance can be affected by variations in illumination, and multipath reflections can reduce the consistency of ultrasonic measurements. Accordingly, the main challenges at the perception level include sensor accuracy, environmental robustness, real-time processing latency, system integration, and the spatiotemporal alignment of multimodal data.

A second challenge is the limited transferability of current application-rate models across crops and operating environments. Many existing algorithms are calibrated using data from specific crop varieties, canopy structures, or geographical regions. Their predictive performance may therefore decline when they are applied to different crops or environmental conditions. In addition, dependence on offline databases or manually entered parameters can restrict their ability to respond to real-time changes in canopy morphology and local microclimatic conditions.

The third challenge concerns the mechanical and hydraulic reliability of the execution system. High-frequency actuation may accelerate wear or increase the risk of malfunction in solenoid valves, while PWM switching can generate pressure fluctuations within the hydraulic circuit. System latency may also introduce spatial offsets between target detection and spray actuation. These effects may be less apparent during short-term laboratory experiments but can accumulate during continuous field operation and contribute to reductions in control accuracy and system reliability.

To translate these challenges into more clearly defined engineering directions, future research could focus on four technical areas.

First, perception systems could place greater emphasis on combining complementary sensing modalities. One potential configuration is the integration of terrestrial three-dimensional LiDAR with multispectral or binocular vision. LiDAR can provide three-dimensional geometric information, including plant height, canopy width, and canopy volume, with relatively limited sensitivity to target color. Multispectral or binocular vision can provide optical, spectral, textural, and depth-related information that supports the identification of pest distributions, weed patches, and disease symptoms. By separating structural characterization from biological-condition assessment, such sensor combinations may improve perception reliability under variable field conditions. However, their performance will still depend on accurate calibration, temporal synchronization, data registration, and computational efficiency.

Second, improving model generalization will require the incorporation of variables that are often omitted from static or offline application models. Spray-volume models could progressively move beyond ground-area-based or simplified Tree Row Volume parameters toward dynamic, multi-factor decision frameworks. Relevant inputs may include localized wind speed and direction, ambient temperature, and relative humidity, because these variables influence droplet evaporation and transport. Dynamic estimates of leaf area density may also provide a more representative basis for regulating application volume than assumptions of uniform foliage distribution, particularly as canopy structure changes during crop development.

Third, improving execution reliability will require further investigation of the mechanical and hydraulic characteristics of PWM-based actuation systems. Important factors include the response time of solenoid valves, wear of the valve spool and seat during repeated high-frequency switching, and changes in the calibrated relationship between duty cycle and flow rate over time. Optimization of valve geometry and actuator structure may help reduce response delay and improve service life. In parallel, hydraulic stabilization strategies should be investigated to reduce transient pressure waves and flow oscillations caused by intermittent valve operation, because these disturbances can influence droplet-size distribution and nozzle atomization.

Fourth, broader technology transfer would benefit from more standardized field-validation procedures. Comparisons among existing studies are often complicated by differences in environmental conditions, sampling methods, and reported performance indicators. Future standardization efforts could establish consistent protocols for measuring canopy deposition and uniformity, collecting ground and airborne drift at defined downwind distances, and evaluating biological efficacy across specified phenological stages. Regulatory and testing frameworks may also need to consider the compatibility and performance of tank-mix adjuvants under high-frequency switching and variable-rate operating conditions. Such standardization would improve the comparability of results and provide a more reliable basis for engineering evaluation and regulatory assessment.

5.4. Conclusions

Agricultural precision spraying is progressing from passive drift mitigation toward active, variable-rate application. However, the reviewed literature indicates that the components of the “perception–decision–execution” framework differ in technological maturity, operational reliability, and readiness for field deployment. A comprehensive assessment of current development should therefore consider both technical performance and practical implementation constraints. At present, several technologies have achieved a relatively high level of operational maturity, including binary target and canopy-gap detection us-

ing filtered ultrasonic or infrared sensors, Tree Row Volume (TRV)-based application models, and hydraulic low-drift or air-induction nozzles. These technologies generally involve moderate implementation costs, relatively simple system architectures, and established field-operating procedures. By comparison, high-resolution terrestrial LiDAR for three-dimensional canopy profiling and multi-nozzle spatially selective spraying systems remain largely at the prototype or experimental stage. More computationally demanding approaches, including deep learning-based pest and weed identification and fuzzy-logic-based variable-rate tank-mixing systems, have mainly been evaluated under laboratory or controlled conditions, and their field reliability requires further validation.

The transfer of perception and decision-making technologies to field applications is constrained by several algorithmic challenges. Heterogeneous data streams, such as LiDAR point clouds and camera images, must be spatially registered and temporally synchronized under strict real-time processing requirements, which can impose substantial computational demands on onboard hardware. Machine-vision models may also be sensitive to variations in natural illumination and often show limited transferability across crops, canopy structures, and environmental conditions. In addition, image-processing and model-inference delays may produce spatial offsets between target detection and spray actuation, particularly at higher travel speeds.

At the execution level, system performance is influenced by the mechanical and hydraulic characteristics of the actuation components. Repeated high-frequency switching of pulse-width modulation (PWM) solenoid valves can contribute to wear of the valve spool and seat. Over extended operating periods, this wear may alter valve response characteristics and cause deviations from the initially calibrated relationship between duty cycle and flow rate. Intermittent fluid delivery can also generate transient pressure waves and flow oscillations within the hydraulic circuit. These disturbances may affect volumetric flow stability and nozzle atomization, with potential consequences for deposition uniformity and drift control.

In addition to technical limitations, economic, operational, and regulatory factors may influence broader field adoption. The cost of high-resolution sensors, onboard processors, electronic controllers, and precision actuators can represent a substantial investment, particularly for small- and medium-scale farms. Operationally, shielding structures and full-boom enclosures may restrict nozzle visibility, complicate maintenance, and reduce maneuverability during headland turns in orchards or other confined environments. From a regulatory perspective, existing testing and registration procedures may not fully address the behavior of tank-mix adjuvants under variable-rate and high-frequency switching conditions. Further development of standardized evaluation protocols may therefore be required.

Future research could focus on improving computational efficiency, actuator reliability, and decision-model adaptability. Lightweight edge-computing platforms and efficient neural networks are needed to support real-time canopy characterization under limited onboard processing capacity. The internal geometry and actuation mechanisms of solenoid valves should also be optimized to reduce response delay and improve durability during repeated high-frequency operation. In parallel, application-volume models should increasingly incorporate dynamic environmental and canopy variables, including local wind speed and direction, temperature, relative humidity, and leaf area density.

Overall, integrating perception, decision-making, and execution technologies within a coordinated system provides a potential pathway for improving pesticide-use efficiency and supporting the field implementation of precision spraying. Continued progress will depend on addressing the combined algorithmic, mechanical, economic, operational, and regulatory constraints that currently limit system reliability and scalability.

Author Contributions: R.Y.: Formal Analysis, Investigation, Writing—Original Draft. J.W.: Formal Analysis, Investigation, Validation. Z.K.: Methodology, Investigation. M.O.: Conceptualization, Methodology, Supervision, Project Administration. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Frontier Technologies R&D Program of Jiangsu (BF2025313).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors thank the School of Agricultural Engineering of Jiangsu University for its facilities and support. During the preparation of this work the authors used ChatGPT 5.5 AI for translation and language editing. The content was reviewed and edited by the authors, who take full responsibility for the publication.

Conflicts of Interest: The authors declare no conflicts of interest.

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