

Review

Research Progress on Intelligent Seeding Technology and Equipment: The Development of Seeders from Multi-Functional Integration to Agricultural Intelligent Agents

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Abstract

Seeding constitutes a key crop-production operation that governs seed spatial arrangement, crop population structure, and potential yield formation, and forms the foundation of precise, efficient, and eco-friendly farming. However, field soil properties, regional climate, and crop agronomic requirements exhibit strong spatio-temporal heterogeneity. Conventional seeding operations based on manual experience and fixed preset parameters cannot meet the demands of large-scale precision agriculture. Enabled by progress in precision agriculture, intelligent sensing, artificial intelligence, and autonomous machinery, modern intelligent seeding systems integrate precision seed metering, high-precision environmental perception, and closed-loop dynamic self-regulation. Such systems can improve plant-spacing uniformity and enable precise seeding-depth control under standard open-field conditions, yet face noticeable performance limitations in GNSS-denied complex environments including dense crop canopies and greenhouses. This review outlines the evolutionary trajectory of seeding machinery and summarizes research progress regarding precision seeding, multi-functional equipment integration, multi-source information perception, and intelligent decision-making. Integrated design principles covering mechanical optimization, electronic control, and perception-driven decision systems are elaborated. Four developmental phases of seeding equipment are identified: mechanical precision operation, electronic intelligent regulation, multi-functional module integration, and intelligent cognitive integration. Current intelligent seeding technologies are constrained by limited adaptability to complex farmland conditions, unstable multi-source data fusion, insufficient long-term operational reliability, and high deployment costs across diverse scenarios, restricting their broad field-scale adoption. Future research should combine agronomic knowledge with artificial intelligence to improve environmental awareness and autonomous decision-making capability, develop low-cost, high-reliability integrated seeding equipment, and support the construction of intelligent agricultural machinery systems.



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Keywords: intelligent seeding; precision agriculture; precise seed metering; intelligent perception; agricultural intelligent agents

1. Introduction

Seeding is a decisive agronomic operation that shapes the initial spatial pattern of crop seeds, governs subsequent population development, and ultimately constrains farmland yield potential. Seeding quality directly affects seedling emergence synchrony, canopy

spatial structure, and the efficiency with which crops capture light, water, and soil nutrients across the growing season. Even moderate spatial irregularity in seed placement can intensify inter-plant competition and reduce the stability of population productivity [1–3]. Large-scale, sustainable, and intelligent production has become important development objective of modern agriculture. Improving farmland resource utilization efficiency and achieving precise crop population management are important goals for the agricultural industry [4]. Traditional seeding machinery relies mainly on mechanical transmission systems and operator experience to adjust operating parameters. However, under variable field conditions and diverse crop production requirements, its adaptability remains limited, resulting in problems such as inaccurate seeding rates, unstable seeding depth, and poor operational consistency. Manual parameter calibration cannot respond to real-time changes in soil moisture and straw coverage during continuous field operation. The rapid development of precision agriculture, artificial intelligence, intelligent sensing, and autonomous operation technologies has provided essential technical support for transforming traditional seeding machinery into precision intelligent equipment [5]. Against this background, a fundamental scientific problem remains unresolved: how to translate crop population requirements under heterogeneous field conditions into real-time machine perception, decision-making, and control. Systematically reviewing the development trajectory of intelligent seeding technologies and clarifying their technical systems and future evolution pathways are therefore of theoretical and engineering significance for promoting the innovation of precision seeding equipment and improving intelligent agricultural machinery systems. The primary objective of intelligent seeding equipment development is to continuously improve seeding accuracy and seedling emergence stability under field conditions. Early seeding equipment relied primarily on mechanical transmission systems to achieve quantitative seed delivery and row arrangement. However, increasing operating speeds, more complex residue conditions in fields, and diversified agronomic requirements among crops have gradually revealed the limitations of traditional mechanical structures in maintaining seed placement uniformity and long-term operational stability [6–8]. Experimental studies have shown that travel speed can significantly affect seeding uniformity and miss-seeding performance, with the maximum miss-seeding index reaching 22.12% under certain operating conditions [2]. Field studies have also demonstrated that conventional seeding depth and downforce settings are typically adjusted before operation and may not continuously adapt to heterogeneous field conditions [3]. With the gradual integration of electric-drive seed metering, working-condition sensing, and automatic control technologies, seeding machinery has overcome some limitations of purely mechanical operation. In a variable-rate corn seeding control system evaluated at travel speeds of 6, 8, and 10 km h⁻¹, seeding accuracy ranged from 98.87% to 99.68%, while compensation of seeding lag substantially reduced the average lag distance from 2.79 m to 0.99 m [9,10]. These technologies enable real-time monitoring of operating conditions and dynamic parameter adjustment, providing a foundation for refined control of the seeding process and autonomous correction of operation quality [11,12].

Based on the continuous improvement of individual seeding precision, modern agriculture has placed higher demands on equipment, including multi-process coordination and precise resource allocation in different field zones. Currently, most planting systems treat land preparation, seeding, and fertilization as separate agricultural operations. Multiple field trips by agricultural machinery not only increase operational costs but also limit further improvements in overall production efficiency. To meet the requirements of conservation tillage and variable-rate fertilization, multi-functional integrated seeding systems have become an important technical approach for improving process coordination. These systems integrate functional modules such as integrated tillage and seeding, syn-

chronous seeding and fertilization, and zonal variable-rate operations, enabling simplified agricultural processes and coordinated regulation of production factors. Such integrated equipment can effectively cut down repeated soil compaction caused by repeated machinery entry. However, multi-functional integrated systems still face limitations in adapting to complex field conditions, coupling and coordination among multiple modules, and long-term operational reliability of the entire machine [13,14].

Digital agriculture, through the deep integration of artificial intelligence and autonomous control technologies with agricultural machinery, enables seeding equipment to achieve environmental perception, operating condition analysis, and adaptive parameter adjustment. This integration promotes the transformation of machinery from local unit automation toward intelligent systems at the whole-machine level. The application of high-precision navigation, multi-source perception, and farmland digital management technologies enables seeding equipment to collect field information in real time and dynamically adjust operating parameters, overcoming the limitations of traditional purely mechanical seeding equipment [15,16]. The concept of agricultural intelligent agents further expands the research framework of intelligent seeding equipment. Its core principle is to integrate three capabilities: environmental perception, agronomic knowledge reasoning, and autonomous execution control, thereby constructing a collaborative operation system involving seeding machinery, field environments, and intelligent decision-making platforms.

Most existing reviews in the field of precision seeding focus primarily on specific aspects, such as seed metering mechanism optimization, individual sensing algorithms, or specialized seeding equipment for particular crops. A systematic understanding of the overall evolution from mechanical performance improvement and multi-functional integration to intelligent upgrading of complete machines remains lacking. Furthermore, existing studies have not fully clarified the relationship between crop agronomic requirements, field operation evaluation criteria, and the hardware and software architecture of intelligent equipment, making it difficult to establish an analytical framework that reveals the long-term development trends of intelligent seeding systems. Limited comparative research has yet to systematically elaborate the matching laws between various crop varieties and intelligent seeding control schemes.

To address these gaps, the scientific purpose of this narrative review is to clarify the co-evolution between agronomic population demands and engineering innovation in seeding equipment and to construct a holistic perception-assessment-decision-execution analytical framework. This framework is intended to provide a systematic basis for understanding how crop requirements, field conditions, equipment technologies, and intelligent control strategies are progressively integrated toward agricultural intelligent agents.

Four explicit research objectives are defined for this review:

- (1) To dissect the staged evolutionary pathway of seeding equipment and distinguish the core technical features of each development stage from mechanical precision operation toward agricultural intelligent agents;
- (2) To build an integrated technical framework that incorporates multi-source environmental perception, online seeding-quality assessment, and multi-layer closed-loop adaptive control for intelligent seeding;
- (3) To compare system architectures and practical application patterns of intelligent seeding technologies across diversified cropping systems and complex field scenarios;
- (4) To synthesize system-level technical bottlenecks and propose targeted future research priorities for intelligent seeding toward agricultural intelligent agents.

The conceptual framework and technological evolution pathway of intelligent seeding equipment are presented in Figure 1.

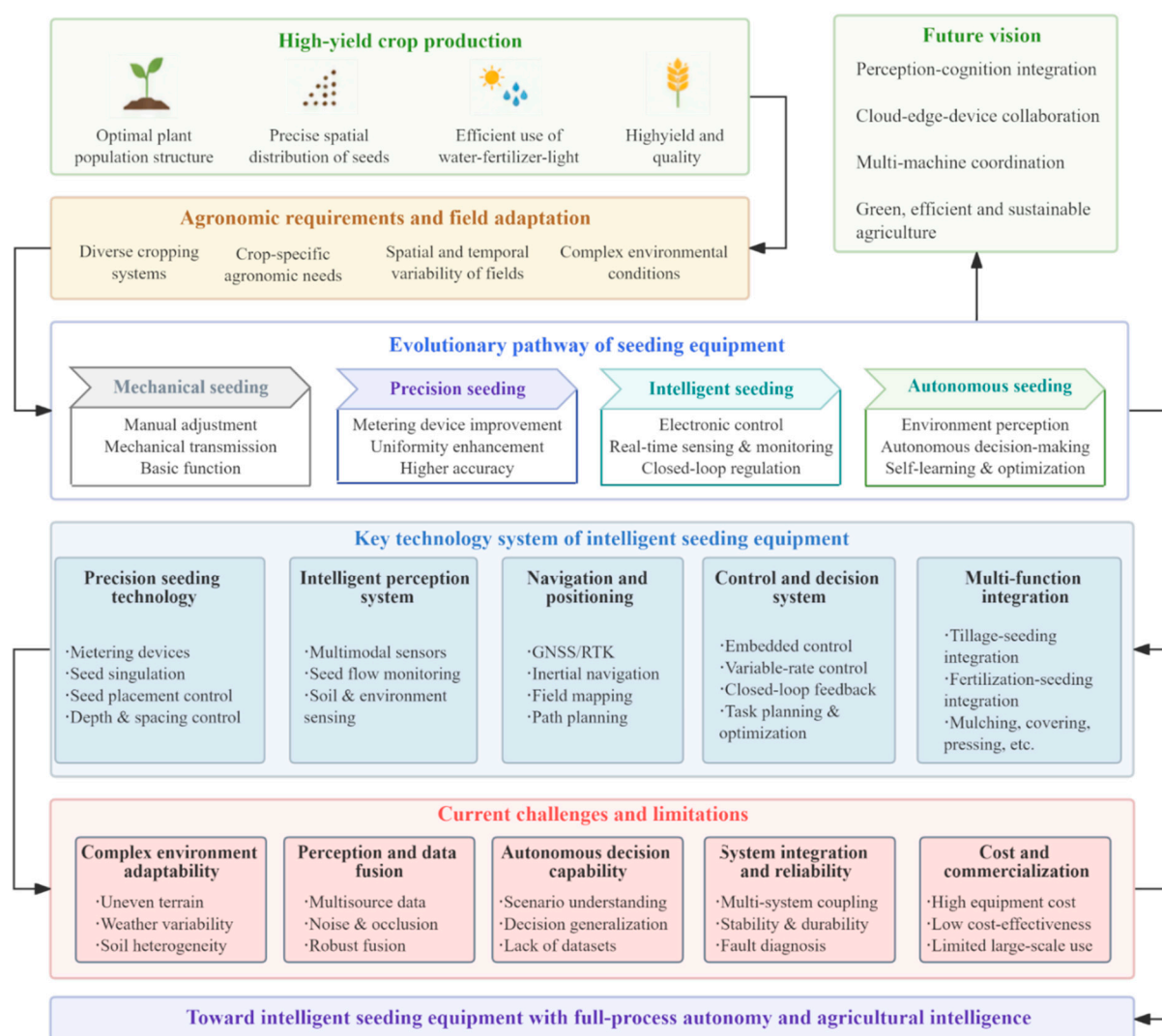


Figure 1. Conceptual framework and evolutionary pathway of intelligent seeding equipment.

2. Materials and Methods

This review adopted a structured literature-retrieval and thematic narrative-synthesis approach to summarize the technological evolution, key components, and future development trends of intelligent seeding equipment. Relevant publications were retrieved primarily from the Web of Science Core Collection and Scopus, with supplementary searches in ScienceDirect, SpringerLink, and Google Scholar to broaden coverage of studies on agricultural machinery, precision agriculture, sensing technologies, artificial intelligence, and autonomous agricultural systems. The literature search covered publications from January 2000 to May 2026, focusing on precision seeding technologies, seed metering and regulation systems, seeding-depth control, multi-source sensing, machine vision, autonomous navigation, variable-rate seeding, agricultural robotics, cloud-edge-device collaborative architectures, digital twins, and agricultural intelligent agents.

2.1. Retrieval Strategy

The search terms were organized into several thematic groups. Keywords within each group were connected using the Boolean operator “OR”, while different groups were combined using “AND” to identify studies related to intelligent seeding systems.

Group One (crop production and seeding objectives): crop production, crop population, sowing, seeding, precision seeding, precision planting, crop establishment, seed distribution, seeding uniformity, planting quality.

Group Two (seeding machinery and operational technologies): seed metering, precision planter, pneumatic seeder, electric-drive seeding, variable-rate seeding, seeding-depth control, no-tillage seeding, tillage-seeding integration, fertilizer-seeding integration, autonomous seeding equipment.

Group Three (sensing, monitoring, and control technologies): multi-source sensing, sensor fusion, machine vision, deep learning, remote sensing, GNSS, navigation, positioning, monitoring system, adaptive control, intelligent control.

Group Four (intelligent agricultural systems and emerging technologies): agricultural robot, autonomous agricultural machinery, artificial intelligence, machine learning, reinforcement learning, cloud-edge-device collaboration, digital twin, agricultural intelligent agent, smart agriculture.

2.2. Inclusion Criteria

Studies were included when they satisfied all three eligibility dimensions: research subject, research content, and literature type.

Research subjects: Studies focusing on precision seeding equipment, seeding-quality control, intelligent agricultural machinery, sensing technologies, autonomous operation, or intelligent decision-making systems. Studies from related domains were retained only when their mechanisms, equipment structures, or sensing-control methods were directly transferable to intelligent seeding scenarios.

Research content: Studies addressing seed-metering mechanisms, seeding uniformity, variable-rate regulation, depth control, no-tillage seeding, multi-functional seeding equipment, operational monitoring, machine vision, navigation, multi-source information fusion, artificial-intelligence-based applications directly associated with seeding operations or seeding-related decision-making systems, or intelligent agricultural system architectures.

Literature type: Peer-reviewed journal articles, high-quality conference papers, review articles, and relevant technical publications were considered. Literature sources were retained when they provided verifiable, reliable information regarding technological principles, equipment development, system architecture, or practical agricultural applications.

2.3. Exclusion Criteria

1. They were unrelated to seeding operations, agricultural-machinery intelligence, or associated enabling technologies.
2. They focused exclusively on crop breeding, physiological mechanisms, irrigation, or fertilization without direct relevance to intelligent seeding equipment, unless they provided evidence directly related to seeding quality, crop establishment, or early population formation.
3. They represented duplicate publications. Where multiple publications reported the same underlying study, only the most comprehensive and informative version was retained.
4. They contained insufficient technical information for comparative thematic analysis, or lacked clear descriptions of equipment structures, sensing methods, control strategies, or practical application scenarios.

2.4. Literature Screening Process

The literature search was performed using the Web of Science Core Collection, Scopus, ScienceDirect, SpringerLink, and Google Scholar. All retrieved records were exported to EndNote (Clarivate Analytics, Philadelphia, PA, USA) for literature management. After merging search outputs, duplicate records were removed by combining automatic

deduplication with subsequent manual verification prior to formal screening. Initial title-and-abstract screening and full-text eligibility assessment were conducted primarily by the first author. Records with ambiguous eligibility or unclear relevance were discussed among all authors, and final inclusion decisions were reached by consensus.

A total of 2022 records were initially identified from the selected databases. After automatic and manual removal of 356 duplicate records, 1666 records remained for title-and-abstract screening. During this stage, 1054 records were excluded because they were unrelated to intelligent seeding equipment, precision seeding technologies, or associated sensing and control systems. The full texts of the remaining 612 records were assessed according to the predefined inclusion and exclusion criteria. A total of 421 records were excluded during the full-text assessment. Of these, 243 were excluded because they lacked sufficient technical information for thematic synthesis, 36 because the full text was unavailable, 16 because of overlapping findings originating from the same study dataset, and 126 because of insufficient relevance to intelligent seeding systems. The remaining 191 studies were included in the systematic literature synthesis. In addition, eight relevant sources identified through supplementary searches were included to provide supporting evidence for specific technical and commercial aspects of intelligent seeding systems. Consequently, a total of 199 sources were included in the final review. The detailed literature identification and screening process, including the reasons for full-text exclusion and the supplementary sources, is illustrated in Figure 2.

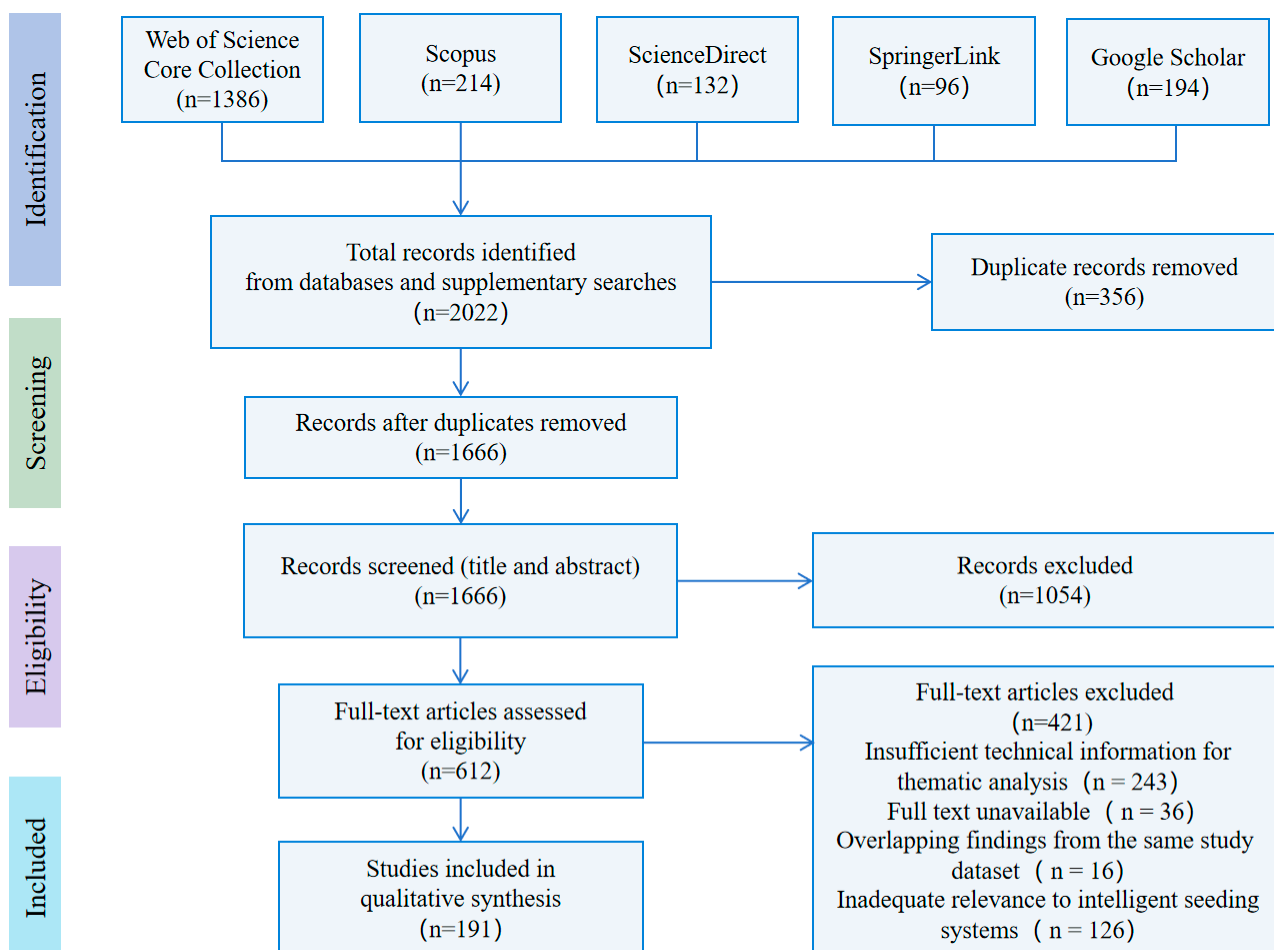


Figure 2. Literature screening flowchart for the review of intelligent seeding technology and equipment.

2.5. Data Extraction and Thematic Analysis

For each included study, data items including publication year, crop or agricultural application, seeding method, technology or equipment configuration, sensing and control strategy, experiment setting, performance indicators, and reported research limitations were extracted. Experiment settings were classified according to the reported validation conditions, including laboratory or bench testing, greenhouse or controlled-environment experiments, field experiments, simulation studies, and conceptual or system-architecture studies, where applicable. Key performance indicators were recorded according to the objectives of each study, such as seed-metering accuracy, miss-seeding rate, multiple-seeding rate, spacing uniformity, seeding-depth accuracy, emergence uniformity, recognition accuracy, positioning accuracy, control error, and operational efficiency.

Guided by the review objectives and the technical characteristics of intelligent seeding systems, the included literature was grouped into five major analytical themes:

- (1) crop-population formation requirements and precision seeding objectives;
- (2) precision seeding equipment and key mechanical technologies;
- (3) sensing-based quality monitoring and adaptive regulation;
- (4) multi-functional integrated seeding equipment and collaborative operation modes;
- (5) intelligent seeding systems based on cloud–edge–device collaboration and agricultural intelligent agents.

A thematic-synthesis approach was adopted to analyze the evolutionary pathway from mechanical-precision improvement toward intelligent autonomous agricultural systems. Given substantial heterogeneity across experimental conditions, crop types, equipment configurations, and evaluation metrics in the source literature, this review prioritizes technological trends, practical application scenarios, and key engineering challenges instead of direct cross-study quantitative comparison.

3. The Formation Characteristics of High-Yield Crop Populations and the Requirements for Precision Seeding

3.1. Structural Characteristics and Formation Mechanisms of High-Yield Crop Populations

Crop yield is the comprehensive outcome of the interaction between individual plant development and the field population microenvironment. Numerous studies in crop cultivation and physiology have demonstrated that high-yield crop populations cannot be achieved simply by increasing plant density per unit area. Instead, it is necessary to optimize plant spatial arrangement, regulate resource competition within the population, and improve farmland resource utilization efficiency to achieve this goal [17,18]. Constructing a structurally balanced crop population is a prerequisite and key factor for achieving stable and sustainable high yields. Seeding occurs at the initial stage of crop production and directly determines the spatial distribution pattern of seeds during the seedling stage, serving as an important starting point for regulating subsequent population development.

An ideal high-yield population should possess three core characteristics: appropriate planting density, uniform spatial distribution of plants, and high population-level light use efficiency [19]. Appropriate density ensures the formation of sufficient productive plants while avoiding excessive competition for light, water, and nutrients caused by overcrowding. Uniform seed spatial distribution can reduce intense competition among plants, promote coordinated canopy and root system development, and improve overall yield potential [20,21]. From the perspective of crop physiological regulation, population structure affects final yield mainly by regulating canopy light interception, dry matter accumulation, and source–sink transport and distribution. Appropriate seed spatial arrangement optimizes vertical light distribution within the canopy and maintains leaf photosynthetic

activity across different layers. Balanced root distribution expands the range of soil water and nutrient acquisition and improves resource utilization efficiency. Uniform emergence reduces growth differences between vigorous and weak plants, thereby stabilizing overall field productivity.

Multiple field experiments have demonstrated the regulatory effects of seeding spatial patterns on crop yield, as shown in Figure 3. Uniform plant spacing can optimize the field light environment, extend dry matter accumulation throughout the growing season, alleviate inter-plant competition, and contribute to stable population productivity. In contrast, irregular seeding patterns can increase growth differences among seedlings, reduce canopy light utilization efficiency, and ultimately result in yield losses [22,23]. Therefore, precise spatial arrangement of seeds is a key agronomic approach for regulating crop population structure and provides theoretical and agronomic foundations for optimizing seeding equipment structures and calibrating operating parameters.

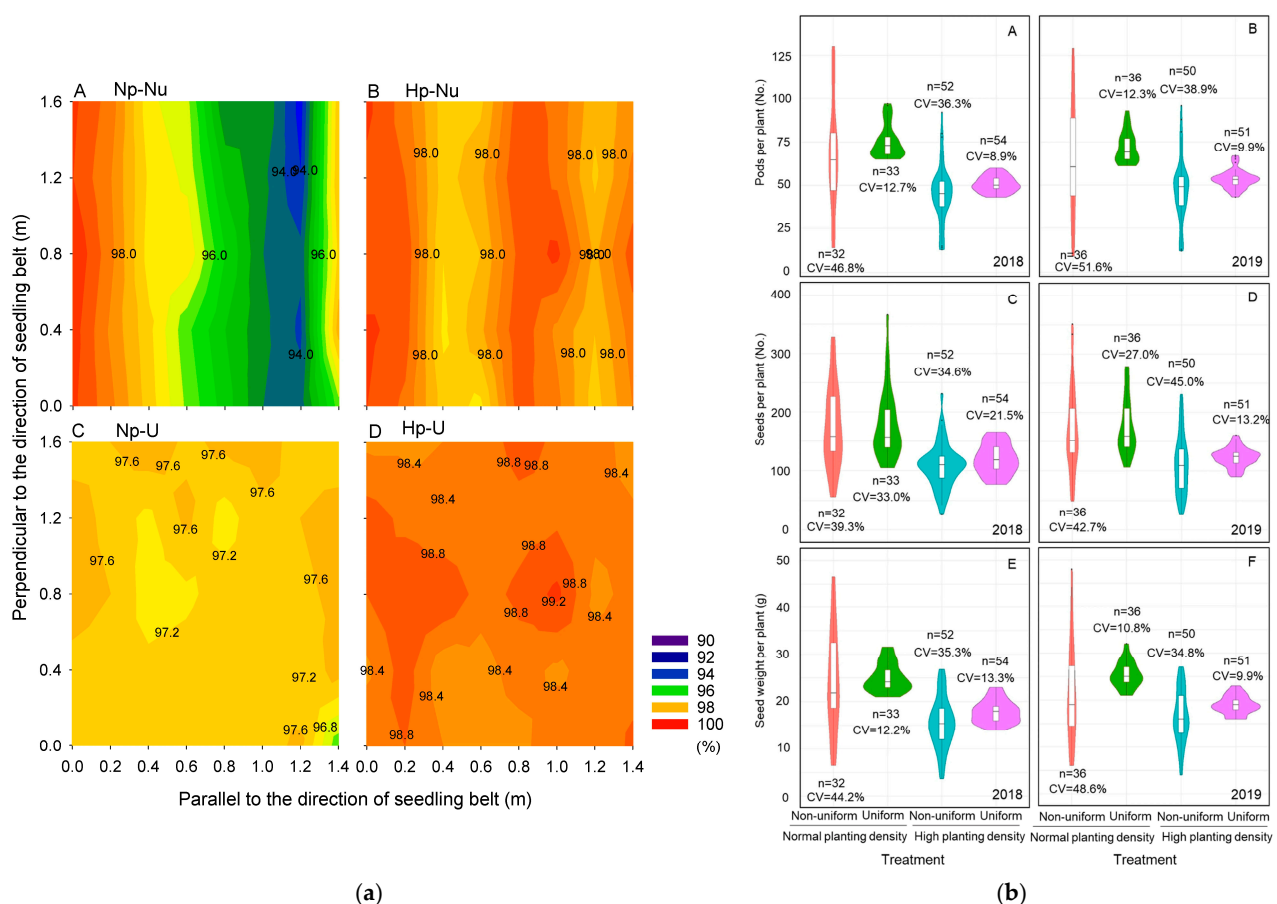


Figure 3. Effects of uniform and non-uniform seeding patterns on soybean canopy light interception and yield components: (a) Contour maps of canopy light interception for four treatments: Np-Nu (A), Hp-Nu (B), Np-U (C), and Hp-U (D). The color gradient from dark blue to deep red denotes an increasing canopy light-interception rate; numbers on the contour lines represent percentage values. (b) Yield-related components under uniform and non-uniform plant distributions at different planting densities, including pods per plant in 2018 (A) and 2019 (B), seeds per plant in 2018 (C) and 2019 (D), and seed weight per plant in 2018 (E) and 2019 (F). Np, normal seeding density; Hp, high seeding density; Nu, non-uniform plant distribution; U, uniform plant distribution; CV, coefficient of variation. Reprinted from reference [23].

Beyond the geometric distribution of seeds, seed placement also determines the spatial resource environment available to individual plants, including above-ground light interception and below-ground soil water, mineral nutrients, and root competition. This

spatial resource environment is jointly influenced by seeding technology, seed placement method, crop physiological characteristics, and key seeding conditions, such as seeding depth, plant-row spacing, sowing date, and tillage practice. Variations in these spatial conditions can alter intra-population resource competition, root–canopy development, and ultimately yield formation. Clarifying these relationships provides a link between crop population theory and the engineering parameters of intelligent seeding equipment [22,23].

In actual farmland, soil fertility, moisture content, and soil compaction usually exhibit spatial variability and significant heterogeneity. Traditional seeding equipment generally applies uniform operating parameters across the entire field, making it difficult to meet the requirements of establishing differentiated crop populations under heterogeneous field conditions. Even under the same seeding density, areas with different fertility levels may generate distinct plant competition patterns, reducing seedling emergence uniformity. Therefore, the development of seeding technologies should not focus only on improving operational accuracy under specific conditions but should also consider field environmental variability and the coordination between seeding parameters and crop population requirements. Precision seeding is designed to meet the agronomic requirements of high-yield crop populations. By dynamically regulating key operating parameters, including seeding rate, plant spacing, row spacing, and seeding depth, precision seeding can establish an optimized spatial arrangement of plants during the seedling stage, thereby improving farmland resource utilization efficiency and yield potential [24].

3.2. The Influence of Population Spatial Distribution on Yield Formation from the Perspective of Plant Resource Competition

The spatial arrangement of plants within fields is a key factor determining the comprehensive utilization efficiency of water, light, and nutrients. Different seeding patterns directly influence plant competition intensity and long-term population stability by shaping seed distribution patterns. As the initial spatial condition during the seedling stage, seed spatial arrangement continuously affects canopy and root system development and plays an important role in final yield formation [20,22,23].

From the horizontal resource-space dimension, the combination of plant spacing and row spacing determines the spatial distribution of light and below-ground resources available to individual plants and thereby influences plant-to-plant competition. This effect is closely related to crop physiological characteristics, including root spreading range, tillering capacity, and canopy expansion habit. Excessively dense planting increases competition among neighboring plants for light, water, and mineral nutrients, resulting in significant growth differences. Conversely, excessively large spacing reduces effective plant population per unit area and leads to inefficient land resource utilization. Therefore, an appropriate spatial arrangement should balance individual plant growth requirements and overall field productivity [20,22].

From the vertical resource-space dimension, seeding depth, as an essential condition of the seeding process, determines the initial vertical position of seeds and subsequently influences seedling emergence and early root development. More uniform seeding depth can reduce differences in emergence and early growth among individual plants, whereas missed seeding, double seeding, and uneven seeding depth can increase population heterogeneity. Such differences may further affect plant-to-plant competition and individual plant productivity [25].

In addition to the two-dimensional spatial arrangement of seeds, sowing date is another important agronomic factor for adapting to field environments and regulating population structure. These two factors interact with each other and jointly determine resource accumulation and final yield formation throughout the crop growing season. Rice cultivation experiments have shown that an appropriate sowing date matched with

regional climatic conditions can optimize seedling growth, improve dry matter allocation, and enhance grain production capacity under precision seeding conditions. Meanwhile, suitable sowing timing can optimize thermal resource utilization during the growing season, avoid high-temperature stress during grain filling, and improve rice appearance and processing quality [26–28]. For major food crops such as winter wheat, significant interactions exist between sowing date and planting density. Coordinated optimization of these factors is an important strategy for balancing tillering competition, reducing ineffective dry matter accumulation, and stabilizing field yield [29]. Improvements in field monitoring, crop phenotyping, and population modeling technologies enable quantitative characterization of crop spatial distribution, providing data support for seeding quality evaluation, population development analysis, and seeding parameter optimization.

3.3. Differentiated Seeding Requirements for High-Yield Crop Populations of Different Crops

Different crops exhibit significant differences in seed characteristics, growth habits, and physiological mechanisms underlying yield formation. Accordingly, their requirements for seed spatial distribution and operational parameters of seeding equipment also vary. The development of precision seeding technology is not simply aimed at improving operational accuracy; rather, it should achieve coordinated optimization among seeding parameters, equipment structures, and agronomic objectives based on crop population development principles. Considering crop production characteristics and physiological requirements, the core demands of precision seeding can be summarized into four dimensions: individual-plant spatial arrangement, population establishment, stable operation under complex field conditions, and low-damage seed handling. The major seeding requirements, representative crops, quantitative performance indicators, and corresponding supporting technologies associated with different crop population development characteristics are summarized in Table 1.

Table 1. Differentiated precision seeding requirements for high-yield crop populations.

Dominant Seeding Requirement	Typical Crops	Core Seeding Demand	Representative Evaluation Indicators	Key Supporting Technologies
Individual-plant spatial control	Maize, peanut	Uniform plant spacing and seeding depth, stable single-seed metering to reduce inter-plant competition	Seeding depth deviation, missed-seeding rate, multiple-seeding rate, spacing uniformity, and operating speed	Pneumatic and electric-drive seed metering, seeding quality monitoring
Uniform population establishment	Wheat	Stable and uniform sowing rate, optimized population distribution for higher spike yield	Seeding rate, spatial uniformity, plant population, and emergence uniformity	Wide-row precision seeding, precision drilling
Complex field establishment	Direct-seeded rice	Stable seeding operation under muddy field conditions with uniform seedling emergence	Seeding rate, seeding depth, emergence uniformity, and operating stability	Anti-blocking seed delivery systems, precision rice direct seeding
Low-damage and flexible seed handling	Crops with irregular-shaped seeds	Low-damage and flexible precision seeding for refined cultivation	Seed damage rate, missed/multiple-seeding rate, spacing uniformity, and operating stability	Flexible seed metering, machine vision recognition, intelligent parameter adjustment

As shown in Table 1, different crop population development characteristics lead to different dominant seeding requirements and corresponding performance indicators. Although the specific seeding constraints vary among crops, their fundamental objective is highly consistent: improving seed spatial arrangement, optimizing field population

structure, and enhancing farmland resource utilization efficiency. These population development characteristics directly determine appropriate seeding processes and equipment configurations. Large-seeded and well-structured crops, such as maize and peanut, achieve yield improvement mainly through individual plant productivity, resulting in strict requirements for plant spacing, seeding depth uniformity, and single-seed metering stability. These crops generally have large and regular seeds; however, mechanical vibration during field operation and crop residue can interfere with seed placement accuracy. Traditional mechanical seed metering devices often suffer from missed seeding, double seeding, and uneven plant spacing. Furthermore, high-speed field operation imposes higher requirements on seeding uniformity and placement stability. Field experiments have demonstrated that optimizing seed number and spatial distribution within peanut planting holes can reduce resource competition among plants, improve light, water, and nutrient utilization efficiency, and facilitate mechanized harvesting [30]. The application of pneumatic seed metering, independent electric-drive seed metering, and online seeding quality monitoring technologies has significantly improved seeding uniformity and seedling population quality in maize and peanut production [31–33].

Wheat is a small-seeded and densely planted crop. Its yield formation mainly depends on the number of productive ears within the population, requiring continuous, stable, and uniform seed distribution. Wide-row precision seeding and precision drilling technologies reshape the spatial distribution of seeds in fields, improving canopy light utilization efficiency and increasing productive ear number. Direct seeding of rice is affected by multiple factors, including muddy field surfaces, soil moisture conditions, and seed moisture content. Therefore, direct seeding equipment needs to achieve accurate seeding rate control, strong adaptability to complex field conditions, and long-term operational stability [34–36].

Seeds of many specialty economic crops often have irregular shapes and thin seed coats, making them vulnerable to mechanical damage. In addition, these crops usually have high seed costs and require highly refined cultivation management. Traditional rigid seed metering equipment with fixed parameters cannot satisfy their production requirements. Therefore, flexible seed metering, machine vision-based seed recognition, and dynamic intelligent parameter adjustment technologies are urgently needed to achieve low-damage customized precision seeding for irregular seeds and diverse production scenarios, including small-scale facility cultivation [37–41]. The differentiated characteristics of crop population development have driven the diversification of seeding technology pathways, while continuously increasing agronomic requirements are promoting the transformation of traditional single-function seeding machinery toward intelligent equipment capable of adapting to multiple production scenarios.

3.4. The Influence of Different Seeding Methods on Crop Population Formation

The seeding method directly determines the spatial distribution pattern of seeds after placement and serves as a key agronomic approach for regulating field population structure, resource competition, and final productivity. Different seeding methods exhibit significant differences in seed distribution patterns, population uniformity, and adaptability to field management during later growth stages. These differences continuously affect crop emergence, canopy development, and final yield from the seedling stage onward [42–44].

Broadcast seeding is a traditional extensive seeding practice characterized by a simple operation process and high field efficiency. However, seeds are distributed randomly without fixed row and plant spacing, which can easily result in uneven seedling population density and intensified competition among plants. Therefore, it can only satisfy basic crop establishment requirements and is insufficient for high-yield and uniform cultivation systems. Currently, broadcast seeding is mainly applied in low-input and low-standard

production systems. Random seed distribution under broadcast seeding can result in uneven plant spacing, increasing heterogeneity in above-ground light interception and below-ground resource competition. Drill seeding establishes regular row spacing through evenly spaced furrow opening, transforming random seed distribution into an orderly row arrangement. It improves field ventilation and light conditions, facilitates mechanical operations such as weeding and crop protection, and is widely used for densely planted crops such as wheat and barley. However, drill seeding mainly controls row spacing, while seed distribution within rows remains relatively random, limiting the regulation of individual plant positioning. Therefore, its potential for improving population uniformity is restricted under high-density and high-yield cultivation systems. Drill seeding creates an ordered above-ground spatial arrangement along rows, but within-row plant spacing remains less precisely controlled, which may maintain uneven patterns of light interception and below-ground resource competition [45–48].

Hill-drop seeding further improves upon drill seeding by dividing continuous seed distribution into independent planting units with defined spacing. This approach creates a more regular population arrangement, reduces excessive competition among plants, and is suitable for medium- and low-density crops such as maize and soybean. However, under high-speed field operation conditions, the stability of hill spacing and within-hill seed number uniformity may decline significantly. Hill-drop seeding partitions relatively independent spatial units for each hill; nevertheless, competition among plants within the same hill may still occur [49,50].

Precision single-seed seeding is a representative technology in modern precision agriculture. Based on high-precision seed metering and placement mechanisms, it enables accurate control of seed quantity and spatial position, reducing excessive competition caused by uneven seed distribution and improving the resource utilization potential of individual plants and crop populations. Unlike traditional extensive planting strategies that increase seeding rates to compensate for poor emergence, precision single-seed seeding optimizes canopy structure and population development by accurately controlling row and plant spacing. It is a key technology for high-yield cultivation of maize and peanut while also imposing higher requirements on seed placement stability and adaptability under diverse field conditions. Precision single-seed seeding creates more clearly separated spatial units for individual plants, which is particularly relevant to crops in which individual-plant productivity contributes strongly to population yield [25,30,51]. These four seeding methods primarily differ in the spatial arrangement and placement pattern of seeds. In contrast, tillage systems such as no-till seeding describe the soil preparation conditions under which seed placement is performed and therefore represent a complementary dimension of seeding system design.

No-till seeding is an important practice in conservation agriculture and represents a tillage system rather than a distinct seed placement pattern. It integrates furrow opening, seed placement, and soil covering into a single operation under residue-covered soil conditions, offering advantages such as reduced soil disturbance and improved soil moisture conservation. However, crop residues and uneven soil surfaces can easily cause machinery blockage and fluctuations in seeding depth. Therefore, no-till seeding equipment requires higher capabilities in residue cutting, active terrain following, and anti-blocking performance. As an essential seeding-process condition, no-till seeding changes the soil conditions surrounding the seed and root zone, which can further affect crop establishment during the early growth stage [52–54]. The increasing demand for precise seed spatial arrangement in high-yield crop production is driving the transition of seeding technologies from extensive seed distribution toward precise placement and intelligent dynamic regulation. Considering the different requirements of crop production systems and field

conditions, the characteristics and limitations of four major seed placement patterns are summarized in Table 2.

Table 2. Characteristics of different seed placement patterns and their effects on crop population formation.

Seeding Mode	Spatial Distribution Characteristics	Effects on Crop Population Formation	Main Limitations
Broadcast Seeding	Random seed distribution without fixed row and plant spacing	Difficult to maintain uniform population structure, resulting in uneven resource competition	Low spatial controllability and poor population uniformity
Drill Seeding	Regular row spacing with continuous seed distribution within rows	Improves field arrangement and facilitates canopy formation in dense crops	Limited control of individual plant spacing
Hill-drop Seeding	Seeds distributed in fixed planting units with defined hill spacing	Reduces excessive competition and improves individual plant spatial balance	Hill spacing stability decreases under high-speed operation
Precision Single-Seed Seeding	Accurate control of seed number and spatial position	Optimizes plant density and improves population uniformity and resource utilization efficiency	Requires high seed-metering accuracy and operating stability

The effects of seed placement patterns on crop establishment are also closely related to local soil conditions and soil preparation practices. Localized soil loosening can modify the soil conditions experienced by developing plants and consequently influence crop establishment and productivity. Field results from soybean production showed that localized soil treatment affected plant development and yield formation, indicating that soil preparation conditions should be considered together with the selected seeding method when evaluating crop establishment [55].

Different seed placement patterns correspond to different crop population formation characteristics and field adaptation requirements, while tillage and soil preparation conditions further influence crop establishment. In practical production, an appropriate combination of seed placement pattern, tillage system, and soil preparation practice should therefore be selected according to crop type, cropping system, and field conditions to achieve optimized seed spatial arrangement and establish balanced high-yield crop populations.

4. Requirements and Key Equipment Technologies for Precision Seeding Operations

Seeding operation is a critical process in crop production systems. Its operational accuracy, stability, and adaptability to field conditions directly determine seedling emergence uniformity and strongly influence the formation of crop populations. Modern agriculture is rapidly developing toward large-scale, high-speed, and precision production. However, soil properties, cropping systems, and field operating conditions exhibit significant spatial variability across different regions. Traditional seeding equipment relies mainly on fixed mechanical structures and operator experience for parameter adjustment, making it difficult to maintain consistent seeding accuracy and operational reliability under complex and dynamic field conditions. To systematically improve seeding quality, modern seeding equipment has increasingly incorporated electronic control, intelligent sensing, and autonomous regulation technologies.

4.1. Core Operation Quality Indicators of Precision Seeding

The quality of precision seeding operations is characterized by multiple field performance indicators that describe the accuracy, uniformity, and stability of seed placement. From the perspective of the seeding process, these indicators can be grouped into quantitative delivery, horizontal spatial distribution, vertical spatial distribution, and crop establishment. Seeding rate accuracy reflects the quantitative control of seed delivery, whereas plant spacing uniformity and seeding depth stability characterize the horizontal and vertical distribution of seeds. Miss-seeding and multiple-seeding directly affect population density and spatial heterogeneity, while emergence uniformity reflects the combined effects of seed placement and seedbed conditions. These indicators are therefore interrelated and jointly determine the quality of crop population establishment [56,57].

The quality of seeding operations depends not only on equipment structure and the accuracy of electronic control systems but is also strongly influenced by complex field environments. Soil compaction, surface roughness, and crop residue distribution can interfere with furrow opening, seed placement, and soil covering processes, resulting in problems such as unstable seeding depth, insufficient seed–soil contact, and inaccurate seed distribution. Conservation tillage systems with full straw residue coverage represent a typical complex operating condition affecting seeding stability. As shown in Figure 4, different tillage practices generate distinct seedbed structures. The degree of residue fragmentation and stubble distribution density directly influence the operating conditions of seeding components. Excessive residue length or high residue density can interfere with seed delivery and furrow opening, thereby reducing seeding depth stability and plant spacing uniformity [2,44,58].

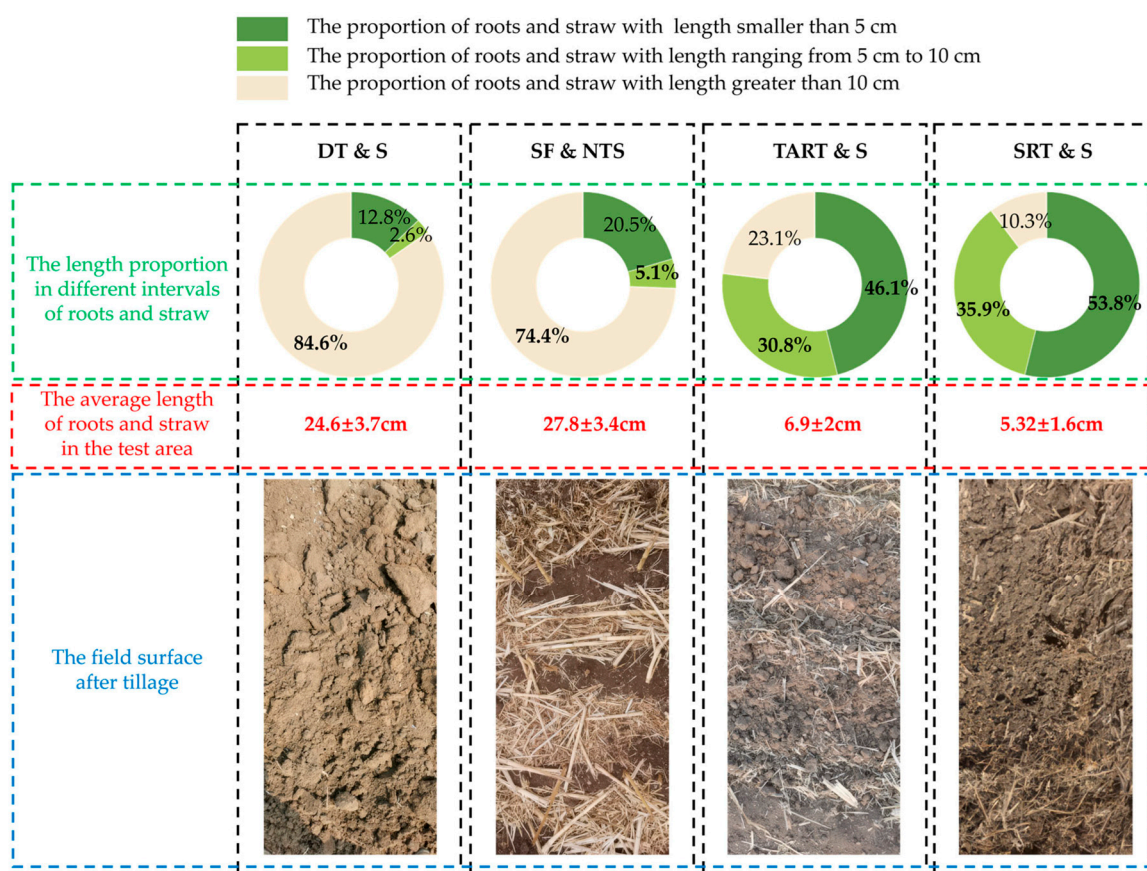


Figure 4. Differences in seedbed straw fragmentation characteristics under different tillage modes. Reprinted from reference [44].

Under high-speed operation, uneven terrain, and spatial variations in soil properties, disturbances during seed metering, placement, and furrow opening can result in missed seeding, multiple seeding, uneven plant spacing, and unstable seeding depth. These limitations have driven precision seeding equipment from isolated mechanical optimization toward integrated systems combining mechanical structures, electronic control, sensing, and feedback regulation [59].

It should be noted that most existing seeding-quality indicators are derived from bench-stand laboratory tests. There remains an incomplete mapping between bench-measured metering indexes and final field emergence performance. Furthermore, trade-offs frequently exist among different indicators: for instance, raising operating speed may improve efficiency but simultaneously degrade spacing uniformity. A unified, field-oriented evaluation standard integrating equipment performance and agronomic establishment effects has not been fully established, representing an important research gap for precision-seeding assessment.

4.2. Precision Seeding Equipment Machinery and Active Control

To meet the requirements of large-scale, high-speed crop production and complex field operations, modern precision seeding equipment development mainly focuses on three key directions: precise seed metering, closed-loop seeding depth control, and coordinated regulation of high-speed plant spacing. These technologies address fundamental operational challenges, including quantitative seed delivery, stable seed placement, and accurate spatial distribution, providing essential technical support for improving precision seeding performance [60].

4.2.1. Precision Seed Metering Control Technology

Precision seed metering is a core component of high-quality seeding operations. Its performance directly affects missed-seeding rate, double-seeding rate, and seed utilization efficiency. The overall performance of a seed metering system is jointly determined by the structural design of the metering device, seed picking mechanism, and driving control strategy [61]. With the development of precision agriculture and intelligent agricultural machinery, seed metering systems have gradually evolved from traditional mechanical transmission mechanisms toward independent electric drive and active control. Seed metering systems can be distinguished according to three related dimensions: metering principle, drive mode, and control strategy. Mechanical and pneumatic devices represent the main metering principles, whereas ground-wheel transmission and independent electric drive represent different drive modes. Variable-rate and adaptive regulation are control strategies that can be implemented on different metering structures. This distinction avoids treating metering mechanisms, drive systems, and control methods as equivalent categories and provides a clearer framework for comparing precision seed metering technologies. These systems exhibit distinct differences in structural principles and environmental adaptability, enabling them to meet the requirements of different crops and production scenarios. Typical structures are shown in Figure 5 [8,62–65]. Despite abundant laboratory validations, predicting pneumatic metering performance under variable on-farm conditions remains challenging and cannot be fully inferred merely from bench-test results.

Mechanical seed metering devices mainly include fluted-roller, cell-wheel, and finger-pickup types. They achieve seed separation and quantitative delivery through mechanical interaction and are characterized by simple structures and convenient maintenance. However, their performance is strongly affected by seed size, shape, moisture content, and operating speed, which can reduce metering uniformity under high-speed conditions [66].

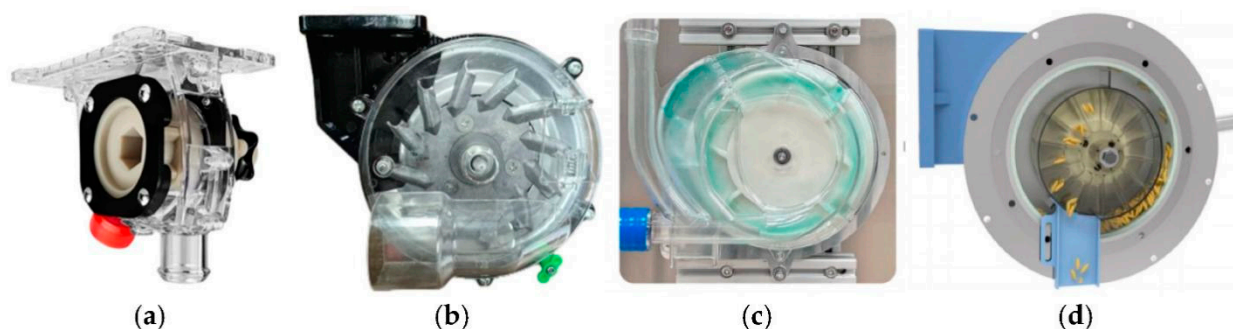


Figure 5. Typical mechanical and airflow-assisted seed-metering devices. (a) Flute roller-type mechanical MDSD; (b) wheel spoon-type mechanical MDSD; (c) double-cavity airflow-assisted MDSD; (d) partition airflow-assisted MDSD. Reprinted from reference [8].

Pneumatic seed metering systems utilize positive or negative pressure airflow to achieve seed adsorption, separation, and controlled release. Their metering performance depends on the interaction among airflow conditions, seed properties, metering-disk motion, and seed-filling state. Compared with mechanical contact-based systems, they effectively reduce seed pickup errors and mechanical damage caused by rigid interactions, thereby weakening the influence of seed physical characteristics on metering stability. They provide excellent single-seed separation performance under high-speed precision seeding conditions and are widely applied in maize and soybean production. However, pneumatic seed metering systems generally have more complex structures and higher energy consumption. Their performance is sensitive to airflow distribution, operating pressure, seed-metering disk speed, and seed-hole conditions. Insufficient or unstable vacuum pressure may reduce seed-holding stability and increase missed seeding, while inappropriate airflow and seed-filling conditions can affect seed pickup and separation. In addition, seed residues and other impurities may accumulate in the suction holes during prolonged operation, causing hole blockage and reducing metering stability [67–71].

Independent electric drive represents a drive-mode transition rather than a separate metering principle. The development of electronic control technologies has promoted the transition of seed metering systems from passive mechanical synchronization toward active regulation. Independent electric-drive seed metering technology eliminates the traditional ground-wheel mechanical transmission mechanism and directly drives the metering device using motors. This approach reduces the influence of wheel slip and transmission errors on metering stability. By adjusting metering speed according to machine travel speed in real time, it enables precise control of seeding rate and plant spacing. This technology overcomes the fixed speed-ratio limitations of traditional systems and provides an important execution foundation for variable-rate seeding, closed-loop control, and intelligent decision-making [72,73].

Experimental results indicate that seed metering performance depends on the interaction among metering principle, seed characteristics, operating speed, and control conditions. Under the reported test conditions, pneumatic vacuum seed metering devices for maize achieved a qualified rate above 94%. In contrast, a conventional air-suction seed metering device tested with small and irregular rice seeds achieved a single-seeding rate of 86.91%, while the multiple-seeding rate reached 9.46% [8].

Although numerous studies have evaluated seed metering performance using laboratory tests and controlled experiments, direct comparison among different technologies remains challenging because reported accuracy, missed-seeding rate, and energy consumption are highly dependent on crop type, seed characteristics, operating speed, and test conditions. In general, pneumatic and electric-drive systems demonstrate better adaptability for high-speed precision seeding, whereas mechanical systems maintain advantages

in simplicity and energy efficiency. However, comprehensive field-based evaluation integrating operational accuracy, reliability, energy consumption, and agronomic outcomes remains insufficient.

These differences indicate that various seed metering mechanisms possess distinct advantages and limitations in terms of structural characteristics, control strategies, and application scenarios. A comparison of mainstream seed metering technologies and their application characteristics is presented in Table 3.

Table 3. Comparative characteristics of mainstream precision seed metering technologies.

Dimension	Type	Typical Crops/ Application	Key Performance Characteristics	Working Conditions	Main Limitations
Metering principle	Mechanical metering	Wheat, rice and other grain crops	Stable seed delivery and metering performance under conventional operating conditions; performance is influenced by seed properties and metering speed	Conventional field conditions; low-to-medium speed operation	Sensitive to seed size, shape and moisture; reduced uniformity at high speed
Metering principle	Pneumatic metering	Maize, soybean, vegetable crops	High single-seed separation capability and good suitability for precision and high-speed seeding	Large-scale field production; medium-to-high speed operation	Relatively high energy demand; sensitive to airflow and seed-filling conditions
Drive mode	Ground-wheel mechanical drive	Conventional precision seeders	Simple transmission structure and direct synchronization between ground travel and metering	Conventional field conditions and relatively stable travel conditions	Affected by wheel slip, transmission errors, and field surface variation
Drive mode	Independent electric drive	Precision planters and intelligent seeders	Independent control of metering speed, rapid adjustment, and compatibility with variable-rate seeding	Precision agriculture and high-speed operating scenarios	Requires electronic control, power supply, and system integration
Control strategy	Variable-rate control	Precision agriculture applications	Spatial adjustment of seeding rate according to field variability and prescription information	Digital farmland and prescription-map-based operation	Requires reliable positioning, field information, and control synchronization
Control strategy	Adaptive regulation	Research prototypes and specialty crop systems	Dynamic adjustment of metering or seeding parameters according to seed, soil, machine, or environmental conditions	Complex or variable conditions	Requires reliable positioning, field information, and control synchronization

4.2.2. Seeding Depth Stability Control Technology

The consistency of seeding depth is a fundamental prerequisite for achieving synchronized seed germination, uniform emergence, and balanced seedling growth. It is also one of the seeding quality indicators most strongly affected by field topography and soil conditions. Farmland soils naturally exhibit spatial heterogeneity in compaction, moisture content, and surface roughness, which can cause fluctuations in actual seeding depth, disrupt the germination sequence, intensify growth differences among seedlings, and reduce crop population uniformity [74].

Traditional seeders generally rely on fixed furrow-opening mechanisms and passive soil-following structures. These systems can only adapt to surface variations through mechanical constraints and lack the ability to actively perceive changes in soil conditions. Therefore, they are unable to effectively compensate for seeding depth deviations caused by environmental disturbances.

Modern precision seeding equipment integrates displacement sensors, soil resistance detection, and electro-hydraulic closed-loop control systems. These technologies enable real-time acquisition of surface fluctuations and furrow-opening resistance, allowing dynamic adjustment of furrow opener depth and operating pressure. As a result, stable seeding depth control can be achieved under heterogeneous soil conditions, improving emergence uniformity across fields [50,75].

Current seeding depth control technology has evolved from passive mechanical adaptation toward active closed-loop regulation. Combined with farmland digital maps and multi-parameter soil sensing technologies, it further enables zone-specific optimization of seeding depth parameters at the field scale, significantly enhancing equipment adaptability to complex and heterogeneous farmland environments. Even with such closed-loop hardware solutions, performance gains are still restricted by sensor noise, actuator response lag and complex soil-straw mixtures encountered under real-farm conditions.

4.2.3. High-Speed Plant Spacing Cooperative Control Technology

The uniformity of plant spacing determines the horizontal spatial distribution of seeds in fields and provides an important foundation for establishing balanced crop populations and reducing resource competition among plants. With the development of large-scale modern agriculture, the required operating speed of seeding machinery continues to increase.

Traditional ground-wheel-sprocket-driven seed metering systems are highly affected by wheel slip and transmission clearance. As travel speed increases, slip-induced errors become increasingly significant. Combined with airflow disturbances during seed delivery, these factors can easily cause irregular plant spacing and increased missed- and double-seeding rates.

Ahmad et al. conducted field experiments on pneumatic maize seeding and found that the missed-seeding index was only 8.33% at a low operating speed of 2.04 km h⁻¹. However, when the speed increased to 8.80 km h⁻¹, the missed-seeding index increased to 13.52%, accompanied by a significant decline in plant spacing uniformity. These results demonstrate that traditional mechanical transmission systems cannot adequately satisfy the requirements of high-speed precision seeding [2,76].

High-speed plant spacing cooperative control technology integrates high-precision travel-speed monitoring, satellite navigation positioning, and independent electric-drive seed metering systems. It enables real-time synchronization between machine speed and seed metering frequency, effectively reducing plant spacing deviations caused by ground-wheel slip and improving seed placement accuracy and spatial distribution uniformity under high-speed conditions.

This technology is well suited for modern large-scale production systems characterized by high-speed operation and dense planting, providing important technical support for large-area precision seeding [77,78]. Accordingly, residual timing delay and seed-ejection disturbances still impose practical limits on ultimate plant-spacing uniformity for high-speed field operations.

4.3. Equipment Adaptation Technologies for Complex Field Conditions

Precision seeding technologies can currently maintain satisfactory operational performance under standardized and relatively flat field conditions. However, actual agricultural fields often involve complex operating environments, including heavy straw residue coverage, soil compaction, uneven terrain, and fragmented field patterns. These conditions impose higher requirements on equipment trafficability, anti-blocking capability, operational stability, and environmental adaptability. Among these scenarios, conservation no-till seeding represents one of the most typical complex field operating conditions [79–81].

Under no-till systems, dynamic variations in crop residue coverage and soil physical properties significantly increase the difficulty of seeding operations. Seeding equipment must not only complete fundamental processes such as furrow opening, seed placement, and soil covering, but also possess strong anti-blocking capability and terrain-following performance.

To better understand and optimize these structural adaptations, numerical modeling methods have increasingly been applied to characterize the dynamic interactions among soil, seeding tools, and crop residues. In particular, the Discrete Element Method (DEM) can simulate soil–tool–residue interactions at the particle level and evaluate variables such as soil disturbance, draft force, residue displacement, and furrow formation. Such modeling provides a quantitative basis for evaluating soil disturbance, draft force, residue displacement, and furrow formation, and for optimizing opener geometry, residue-cutting structures, and operating parameters under no-till conditions [82–84].

Current seeding equipment mainly improves operational stability under complex field conditions through mechanical structure optimization, including residue cutting, anti-blocking and residue-guiding mechanisms, and surface-following devices. Typical operating performance of no-till seeders and residue-cutting components is shown in Figure 6 [48,85].

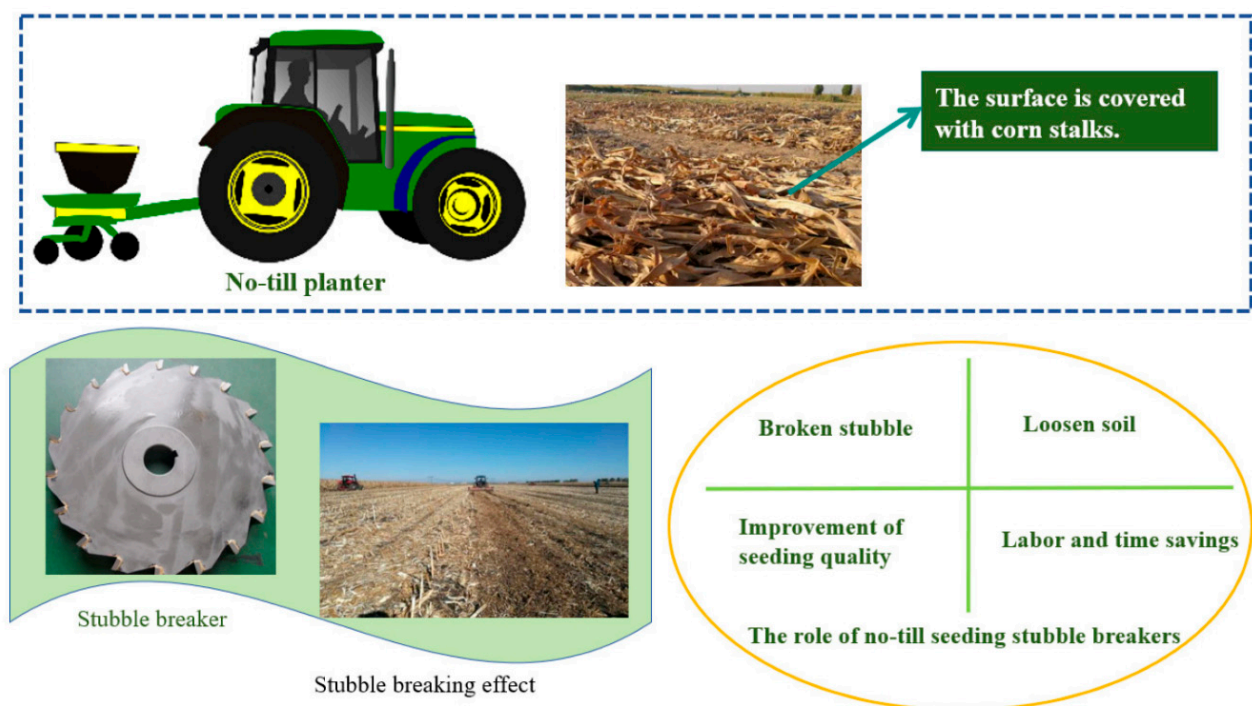


Figure 6. No-till planter and working effect of stubble breaking cutter under straw-mulching field. Reprinted from reference [80].

At present, adaptation to complex field environments still relies mainly on mechanical optimization approaches, such as residue cutting, blockage prevention, and terrain following. However, fixed mechanical structures have limited capability for dynamic adaptation to changing field conditions. The integration of environmental perception technologies and intelligent closed-loop control provides a promising pathway for improving autonomous adaptation and dynamic regulation capabilities of seeding equipment.

5. Intelligent Perception-Supported Seeding Quality Monitoring and Operation Regulation

Traditional seeding equipment mainly relies on mechanical limit structures and preset operating parameters to complete seed metering operations. During field operation, its capability for perceiving environmental conditions and equipment status is limited, making it difficult to maintain stable performance under complex field conditions [69]. With the advancement of smart agricultural technologies, seeding equipment has evolved from

conventional mechanical units toward integrated, information-driven operation platforms incorporating environmental sensing, quality assessment, and dynamic parameter regulation. Among these technologies, intelligent sensing provides fundamental data support throughout the seeding process, quality assessment algorithms enable the identification of operational abnormalities and performance variations, and closed-loop control modules achieve real-time optimization of operating parameters. Collectively, these technologies establish a comprehensive technical framework for intelligent seeding systems [12,16].

5.1. Multi-Source Information Perception Technologies in the Seeding Process

Accurate acquisition of field environmental parameters, machinery operating status, and real-time operational data is essential for intelligent seeding equipment to achieve working-condition recognition and adaptive parameter adjustment. Agricultural fields exhibit strong spatial heterogeneity, complex operating environments, and frequent dynamic variations in environmental parameters. A single sensing device cannot fully characterize changes in field conditions and equipment status during seeding operations [86].

Therefore, multi-sensor collaboration and multi-source information fusion technologies have gradually been introduced into seeding equipment. These technologies enable the acquisition and integration of heterogeneous information from multiple sensing sources, providing data support for intelligent operation monitoring and decision-making [87,88]. Yet imperfections at the perception layer, including sensor drift and inconsistent sampling scales, may propagate and impair downstream assessment and decision outputs.

At the conceptual level, the overall technical system can be organized into three functional layers: perception, analysis, and execution, as illustrated in Figure 7. In intelligent seeding, the perception layer integrates soil sensors, industrial cameras, unmanned aerial vehicles (UAVs), and BeiDou positioning terminals to collect multi-source field information. The analysis layer employs data preprocessing, multi-source information fusion, and artificial intelligence algorithms to interpret the acquired data and evaluate operational conditions. The execution layer consists of electronic control components integrated into agricultural machinery to realize adaptive functions, such as variable-rate seeding and active seeding depth adjustment.

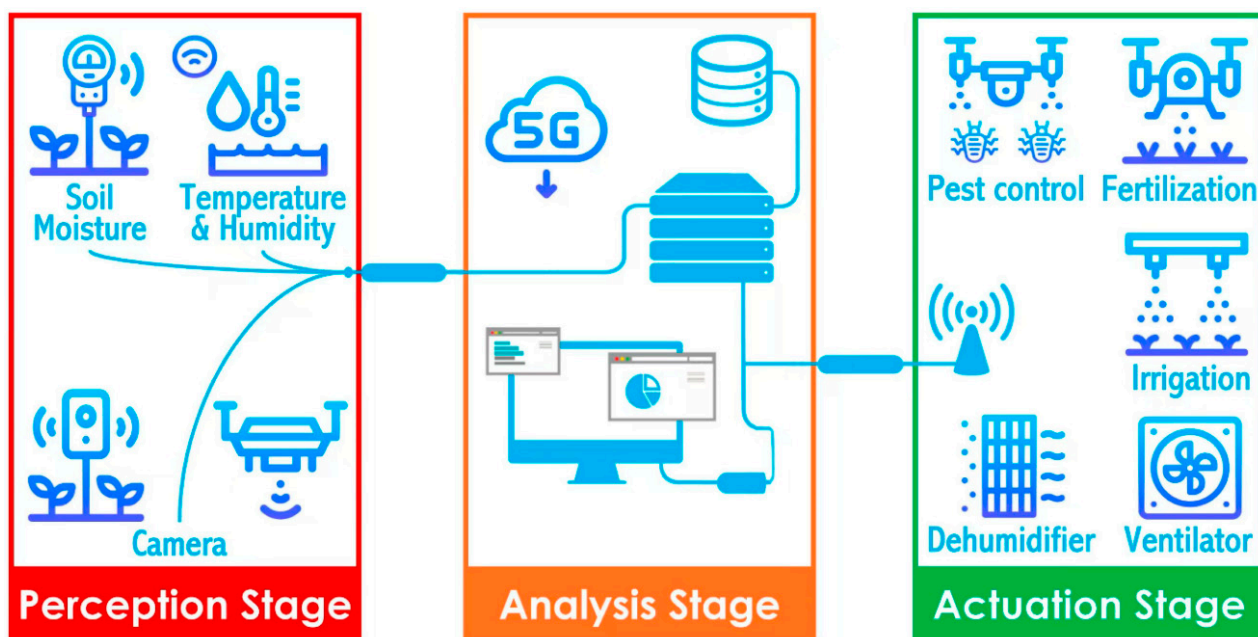


Figure 7. General conceptual framework of perception, analysis, and execution for precision crop management. Reprinted from reference [89].

5.1.1. Soil Environment Perception Technologies

Soil conditions are critical factors influencing crop establishment and population formation. Soil moisture, temperature, compaction, hardness, and their spatial variability can affect seed germination conditions and early seedling growth [90–93]. Traditional seeding equipment generally applies uniform operating parameters throughout the field, making it difficult to adapt to spatial variations in soil conditions. This limitation can result in inconsistent seeding depth, uneven soil covering around seeds, and reduced emergence uniformity [94].

The development of agricultural sensing technologies has promoted the transformation of soil monitoring from manual point sampling toward real-time online sensing integrated with machinery. Currently, seeding equipment can incorporate sensors for soil pressure, moisture content, temperature, and near-infrared spectroscopy to continuously acquire key soil parameters during operation. Multi-sensor collaborative monitoring provides comprehensive information on soil conditions within the seeding zone, supporting dynamic adjustment of seeding parameters and intelligent field decision-making [95–97].

Considering the strong spatial heterogeneity of farmland soils, soil sensing technologies can provide spatial information on soil properties for precision agricultural management. On-the-go and proximal soil sensing approaches enable the acquisition and mapping of spatially variable soil properties, which can be integrated into digital soil maps to support site-specific management and variable-rate input application [98,99].

Current soil sensing systems are developing toward higher stability, multi-parameter integration, and long-term continuous operation. While automatic sensor calibration, environmental noise filtering, and optimized data fusion algorithms can partly improve soil-information acquisition reliability under complex farmland conditions, high hardware cost and susceptibility to soil debris restrict large-scale on-seeder deployment and hinder practical application for autonomous soil perception in intelligent seeding systems [100,101].

5.1.2. Visual Perception Technologies for Seed Metering Processes and Seedling Conditions

Machine vision is a key technology enabling intelligent seeding equipment to obtain real-time operational information. Compared with conventional contact sensors, vision-based systems provide rich spatial information and offer significant advantages in monitoring seed movement trajectories, recognizing seed placement status, and analyzing crop population characteristics during the seedling stage [102].

During seeding operations, high-speed industrial cameras can continuously capture images of seed conveying, placement, and falling processes. Combined with image enhancement techniques and lightweight deep learning algorithms, these systems can identify seed placement conditions in real time under field operating conditions. In parallel, machine vision and deep learning techniques have increasingly been applied to agricultural crop and seedling detection. For example, aerial imagery combined with deep learning has been used to identify paddy seedlings, demonstrating the potential of vision-based methods for automated agricultural monitoring. Deep learning-based approaches have also been explored for crop and seedling classification and for the assessment of individual seed quality. These developments have contributed to the broader application of deep learning frameworks in agricultural visual perception [103–106].

Beyond real-time monitoring of seed placement at the machine level, machine vision technology has also been extended to crop seedling population assessment. By using ground robots, UAVs, and multispectral imaging systems to collect field images during early growth stages, researchers can extract characteristic parameters such as seedling

distribution, emergence uniformity, and missing seedling rate, providing data support for evaluating seeding and crop establishment performance [107,108].

However, field visual perception is strongly affected by variations in illumination, soil background, weed interference, and plant occlusion, which reduce recognition stability. While image enhancement, multi-source visual information fusion, and lightweight deep learning model optimization have become major approaches for improving system reliability, most models deliver satisfactory performance only under controlled datasets. Real-field generalization remains a key obstacle limiting practical onboard deployment [109–112].

As shown in Figure 8, UAV-based seedling monitoring generally consists of five steps: image acquisition, preprocessing, target segmentation, feature extraction, and population parameter estimation. Traditional image processing approaches mainly rely on color and texture features to distinguish crop seedlings from background information. Vegetation-index-based threshold segmentation methods can reduce soil background interference, extract plant spatial distribution information, and calculate parameters such as plant spacing, missing seedling rate, and population uniformity.

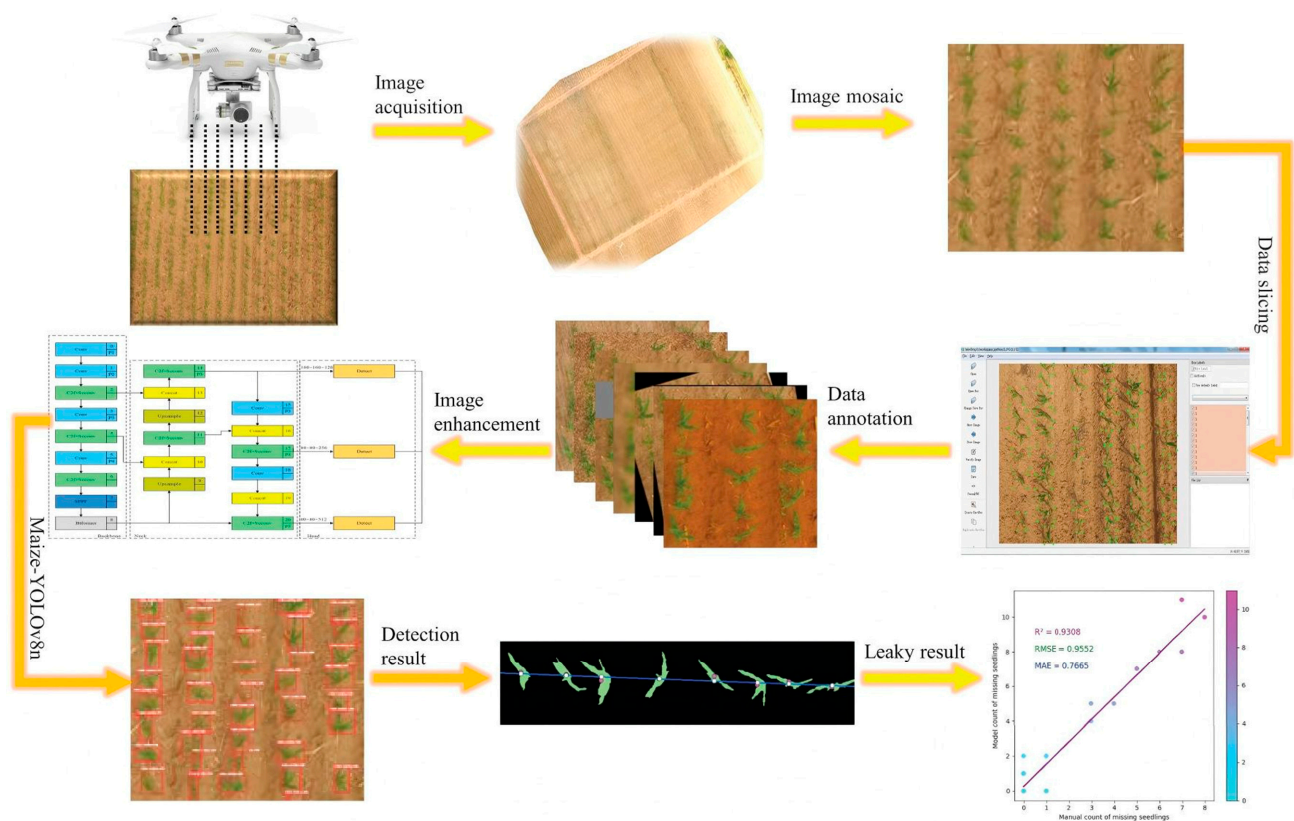


Figure 8. Overall technical workflow of UAV-based crop seedling detection and monitoring system. Reprinted from reference [113].

The development of artificial intelligence has promoted the application of machine vision and deep learning techniques to crop and plant recognition in agricultural environments. Machine vision provides a basis for automated visual assessment and field deployment, while deep learning methods, including convolutional neural networks and object detection approaches, have been increasingly applied to agricultural image analysis. These approaches can improve the automated extraction and recognition of crop-related visual features under challenging field conditions, providing information support for subsequent intelligent assessment of seeding and crop establishment conditions [114,115].

5.1.3. Spatial Positioning and Operation Trajectory Perception Technology

High-precision positioning and spatial information acquisition technologies provide important support for intelligent agricultural machinery to achieve accurate operation, navigation, and trajectory tracking. In autonomous agricultural operations, deviations in vehicle position and trajectory can affect the consistency of field operations and the accuracy of row following. Vision-based crop-row detection and autonomous navigation methods have therefore been developed to improve in-field trajectory following under variable field conditions [116]. Accurate acquisition and evaluation of motion parameters, including trajectory and speed, also provide an important basis for improving autonomous agricultural operation accuracy [117].

The BeiDou navigation system and centimeter-level high-precision Global Navigation Satellite System (GNSS) positioning provide reliable global spatial references for intelligent seeding equipment and support high-precision autonomous navigation and path tracking. However, GNSS-based positioning may become degraded or unavailable under vegetation occlusion, near structures, or other signal-limited conditions. Complementary sensing technologies, including LiDAR-based simultaneous localization and mapping (LiDAR-SLAM), visual odometry, and visual-inertial odometry (VIO), can provide local position and motion information in such conditions. Multi-sensor fusion combining GNSS with vision, LiDAR, and inertial measurements can further improve the continuity and robustness of localization and trajectory perception. For example, GNSS, stereo vision, and inertial measurements have been tightly integrated with SLAM for autonomous field robots, demonstrating improved localization performance in arable farming environments [118,119].

In addition to the spatial positioning function, the navigation and positioning system can integrate farmland geographic information, plot attributes, real-time operation data, digitally store seeding points, movement trajectories, and field environment information, build a spatial database for the entire seeding process, and support subsequent precise farmland management throughout the crop production cycle [118,120,121].

The current agricultural machinery navigation system is gradually shifting from single-path tracking control to comprehensive management of farmland spatial information. Relying on the coordinated operation of positioning perception, path planning, and trajectory tracking, it integrates and fuses the spatial data of machinery, field environment, and plots, providing stable position perception capabilities for the intelligent seeding system. The entire hierarchical technical architecture is shown in Figure 9. Beyond these classical trajectory-tracking controllers, deep reinforcement learning (DRL) provides a promising framework for handling coupled and nonlinear system dynamics. In particular, twin-critic architectures such as the twin delayed deep deterministic policy gradient (TD3) algorithm employ two critic networks to reduce value overestimation bias during policy learning, which can improve control robustness under complex dynamic interactions. Recent trajectory-tracking studies have demonstrated the application of TD3 to nonlinear coupled systems, highlighting its potential for handling cross-coupling effects that are difficult to model explicitly using conventional control methods [122]. Such learning-based control approaches provide a potential direction for intelligent agricultural machinery trajectory tracking, particularly when system dynamics and environmental disturbances are difficult to characterize accurately. Even so, complementary positioning schemes including SLAM and visual-inertial odometry introduce extra computational burden and remain prone to drift within dense crop-canopy environments.

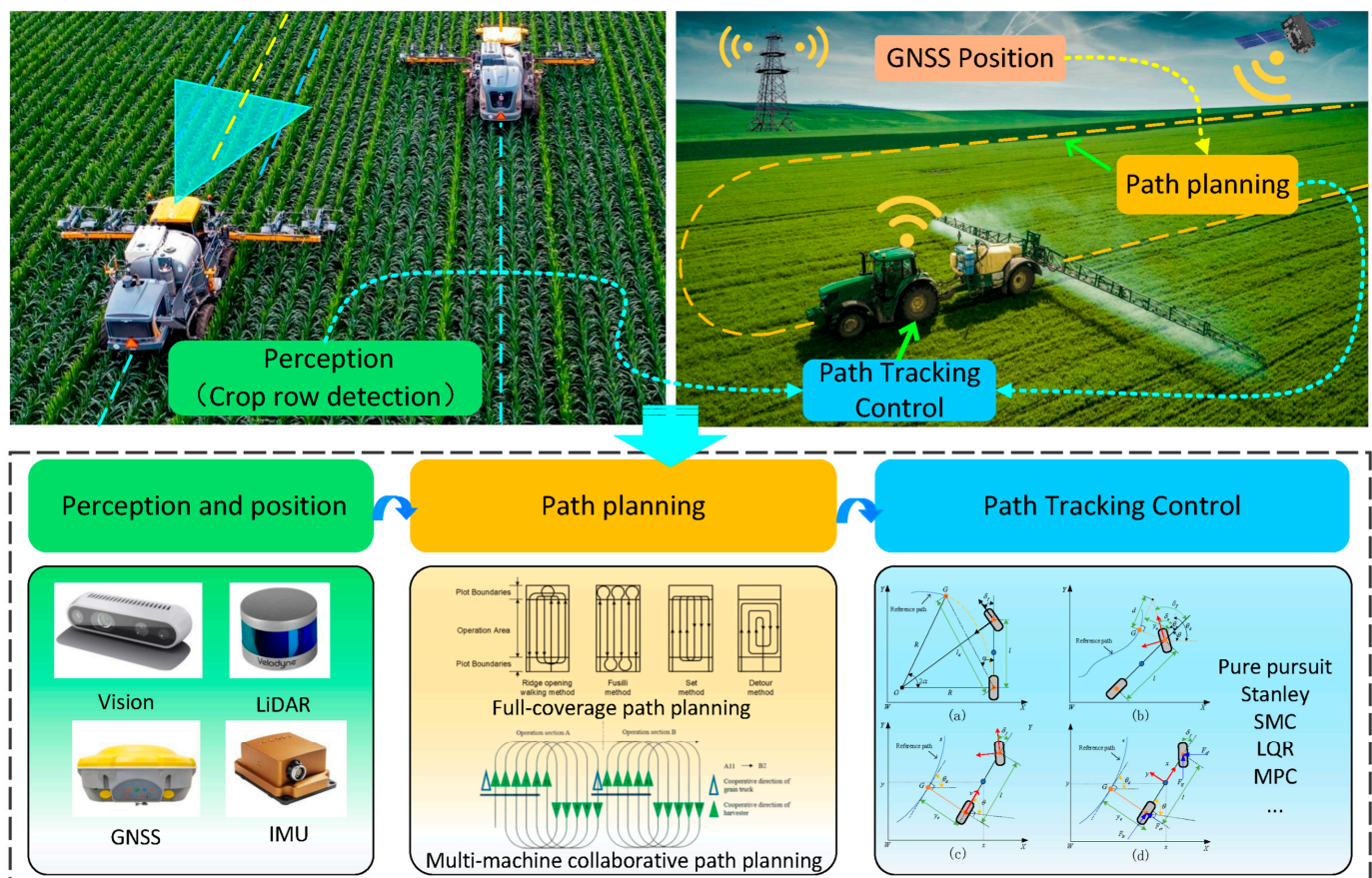


Figure 9. Autonomous navigation technology for agricultural machinery in the field. Reprinted from reference [118].

5.2. Online Monitoring and Intelligent Assessment of Seeding Quality

Precision seeding requires not only accurate regulation of operating parameters throughout the operation process but also quality assessment and feedback adjustment based on field emergence performance. Traditional seeding quality evaluation mainly relies on manual field sampling surveys, which are characterized by low detection efficiency, long evaluation cycles, and strong subjectivity. These limitations make it difficult to satisfy the requirements of dynamic and full-process quality monitoring in large-scale farmland. The rapid development of machine vision, unmanned aerial vehicle (UAV) remote sensing, and artificial intelligence technologies has promoted the transformation of seeding quality assessment from experience-based manual judgment toward automated online monitoring, quantitative digital analysis, and intelligent comprehensive evaluation [123–125].

Current intelligent seeding quality monitoring systems generally consist of three levels: on-machine monitoring of seeding operations, field evaluation of seedling emergence performance, and analysis of crop population structure. By integrating real-time equipment-based detection with remote sensing-based field monitoring, these systems enable quantitative assessment of seeding quality throughout the entire production process and provide data support for the optimization of operating parameters [126]. Reliable assessment largely depends on upstream sensing quality; sensing noise and bias can distort evaluation outcomes and weaken control credibility.

5.2.1. Quality Monitoring During the Seed Metering Process

Traditional seeding equipment mainly relies on mechanical structures to maintain stable seed metering performance and generally lacks integrated capabilities for real-

time detection of abnormal conditions, such as missed seeding, multiple seeding, and seed-flow blockage. Without dedicated monitoring systems, these abnormalities may remain undetected during field operation, delaying fault identification and corrective actions [127,128].

Machine vision-based monitoring has been increasingly applied to the assessment of seeding and planting performance. In particular, industrial cameras combined with deep learning-based object detection have been used to monitor missed-seeding events in air-suction seed meters and support subsequent reseeding decisions. At the crop establishment stage, UAV-based image detection has also been applied to identify missing maize seedlings and provide information for subsequent replanting decisions [113,129]. These vision-based approaches provide complementary means for evaluating seeding-related performance at the machine and crop-establishment levels.

The integration of deep learning algorithms, including convolutional neural networks and lightweight object detection models, into seed-metering performance evaluation can improve seed detection and trajectory-tracking accuracy under high-speed operating conditions. Recent research has demonstrated that improved YOLO-based object detection combined with object tracking can be used to evaluate the actual operating performance of high-speed maize seed-metering devices [130]. Such vision-based monitoring enables continuous recording of seed movement and metering performance during operation, providing timely data for seeding quality evaluation and supporting subsequent closed-loop control. Even so, existing solutions mainly target obvious seed-drop faults, while robust identification of subtle compound faults such as partial blockage remains insufficiently explored.

5.2.2. Evaluation of Field Seeding Performance

The emergence status and spatial distribution characteristics of crop populations are the ultimate quantitative indicators for evaluating seeding machinery performance and the effectiveness of seeding technologies. Field seeding performance is jointly influenced by multiple factors, including soil conditions, seeding depth uniformity, seed metering stability, and climatic environment. Monitoring only the local operation status of machinery cannot fully represent the overall seeding quality at the field scale. Therefore, comprehensive evaluation should integrate field seedling phenotypic information.

Unmanned aerial vehicle (UAV) remote sensing, ground-based mobile vision platforms, and multi-source image acquisition technologies provide new approaches for rapid assessment of seeding quality in large-scale farmland. By collecting crop images during the seedling stage and applying image processing, target recognition, and spatial analysis algorithms, information such as plant counts, spatial coordinates, missing-seedling areas, and crop-row distribution can be automatically extracted to support rapid and quantitative evaluation of field seeding performance [131,132].

Vision-based field evaluation methods overcome some limitations of traditional manual surveys, such as limited sampling coverage and low measurement efficiency, and provide an efficient approach for large-scale field monitoring. Machine vision techniques have been applied to plant and crop analysis under field conditions, providing a basis for objective evaluation of crop distribution and seeding performance [102]. Quantitative indicators such as sowing uniformity and emergence uniformity can be used to characterize seeding quality. Li et al. evaluated hybrid rice sowing uniformity using image processing and an improved YOLOv8n-based object detection model, demonstrating the potential of vision-based methods for objective sowing quality assessment [133]. Liu et al. used UAV RGB imagery to evaluate emergence uniformity and identify missing-seedling regions in mechanically sown wheat, demonstrating the feasibility of image-based methods for

large-scale field evaluation [134]. Nevertheless, seedling-stage image-based evaluation is inherently retrospective and cannot provide direct feedback during the seeding operation.

5.2.3. An AI-Driven Quality Evaluation Model

In complex farmland environments, the assessment of seeding quality is easily disturbed by fluctuations in illumination, soil background, and differences in seedling growth. The detection accuracy and adaptability of traditional fixed-threshold rule-based algorithms are insufficient under variable field conditions. Benefiting from autonomous feature extraction and nonlinear representation capabilities, artificial intelligence provides effective approaches for the automated assessment of seeding quality under complex working conditions, drawing on direct case studies as well as relevant agricultural visual-detection research [108,135,136].

AI-based methods are progressively enabling a multi-level evaluation of seeding and crop establishment quality. At the seedling level, object-detection models can identify defects such as missing seedlings, while image-based detection and spatial analysis can characterize seed-spacing-related indicators of seeding quality [137,138]. At the crop-establishment level, object-detection-based image analysis has been used to assess rice seedling planting conditions and support the evaluation of transplanting operation quality [139]. Semantic segmentation methods can further provide detailed spatial information for rice seedling identification and mechanical transplanting quality assessment [140]. In addition, a State Space Model (Mamba)-based detection framework has been developed for UAV-based rice seedling deficiency detection, demonstrating the potential of advanced deep-learning architectures for identifying missing seedlings under complex field conditions [141]. These studies demonstrate that AI-based detection and segmentation methods can provide complementary information from different levels and spatial perspectives for seeding and crop establishment quality evaluation. By integrating multidimensional perception information, AI-driven evaluation models can improve the robustness of quality assessment and provide information support for subsequent closed-loop parameter regulation. However, most models are trained on scenario-specific datasets, and cross-crop and cross-field generalization remains a prominent practical challenge.

5.3. Adaptive Seeding Parameter Regulation Based on Closed-Loop Perception Feedback

Compared with traditional agricultural machinery operating under fixed parameter settings, intelligent seeding equipment can dynamically adjust operating conditions based on real-time perception data, enabling a transition from uniform parameter-based operation toward adaptive dynamic control. By integrating multi-source perception, intelligent seeding quality assessment, and parameter regulation technologies, modern intelligent seeding systems establish a multi-layer closed-loop control framework consisting of environmental perception, working-condition assessment, parameter decision-making, and execution regulation. This framework enables machinery to adapt autonomously to soil spatial variability, environmental disturbances, and changing field conditions, thereby maintaining stable seeding performance throughout the operation process [142].

5.3.1. Variable-Rate Seeding Control Technology

The variable-rate seeding system integrates farmland digital maps with soil physical and chemical properties, historical yield information, and real-time environmental sensing data collected by agricultural machinery. By evaluating the production potential of different management zones, the system generates differentiated seeding strategies. During field operation, high-precision positioning technology is used to determine the spatial coordinates of machinery. Recent studies have demonstrated the feasibility of integrating soil-property sensing and electric-drive seed metering to adjust seeding rates according to

spatial variations in soil fertility. For example, a soil organic matter sensor-based variable-rate seeding system for maize can determine seeding rates according to real-time SOM measurements and implement rate adjustment through motor speed control [8,143].

In practical field applications, seeding density can be increased in areas with high soil fertility and greater yield potential to achieve target production goals. Conversely, reduced seeding rates can be applied in areas with limited soil resources, allowing seed input to better match local yield potential. Variable-rate seeding technology promotes a transition from uniform field-wide planting toward site-specific management based on spatial variability. In addition, intelligent seeding rate control systems can incorporate individual control of seed-metering units to reduce double-seeded areas caused by field overlap. Studies of automatic section control have reported average seed savings of approximately 4.3%, while double-planted areas in maize have been associated with yield losses of approximately 17% compared with normally planted areas [8]. These results indicate that intelligent seeding control can improve the efficiency of seed allocation while reducing yield penalties associated with excessive planting density in overlapped areas. In practice, the benefits of variable-rate seeding depend not merely on actuator precision but also on the quality of upstream soil and yield-based prescription maps.

5.3.2. Active Seeding Depth Control Technology

Seeding depth uniformity directly determines the consistency of the seed germination environment and represents a key indicator for precision seeding quality control. Traditional seeders mainly rely on passive mechanical profiling mechanisms to adapt to terrain variations. Under conditions involving rapidly changing soil resistance and uneven terrain, these systems cannot compensate for seeding depth deviations in real time, making stable crop emergence difficult to achieve [144,145].

Active seeding depth control technologies integrating soil resistance sensing, machine attitude detection, and electro-hydraulic regulation have gradually matured. These systems collect real-time information on field resistance and machine posture, dynamically adjust furrow opener depth and press wheel pressure, improve seeding depth stability under heterogeneous soil conditions, and enhance emergence uniformity [146–148]. In practice, actuator response lag and complex soil-straw mixtures limit real-time compensation efficacy under practical field conditions.

5.3.3. Feedback-Based Closed-Loop Control System for Seeding

Feedback control is a core component enabling autonomous operation of intelligent seeding equipment. Its fundamental principle is to utilize real-time monitoring information to identify operating conditions and drive actuators to rapidly compensate for deviations. Modern intelligent seeding systems integrate machine vision monitoring, soil environment perception, and multi-source machinery operation data to identify operational abnormalities in real time, including missed seeding, double seeding, uneven seed distribution, and excessive seeding depth.

The basic closed-loop control process can be expressed as the deviation between the target and measured seeding parameters:

$$e_k = r_k - y_k$$

where r_k represents the target seeding parameter, y_k represents the corresponding measured value, and e_k denotes the control deviation. The actuator input can then be determined according to the control deviation and the selected control strategy:

$$u_k = \pi(e_k)$$

where u_k represents the actuator input and $\pi(\cdot)$ denotes the control strategy. In practical seeding systems, feedback control strategies such as fuzzy control and PID-based control have been applied to electric-drive seed metering and active seeding-depth regulation. For example, multi-sensor fusion combined with fuzzy PID control has been used to regulate seeding depth under varying terrain conditions, while closed-loop electric-drive seeding systems have incorporated motor modeling and feedback control to improve seeding accuracy [147,149]. When abnormal operation conditions are detected, the system can automatically adjust execution parameters, including seed metering speed, machine travel speed, and soil covering or pressing pressure, according to predefined control strategies. This enables rapid correction of operation deviations and restoration of stable seeding performance. Closed-loop control reduces dependence on manual intervention during seeding operations and promotes a transition from post-operation adjustment toward perception-driven real-time autonomous regulation. Consequently, the environmental adaptability and operational stability of seeding equipment under complex field conditions are significantly improved [149]. Yet, most reported closed-loop schemes rely heavily on preset thresholds, and genuine end-to-end autonomous decision-making for highly variable farmland environments remains confined to research prototypes.

Intelligent perception technologies have promoted the transformation of seeding equipment from conventional mechanically driven units toward digital intelligent operation platforms. The complete technical process involves collecting multi-source information on field environments and machinery operating conditions, quantitatively evaluating seeding quality through artificial intelligence models, and adaptively regulating operating parameters through closed-loop control strategies. Through the integration of perception, assessment, and regulation, a hierarchical intelligent seeding technology framework has been established. However, current intelligent seeding systems still face several limitations, including insufficient adaptability under complex and extreme field conditions, limited cross-regional generalization capability, and inadequate autonomous decision-making ability. In addition, many existing control strategies still depend heavily on preset thresholds and local optimization methods. Future research should further integrate farmland multidimensional databases, advanced artificial intelligence algorithms, and autonomous collaborative control technologies to enhance environmental understanding, dynamic optimization capability, and intelligent decision-making performance. These developments will provide theoretical foundations and technical support for the development of integrated intelligent seeding equipment systems.

6. Development of Multi-Functional Integrated Seeding Equipment and Collaborative Operation Modes

Modern agriculture requires higher levels of operational efficiency, resource utilization, and coordination among agronomic processes. Improving individual seeding functions alone is no longer sufficient to satisfy the requirements of integrated multi-process field operations. Multi-functional equipment integration has become an effective approach for improving field operation efficiency, reducing repeated machinery passes, and enhancing the adaptability of agronomic processes. By integrating independent operation modules, including tillage and soil preparation, precision seeding, and variable-rate fertilization, modern seeding equipment has gradually evolved from single-function machines into multi-functional integrated operation platforms. Early seeding equipment primarily focused on individual processes such as quantitative seed delivery, furrow opening, and soil covering. However, agricultural production involves a continuous chain of operations, including land preparation, seeding, fertilization, and field management, among which strong technical interactions exist. Reliance on independent machinery for each operation

increases the number of field passes and operational costs, while also causing poor coordination among processes and reducing overall production efficiency. To address these challenges, modern seeding equipment has overcome the limitations of single-function structures by integrating multiple agronomic operation modules, enabling simultaneous completion of tillage, soil preparation, seeding, and fertilization. Through optimized structural configuration and coordinated process integration, multi-functional equipment improves operational efficiency and enhances compatibility with agronomic requirements. Moreover, it provides a hardware foundation for the integration of intelligent sensing and autonomous control systems into seeding machinery, drawing on concepts of integrated field operation platforms and multilayer control architectures [15,150].

It should be emphasized that multi-functional equipment integration mainly focuses on expanding hardware capabilities, aiming to improve operation coverage and coordination among agricultural processes. In contrast, intelligent seeding systems emphasize environmental perception, autonomous decision-making, and dynamic optimization of operating parameters. These two technological pathways complement each other and jointly promote the transformation of traditional seeding machinery toward intelligent agricultural equipment.

6.1. Integrated and Coordinated Operation Technology for Tillage, Preparation and Seeding

Under conventional production systems, soil tillage and seeding are generally performed by separate machines, resulting in fragmented operation processes, multiple field passes, and increased soil disturbance. Meanwhile, tillage and soil preparation quality directly determines seedbed conditions. Soil fragmentation, surface leveling, and seeding depth stability are all strongly influenced by preceding soil preparation operations. Therefore, effective coordination between these processes is essential.

The integrated tillage–soil preparation–seeding machine combines multiple functional units, including residue management, rotary tillage, soil preparation, furrow opening, seed metering, soil covering, and compaction. It enables simultaneous completion of soil treatment and seeding operations within a single field pass. Compared with separated sequential operations, this type of multi-functional machinery reduces repeated field traffic, improves operational efficiency per unit area, and minimizes variations in seeding quality caused by poor coordination among different machines. From the perspective of whole-machine design, the key challenge of integrated tillage and seeding technology lies in the coordinated matching between front-end soil treatment modules and rear-end seeding units. The front-end tillage module improves soil physical conditions and creates suitable seedbeds for crop establishment, whereas the rear-end seeding unit adjusts seed delivery according to travel speed and soil conditions, ensuring accurate spatial seed placement.

The power matching between front and rear modules, synchronization of operating speeds, and optimization of structural parameters are critical for maintaining stable continuous operation of the entire machine [151,152].

Currently, integrated tillage and seeding equipment has developed into a relatively mature structural system, with soil tillage and preparation modules and seeding execution units as its core components. Different functional modules achieve continuous operation through coordinated mechanical structures and power transmission systems. A typical structure of compound tillage and seeding equipment is shown in Figure 10 [64].

With the widespread adoption of conservation tillage and increasingly complex field conditions, further improvements are still required in the adaptive coordination among functional modules of integrated tillage and seeding equipment. Existing studies mainly focus on optimizing soil treatment mechanisms, seeding components, and whole-machine operation coordination to improve stability and comprehensive performance under com-

plex field conditions [64]. The performance of multi-functional soil working systems also depends on the ability of the working bodies to provide the required soil treatment quality in field conditions. Analysis of the performance of tillage units equipped with flexible working bodies shows the importance of adaptation of the working elements to variable soil conditions, and thus is relevant for the design of the integrated soil preparation and seeding machinery [153].

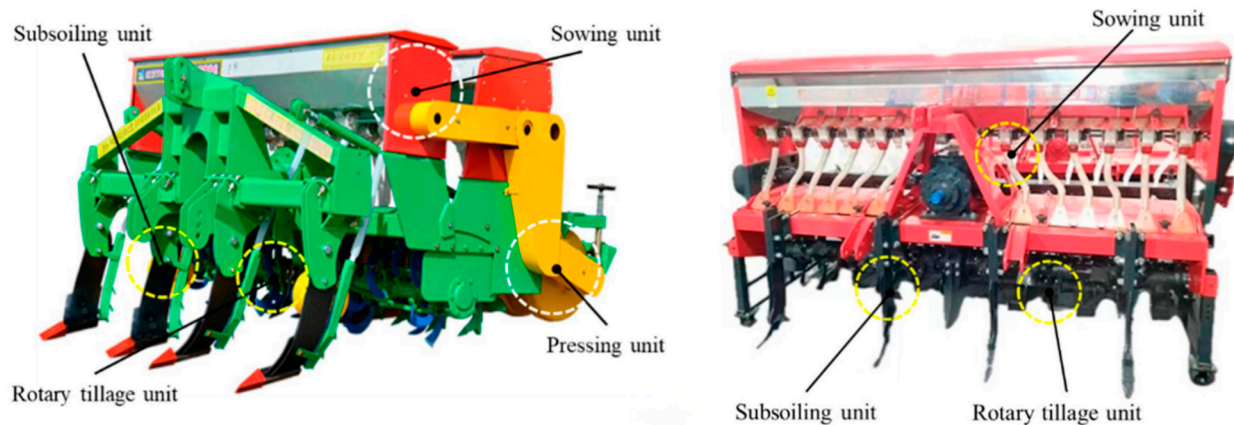


Figure 10. Prototype of partial subsoiling and rotary tillage combined seeder. Reprinted from reference [64].

6.2. Synchronous Seeding and Fertilization Technology

There is a close agronomic coupling relationship between seeding and nutrient supply. Under traditional production systems, seeding and fertilization are usually performed separately using different machines, which increases machinery operation costs and may result in spatial mismatches between seed placement and fertilizer distribution, thereby reducing nutrient use efficiency.

Synchronous seeding and fertilization technology integrates independent seed-metering and fertilizer-application systems to achieve simultaneous seed placement and nutrient application. Modern integrated seed–fertilizer equipment is typically equipped with independent electric-drive control systems, enabling coordinated and dynamic regulation of seeding and fertilization rates. The hardware control architecture of such equipment is illustrated in Figure 11 [154].

By considering crop root development characteristics and nutrient uptake patterns, modern seed–fertilizer synchronous machines can achieve multiple application modes, including seed–fertilizer co-placement at the same depth, layered fertilization, and side-deep fertilization. These approaches enable fertilizer distribution to better match crop nutrient requirements during different growth stages [155]. Among them, side-deep fertilization places fertilizer at an appropriate position beside and below the seed, preventing direct fertilizer damage while facilitating nutrient uptake by developing roots. Layered fertilization adjusts the vertical distribution of nutrients according to soil migration characteristics of different fertilizer components. These technologies have promoted the development of seeding equipment beyond simple mechanical integration of seeding and fertilization functions toward coordinated optimization of seed–fertilizer spatial arrangement and agronomic processes [156–158].

With the advancement of precision agriculture technologies, synchronous seed–fertilizer operation has evolved from simple operational synchronization toward precise spatial matching between seeds and nutrients. By optimizing the relative spatial relationship between seeds and fertilizers and coordinating operation parameters, fertilizer utilization efficiency and seedling growth adaptability can be improved. However, the

universal adaptability of such equipment across different crops and planting systems still requires further improvement to satisfy diversified agricultural production demands [159].

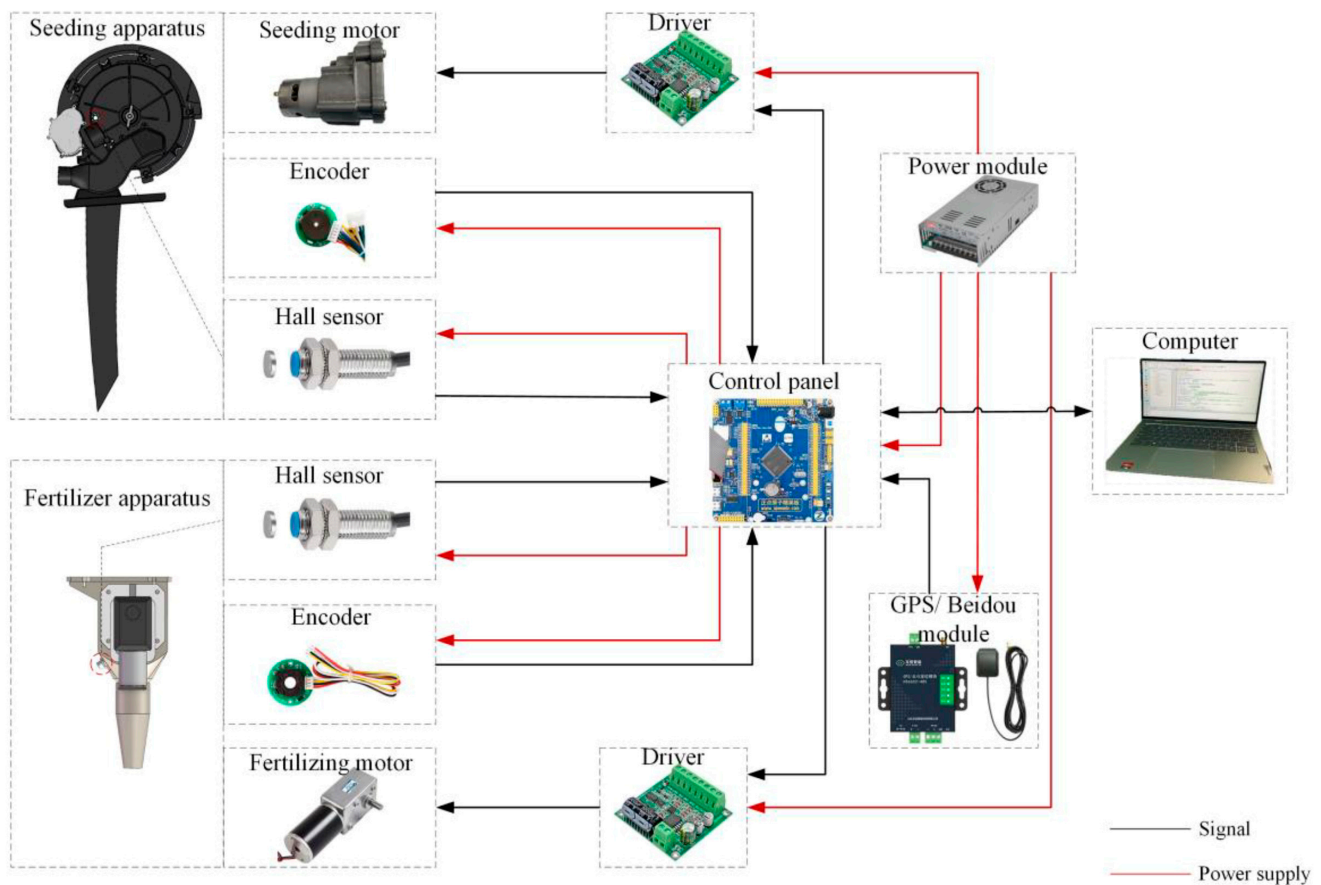


Figure 11. Schematic diagram of equipment control hardware circuit of seed-fertilizer co-seeding device. Reprinted from reference [154].

6.3. Modular Integration and Multi-Scenario Adaptation Technology

The differentiated requirements of cropping systems, crop types, and field operating environments have imposed higher demands on the adaptability and versatility of seeding equipment. Traditional fixed-structure seeders are often designed for specific crops and relatively uniform field conditions, which limits their adaptability to diversified cropping systems and heterogeneous field environments. Crop rotation and differences in field conditions therefore require seeding equipment to provide greater operational flexibility and adaptability across production scenarios [160,161].

Modular integration technology enables independent design of functional units, including furrow openers, seed-metering devices, fertilization systems, and soil covering and compaction components. By flexibly combining different modules, equipment functions can be adjusted according to specific field conditions and production requirements. Most large-scale integrated tillage–seeding and seed–fertilizer combined machines currently adopt standardized reciprocating operation patterns. However, actual agricultural fields often contain small, fragmented, and irregularly shaped plots. Under such conditions, standardized operation paths may result in inefficient path planning and reduced operational efficiency. A comparison between conventional machinery operation routes and fragmented field layouts is shown in Figure 12 [162].

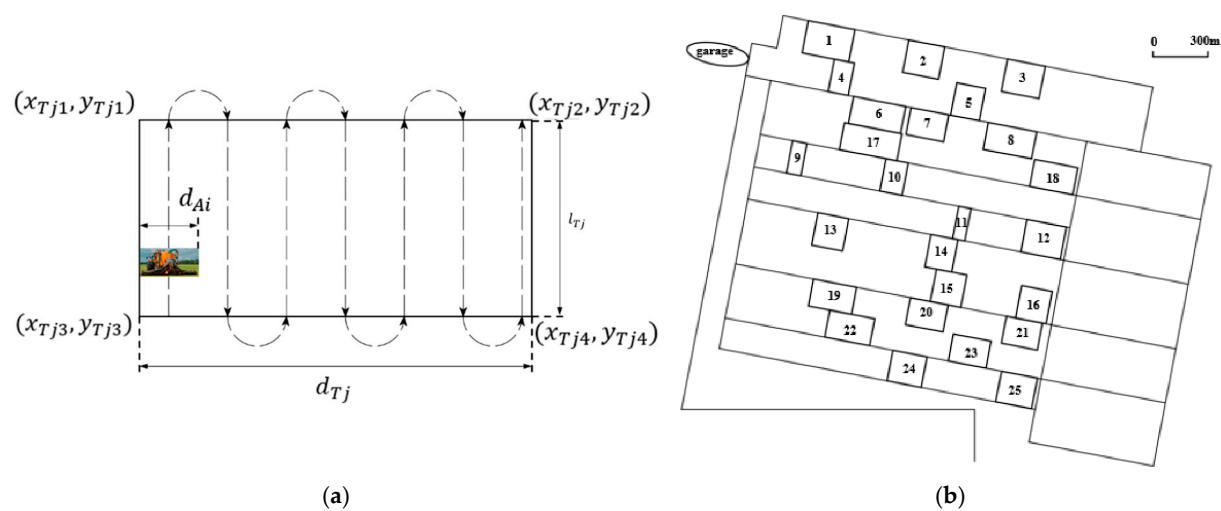


Figure 12. Reciprocating operation path of integrated seeding and fertilizing machine and distribution of fragmented farmland. (a) Single machine full-coverage operation route. T_j denotes a rectangular field plot; (x_{Tj1}, y_{Tj1}) , (x_{Tj2}, y_{Tj2}) , (x_{Tj3}, y_{Tj3}) , (x_{Tj4}, y_{Tj4}) are four vertex coordinates of field T_j ; d_{Ai} is the working width of agricultural machinery; d_{Tj} and l_{Tj} represent the width and length of field T_j , respectively; (b) layout of scattered experimental plots. Reprinted from reference [162].

Compared with traditional fixed-function machinery, modular seeding systems can flexibly configure functional components according to regional cropping systems, crop characteristics, and field conditions, improving equipment utilization and cross-scenario adaptability. These systems are suitable for diverse production environments, including wheat–maize rotation systems, no-tillage farming with residue retention, and precision seeding of specialty crops [152,163].

The refinement of agricultural production and diversification of production demands have accelerated the adoption of modular designs in seeding equipment. Seeding machinery is gradually evolving from fixed-function single-purpose machines toward re-configurable and multi-functional operation platforms. Improving the standardization of functional modules and the flexibility of machine configuration can further enhance the adaptability of multi-functional seeding equipment across different regions, crops, and farming systems. Representative tillage-seeding-fertilization integrated schemes are summarized comparatively in Table 4. However, multi-functional integration mainly addresses challenges associated with process expansion and mechanical coordination, with optimization focused primarily on equipment structure and operational processes. Under complex and dynamic field environments, future seeding equipment still requires deeper integration of environmental perception and intelligent closed-loop control technologies to enhance autonomous adaptability and support the development of complete intelligent seeding systems.

Table 4. Comparative summary of typical tillage-seeding-fertilization integrated solutions.

Integration Solution	Main Structural Features	Applicable Cropping and Field Scenarios	Core Advantages	Key Practical Limitations
Rotary-tillage combined tillage-seeding unit	Integrated rotary tillage and seeding mechanism; one-pass soil preparation and sowing	Conventional tilled fields; wheat-maize rotation; sufficient soil moisture	Good seedbed quality; high operation efficiency	Poor performance under heavy straw residue; high power consumption
No-tillage compound seeder	Residue-cutting mechanism with opener and seeding-fertilization metering, without prior soil turning	Conservation tillage; straw-mulched no-till fields	Reduces soil disturbance; preserves soil moisture	Prone to blockage; high requirement for residue pretreatment

Table 4. *Cont.*

Integration Solution	Main Structural Features	Applicable Cropping and Field Scenarios	Core Advantages	Key Practical Limitations
Side-deep fertilization integrated seeder	Independent seed-metering and fertilizer-metering units; spatial separation of seed and fertilizer placement	Grain crops including maize, soybean and wheat; high-yield fertilization-intensive fields	Avoids fertilizer burn; improves nutrient utilization	Complex transmission structure; higher manufacturing cost
Modular reconfigurable tillage-seeding-fertilization platform	Detachable functional modules for tillage, seeding and fertilization; flexible module combination	Diversified rotations; fragmented small plots; multi-crop production	Strong multi-scenario adaptability; flexible function switching	Requires precise module docking; lack of unified industry standards
Lightweight mounted combined seeding-fertilization implement	Simplified compound mechanism matched for small and medium tractors	Hilly areas; small-scale family farms	Low cost; good trafficability for small fields	Limited working width; poor performance under heavy residue

6.4. Recent Developments in Commercial Seeding Equipment

Recent commercial seeding equipment has increasingly incorporated technologies related to multi-functional integration, high-speed operation, electronic control, and precision field management. These developments provide practical examples of the technological trends discussed above and demonstrate the continued integration of mechanical, electronic, and digital technologies in modern seeding machinery.

Major international manufacturers, including HORSCH, Väderstad, AMAZONE, Maschio Gaspardo, Kverneland, KUHN, John Deere, and Kinze, have introduced commercial seeding equipment incorporating various combinations of pneumatic or vacuum seed metering, electric drive, individual row control, section control, variable-rate application, depth regulation, fertilization, and electronic monitoring. Representative commercial product families, such as HORSCH Maestro, Väderstad Tempo, AMAZONE Precea, Kverneland Optima, KUHN MAXIMA, and John Deere ExactEmerge and MaxEmerge systems, reflect the increasing application of these technologies in commercial seeding machinery. The specific configurations vary among manufacturers and equipment models according to crop type, operating conditions, and functional requirements [164–171].

These commercial developments indicate that multi-functional seeding equipment is increasingly integrating electronic control with seed metering, seed placement, fertilization, depth regulation, and field operations. This development is consistent with the transition of seeding machinery from mechanically integrated platforms toward electronically controlled and digitally connected systems, providing an important equipment foundation for further development of intelligent seeding technologies.

7. An Integrated Intelligent Seeding System Enabled by Agricultural Intelligent Agents

Seeding equipment has progressively expanded from single-function machinery toward multi-functional and increasingly intelligent operation platforms. During this development, mechanical integration, electronic regulation, environmental perception, and autonomous decision-making have evolved with different degrees of overlap rather than through a strictly sequential process. Farmland environments inherently exhibit significant spatial heterogeneity, while crop production objectives and field operating conditions vary dynamically across regions. Mechanical integration and fixed-parameter regulation alone are insufficient to achieve autonomous adaptation throughout the entire seeding process. Modern integrated intelligent seeding systems combine multiple technologies, including environmental perception, intelligent decision-making, and autonomous execution and regulation, promoting the transformation of seeding machinery from standardized pre-

cision operation equipment into intelligent field operation systems with environmental cognition and dynamic parameter adjustment capabilities. Agricultural intelligent agents represent an emerging framework that further extends these capabilities by integrating environmental perception, knowledge-based reasoning, task planning, and autonomous decision-making into agricultural operation processes [172–175].

Traditional seeding equipment follows an operation mode based on manually preset parameters and passive mechanical execution. The selection of seeding parameters mainly depends on operator experience, making it difficult to adapt to variations in soil physico-chemical properties within fields, crop-specific cultivation requirements, and uneven spatial distribution of agricultural resources. The application of electric-drive systems, onboard sensing technologies, and autonomous agricultural machinery has enabled seeding equipment to achieve local condition monitoring and single-parameter adjustment. However, most existing intelligent equipment mainly focuses on optimizing individual functional modules and lacks the capability to comprehensively analyze overall field production conditions. Consequently, its ability to autonomously interpret production objectives, incorporate broader agronomic knowledge, and perform task-level decision-making remains limited [176–178].

The agricultural intelligent agent framework provides a potential paradigm for the further intelligent upgrading of seeding equipment. The core concept is not simply the integration of various sensors, electronic control modules, and autonomous control algorithms, but the construction of a goal-oriented intelligent system capable of interpreting production objectives, applying agronomic and operational knowledge, and autonomously organizing tasks and control actions. In contrast to an autonomous seeding system that primarily performs predefined sensing, decision-making, and control functions, an agricultural intelligent agent is expected to possess three additional capabilities: (i) goal-oriented reasoning, through which high-level production objectives can be translated into operational decisions; (ii) knowledge-based adaptation, through which agronomic knowledge and accumulated operational experience can be incorporated to adapt strategies to changing field conditions; and (iii) task-level autonomy, through which the agent can plan, coordinate, and adjust multiple seeding-related tasks rather than merely regulate individual operating parameters. Accordingly, the agent framework connects environmental perception, goal interpretation, task planning, autonomous machinery execution, and feedback-based strategy adaptation into a higher-level closed-loop process. Through this framework, seeding equipment can progress from autonomous execution of predefined control strategies toward intelligent field operation systems capable of adapting their operational strategies to production objectives and changing field conditions [172].

Different from traditional automated agricultural machinery that executes pre-programmed control logics, the agricultural intelligent agent adopted in this review is defined as a goal-oriented operational architecture. Its core objective is to translate high-level agronomic production goals into actionable machine behaviors through a closed-loop process. This architecture consists of four interconnected functional modules: (1) environmental perception module, which collects multi-source information on soil conditions, crop status, and machinery operating states from onboard sensors and farmland spatial databases; (2) agronomic knowledge reasoning module, which interprets field observations using embedded agronomic rules and domain knowledge and transforms production requirements into concrete operational objectives; (3) task-level planning and decision-making module, which generates, adjusts, and optimizes operational strategies dynamically rather than merely following fixed preset parameters; and (4) autonomous execution and feedback adaptation module, which sends control commands to seeding actuators, collects real-time operational feedback, and revises strategies according to observed field conditions

and operational outcomes. Thus, the distinction between agricultural intelligent agents and traditional automated machinery lies primarily in the level and mode of decision-making: traditional automated machinery mainly executes predefined parameters and fixed control logics, whereas an agricultural intelligent agent emphasizes goal interpretation, knowledge-based reasoning, task-level planning, and adaptive strategy revision. This conceptual distinction provides the basis for the subsequent discussion of environmental perception, intelligent decision-making, autonomous execution, and cloud–edge–device collaboration in intelligent seeding systems.

The intelligent development of seeding equipment can be described through four representative technological dimensions: mechanical precision operation, electronic intelligent regulation, multi-functional module integration, and intelligent cognitive integration. These levels represent the progressive development of equipment from mechanical precision operation toward higher degrees of electronic regulation, functional integration, and intelligent decision-making, although some capabilities may develop concurrently. In particular, electronic regulation and multi-functional integration may coexist within the same equipment system, while intelligent cognitive integration based on agricultural intelligent agents remains an emerging direction. The multi-functional module integration level represents the integration of multiple agricultural functions within a single operation platform, characterized by the coordinated combination of functions such as tillage, seeding, and fertilization.

At the mechanical precision operation level, the primary objective was to improve seeding uniformity and overall operational stability. By optimizing seed-metering device structures, transmission mechanisms, and geometric parameters of working components, improvements were achieved in seeding rate consistency, seeding depth stability, and row spacing accuracy [179]. At this level, equipment performance mainly relied on mechanical constraints, without environmental information acquisition or feedback regulation mechanisms. Seeding parameters were generally determined according to technical standards or operator experience and could not respond to real-time changes in field conditions.

The electronic intelligent regulation level is characterized by the adoption of electronic control units and various sensing technologies. At this level, seeding machinery incorporates digitally adjustable functions into mechanical operating systems. Through independent electric-drive seed metering, real-time condition monitoring, and satellite navigation-based autonomous driving technologies, equipment can adjust basic operating parameters, such as seeding rate and traveling speed, during operation, thereby improving field operation stability [180]. Electronic regulation can coexist with multi-functional mechanical integration, and its implementation does not necessarily represent a distinct chronological stage. Intelligent upgrades at this level are mainly focused on individual functional modules, while the overall system may still rely on manually predefined operating objectives and have limited capability to comprehensively analyze the entire farmland production environment.

Current seeding equipment is increasingly incorporating elements of intelligent cognitive integration, where multi-dimensional sensing, digital farmland databases, and hierarchical intelligent control technologies are deeply integrated. The equipment can collect information on soil conditions, crop cultivation requirements, and historical production data, and generate optimized operation strategies, providing fundamental technical support for integrated intelligent seeding systems based on agricultural intelligent agents [4].

To provide a quantitative assessment of the technological characteristics discussed in this section, representative intelligent seeding technologies and systems were compared in terms of accuracy, operating speed, reliability, cost, and technology maturity (Table 5). The reported values were retained with their original units and evaluation definitions to

avoid inappropriate normalization across different crops, equipment configurations, and experimental conditions.

Table 5. Quantitative comparison of representative intelligent seeding technologies and systems.

Technology/ System	Accuracy/ Performance	Operating Speed	Reliability/ Robustness	Cost	Technology Maturity	References
Pneumatic precision seeding	QFI: 74.07–75.93%; miss index: 8.33–13.52%; multiple index: 10.18–17.59%	2.04–8.80 km h ^{−1}	QFI and miss/ multiple indices significantly affected by tillage level and travel speed	NR	Field-tested	[2]
Electric-drive precision seeding	QFI: 98.4% in tillage field and 86.8% in no-tillage field	4–10 km h ^{−1}	Speed-measurement method significantly affected QFI and multiple index; field condition affected performance	NR	Field-tested under tillage and no-tillage conditions	[78]
VRS control with lag compensation	SA: 98.87–99.68%; SCV: 0.16–0.85%; LD: 0.27–2.82 m	6–10 km h ^{−1}	Field SA: 96.62–99.07%; mean 97.64%; SCV: 0.45–1.56%; mean LD: 0.57 m	Low-cost prototype reported; absolute cost NR	Laboratory and field validated	[9,10]
SOM-based VRS	Bench SA > 99%; SCV < 0.4%; field SA 92.03%; SCV 6.21%; mean LD 1.13 m	NR	Clear reduction in performance from bench to field conditions	NR	Bench and field validated	[143]
Real-time seed-metering monitoring	Seed-quantity detection error < 2.0%; miss-index error < 0.4%; multiple-index error < 0.5%	Metering-wheel speeds: 9, 18, 27 rpm	Detection performance affected by seed size	Low-cost sensor reported; absolute cost NR	Laboratory and field monitoring validation	[127]
Laser-based seed monitoring	Signal rise time ≈ 500 ns; real-time seed counting and miss detection demonstrated	NR	Designed for real-time monitoring and fault detection	Cheap components reported; absolute cost NR	Laboratory prototype	[124]
Multi-sensor sowing-depth control	Average depth error: 4.496–6.434 mm with fuzzy PID under tested terrain conditions	NR	Error reduction of 10.7–22.9% relative to no control	NR	Bench validation	[147]

Note: NR, not reported; QFI, quality of feed index; SA, seeding accuracy; SCV, seeding coefficient of variation; LD, lag distance. Quantitative indicators retain the definitions used in the original studies and are not directly equivalent across different systems. The reported results demonstrate that intelligent seeding performance varies with crop type and field conditions. For maize, performance differed substantially between tillage and no-tillage conditions, while the soil-organic-matter-based variable-rate seeding system showed a decline in seeding accuracy from bench to field conditions. Real-time seed-metering monitoring also demonstrated low detection errors for soybean. Multi-sensor sowing-depth control further showed different performance under flat, gently sloped, and undulating terrain. These results indicate that crop characteristics, tillage conditions, terrain, and other field-specific factors can substantially affect intelligent seeding performance, highlighting the importance of field-based validation.

7.1. Environmental Perception and Farmland Spatial Cognition of Intelligent Seeding Systems

Whole-field environmental perception provides the fundamental basis for intelligent seeding systems to achieve precise decision-making and autonomous parameter adjustment. Unlike traditional machinery that relies on manually preset parameters, integrated intelligent seeding systems utilize multi-source sensing technologies to simultaneously acquire machinery positioning information, seedbed soil conditions, and multi-dimensional operational status data. These data provide essential support for adaptive seeding parameter optimization and closed-loop autonomous control.

High-precision satellite positioning is a key technology enabling autonomous driving and standardized precision operation of seeding equipment. Under manual driving conditions, machinery trajectories are easily affected by operator experience and field surface variations, resulting in problems such as inconsistent row spacing, repeated seeding in certain areas, and missed seeding near field boundaries. These problems not only reduce seeding uniformity but also interfere with subsequent mechanized operations, including fertilization, crop protection, and harvesting.

The application of differential GNSS, Real-Time Kinematic (RTK) centimeter-level positioning, and autonomous agricultural machinery control systems enables field machinery to obtain accurate geographic coordinates and perform automatic path planning and trajectory tracking [181]. Besides maintaining consistent row spacing, high-precision positioning also provides a unified spatial reference for farmland data acquisition and zoned variable-rate operations. However, positioning information only describes machinery location and cannot reflect spatial variations in soil fertility, water availability, or crop growth potential. Therefore, multiple environmental sensors are required to achieve a transition from simple positioning to comprehensive farmland environmental cognition.

Farmland environments exhibit strong spatio-temporal heterogeneity, and a single sensor type cannot fully characterize field production conditions. Therefore, multi-sensor information fusion has become a core technical approach for intelligent seeding systems [182,183]. Currently, sensing systems equipped on intelligent seeding machinery can generally be classified into three categories: soil environment sensing, field surface condition sensing, and machine operation monitoring.

Soil sensing modules collect information on seedbed physical properties and spatial variability, providing data support for site-specific management and variable-rate seeding [98]. Surface condition sensing can identify obstacles during field operations, thereby improving equipment adaptability under complex field conditions [184]. Machine condition monitoring can capture seed-metering status and operational data, supporting quantitative evaluation of seeding quality and real-time identification of abnormalities such as missed and multiple seeding [127].

By relying on multi-source heterogeneous data fusion algorithms and field condition analysis models, intelligent seeding systems can move beyond fixed-parameter operation toward dynamic identification of spatial field variations and adaptive regulation. However, the extent to which such capabilities can support robust autonomous optimization remains dependent on sensing reliability, computational performance, and field validation. However, in complex field environments, issues including low sensor signal-to-noise ratios, insufficient real-time performance of multi-source data fusion, and high hardware costs remain major barriers limiting large-scale application of intelligent seeding systems [185].

7.2. Intelligent Decision-Making and Variable-Rate Seeding Supported by Digital Farmland Models

Environmental perception technology addresses the acquisition of field information, whereas digital farmland models and intelligent decision-making algorithms transform massive amounts of collected data into actionable insights and enable global optimization of operation strategies. These technologies constitute a critical link in upgrading seeding equipment from passive precision execution to active autonomous regulation.

Digital farmland models integrate soil physicochemical properties, historical crop yield data, and spatial environmental information to construct geographically referenced digital archives with comprehensive production attributes, providing a standardized database for hierarchical decision-making in precision agriculture [186]. Traditional seeding systems generally apply uniform operation parameters across entire fields, making them unable to respond to spatial variations in production conditions. Digital farmland models can

accurately characterize the spatial variability of soil fertility, moisture content, and soil layer structure, identify differentiated production potentials, and provide decision support for zoned variable seeding. Based on historical yield data, zonal seeding prescription maps can be generated to determine optimal seeding rates for different production zones. A typical example is shown in Figure 13 [8].

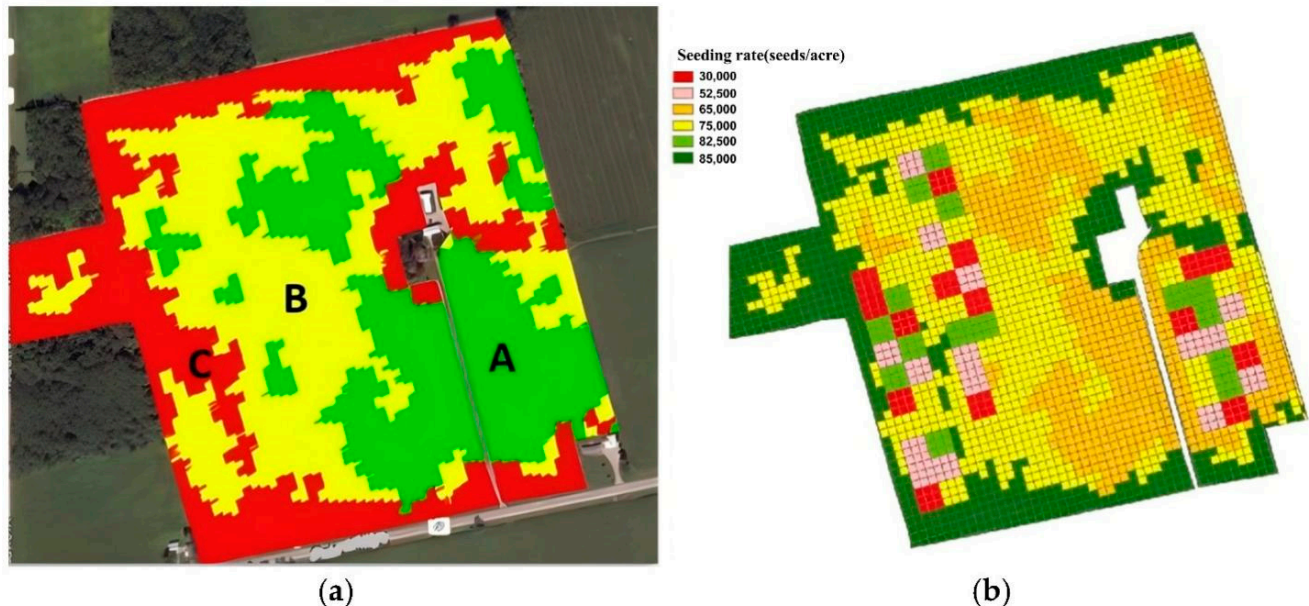


Figure 13. Yield zoning and corresponding optimal seeding prescription map of field plots. (a) Historical yield distribution, where A, B and C separately represent high, medium and low yield zones; (b) optimal seeding rate prescription map. Reprinted from reference [8].

The prescription map generated from the farmland spatial database serves as the core carrier for implementing variable-rate seeding. Traditional constant-rate seeding cannot accommodate regional differences in soil nutrients, moisture conditions, and yield potential. Variable-rate seeding dynamically adjusts the seeding rate according to spatial field zoning, enabling seed input density to better match regional production capacity. In contrast, variable-depth seeding adjusts seeding depth according to spatial variations in soil conditions and agronomic requirements. Although variable-rate and variable-depth seeding can be integrated within the same intelligent seeding system, they represent distinct control functions with different target parameters and decision criteria. These differentiated control strategies can improve the matching between seeding operations and spatially heterogeneous field conditions and contribute to the formation of balanced and stable crop populations [187,188].

Variable-rate seeding promotes the transition of seeding operations from uniform parameter-based management to spatially differentiated adaptive management, representing a typical application of precision agriculture concepts in the seeding process. With advances in farmland data acquisition and artificial intelligence optimization algorithms, variable seeding is no longer limited to single-parameter adjustment but is gradually incorporating soil conditions, crop variety characteristics, and annual yield targets for multi-parameter collaborative optimization [142].

Furthermore, digital twin technology represents an emerging approach for optimizing seeding processes. By establishing bidirectional information interaction between physical farmland systems and virtual digital models, digital twin-based systems could potentially simulate crop growth and yield responses under different seeding strategies and support the evaluation of alternative operation schemes [189,190]. However, the application of digital

twins to fully integrated seeding systems remains largely at the prototype or emerging stage, particularly with respect to continuous field-data integration, real-time model updating, and long-term field validation.

7.3. Unmanned Intelligent Seeding Equipment and Autonomous Operation Systems

Environmental perception and intelligent decision-making systems provide seeding machinery with capabilities for information acquisition, operation condition analysis, and strategy optimization, while autonomous execution technologies convert optimal decisions into standardized field operations. The integrated application of automatic navigation, independent electronic control units, and hierarchical intelligent control technologies has transformed traditional seeding operations that rely on manual driving and experience-based management into intelligent operation platforms integrating autonomous perception, decision-making, and unmanned execution.

In large-scale contiguous farmland production, unmanned tractors equipped with intelligent seeding units represent the primary application mode of unmanned seeding. These systems rely on differential satellite positioning, automatic steering control, and closed-loop regulation of operating parameters to complete seeding tasks along predefined paths. They provide highly stable driving trajectories and operation performance. Compared with manually operated machinery, unmanned seeding systems reduce human-induced operational errors, maintain consistent field operation standards, and provide reliable equipment platforms for variable-rate seeding and zoned fertilization [191,192].

For specific scenarios such as hilly terrain, greenhouse production, and small fragmented fields, lightweight autonomous seeding equipment, characterized by compact structures and flexible mobility, can complement large-scale unmanned seeding platforms and expand technical solutions for unmanned operations under complex conditions [193,194].

Multi-machine collaborative scheduling technology further extends the operational capability of unmanned agricultural machinery. Multiple intelligent seeding units can perform parallel operations through wireless communication, dynamic task allocation, and cooperative path optimization according to field area and operation progress, thereby improving operational efficiency and resource utilization in large-scale farmland systems. To address challenges such as task imbalance and coordination among multiple machines, intelligent optimization algorithms, including the Chaos–Cauchy Fireworks Algorithm (CCFWA), have been applied to agricultural machinery collaborative scheduling. Compared with conventional metaheuristic methods such as the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), CCFWA introduces chaotic population initialization and Cauchy mutation to improve population diversity and reduce the risk of premature convergence. In multi-machine collaborative task allocation, CCFWA has demonstrated better solution quality and stability than GA, PSO, and the conventional Fireworks Algorithm, while maintaining a relatively fast convergence rate. The solution framework of the Chaos–Cauchy Fireworks Algorithm for multi-agricultural-machinery collaborative scheduling is shown in Figure 14 [162].

Existing studies have demonstrated the potential of multi-machine collaborative operation systems in large-scale unmanned farming. However, challenges including unstable wireless communication in field environments, high acquisition costs of unmanned equipment systems, and insufficient adaptability of scheduling algorithms for complex and irregular fields still restrict large-scale deployment [162,195].

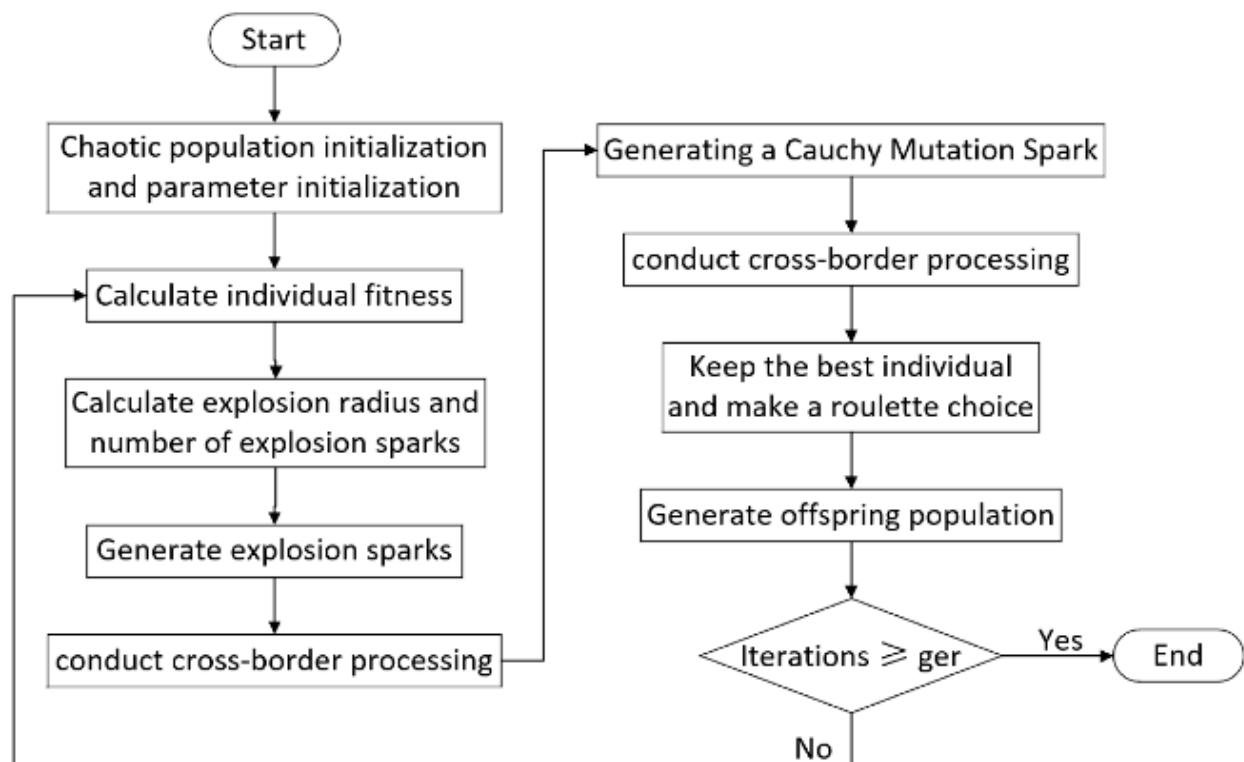


Figure 14. Solution framework of Chaos–Cauchy Fireworks Algorithm for multi-machine collaborative scheduling. Reprinted from reference [162].

The development focus of unmanned intelligent seeding equipment is gradually shifting from automated driving toward more comprehensive autonomous execution of the seeding process. Nevertheless, current systems still face limitations in perception accuracy under highly complex field conditions, long-term operational reliability, and economic feasibility. Further improvements require the integration of advanced sensors and intelligent control algorithms to enhance overall machine performance.

7.4. Operation System of Seeding Agents Under the Cloud–Edge–Device Collaborative Architecture

With the continuous increase in data generated by sensors integrated into intelligent seeding equipment, the limited computing capability of a single on-board controller makes it difficult to support real-time data analysis and long-term global model optimization under complex field conditions. The cloud–edge–device collaborative computing architecture provides a potential framework for distributing data processing and autonomous operation tasks within seeding-agent systems by hierarchically allocating local real-time control, edge computing, and cloud-based global model optimization tasks. The stable operation of intelligent seeding systems depends on real-time information exchange and coordination among three core modules: perception, decision-making, and execution. Among them, the vehicle-mounted terminal serves as the direct interaction interface between the agricultural intelligent agent and the farmland environment. It integrates positioning modules, multi-source environmental sensors, and electronic control actuators to complete field data acquisition, operation status feedback, and the execution of seeding commands. The overall hardware architecture and information interaction process of the maize no-tillage dense-planting precision seeder are shown in Figure 15 [155].

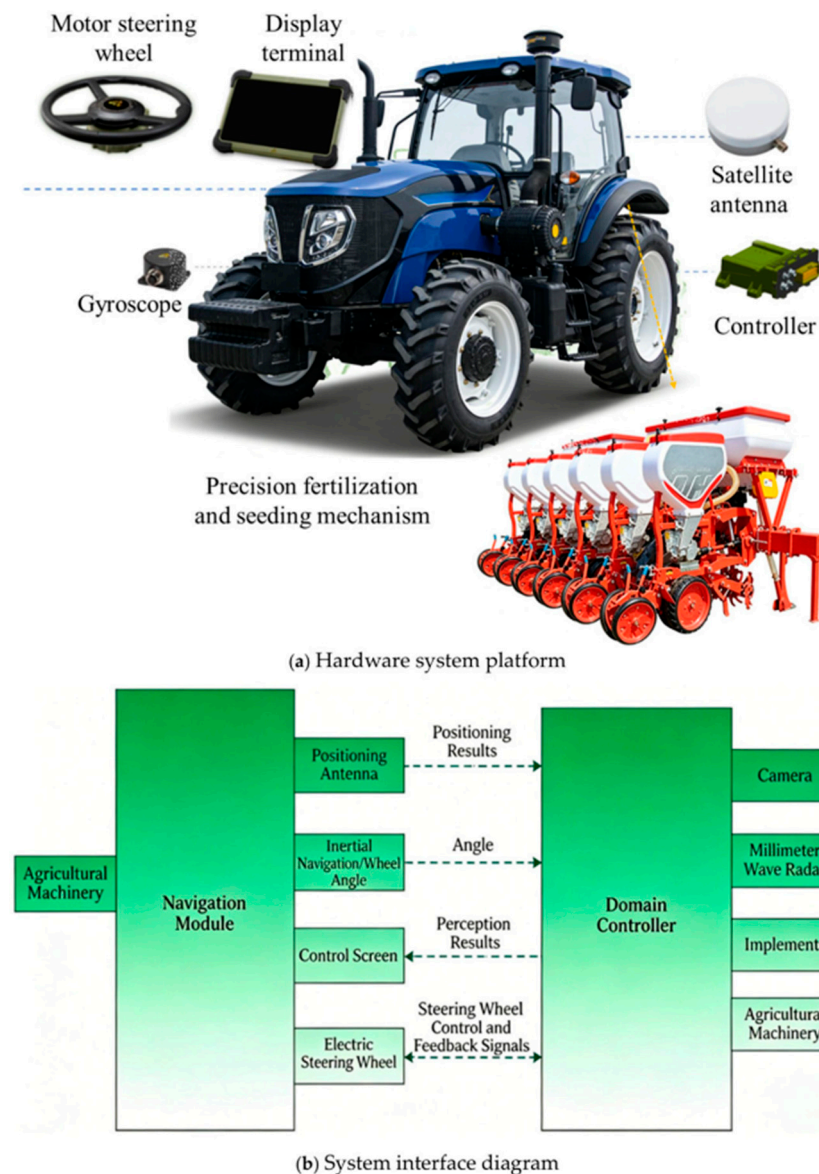


Figure 15. Hardware system and system interface diagram of no-tillage dense planting precision seeder for maize. Reprinted from reference [155].

To meet the requirements of massive data processing and hierarchical autonomous decision-making in intelligent seeding systems, a hierarchical software architecture can be organized to support equipment-level control, edge-side real-time processing, and cloud-based data analysis. At the software level, functions can be distributed according to the cloud–edge–device architecture: the on-board terminal performs real-time equipment control, the edge computing unit conducts rapid local data processing, and the cloud server provides large-scale data storage and model analysis [196,197]. For high-speed precision seeding, increasing operating speed reduces the time available for sensing, decision-making, and actuation over a given travel distance, making control delay increasingly important. The spatial error caused by a control delay can be approximated as

$$\Delta x = vT$$

where Δx is the spatial displacement during the delay, v is the operating speed, and T is the total latency of sensing, data processing, communication, and actuation. Thus, for a specified allowable spatial error $\Delta x_{\max}$, the corresponding latency should satisfy

$$T \leq \frac{\Delta x_{\max}}{v}$$

This relationship indicates that the allowable latency decreases as operating speed increases. Experimental studies on variable-rate corn seeding control have shown that operating speed significantly affects seeding lag and seeding performance, highlighting the need for timely processing and control during high-speed operation [9]. Therefore, latency-sensitive tasks such as sensor-data processing, seeding-state monitoring, and real-time parameter adjustment are more suitable for vehicle-mounted or edge-side execution, whereas cloud computing is more appropriate for non-time-critical tasks such as large-scale data storage, model training, and cross-field data analysis [196,197]. The hierarchical software architecture of the precision seeding control system is shown in Figure 16 [155].

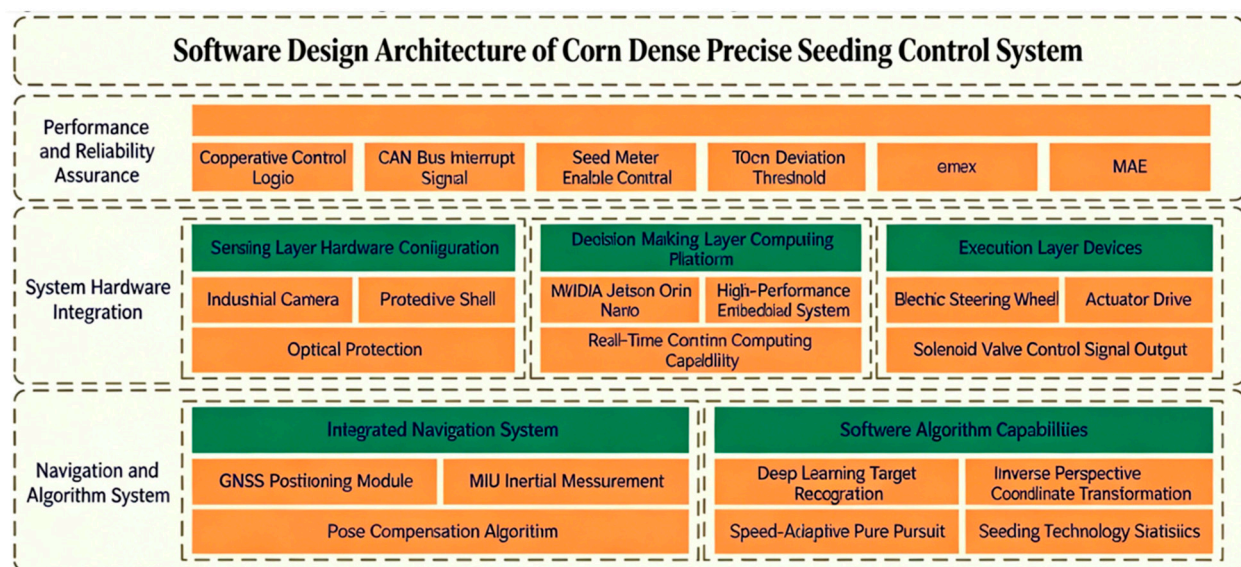


Figure 16. Hierarchical software architecture of precision seeding control system. Abbreviations: CAN, Controller Area Network; MAE, Mean Absolute Error; Gmax, maximum gain; Pure Pursuit, pure pursuit navigation algorithm. Reprinted from reference [155].

The cloud–edge–device collaborative hardware and software framework divides the farmland data processing chain into three layers: vehicle-mounted terminals, edge computing nodes, and cloud servers. The vehicle-mounted terminal relies on integrated sensors and electronic control hardware to collect field environmental information and machine operation data, while directly controlling seed and fertilizer metering mechanisms to complete basic seeding operations [155]. The edge layer can locally process sensor data and generate rapid adjustment commands for seeding parameters, thereby reducing communication latency and dependence on remote cloud routing for latency-sensitive control tasks. The cloud layer can provide centralized data storage and computational resources for large-scale agricultural data analysis and model development [197]. On this basis, future intelligent seeding systems could further integrate multi-year and multi-field farmland datasets, digital farmland records, and continuously updated decision-making models to improve adaptability across different soils, crops, and farming systems. Compared with traditional agricultural machinery equipped with single on-board controllers that can only perform local parameter adjustment, the cloud–edge–device collaborative architecture, supported by standardized communication interfaces and hierarchical decoupled software systems, connects the entire chain of data acquisition, multi-source information fusion, decision generation, and dynamic machinery control. This significantly improves information

exchange efficiency among multiple seeding devices and enhances adaptive regulation capability under variable field conditions [198,199].

Based on the cloud–edge–device collaborative computing architecture, integrated intelligent seeding systems can establish a hierarchical closed-loop framework for field perception, local decision-making, equipment control, and operation evaluation. At the perception layer, vehicle-mounted and field sensors acquire heterogeneous information related to soil conditions, crop or surface characteristics, and machinery operating status. The cognitive layer integrates multi-source sensing data through hardware and communication interfaces to characterize field and machinery operating conditions. At the decision-making layer, latency-sensitive tasks can be processed by lightweight algorithms deployed on vehicle-mounted or edge computing units, enabling real-time adjustment of seeding parameters, whereas computationally intensive analysis and historical data management can be performed at the cloud level. The execution layer then converts local or cloud-assisted decisions into control commands for seed and fertilizer metering mechanisms, thereby enabling dynamic regulation of operating parameters. Following field operations, operation-quality information and crop establishment or emergence observations could be further integrated into cloud-based data systems for subsequent analysis and evaluation. Such cloud–edge–device collaboration provides a potential pathway toward continuous model updating and adaptive seeding control under diverse field conditions, while farm-level closed-loop quality evaluation and standardized data sharing remain important directions for further development of intelligent precision seeding systems.

Despite the potential of cloud–edge–device collaboration for intelligent seeding, its integration with seeding equipment still faces several challenges. Challenges including inconsistent data standards among agricultural machinery platforms, insufficient wireless communication coverage in open farmland environments, and limited generalization capability of cloud-based intelligent models restrict large-scale deployment. Addressing these challenges requires future intelligent seeding systems to simultaneously improve hardware integration and long-term field reliability, optimize hierarchical software and algorithm frameworks, and deeply integrate agronomic growth mechanisms, agricultural machinery control strategies, and multi-dimensional farmland data resources.

Overall, the four-level framework describes the intelligent development of seeding equipment in terms of mechanical precision optimization, electronic control and digital parameter regulation, multi-functional operation integration, and intelligent cognitive integration. These capabilities may overlap and develop concurrently within different equipment systems, while agricultural intelligent agents represent an emerging direction of intelligent cognitive integration. With the continuous convergence of agricultural big data, deep learning, and autonomous agricultural machinery control technologies, future seeding equipment will evolve into integrated intelligent agricultural operation platforms capable of independently perceiving and analyzing farmland environments, adapting to differentiated crop production objectives, and continuously optimizing operation strategies.

8. Challenges and Future Development Trends of Intelligent Seeding Technology

At present, intelligent seeding equipment has achieved significant progress in electrically driven precision seeding, automatic closed-loop control, multi-source environmental perception, and digital farmland management. However, field operation environments are inherently complex and characterized by dynamic spatio-temporal variations. The practical implementation of intelligent perception and autonomous regulation technologies remains constrained by the quality of field data acquisition, the cross-scenario generalization capability of intelligent models, the engineering reliability of complete machines, and the cost

of industrial deployment. Therefore, accurately identifying key technological bottlenecks and establishing an evolutionary pathway compatible with diverse agricultural production systems are essential for promoting the transition of intelligent seeding equipment toward agricultural intelligent agent systems.

8.1. Key Challenges

Intelligent seeding systems exhibit distinct levels of technological maturity across application scenarios. From the perspective of practical deployment and validation, relevant technologies can be broadly classified as commercially deployed, field validated, prototype validated, or conceptual/emerging. Some technologies, including electric-driven seed metering, automatic section control, GNSS-based guidance, and closed-loop seeding-depth regulation, have demonstrated robust field performance and have been implemented in commercial agricultural machinery for large-scale field operations. Other technologies, such as machine-vision-based monitoring and multi-source perception systems, have achieved field validation in specific applications but still face challenges in robustness and generalization under diverse field conditions. In contrast, high-level autonomous decision-making, digital-twin-based optimization, and agricultural intelligent agents remain primarily at the prototype-validated or conceptual/emerging stages, with limited large-scale field validation and commercial deployment. Therefore, future development should pursue not only technological innovation but also the practical transition from experimental prototypes toward robust, field-deployable solutions.

Intelligent seeding systems encounter multiple intertwined technical and practical-application bottlenecks. To improve readability for industry-oriented readers, major challenges, their root causes, and corresponding proposed solutions are consolidated in Table 6.

Table 6. Summary of key challenges, root causes, and proposed solutions for intelligent seeding systems.

Challenge category	Main Challenge Description	Root Cause	Proposed Solution Direction
Multi-source perception and intelligent decision-making	Insufficient robustness of multi-source data fusion; poor cross-region and cross-crop generalization of intelligent decision models	Field illumination variation, straw residue interference and sensor drift; scarcity of diversified field datasets; model over-fitting risks	Develop anti-noise multi-source fusion algorithms; build multi-condition field datasets; adopt agronomy-knowledge-augmented artificial-intelligence models
Equipment intelligence and engineering reliability	Degraded electromechanical integration performance under harsh farmland conditions; inadequate automatic fault-diagnosis capability	Dusty, high-vibration, wide-temperature agricultural operating environment; insufficient hardware-protection design for sensing and electronic components	Strengthen hardware environmental-protection and vibration-isolation design; optimize electromechanical co-design and embed fault-diagnosis functions
Multi-crop and multi-scenario adaptability	Difficult rapid re-configuration for diverse seed types, crop-rotation systems and fragmented small-size fields	Predominantly fixed-structure machinery; lack of standardized reconfigurable modular interfaces	Develop standardized modular reconfigurable seeding units to support rapid function switching for different crops and farming patterns

Table 6. Cont.

Challenge category	Main Challenge Description	Root Cause	Proposed Solution Direction
Commercial-scale popularization and deployment	High hardware cost; high-skill operation threshold for end-users; imperfect supporting operation-maintenance service systems	Expensive high-grade positioning and multi-sensor hardware; immature socialized operation and maintenance services	Localize core sensing-control components to cut hardware cost; promote machinery-sharing and socialized agricultural service modes
Laboratory-to-field performance validation	Discrepancies between laboratory-measured seeding performance and actual field emergence and yield	Controlled laboratory conditions cannot fully reproduce heterogeneous soil properties, surface residues, terrain variation, machine vibration, and subsequent weather and biotic stresses	Combine standardized laboratory testing with multi-condition field validation and establish laboratory-to-field performance evaluation protocols
Engineering barriers to practical-scale deployment	Limited sensor durability, energy availability, connectivity, interoperability, and field maintainability	Harsh operating environments; limited machine power supply and network coverage; proprietary interfaces; limited technical service accessibility	Develop ruggedized and energy-efficient hardware; strengthen edge/offline capabilities; standardize interfaces and modularize components; improve field maintainability

8.1.1. Insufficient Generalization Capability of Multi-Source Perception Fusion and Intelligent Decision-Making

The autonomous operation loop of intelligent seeding equipment highly depends on accurate perception of farmland environments and stable machine operation. Various sensing technologies, including machine vision, soil physical and chemical sensors, RTK positioning, and satellite remote sensing, have established the data foundation for field condition recognition and dynamic adjustment of operating parameters. However, in open-field environments, variations in illumination, heterogeneous soil conditions, straw residue interference, and mechanical vibration can significantly reduce sensor signal quality, resulting in data drift and measurement errors. Moreover, data collected by different sensing devices exhibit considerable heterogeneity in spatial resolution, sampling frequency, data format, and measurement accuracy. Consequently, achieving a balance between real-time performance and robustness in multi-source data alignment, feature fusion, and noise reduction remains a major challenge for intelligent perception systems.

Meanwhile, agricultural field data exhibits strong regional specificity. Collecting cross-regional and cross-crop datasets is costly, and existing datasets often lack sufficient coverage. Current machine learning and optimization algorithms are prone to overfitting, leading to considerable declines in decision-making accuracy when applied to different regions or crop varieties. Improving the robustness of multi-source heterogeneous information fusion and enhancing the cross-scenario adaptability of intelligent models are fundamental for achieving reliable perception and autonomous dynamic regulation of seeding equipment.

8.1.2. Insufficient Integration of Intelligent Functions and Engineering Reliability of Equipment

The integration of intelligent sensing, onboard electronic control, wireless communication, and edge computing modules has greatly enhanced the data acquisition and autonomous regulation capabilities of seeding equipment. However, these additions also in-

crease the complexity of mechanical–electrical integration and impose higher requirements on environmental adaptability and anti-interference performance. Agricultural machinery typically operates for long periods under harsh conditions involving high dust levels, strong vibration, and large fluctuations in temperature and humidity. Consequently, sensor components, electronic control units, and wireless communication modules are susceptible to signal attenuation, wiring failures, and aging-related degradation. Hardware-level protection measures, such as sealed enclosures with appropriate IP ratings, vibration-resistant mounting, and protective or self-cleaning structures for optical sensing components, can help reduce the effects of dust, moisture, vibration, and surface contamination on sensing and electronic systems.

Most intelligent seeding prototypes can maintain high operational accuracy only under flat and standardized test conditions. During long-term field operation, limitations remain in areas such as automatic fault diagnosis, component maintenance costs, and overall system stability. Future equipment development should not focus solely on increasing intelligent functions but should simultaneously emphasize the protection of key electronic components, optimization of mechanical–electrical integration, and coordinated improvement of intelligent control performance and engineering reliability. In particular, environmental protection, vibration isolation, sensor contamination management, and reliable electrical connections should be considered together with intelligent control algorithms to improve the long-term stability and field applicability of intelligent seeding equipment.

8.1.3. Insufficient Adaptability to Multiple Crops and Application Scenarios

The current mainstream precision intelligent seeding equipment is mainly developed for standardized production of single grain crops, and can only adapt to specific seed characteristics, fixed row and plant spacing requirements, and standardized field conditions. However, significant differences exist among crops in seed size, thousand-grain weight, and germination characteristics. The optimal seeding density for population establishment and fertilizer placement strategies also vary considerably, imposing differentiated requirements on seed metering mechanisms, electronic control strategies, and operation control systems. Moreover, planting systems and conservation tillage practices differ substantially across regions. For the same crop, seeding parameters vary under different scenarios, including no-tillage, rotary tillage, crop rotation, and fragmented fields. The fixed structural design of current machinery limits rapid functional switching and flexible reconfiguration. Therefore, developing standardized, modular, and reconfigurable structures to enable rapid adaptation to different crops and farming systems will be a key direction for next-generation intelligent seeding equipment.

8.1.4. The High Cost of Intelligent Equipment Restricts Large-Scale Adoption

Intelligent seeding machines integrate centimeter-level positioning modules, multiple environmental sensors, independent electric-drive execution systems, and cloud–edge–device data interaction units. The hardware manufacturing and software development costs are generally higher than those of traditional mechanical seeders. The economic return of intelligent seeding equipment is closely related to farm scale, annual equipment utilization, equipment configuration, and local production conditions. For large-scale agricultural enterprises, higher annual operating acreage can distribute the initial equipment investment over more hectares and potentially shorten the effective payback period through labor savings, improved operational efficiency, and potential yield benefits. In contrast, small and medium-sized farms may face longer payback periods because the same capital investment is distributed over a smaller operating area. Nevertheless, a universal cost range, payback period, or equipment-utilization threshold cannot be established from the available studies

because these economic parameters vary substantially with equipment configuration, annual operating area, labor costs, cropping systems, and local production conditions. Therefore, the economic feasibility of intelligent seeding equipment should be assessed not only by its initial cost but also by equipment utilization, annual operating area, labor savings, and expected productivity gains.

Meanwhile, intelligent systems require professional operations, including farmland data management, control parameter calibration, and software and hardware fault diagnosis, which increases the technical requirements for farmers and agricultural machinery operators. In addition, professional operation and maintenance service systems remain underdeveloped. Future efforts should focus on localizing key sensing and electronic control components, promoting standardized integrated designs to reduce hardware costs, and developing agricultural machinery sharing and service models. These measures will lower the adoption threshold, reduce the economic burden on small and medium-sized agricultural producers, and improve the economic feasibility and market potential of intelligent seeding equipment.

8.1.5. Laboratory-to-Field Performance Gap

Laboratory tests of seed dosage and seeding performance are generally conducted under controlled and idealized conditions, including uniform soil substrates, stable environmental humidity and temperature, limited surface straw residues or soil clods, and relatively low mechanical vibration. Therefore, indicators measured in the laboratory, such as seed spacing variation, theoretical seed placement accuracy, and laboratory germination rate, often reflect the upper-bound performance of seeding equipment.

In contrast, actual field environments contain heterogeneous soil properties, surface residues, terrain undulation, and machine vibration during travel. These disturbance factors can contribute to seed bouncing, inconsistent seed covering, and spatial variation in soil moisture around the seeds after sowing. Consequently, the field emergence rate may be lower than the laboratory germination rate, while final crop yield is further affected by subsequent weed competition, pests, diseases, and weather fluctuations.

A clear performance gap may therefore exist between laboratory-measured seed dosage indicators and ultimate field outcomes. Laboratory tests are suitable for the relative comparison of machine performance, whereas field trials are indispensable for evaluating actual crop emergence and yield under real farming conditions. Future evaluation of intelligent seeding equipment should therefore combine standardized laboratory testing with multi-condition field validation to establish a more comprehensive assessment framework.

8.1.6. Obstacles to Practical-Scale Application

Despite promising performance of intelligent seeding subsystems under prototype test conditions, several engineering barriers still limit their reliable and continuous deployment under real field conditions.

Sensor durability: Long-term field deployment exposes sensors to dust, moisture, vibration, and temperature variation, which may cause lens fouling, signal drift, and component aging. Therefore, sensor selection and protective design should consider long-term environmental exposure and maintainability rather than only measurement accuracy under controlled conditions.

Energy requirements: On-board perception, high-speed image processing, edge computing, and wireless data transmission increase overall power consumption. The limited power supply capacity of tractors and working machines can constrain the simultaneous integration of multiple power-intensive intelligent modules. Energy-efficient sensing,

computing, and communication strategies are therefore needed to support continuous field operation.

Connectivity infrastructure: Remote data interaction in cloud-edge collaborative schemes depends on stable wireless communication. Some rural and farmland areas have limited cellular network coverage, signal attenuation, or high-latency transmission, which can impede real-time data exchange and cloud-driven decision execution. Local edge processing and temporary offline operation can therefore be incorporated to reduce dependence on continuous network connectivity.

Hardware/software interoperability: The lack of unified industrial interface standards creates interoperability barriers. Sensors, controllers, and machinery from different manufacturers often adopt proprietary communication protocols. Difficulties in cross-vendor data access, parameter configuration, and system integration increase the complexity of upgrading existing conventional seeders with intelligent perception and control functions. Standardized communication interfaces, data formats, and modular hardware/software architectures are therefore needed to facilitate cross-platform integration.

Field maintenance and serviceability: Long-term field deployment also requires convenient sensor calibration, component replacement, fault diagnosis, and software maintenance. Limited access to specialized technical services in some agricultural areas can increase downtime when intelligent components fail. Future equipment design should therefore consider maintainability and modular replacement together with sensing and control performance.

8.2. Future Development

Future development of intelligent seeding technology should follow a hierarchical pathway from solving immediate engineering bottlenecks to achieving long-term autonomous intelligence. In the near term, research priorities should focus on improving engineering reliability, multi-source perception robustness, and the field adaptability of existing intelligent equipment. In the medium term, knowledge-enhanced artificial intelligence, digital farmland models, cloud-edge-device collaborative architectures, and modular equipment systems will provide technical support for adaptive operation and cross-scenario deployment. In the long term, unmanned multi-machine collaboration and agricultural intelligent agents are expected to enable autonomous planning, decision-making, and continuous optimization of seeding operations.

8.2.1. Optimization of Agricultural AI Models for Seeding Decision-Making

At present, intelligent seeding systems still mainly rely on manually preset process parameters and fixed rule-based control strategies, which limits their ability to autonomously identify and dynamically adapt to complex and heterogeneous farmland environments. With the continuous accumulation of farmland production datasets and the advancement of agricultural artificial intelligence technologies, intelligent models will play an increasingly important role in analyzing farmland spatial heterogeneity, identifying crop nutrient requirements, and globally optimizing variable seeding strategies throughout the production process.

The next-generation intelligent seeding system will integrate vehicle-mounted vision, multi-parameter soil sensing, satellite remote sensing, multi-year historical yield databases, crop growth mechanisms, and agricultural knowledge bases to develop multimodal agricultural AI models. These models will drive seeding decision-making systems to transition from experience-based and rule-based control toward a dual-driven mode combining field measurement data and agricultural knowledge, enabling autonomous and differentiated planning at the field scale.

8.2.2. Virtual-Real Collaborative Optimization Supported by Digital Farmland Models

Traditional seeding operations rely on field trials and repeated parameter adjustments to determine optimal operation conditions. This process is time-consuming and requires substantial material and labor inputs. Moreover, it is difficult to quantitatively evaluate the effects of spatial variations in soil properties, water availability, and nutrient conditions on crop emergence. Digital farmland archives and digital twin technologies provide new approaches for pre-validation of seeding processes and global optimization of operation parameters.

By constructing high-fidelity virtual models that enable bidirectional real-time mapping between farmland environments, crop growth processes, and machinery operation states, digital twin systems can simulate and predict the effects of different seeding rates, seeding depths, and seed-fertilizer placement strategies. They can further evaluate the influence of different parameter combinations on crop population formation, significantly reducing the need for large-scale field experiments and improving the scientific basis of operation decisions.

By integrating soil physical and chemical properties, crop growth models, and dynamic machinery operation data, a geographically referenced digital farmland model can be established to provide quantitative support for variable seeding and zonal fertilization. The digital twin simulation platform can be deeply integrated with real-time vehicle-based intelligent decision-making algorithms, enabling virtual operation verification before field deployment, dynamic correction during operation, and feedback-driven optimization after operation. This process facilitates the transition from manual trial-and-error adjustment to data-driven autonomous decision-making.

8.2.3. Unmanned Intelligent Seeding and Multi-Machine Collaborative Operation System

Autonomous driving of agricultural machinery, fully electronic control execution, and remote monitoring technologies are continuously advancing. Unmanned intelligent seeding units are expected to become standard operating equipment for large-scale farms. Equipped with integrated tillage, seeding, and fertilization units, unmanned traction platforms can effectively eliminate trajectory deviations and seeding rate fluctuations caused by manual operation, unify regional field operation standards, and provide reliable hardware support for high-precision variable seeding.

With further technological development, multi-machine collaborative intelligent operation systems will emerge. Multiple intelligent units for seeding, fertilization, and tillage can rely on wireless networking to achieve shared operational information, dynamic task allocation, and coordinated path planning. These systems can operate cooperatively according to field size and soil zones, improving large-scale farmland operation efficiency and promoting the transition from single-machine automation to collaborative intelligence among agricultural machinery clusters.

8.2.4. Modular Intelligent Seeding Equipment and Large-Scale Adoption

The large-scale industrialization and application of intelligent seeding technology depend not only on improvements in core operation performance but also on equipment cost and maintenance convenience. In the future, standardized and modular design concepts should be further implemented through lightweight multi-functional units and domestically developed key sensing and electronic control components, thereby reducing manufacturing costs and simplifying fault repair and component replacement.

Through rapid assembly and replacement of seed metering, furrow opening, and fertilization modules, a single machine can adapt to the seeding requirements of various grain, economic, and specialty crops, improving annual equipment utilization. Meanwhile,

improving agricultural machinery sharing and socialized service systems can reduce equipment acquisition costs, lower the adoption threshold for small and medium-sized operators, and promote the application of intelligent seeding equipment across farmland scenarios with different scales.

Overall, several factors, including limited adaptability to complex field environments, insufficient robustness and efficiency of multi-source information fusion, weak cross-scenario generalization of intelligent models, inadequate engineering reliability of agricultural machinery, and high costs of industrial deployment, collectively constrain the large-scale application of intelligent seeding equipment. Existing commercial technologies, such as precision seed metering, electronic drive control, and automatic row management, have already achieved practical field application, whereas advanced functions including autonomous perception, knowledge-driven decision-making, and intelligent agent-based operation still require further validation under diverse agricultural conditions. Future research should promote the interdisciplinary integration of agricultural machinery design, crop production knowledge, artificial intelligence, and Internet of Things technologies, driving the evolution of seeding equipment from single-parameter closed-loop control toward integrated intelligent operation systems with comprehensive environmental perception, hierarchical autonomous decision-making, and continuous optimization of operation strategies.

9. Conclusions and Prospects

Seeding is a critical operation in crop production that directly affects field population structure, resource utilization efficiency, and yield potential. This review systematically summarizes the technological framework, evolutionary pathway, and major challenges of intelligent seeding equipment, and identifies the key elements driving its development: multi-functional mechanical integration provides the hardware foundation for intelligent upgrading; multi-source environmental perception and knowledge-driven decision-making constitute the core intelligence layer; cloud–edge–device collaborative computing provides the computational architecture for autonomous operation; modular reconfiguration and unmanned collaborative systems enable adaptation to diverse production scenarios; and reliable, cost-effective engineering design provides the foundation for large-scale deployment.

From the perspective of technological evolution, intelligent seeding equipment has progressed through successive stages, including mechanical precision improvement, electronic intelligent regulation, multi-functional operation integration, and cognitive intelligent systems. Mechanical innovations, such as improved seed metering mechanisms, integrated tillage-seeding operations, and synchronized seeding-fertilization systems, have promoted the transition from single-function operations to multi-agronomic process coordination. Subsequently, multi-source sensing, variable-rate regulation, and autonomous navigation technologies have enabled equipment to perceive spatial heterogeneity and dynamically adjust operational parameters. Further integration of cloud–edge–device collaborative architectures has facilitated the development of intelligent seeding systems with autonomous perception, decision-making, execution, and feedback capabilities, accelerating the transformation from standardized machinery to adaptive intelligent agricultural platforms.

Although significant progress has been achieved in precision seeding, multi-functional operations, and autonomous control, intelligent seeding systems still face several challenges. These include insufficient robustness of multi-source perception under complex field conditions, limited generalization of intelligent algorithms across regions and crops, inadequate long-term reliability of electromechanical integrated systems, and relatively high costs associated with equipment acquisition and maintenance.

From a technology maturity perspective, this review distinguishes technologies according to their demonstrated level of practical deployment and validation. Commercially deployed technologies include electric-driven seed metering, GNSS-based guidance, automatic section control, and selected closed-loop seeding-depth regulation systems that have been implemented in agricultural machinery and validated in practical field operations. Machine-vision-based monitoring and variable-rate seeding have achieved field validation in specific applications, although their robustness, generalization across field conditions, and long-term operational performance still require further assessment. In contrast, cloud-edge collaborative learning, digital twin-based optimization, agricultural intelligent agents, and high-level autonomous decision-making remain predominantly at the prototype-validated or conceptual/emerging stages, with limited comprehensive field validation and large-scale commercial deployment in seeding scenarios.

Future development should focus on improving robust environmental perception, developing agricultural-knowledge-enhanced AI models, and establishing reliable cloud-edge-device architectures. Meanwhile, modular equipment design, engineering optimization, and service-oriented deployment models will be essential for accelerating the transition of intelligent seeding technologies from experimental prototypes to large-scale agricultural applications. Finally, improving the localization of core electronic components, enhancing engineering reliability, and integrating agricultural machinery service models will be essential for reducing application barriers and accelerating the transition of intelligent seeding technologies from experimental prototypes to large-scale field applications.

In conclusion, intelligent seeding equipment is undergoing a critical transition from precision agricultural machinery toward autonomous intelligent agricultural systems. Future advances will depend on deeper integration among agricultural machinery, agronomy, artificial intelligence, and digital technologies to overcome limitations across perception, decision-making, and engineering implementation, thereby providing essential equipment support for the digital and unmanned transformation of crop production systems.

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