

Review

From Field Sensing to Smart Spreading: A Comprehensive Review of Variable Rate Fertilization Technologies in Precision Agriculture

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Abstract

The escalating pressure on global food security, driven by the decline in per capita arable land area and widespread soil degradation, necessitates a paradigm shift from conventional uniform fertilization to more precise nutrient management strategies. Variable rate fertilization (VRF) has emerged as a key enabler of sustainable intensification, offering the potential to enhance crop yield, optimize fertilizer use efficiency, and mitigate environmental impacts. This paper provides a comprehensive review of the current state of VRF research, focusing on (i) field characterization methods using soil and vegetation indices, (ii) decision-support models for variable-rate nutrient application, and (iii) the design and operation of VRF applicators. By synthesizing recent advances and identifying persistent challenges, this review aims to provide a scientific basis and practical pathways for implementing VRF across diverse cropping systems.

Keywords: variable rate fertilization; vegetation indices; decision-making models; variable-rate fertilizer applicators

1. Introduction

The imperative to optimize fertilizer management has never been more urgent, as global agricultural systems face the dual challenge of ensuring food security while mitigating environmental degradation. In 2023, the global cropland area was approximately 1.6 billion hectares, accounting for more than 1/9 of the global land area [1]. Although total cropland expanded by 5% between 2001 and 2023, rapid population growth led to an 18.6% decline in per capita cropland area over the same period [2]. Concurrently, approximately 29% of the world's agricultural land has been degraded due to anthropogenic activities, further exacerbating pressures on food production systems [1]. A primary driver of this degradation is inappropriate fertilization practices. While soil nutrients exhibit considerable spatial heterogeneity within and across fields, conventional farming continues to rely on uniform fertilizer application, resulting in inefficient nutrient uptake and substantial environmental residuals [3]. To compensate for declining productivity on limited land resources, farmers often increase fertilizer inputs, thereby perpetuating a vicious cycle of



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land degradation and excessive fertilizer use. Indeed, FAO data indicate that while the global nitrogen surplus rose nearly sixfold from the 1960s to the 2010s, crop nitrogen uptake increased only 3.4-fold over the same period [4]. These trends underscore a critical gap between nutrient application and crop utilization, which not only compromises cropland quality but also limits yield potential per unit area [5]. Consequently, transitioning from traditional uniform fertilization to spatially explicit, variable-rate strategies has become imperative for sustainable intensification and food security.

In response to the environmental and agronomic drawbacks of conventional uniform fertilization, the concept of variable rate fertilization (VRF) was introduced in the United States in the early 1990s. Field trials have since validated its potential to enhance nutrient use efficiency, boost crop yield and quality, and improve the economic returns of crop production by accounting for the spatial variability of soil properties and crop growth within a field. Despite these benefits, the practical adoption of VRF faces significant barriers. Early approaches, such as grid-based soil sampling or intensive crop monitoring at multiple growth stages, are labor-intensive and time-consuming, imposing a substantial operational burden on farmers [6]. This labor cost, coupled with the need to reduce excess fertilizer application while sustaining high yields, has driven the search for more efficient and automated solutions. Consequently, global efforts are increasingly focused on integrating modern technologies to overcome these limitations. For instance, China's 14th Five-Year National Plan for the Green Development of Agriculture (2021) explicitly promotes technology-driven strategies to reduce chemical fertilizer usage and increase nutrient use efficiency [7]. Central to this technological transformation is the paradigm of precision agriculture, which recognizes fields as spatially variable systems and leverages modern information technologies—such as remote sensing and geographic information systems (GIS)—to adapt management practices accordingly [8]. By enabling site-specific operations, precision agriculture provides the foundational framework for implementing VRF in a practical and scalable manner [9]. Within this framework, VRF stands as a core technology for sustainable intensification, offering a pathway to reconcile productivity goals with environmental stewardship [10].

Soil is the material foundation of crop growth [11]. Soil organic matter content and soil properties are essential for assessing the quality of cultivated land resources, and poor soil texture significantly reduces crop yield [3]. Given that croplands around the world are highly diverse and exhibit strong spatial heterogeneity, the appropriate utilization of soil resources is essential to ensure stable and high yields [11]. In China, cropland quality is generally low, with extensive areas of medium- and low-yielding cropland [12]. In an effort to improve yields from medium- and low-yielding cropland, cultivators often ignore the spatial heterogeneity of soil fertility and instead apply chemical fertilizers uniformly and in excessive amounts, which leads to further degradation of cropland resources [13]. Approximately 60% of nitrogen fertilizer applied globally is used for crop production, but only 1/3 is absorbed by crops [3]. While excessive application of fertilizer has increased production costs, it has failed to yield a commensurate increase in production efficiency [14]. Excessive use of fertilizers will lead to water eutrophication, soil acidification, accumulation of heavy metals, increased pests, and other problems [15]. As an important part of agricultural ecosystems, soil is vulnerable to degradation from excessive chemical fertilizer use, which directly impairs crop growth, reduces photosynthetic and transpiration efficiency, and ultimately results in lower yields and reduced income for cultivators. Rational fertilization should be carried out based on the spatial heterogeneity of soil fertility, which is conducive to reducing fertilizer input, enhancing fertilizer use efficiency, ensuring crop quality, and increasing yield per unit area [16]. Regarding rational fertilization technology, scientists have conducted extensive research. Studies have shown

that, compared with traditional fertilization methods, incorporating biochar with half the standard chemical fertilizer application rate can reduce harm to human health by approximately 54% and decrease greenhouse gas emissions by 46% [17]. Ju indicated in the research that rational fertilization can help achieve target yields, improve crop quality, enhance economic benefits, and increase soil fertility [18]. Yang proposed that designing a rational fertilization regime can optimize the function of the soil microbial community, enhance soil ecosystem services, strengthen the capacity to prevent plant diseases, and reduce negative environmental impacts [19]. Wang demonstrated in their study that scientific fertilization management is one of the main factors for sustaining long-term, stable high yields in horticultural fruit and vegetable crops [20]. Crop yield is the result of the interaction among genetics, environment, and agricultural management [21]. Thus, besides the genetic characteristics of crop varieties and uncontrollable environmental conditions, conducting VRF according to crop growth stages and soil characteristics in different regions is the key to promoting crop growth and ensuring high and stable yields [22].

Conventional agricultural fertilization practices predominantly rely on empirical judgment, treating the field as a homogeneous entity and applying uniform application rates [8]. While this approach ensures basic crop yields, it inevitably leads to resource wastage and environmental risks owing to the neglect of intra-field spatial variability in soil properties and crop growth. VRF technology, grounded in the principles of precision agriculture, utilizes modern sensing and information technologies to dynamically adjust fertilizer application rates in response to real-time field conditions, thereby enabling refined management of farmland. Currently, the field application of VRF technology remains limited, primarily attributable to high costs, complex data processing procedures, sensor susceptibility to interference in complex field environments, and the lack of standardized operational workflows. In contrast to recent reviews focusing on isolated technical aspects, this review aims to comprehensively summarize recent research progress in VRF, conduct an in-depth analysis of the technical bottlenecks constraining its application, and propose future development strategies. By analyzing the technology through the three dimensions of perception, decision-making, and execution, this review provides a scientific foundation for the transition of VRF technology from theoretical research to practical field application.

2. Perception: Field Characterization and Data Acquisition

In conventional VRF systems, fields are typically partitioned into management zones, where fertilization plans are derived from manual soil sampling. However, the inherent spatial heterogeneity of soil limits the accuracy of nutrient quantification using this approach. Furthermore, most traditional strategies focus exclusively on pre-planting conditions, applying variable rates solely to base fertilizers while neglecting dynamic crop nutrient requirements during the growing season. Traditional VRF is often labor-intensive and fails to achieve optimal precision [23]. These limitations are particularly acute in large-scale agricultural operations. Therefore, there is a critical need for rapid, precise measurement methods to accurately characterize both soil spatial heterogeneity and crop growth status. Currently, the primary approaches for acquiring soil information in cropland include prescription map-based methods for VRF and sensor-based real-time monitoring systems [24]. Figure 1 illustrates the complete workflow of a map-based VRF system, which is from UAV-based data acquisition to prescription map generation and finally to variable-rate application. In contrast, Figure 2 shows the operational architecture of a sensor-based VRF system [25]. Here, the decision model resides on the onboard computer, enabling immediate rate adjustment. However, the schematic also reveals a key vulnerability: sensor readings are taken at a single point ahead of the applicator, assuming that soil

properties do not change significantly over the short distance—an assumption that often fails in heterogeneous fields.



Figure 1. Map-based variable rate fertilization (VRF) system (a) UAV-based farmland quality assessment; (b) Execution of VRF prescription map (c) Working process of variable rate fertilizer applicator.

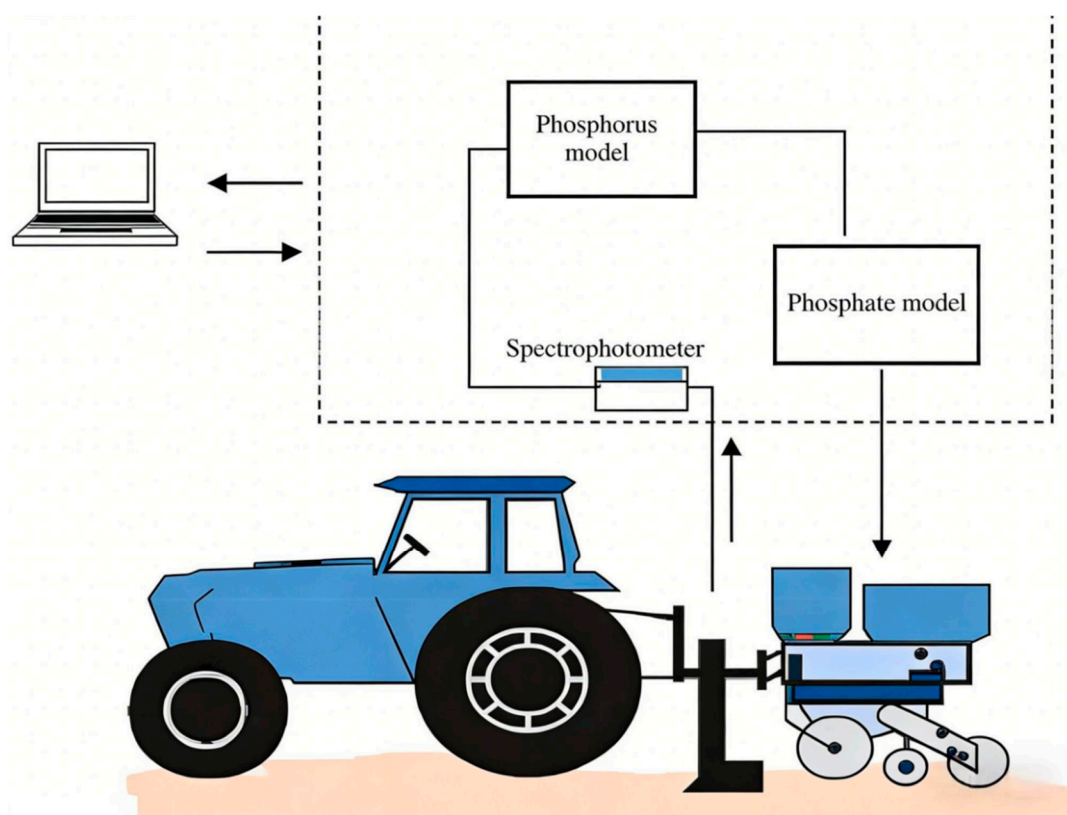


Figure 2. Sensor-based VRF system (reprinted from Ref. [25]) Soil information is acquired by the onboard spectrophotometer, transmitted to the onboard computer, and subsequently utilized to determine the fertilisation rate based on the decision-making model. The onboard computer can be implemented as an edge-based processing unit suitable for both ground and aerial platforms.

In precision agriculture, the Global Positioning System (GPS) receivers are integral to the positioning and navigation of agricultural machinery and drones. High-precision GPS not only provides geographic coordinates but also captures elevation data, enabling the derivation of terrain-related parameters such as slope and aspect, thereby playing a critical role in agricultural data collection [26]. Spatial distribution maps of soil nutrients at the field scale can be generated using GPS receivers and data loggers for cropland data collection, which enables the characterization of soil nutrient spatial heterogeneity [27]. Currently, in China, precision fertilization is primarily implemented based on VRF prescription maps, which are generated by combining crop fertilization models with digital image analysis to

guide machinery operations [28]. Concurrently, research on VRF using sensor-based real-time monitoring systems is advancing progressively. In these systems, sensors mounted on agricultural machinery collect real-time data on soil properties and vegetation indices. The data is then processed by dedicated models to determine crop nutrient requirements, which in turn are used to dynamically adjust fertilizer application rates via the applicator's discharge control system.

2.1. Offline Perception: Prescription Maps from Remote Sensing

To mitigate initial investment and labor costs, modern VRF technology integrates GPS, geographic information systems (GIS), unmanned aerial vehicle (UAV)-based remote sensing, and in-field soil sensing to acquire plot-specific data and generate spatial maps of soil and crop attributes. By synthesizing crop growth stages and vigor across varieties, fertilizer demand patterns are identified to develop site-specific prescription maps, which are subsequently uploaded to a variable-rate fertilizer applicator to facilitate automated, map-driven field operations. Kayad et al. (2021) [29] derived green normalized difference vegetation index (GNDVI) maps of maize from the milk-ripe to physiological maturity stages from Sentinel-2 satellite imagery 2016–2018, and a composite GNDVI map was generated via temporal averaging. Given the significant positive correlation between soil electrical conductivity (EC) and nitrogen (N), phosphorus (P), and potassium (K), historical yield maps were integrated with soil apparent EC maps to develop a nitrogen fertilization prescription map for guiding variable-rate N application (Figure 3). Relative to conventional uniform N application, the variable-rate approach increased maize grain yield by approximately 31% while reducing the N application rate by approximately 23% [29,30]. Soil pH is a pivotal factor governing phosphorus (P) bioavailability. Extensive research indicates that neutral soil environments maximize soluble phosphate concentrations, thereby optimizing conditions for plant uptake [31]. Consequently, mapping the spatial variability of soil pH offers a strategic basis for precision phosphorus fertilization. To meet this need, Mohammed et al. developed an alizarin-based screen-printed electrode, enabling real-time, continuous, and rapid in situ monitoring of soil pH in the field [32]. Similarly, soil organic matter (SOM) serves as another critical indicator for assessing soil fertility and guiding variable-rate fertilization (VRF), exerting profound effects on soil structure, plant nutrition, and microbial community dynamics. Therefore, its rapid and accurate quantification is equally indispensable for effective VRF management [33,34]. To this end, Uddin et al. proposed a data-driven predictive framework that integrates multispectral unmanned aerial vehicle (UAV) imagery with ground-based embedded sensor data—including soil pH, temperature, humidity, and N, P, and K content. By leveraging a random forest algorithm, they successfully predicted SOM concentrations, providing a robust scientific basis for generating VRF prescription maps [35]. Argento et al. (2021) [36] acquired soil and crop remote sensing data using a quadrotor unmanned aerial vehicle (UAV) equipped with a multispectral camera, utilizing the normalized difference red edge index (NDRE) as an indicator of crop nitrogen status. Compared with conventional uniform fertilization, the VRF treatment reduced the nitrogen application rate by 5% to 40% and improved nitrogen use efficiency by approximately 10% [36]. Furthermore, Guan et al. (2025) [37] acquired multispectral imagery at the pre-heading stage using a UAV to enhance wheat grain protein content. The derived normalized difference vegetation index (NDVI) was utilized to generate a variable-rate nitrogen topdressing prescription map for in-field application [37]. Although multispectral sensors are widely employed for plant nitrogen retrieval, previous studies have indicated that hyperspectral sensors possess substantial potential for detecting nitrogen deficiency. This is attributed to their capacity to provide dense, continuous narrow bands, enabling the accurate quantification of foliar protein constituents. Con-

versely, multispectral sensors utilize discrete, broad bands; during spectral integration, this characteristic results in the loss of critical spectral information, thereby compromising analytical accuracy [38]. In addition to satellite- and UAV-based remote sensing, proximal crop sensing data acquired from sensors mounted on agricultural machinery can also be utilized to generate VRF prescription maps. For instance, a GreenSeeker (NTech Industries Incorporation, Ukiah, CA, USA) active optical sensor was mounted on a tractor boom to collect canopy reflectance data during the tillering and flag leaf stages of wheat. The controller process sensor data in real time to calculate the NDVI, which is integrated with crop models to generate nitrogen fertilizer prescription maps for guiding variable-rate nitrogen application [39].

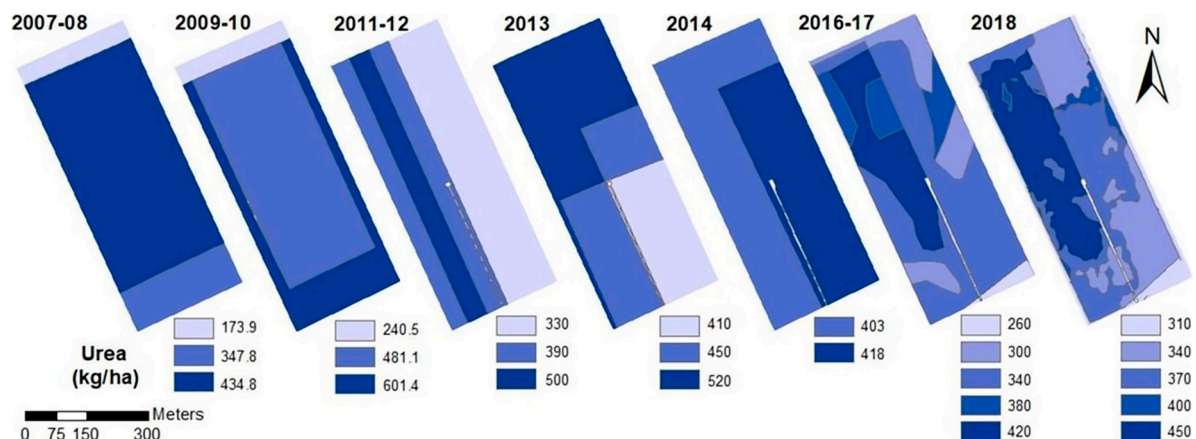


Figure 3. Nitrogen application prescription maps (reprinted from Ref. [30]) Evolution of VRF Prescription Maps (2007–2018) by Kayad et al. [29].

Because nitrogen is highly mobile in soil and prone to leaching, current research on variable-rate fertilization has largely focused on nitrogen application. Most studies on VRF technology use drones to collect vegetation indices and generate prescription maps for supplemental fertilization. Although broadband vegetation indices (e.g., NDVI) cannot directly reflect nitrogen deficiency, they exhibit a stronger correlation with crop growth status and phenotypes than the Modified Chlorophyll Absorption Reflectance Index (MCARI) and SPAD values, which directly reflect chlorophyll content within plants [40,41]. Particularly under dense canopy conditions prone to spectral saturation, NDRE exploits the penetration capability of the red-edge band to probe deeper vegetation layers, thus overcoming saturation limits and ensuring accurate late-season crop monitoring [42]. These reviewed studies show that prescription-map based VRF has evolved from early grid-soil sampling to the use of UAV/satellite multispectral imagery, with vegetation indices (e.g., NDVI, NDRE, GNDVI) becoming the dominant data source for nitrogen prescription maps. The main advantage lies in large spatial coverage and pre-season planning, which suits large-scale, mechanized farms. However, several limitations are consistently reported across studies: (i) image acquisition is heavily affected by weather and illumination; (ii) multispectral sensors lose subtle spectral information because of discrete broad bands, whereas hyperspectral sensors, despite higher accuracy, introduce large data volumes and processing challenges; (iii) most prescription maps rely on single-date or pre-planting data and thus cannot capture dynamic crop nitrogen demand during the growing season. Future progress will require balancing spatial resolution, spectral detail, and temporal revisit frequency. Furthermore, relying solely on cropland assessments may not provide a sufficient basis for developing optimal variable rate fertilization (VRF) strategies. However, vegetation activity in drainage ditches can serve as a valuable proxy for field nitrogen leaching, offering critical supplementary information for decision-making processes.

2.2. Online Perception: Real-Time Sensing from Proximal Platforms

Soil and plant tissue analysis is often time-consuming and labor-intensive, requiring specialized software to generate prescription maps—a process that imposes high technical demands on users. In contrast, VRF strategies utilizing high-resolution embedded sensors can effectively circumvent these limitations. Such approaches facilitate the real-time assessment of crop nutrient status through continuous monitoring of canopy spectral reflectance or other physiological indicators [14,24,43]. Maleki et al. integrated an optical unit coupled with a visible–near-infrared (Vis–NIR) spectrometer onto a sub-soiler to acquire subsurface soil spectral data. These data were subsequently processed using a pre-calibrated chemometric model to predict soil phosphorus concentration in real time, thereby enabling site-specific variable-rate phosphorus fertilization. Relative to conventional uniform application, this approach reduced phosphorus fertilizer use by approximately 1.25 kg ha^{-1} while increasing maize grain yield by 336 kg ha^{-1} [25]. Dou et al. developed a vehicle-mounted soil EC sensor based on the four-terminal “current–voltage” measurement principle, installed on the front suspension of an agricultural implement. By integrating this sensor with a rear-mounted fertilizer spreader, a real-time VRF system was established. This configuration allows for the dynamic adjustment of fertilizer application rates in response to spatial variability in soil EC, achieving high control accuracy with an average error of only 7.89% [44]. Addressing the development of smart agriculture in China, Hu et al. developed an integrated system comprising an NDVI sensor, a data processing unit, and a VRF controller. The sensor utilizes solar radiation as an illumination source to simultaneously measure canopy reflectance in the red and near-infrared (NIR) bands for real-time NDVI calculation. Based on these values, the data processing unit determines the optimal fertilizer application rate. Subsequently, the VRF controller adjusts the rotational speed of the metering shaft in accordance with travel speed and application requirements, thereby achieving real-time VRF [45]. Chen et al. developed a field-scale variable-rate nitrogen topdressing applicator equipped with six spectral sensors and a signal conditioner to enable real-time measurement of wheat NDVI and on-the-go determination of application rates. The system modulates fertilizer output by synchronously adjusting the metering shaft speed and the discharge gate opening, demonstrating a control accuracy exceeding 90%. Compared with uniform nitrogen application, this variable-rate approach increased the total nitrogen applied by approximately 28 kg ha^{-1} [46]. Hagn et al. delineated management zones based on spatial heterogeneity and determined target yields using historical yield maps. They integrated real-time plant nitrogen uptake data, collected by tractor-mounted sensors, into the fertilization algorithm to achieve variable-rate nitrogen application for winter wheat [47].

Real-time sensor-based VRF systems use proximal sensors (Vis–NIR spectrometers, soil EC sensors, active optical NDVI sensors) mounted on agricultural machinery to enable “sensing-while-applying”. Compared with prescription-map methods, the key advantage is immediate responsiveness to within-field spatial heterogeneity, avoiding off-line processing delays. Among the technologies, soil EC sensors offer low cost and rapid response but are sensitive to environmental fluctuations; active NDVI sensors are simple to use but only indicate canopy vigor; Vis–NIR spectrometers provide high accuracy but are expensive. Common limitations across studies include: susceptibility to vibration, temperature, humidity, and light variations; a lack of universally applicable calibration models; and difficulties in synchronizing multiple sensors. Improving sensor robustness and simplifying calibration procedures are critical for wider adoption.

2.3. Offline vs. Online Perception: Trade-Offs and Selection Guidance

Prescription-based and sensor-based variable-rate fertilization methods are the two primary technical paradigms in precision agriculture, exhibiting significant divergence in adaptability, data dependency, temporal responsiveness, and implementation costs. Regarding data dependency and temporal variability, prescription-based methods rely heavily on historical data or pre-collected remote sensing imagery. Although advantageous for long-term planning, this reliance limits their capacity to adapt to dynamic in-field variations and crop growth stages. In contrast, sensor-based real-time monitoring systems provide immediate feedback and exceptional adaptability, enabling rapid responses to spatio-temporal heterogeneity during crop development, thereby facilitating refined management. In terms of implementation costs and technical requirements, prescription-based methods typically entail substantial upfront investments in data processing and software, despite offering standardized operational procedures. In contrast, while sensor-based systems simplify operational workflows, they incur higher hardware expenditures. Furthermore, these systems are susceptible to noise interference from environmental factors, such as light and temperature fluctuations, as well as mechanical vibrations, posing significant challenges to system robustness. Consequently, prescription-based methods are better suited for long-term, large-scale nutrient management planning, whereas sensor-based real-time systems offer distinct advantages in addressing dynamic crop variability. However, variable-rate fertilization (VRF) strategies relying on vegetation indices are inherently reactive, as they typically detect crop responses only after nutrient deficiencies have visibly impaired crop performance, thereby failing to provide early warnings. In contrast, monitoring soil electrical conductivity (EC) offers a proactive approach that effectively mitigates this limitation. As shown in Table 1, we compared the two VRF paradigms across six criteria that expose fundamental trade-offs: spatial accuracy vs. temporal responsiveness, data dependency vs. cost, and environmental sensitivity vs. ease of use. The fundamental distinction lies in when the field information is incorporated: before the season (prescription map) versus during the operation (real-time sensors). This temporal shift creates a consistent inverse relationship between spatial accuracy and temporal responsiveness across all studies reviewed. In practice, prescription-map methods are preferable for large fields (>10 ha) when within-field variability is stable and predictable (e.g., soil organic matter patterns), whereas real-time sensors are indispensable for small or highly variable fields requiring in-season response. No hybrid or single approach can simultaneously optimize all six criteria; therefore, field-specific diagnosis of variability type and operational constraints remains the only valid basis for method selection.

Neither prescription-map nor real-time sensor methods are universally superior; their suitability depends on application context. Prescription-map methods are better suited for long-term planning, large uniform fields, and situations where soil nutrient spatial variability is stable and does not require high-frequency adjustment. Real-time sensor methods excel for in-season topdressing, highly variable fields, and small farms lacking advanced data processing capacity. A growing number of studies point to hybrid strategies (prescription map pre-planning with real-time sensor correction) as a promising direction, although system complexity and cost remain barriers. Practitioners should make choices based on field size, spatial variability, budget, and technical support.

Table 1. Structured comparison of prescription-map-based and real-time sensor-based VRF methods.

Criterion	Prescription-Map-Based VRF	Real-Time Sensor-Based VRF
Spatial accuracy	Moderate to high (depends on remote sensing resolution and interpolation)	High (continuous, site-specific sensing)
Temporal responsiveness	Low (off-line processing, delayed action)	High (immediate, on-the-go adjustment)
Data dependency	High (requires historical data, remote sensing, GIS expertise)	Low to moderate (requires sensor calibration, real-time readings only)
Initial cost	Moderate (software, occasional imagery)	High (sensors, onboard computer)
Operational cost	Low after map generation	Moderate (maintenance, recalibration)
Environmental sensitivity	High (cloud cover, illumination changes)	High (vibration, temperature, humidity, dust)
Ease of use for farmers	Low (needs data processing skills)	Moderate (automated but requires calibration)
Best-suited scenarios	Large, stable fields; long-term planning; pre-season application	Small to medium fields with high variability; in-season topdressing; farms with limited data processing capacity

2.4. Supplementary Perception Approaches: Single-Sensor and Multi-Source Fusion

2.4.1. Single-Sensor Approaches

Beyond prescription maps and real-time sensor systems, simpler single-sensor strategies offer alternative pathways for VRF, particularly in resource-limited settings. For image-based analysis, Gong et al. utilized a smartphone to extract maize canopy cover across varying growth stages and measurement heights. They developed a lightweight MobileNetV3 U-Net model for canopy image segmentation by replacing the encoder backbone of the original U-Net with MobileNetV3. This modification substantially reduced both the number of model parameters and the size of the weight file, holding promise for elucidating the relationship between canopy cover and crop nitrogen demand [14]. However, visible-light analysis remains highly sensitive to ambient lighting conditions—shadows, cloud cover, and strong light reflections can significantly reduce accuracy. For single-plant precision, Li et al. integrated a D435i depth camera with the YOLOv5 object detection algorithm to accurately localize the stem-root junction of individual crops, enabling a pressurized fertigation system to inject liquid fertilizer directly into the soil adjacent to the crop stem [48]. Although depth cameras capture high-quality 3D point cloud data, they require more efficient segmentation algorithms to enhance recognition robustness against complex background noise [49].

The single-sensor approaches discussed above typically focus on one type of measurement (e.g., canopy cover or depth). When multiple environmental variables need to be considered, a single sensor becomes insufficient. In such cases, multi-sensor arrays can provide richer information. For instance, Du et al. deployed a multi-sensor array comprising soil EC, air temperature and relative humidity, and soil moisture sensors to acquire critical environmental data. Following preliminary processing by a microprocessor, the data were transmitted via a gateway to a central control unit, where outliers were removed. The cleaned data were subsequently uploaded to a cloud-based platform and fed into a decision support system, which generated control signals to regulate the on/off operation of fertilizer injection pumps, thereby enabling precision fertilization [50]. While this multi-sensor approach improves information richness, its complexity and cost pose challenges for widespread adoption. This trade-off between simplicity and accuracy leads naturally to the discussion of multi-source data fusion in the following subsection.

2.4.2. Multi-Source Data Fusion

Single-sensor-based approaches in crop phenotyping are often constrained by inherent limitations. However, multi-source data fusion effectively addresses these shortcomings, thereby enhancing the accuracy and robustness of target recognition in agricultural applications [51,52]. Chen et al. paired RGB and depth data, where the former captures spectral and textural phenotypic features, while the latter encodes three-dimensional structural morphology and spatial architecture of crops, thereby enhancing inter-modality complementarity and improving the robustness of target recognition [53]. Malamiri et al. integrated UAV and satellite imagery to generate a fused product characterized by both high spatial and high spectral resolution, thereby compensating for the limitations inherent in individual monitoring platforms. This approach preserved effective spectral information while enhancing the spatial resolution to 20 cm, which significantly improved the capability for crop feature discrimination [54]. Zhang et al. integrated ground-level hyperspectral data with UAV-derived multispectral data using a spectral response function convolution calculation method. Consequently, the absolute values of the correlation coefficients between various spectral indices and apple tree canopy nitrogen content were increased to the range of 0.55–0.68 [55]. Su et al. extracted spectral and textural features of winter wheat using a multispectral sensor mounted on a UAV. By integrating feature selection and fusion strategies, they developed a SPAD estimation model with high accuracy. Compared to models utilizing single-type features as input, the proposed model demonstrated significantly improved stability and precision [56]. In the context of variable-rate fertilization, Ulloa et al. implemented a mobile robotic platform equipped with visible and multispectral sensors to calculate plant-specific NDVI for precise identification of nutrient deficiency phenotypes. As shown in Figure 4, a central control system triggers solenoid valves to initiate fertilization upon positioning the robotic arm at the target plant base. The system subsequently applies fertilizer in a circular pattern around the root zone before automatically closing the valves, thereby achieving spatially precise, single-plant fertilization [57]. Multispectral sensors capture spectral data in the visible and near-infrared bands, providing a wealth of environmental information [58]. In contrast, hyperspectral sensors offer greater spectral detail, enabling the detection of subtle crop growth variations and accurate characterization of farmland spectral signatures [59]. Despite providing rich phenotypic data, these sensors are typically costly and generate massive datasets, posing significant processing challenges. Although multi-source data fusion enhances the decision-making capability of target recognition models, it is not without limitations. The heterogeneity of multi-source data represents a primary technical challenge, as variations in sensors, platforms, and resolutions lead to difficulties in integrating data formats, spatial resolutions, spectral characteristics, and radiometric features [60]. Furthermore, the integration of multi-source data entails substantial data volumes, imposing high demands on computational resources. Combining imagery acquired at different times and by different sensors may result in inconsistencies in the subsequent fused products [60]. Therefore, in VRF research, investigations into data integration methodologies must be conducted in parallel with the application of multi-source data fusion to further improve the accuracy of identifying crop nutrient requirements.

Beyond mainstream prescription-map and real-time sensor approaches, low-cost single-sensor methods (e.g., smartphone imaging [14], single EC sensors [44]) provide accessible entry points for smallholders, but their accuracy and stability are substantially lower than those of multi-source fusion systems. Multi-source data fusion (RGB + depth [53], hyperspectral + multispectral [55], ground + UAV/satellite [55]) has proven effective in improving nutrient diagnosis accuracy, with feature-level fusion generally outperforming decision-level fusion. However, two universal bottlenecks are reported: (i) heterogeneity in

data formats, spatial/temporal resolutions, and radiometric characteristics across sensors; (ii) high computational demands. Lightweight fusion models and edge computing are identified as key future directions.

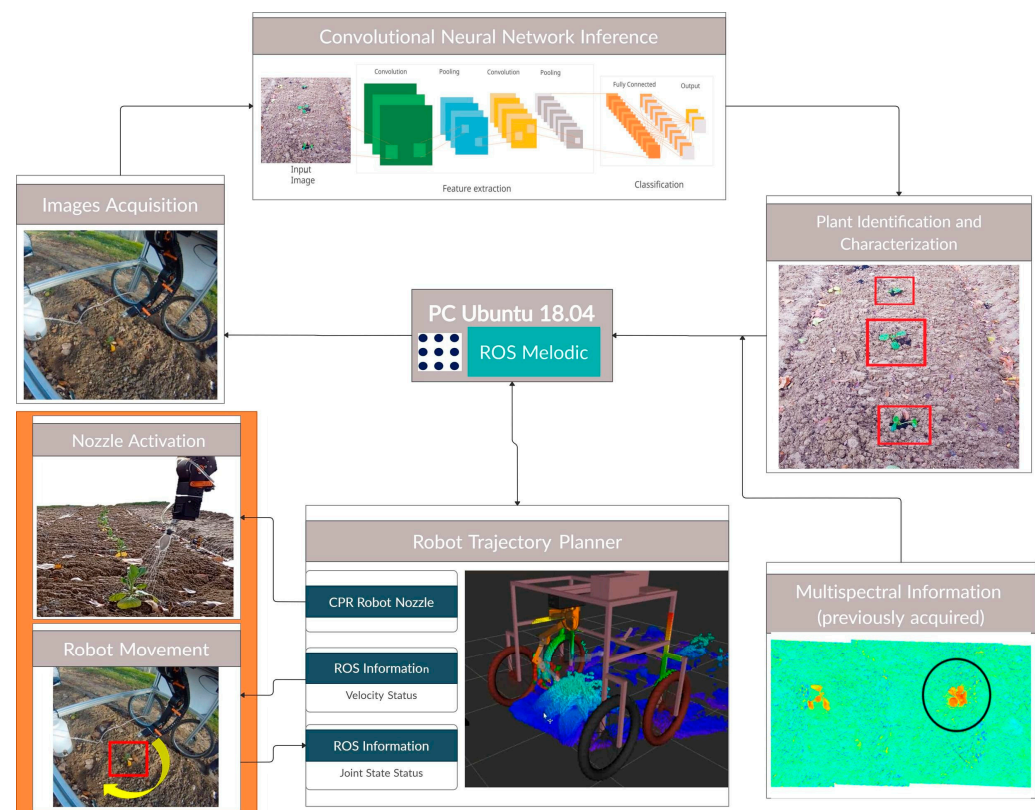


Figure 4. Integration scheme of all the sub-systems to develop robotic fertilization using Convolutional Neural Network (CNN) (reprinted from Ref. [57]) Images captured by the RGB and multispectral cameras mounted on the platform are transmitted to the Robot Operating System (ROS). Subsequently, the system identifies the target plants requiring fertilization via a CNN, accurately localizes the fertilization distance, and completes the application of liquid fertilizer.

3. Decision-Making: Models for Variable-Rate Nutrient Recommendation

Current research on crop water and nutrient management models predominantly focuses on the Agricultural Production System Simulator (APSIM) and the Decision Support System for Agrotechnology Transfer (DSSAT), which are widely employed in field-scale systems for major cereals such as rice, maize, and wheat [61]. Thompson et al. reported that, in the absence of remote sensing inputs, APSIM accurately simulated grain yield across experimental and historical seasons under varying nitrogen rates. However, the model exhibited considerable uncertainty in predicting the economically or agronomically optimal N rate. While APSIM adequately captures soil nitrogen transformation and availability, it lacks the precision required for nitrogen fertilizer recommendations [62]. To address this, Nowatzke et al. integrated in-season remote sensing data to refine plot-scale yield simulations aligning model outputs with machine learning predictions based on plant physiological traits. These improved yield estimates were subsequently used to recalibrate APSIM, significantly enhancing the model's accuracy in simulating soil nutrient dynamics [63]. Similarly, Kumar et al. utilized the Crop Environment Resource Synthesis (CERES-Maize) model within DSSAT to simulate soil nitrogen dynamics across diverse tillage practices. The model effectively accounts for genotype, environment, and management interactions to predict the optimal nitrogen rate for maximizing maize grain yield [64]. In another application, Nowatzke et al. integrated site-specific climatic data into the DSSAT framework to predict

the agronomically optimal nitrogen rate for wheat. Variable-rate nitrogen prescription maps were generated by integrating proximal sensing-derived estimates of actual crop nitrogen uptake. Field validation demonstrated that this prescription fertilization strategy significantly outperformed uniform nitrogen application, resulting in superior grain yield and protein concentration [62]. Beyond the APSIM and DSSAT models, researchers have investigated alternative modeling frameworks. Ren et al. developed the phenology- and LAI-weighted nitrogen prescription recommendation system (PWNPRS) by quantifying the dynamic relationship between rice leaf area index (LAI) and nitrogen application rates across key phenological stages. This model accurately determines the optimal timing and rate of nitrogen application by monitoring LAI through remote sensing [65].

Furthermore, Ma et al. established a three-layer back-propagation (BP) artificial neural network (ANN) for site-specific fertilizer recommendations. Using soil nutrient availability and target maize yield as inputs, the model outputs spatially explicit application rates for nitrogen, phosphorus, and potassium. Validation indicated that the model accurately reflects maize nutrient demand for target yields below $9750 \text{ kg} \cdot \text{ha}^{-1}$, demonstrating its efficacy in supporting VRF strategies [66]. Distinct from the aforementioned mechanistic models and purely empirical models, hybrid models integrating Radiative Transfer Models (RTM) with machine learning algorithms offer high computational efficiency and flexible workflows while maintaining a sound biophysical basis. By generating training datasets via RTM simulations, these models eliminate reliance on field-measured data during the training phase, thereby effectively mitigating the generalization issue often caused by over-dependence on training datasets in decision models [38]. While process-based models like APSIM and DSSAT offer a robust theoretical framework for nutrient dynamics, they often fail to adequately account for field-scale fluctuations in nutrient availability driven by soil spatial heterogeneity. Consequently, this limitation introduces interannual uncertainty in practical applications, potentially leading to suboptimal management decisions. Integrating remote sensing-derived field data with crop variety parameters into these models enables the simultaneous consideration of both crop growth status and long-term soil fertility balance, thereby significantly improving the precision of variable-rate fertilization. Beyond the choice of model architecture, the algorithms that drive real-time decision-making are equally critical. Commonly used algorithms include inverse levy flight-particle swarm optimization (IL-PSO) for parameter tuning, BP for neural network training, and fuzzy PID controllers for closed-loop regulation. The selection of an algorithm typically involves trade-offs between computational speed and optimization accuracy. For edge-based deployment, lightweight algorithms such as MobileNetV3 (for image segmentation) or simplified fuzzy logic controllers are preferred over computationally intensive methods.

In summary, VRF decision models can be grouped into three categories. (i) Mechanistic models (APSIM, DSSAT): they capture soil-crop-climate interactions, making them suitable for long-term soil fertility balance, but they require many parameters, are difficult to calibrate, and typically underutilize in-season remote sensing data. (ii) Purely data-driven models (e.g., BP neural networks): they are computationally fast and require no prior mechanistic knowledge, but they need large labelled datasets and often suffer from poor generalization. (iii) Hybrid models (RTM + machine learning): they generate training data via radiative transfer models, eliminating the need for extensive field measurements, while retaining a biophysical basis and high computational efficiency. Recent studies consistently show that integrating in-season remote sensing data into either mechanistic or hybrid models significantly improves prediction accuracy of optimal nitrogen rates. The main research gap is the development of explainable, lightweight hybrid models suitable for real-time field decision-making.

4. Execution: Hardware and Control for Variable-Rate Application

4.1. Application Platforms: Ground-Based and Aerial Systems

VRF equipment utilizes decision-making information derived from prescription maps or models to precisely modulate fertilizer application rates and spatial coverage. The specific configuration of the VRF applicator is contingent upon the methodologies employed for soil and crop data acquisition. In terms of variable-rate application control, Shi et al. integrated proximal spectral sensing with a VRF expert decision-support system to generate real-time target fertilizer application rates, utilizing the Raun nitrogen response-based fertilization model. These target rates served as inputs for the inverse levy flight algorithm-particle swarm optimization-multilayer perceptron (ILPM) algorithm to determine the optimal opening width and rotational speed of the fertilizer metering unit [66]. Furthermore, Shi et al. engineered a centrifugal VRF applicator equipped with a closed-loop feedback system that relays real-time operational parameters—including tractor forward speed, spinner disc rotational speed, and hopper gate opening—to an onboard computer. This integrated system dynamically modulates the nitrogen application rate in response to the in-season growth status of rice, demonstrating temporal control aligned with phenological stages [67]. To achieve this, the closed-loop architecture integrated three feedback signals—gate opening, disc speed, and vehicle speed—with Beidou navigation for speed correction (Figure 5). Notably, no direct mass flow measurement is fed back, meaning the system relies on indirect control. This design choice reduces hardware cost but limits accuracy when fertilizer properties (e.g., granule size, density) vary.

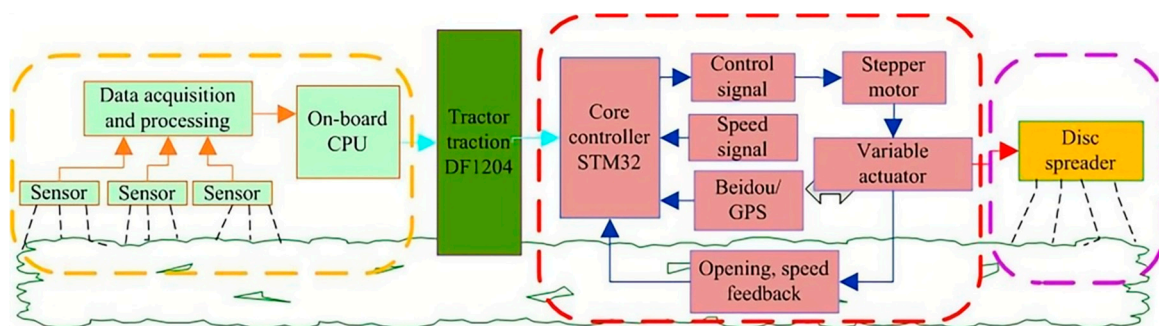


Figure 5. VRF flow diagram (reprinted from Ref. [67]) On-board sensors acquire farmland operation data in real time, which is then transmitted to the on-board CPU after processing. The core controller generates control commands based on this data to drive the stepper motor and regulate the actuator, thereby controlling the fertilization operation of the centrifugal spreader. Simultaneously, the system feeds back the opening and speed feedback of the spreader via sensors, and integrates the travel speed of the agricultural vehicle with Beidou navigation positioning signals to achieve VRF control.

For spatial application control, conventional commercially VRF applicators are generally incapable of achieving single-plant precision fertilization. To address this limitation, Chattha et al. retrofitted a commercial granular fertilizer spreader to facilitate not only site-specific prescription maps but also real-time monitoring of nutrient application at the individual plant level, while enabling independent control of nozzle pair or array for targeted fertilization [68]. Both prescription map-driven and sensor-guided VRF systems inherently exhibit a temporal delay between agronomic decision-making and actual fertilizer placement, which can compromise application accuracy. To mitigate this latency-induced error, strategies should encompass not only the enhancement of onboard computational efficiency but also the optimization of fertilizer applicator design and dynamic response characteristics. Maleki et al. mounted a soil sensor and a spectral reflectance sensor on the forward section of the agricultural machinery [69]. They applied a calibrated time delay to synchronize sensing data with the implement's response, thereby improving the

coordination between sensing and variable-rate application [45]. This synchronization, however, is constrained by the physical layout of the machinery. As shown in Figure 6, the distance L between the sensor and the furrow opener creates a fundamental trade-off: a larger L allows more processing time but increases the spatial mismatch between the sensed soil property and the actual application point. Maleki et al. optimized L to balance these two competing effects.

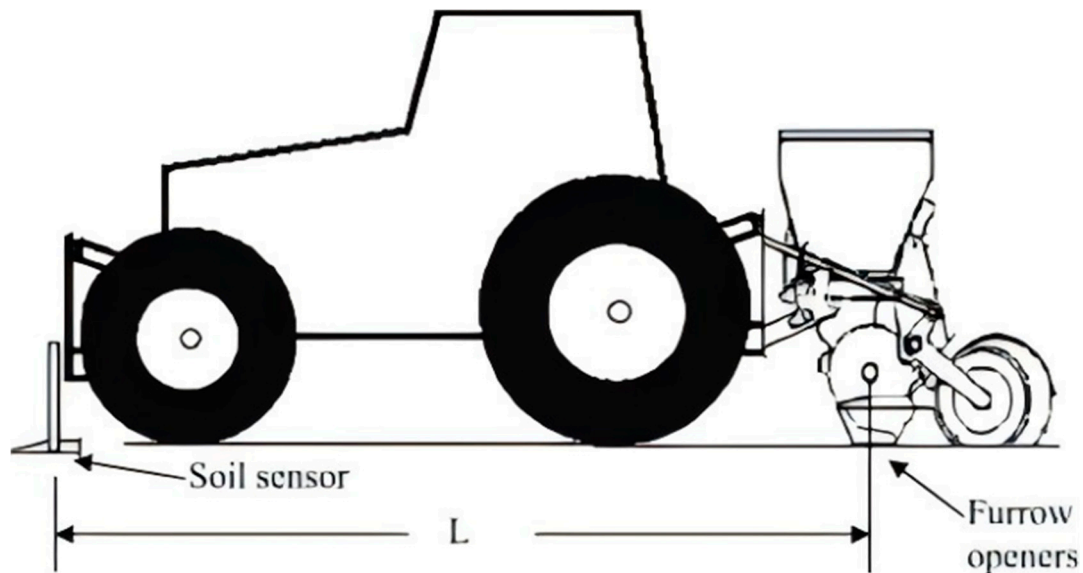


Figure 6. Schematic diagram of soil sensor position (reprinted from Ref. [69]) The soil sensor is mounted on the front end of the VRF applicator, The metering device is located at the rear end of the implement. L denotes the distance between the sensor and the furrow opener.

Beyond synchronization delays, the dynamic characteristics of fertilizer delivery also affect accuracy. Shi et al. reported that the fertilizer drop lag distance increases linearly with the applicator's travel speed, whereas the fertilizer flow rate initially decreases and subsequently increases during operation. The employment of a lead-screw-slider actuator as the metering mechanism significantly reduces the drop lag distance and shortens the system response time, thereby enhancing the accuracy of the application rate [70]. Zhou et al. developed a liquid fertilizer deep-placement control system employing a fuzzy proportional integral derivative (PID) control algorithm to facilitate variable-rate application. When compared with conventional VRF applicators, the system shortens the response time by approximately 5 s and confines the application error to within 10%. By integrating precision VRF with real-time targeted delivery, this approach builds upon precision fertilization principles to further reduce fertilizer consumption and enhance crop yield [71].

In addition to ground-based machinery, aerial platforms offer distinct advantages for specific terrain conditions. Although VRF application machinery shows great promise for large-scale farming, variable-rate fertilization using manned aircraft and fertilizer-spreading drones yields superior results in hilly terrain. Grafton et al. utilized the Intelispray+ system to control variable-rate fertilizer application and equipped the aircraft with LiDAR to maintain a stable flight altitude. The results demonstrated that this method accurately identifies boundaries where fertilizer application rates change and responds promptly, thereby ensuring the precision of variable-rate fertilization [72]. While the transition of variable-rate application technology from ground-based agricultural machinery to aerial platforms has further improved operational efficiency, it still faces significant challenges, primarily due to limitations related to payload capacity, weather conditions, and downwash flow interference [73].

4.2. Flow Measurement and Closed-Loop Control Systems

High-precision fertilization necessitates the precise alignment of the fertilizer source, rate, timing, and placement with specific crop requirements. Accurate measurement of fertilizer mass flow is a prerequisite for precise control in VRF. Current monitoring methodologies are generally categorized into direct and indirect approaches. Indirect strategies, such as the operational parameters method and the hopper weight-based method, estimate flow rates by monitoring the mechanical parameters of metering components [74]. As summarized in Table 2, while these approaches are cost-effective and conducive to large-scale implementation, their calibration models are outdated and struggle to accommodate modern fertilization techniques. Furthermore, they are susceptible to ambient humidity, which limits their applicability to hygroscopic fertilizers. Similarly, methods employing pressure sensors or LiDAR to monitor hopper weight necessitate structural modifications. Although suitable for bulk materials, these systems exhibit low resolution and are susceptible to significant errors at low application rates. In contrast, direct measurement techniques—including capacitive, photoelectric, and Microwave Doppler and Laser Doppler methods—enable direct monitoring of granular fertilizer flow with high accuracy and row-specific capabilities. However, the application of these sensors is constrained by specific limitations: capacitive sensors are vulnerable to vibration and electrical noise; photoelectric sensors are highly sensitive to moisture; and microwave sensors are prone to electromagnetic interference and entail high operational costs. Although imaging-based methods offer high precision and non-intrusive installation require substantial computational resources and are significantly affected by dust accumulation.

Table 2. Existing and emerging fertilizer mass flow rate measurement technologies [70].

Categories	Techniques	Advantages	Disadvantage	Accuracy Range	Field Limitations
Indirect	Hall effect/encoder/Potentiometer	Simple design; Low cost	Sensitivity to moisture;	93.7–98.6%	Incompatible with hygroscopic fertilizers; over-reliance on calibration model
	Pressure transducer/Laser radar	simple principle; Non-invasive; Suitable for bulk measurement	Low resolution at low flow rates; Structural complexity	95.2–97.7%	Require significant modifications of the hopper; cannot detect single row
Direct	Capacitance sensor	Compact; lightweight, can be installed on the fertilizer pipe	Sensitive to Environmental temperature and humidity Cannot detect overlapping fertilizer particles; probe can easily be coated by dust	96.3–98.1%	Influenced by vibration and noise; Unsuitable for multi-fertilizer blends
	Infrared (IR) sensors	cost-effective; ease integration		95.9%	Requires frequent cleaning; influenced by particle pulsation and moisture
	Microwave doppler Laser Doppler	simple structure and easy installation; realize single-row detection	electromagnetic interference; Limited spatial resolution	95.0–97.2%	Influenced by electromagnetic interference from the tractor; Cost-prohibitive for small farms
	CCD Camera	High precision; non-intrusive	Computational load; Dust occlusion	93.7%	Requires controlled lighting and a darkroom; requires large data processing hardware

The precise measurement of fertilizer mass flow is a prerequisite for accurate VRF; however, the integration of a closed-loop control system is imperative to enhance overall control performance [24]. In the context of VRF, real-time feedback control systems utilize the measured application rate as the input, facilitating the dynamic adjustment of metering

parameters—such as gate opening and metering shaft speed—by continuously comparing the target rate with the actual value. Consequently, the system dynamically regulates fertilizer output, effectively mitigating errors induced by factors such as granule caking and variations in tractor speed. For instance, Tola et al. developed a closed-loop control system capable of real-time rate adjustment based on optical sensors for granular flow measurement, and demonstrated that the overall system error was maintained within $\pm 5\%$ with a response time ranging from 0.95 to 1.90 s [75]. Furthermore, Back et al. employed a CCD camera to capture images of falling fertilizer for actual rate calculation, comparing the performance of open-loop and closed-loop systems. The findings indicated that the closed-loop control system outperformed the open-loop system in terms of root mean square error (RMSE) and measurement accuracy [76].

5. Challenges and Limitations in VRF Adoption

The advent of technologies such as GPS, remote sensing, and the Internet of Things (IoT) has significantly advanced precision agriculture. In the United States, farms adopting precision agriculture practices yield profits 163 dollars per hectare higher than conventional farms. However, despite the potential for increased profitability, the adoption rate of VRF technologies remains below 20% in most regions [77,78]. This is largely owing to the fact that smallholder farmers often lack the financial capacity to afford the high initial costs of such technologies, even when potential gains exist [79,80]. For smallholder farmers, the promotion of conservation tillage techniques holds greater practical urgency relative to variable-rate fertilization techniques. Current sensing methods face inherent limitations. Remote sensing technologies, comprising satellites and UAVs, are constrained by relatively low spatial resolution and susceptibility to weather conditions such as lighting variations. In contrast, vehicle-mounted proximal sensing technologies operate closer to target crops, delivering higher spatial resolution and thereby enhancing the accuracy of prescription maps for variable-rate fertilization; however, it suffers from data gaps in certain areas due to terrain constraints [78]. The agricultural system is inherently complex, necessitating the collection of vast amounts of field data. The subsequent in-depth data analysis often exceeds the technical capabilities of farmers [77]. Furthermore, the development of predictive models relies heavily on extensive data annotation. Low-resolution data tends to blur the distinctions between areas requiring different nutrient inputs, thereby increasing both labor demands and fertilization errors. Additionally, commercially available VRF machinery predominantly employs indirect methods to measure application rates. This often results in significant discrepancies in fertilization rates across different rows, even when the metering shaft operates at a uniform rotational speed, leading to substantial inaccuracies [81]. In particular, complex terrain characterized by frequent fluctuations in elevation and soil type poses significant challenges to agricultural machinery. These conditions not only introduce significant noise to sensor data and cause positioning errors during operations but also compromise the precision of fertilizer application. Conversely, the application accuracy of both drone-based and manned aerial systems remains highly dependent on favorable weather conditions. In summary, the integration of agricultural machinery and sensors is considerably challenging due to multifaceted constraints. There is an urgent need for interdisciplinary collaboration to establish a simple, executable, and cost-effective VRF framework that seamlessly integrates sensing, decision-making, and actuation.

6. Conclusions

VRF has proven effective in reducing fertilizer input and increasing nutrient use efficiency; however, its adoption remains below 20% in most regions. Our comparative analysis reveals three key insights. First, prescription-map methods are more cost-effective

for large, spatially stable fields, whereas real-time sensor methods excel in fields with high temporal variability (e.g., in-season nitrogen response after rainfall). Second, hybrid models (RTM + machine learning) represent the most promising direction for decision-making, as they combine a physical basis with computational efficiency and require minimal field-measured data. Third, the single largest barrier to adoption is not sensor accuracy but the lack of standardized, low-cost workflows for smallholders. Future research should prioritize (i) lightweight hybrid models deployable on edge devices for real-time decisions; (ii) interoperable prescription map standards and ISOBUS-compatible hardware; and (iii) field-validated, low-cost sensing solutions tailored to smallholder farming systems.

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