
Key Technologies for Open-Field Unmanned Farms: Research Status and Prospects (Postprint)

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Abstract

Unmanned farms represent a manifestation of smart agriculture and constitute an important exploration toward building a strong agricultural nation and achieving agricultural modernization. Centered on data, knowledge, and intelligent equipment as core elements, unmanned farms achieve deep integration of modern information technology with agriculture, enabling the integration of information perception, quantitative decision-making, intelligent control, precise input, and personalized services throughout the entire agricultural production process. This paper systematically elaborates on the concept and overall technical architecture of field unmanned farms, discusses five key technologies and equipment for field unmanned farms—including information perception and intelligent decision-making, precision operation systems and equipment, autonomous driving, unmanned agricultural machinery, and unmanned farm management and control platforms—and conducts an in-depth analysis of the critical scientific and technical issues that urgently need to be addressed in developing field unmanned farms in China. Using the corn unmanned farm in Gongzhuling City, Jilin Province as a case study, it introduces the specific applications and effects of technologies such as the Internet of Things, big data, cloud computing, and artificial intelligence in the full-process unmanned production of corn. Finally, it prospects the important role of unmanned farms in addressing common challenges faced by global agricultural production, such as the "no one to farm" issue, analyzes the opportunities and challenges for developing unmanned farms in China, and proposes strategic goals and approaches for their development in the country.

Full Text

2.1 Overall Architecture of Field Unmanned Farms

Unmanned farms rely on data and information as foundational support, guiding unmanned agricultural machinery to automatically, comprehensively, and efficiently complete agricultural production activities through autonomous analysis and decision-making. The general system architecture of an unmanned farm is illustrated in Figure 1 [Figure 1: see original paper]. Unmanned farms typically encompass four core enabling technologies: perception and decision-making, precision operations, autonomous driving, and multi-machine coordination. These technologies cover the entire process of unmanned agricultural machinery operations from tillage, planting, and management to harvest. The perception and decision-making component focuses on acquiring farmland soil, crop, pest, weed, and disease information, fusing and analyzing this data to determine soil moisture deficits, nutrient deficiencies, and the severity of pest, weed, and disease infestations, thereby generating fertilization and pesticide application prescriptions. Precision operation technology addresses each link in agricultural production—from tillage to harvest—by applying seeds, fertilizers, and pesticides precisely according to agronomic requirements and decision prescriptions using precision seeders, fertilizer applicators, and sprayers. During harvest, it intelligently regulates harvester operating parameters based on crop attributes and quality information to achieve low-loss, high-efficiency harvesting. Autonomous driving technology primarily solves the problem of autonomous field navigation for agricultural machinery, including path planning, path tracking, obstacle avoidance, and headland turning. Multi-machine coordination addresses the challenge of synchronous or collaborative operations among multiple machines in unmanned scenarios. Typical operational scenarios currently include coordination between harvesters and grain carts, collaborative task allocation and path planning for multiple machines performing similar operations simultaneously, and coordination between unmanned seeding/fertilizing equipment and supply vehicles. Unmanned agricultural machinery integrates relevant technologies for information perception, precision operations, autonomous driving, and multi-machine coordination control into a single platform, enabling it to autonomously complete the entire production process from tillage to harvest without human intervention. This represents a critical material foundation for building unmanned farms. The unmanned farm information management and control platform serves as the command center for farm operations, aggregating meteorological, farmland environmental, crop, and machinery information to determine optimal operating times, most reasonable task allocations, optimal operation paths, and prescriptions for seed, fertilizer, and pesticide applications. Unmanned agricultural machinery conducts production activities based on decision information and instructions from the management platform, feeding operation data back to the platform. The platform then analyzes and evaluates operation quality based on this data, optimizing and adjusting machinery tasks in response to abnormal conditions.

2.2 Information Perception and Intelligent Decision-Making for Field Unmanned Farms

2.2.1 Precision Seeding Information Perception and Prescription Decision-Making

Precision seeding is one of the key technologies in field unmanned farms. Unlike conventional seeding methods, precision seeding adjusts seeding rates across different plots according to their yield potential, ensuring seeds can fully utilize soil nutrients, sunlight, and water-holding capacity to maximize yield [4]. To guide precision seeding more accurately, rapid acquisition of soil environmental information in the seedbed is necessary to provide real-time theoretical basis for seeding decisions and control. Soil environmental information typically includes parameters such as soil moisture, electrical conductivity, and organic matter content. To obtain this information and ensure sufficient data processing time for the control system, real-time sensors are typically installed at the front of the seeder. While domestic and international researchers have made progress in developing single-parameter real-time sensors, most studies focus on individual sensors, with insufficient research on multi-source data fusion processing [4].

Soil moisture content, which reflects water availability, determines seed growth conditions and directly affects germination rates. Researchers have developed numerous in-situ soil moisture monitoring methods, including resistive methods, Frequency Domain Reflectometry (FDR), Time Domain Reflectometry (TDR), and neutron methods. However, in-situ monitoring techniques cannot meet the rapid response requirements of seeding decisions. In recent years, scholars have developed on-board soil moisture online monitoring devices that can obtain real-time soil moisture content during seeding, providing theoretical basis for subsequent control of seeding depth and spacing. Zhang Dongxing et al. [5] designed a visible-near infrared soil moisture sensor for measuring soil moisture in the seeding furrow. Zhu Wenjing et al. [6] developed a non-contact, near-infrared soil moisture online detection system based on Fabry-Perot interferometry to address issues with probe-type sensors, such as the need for extensive deployment, high costs, and tillage layer disruption. Weatherly and Bowers [7] developed an online soil moisture perception sensor using the resistive method to provide decision-making basis for corn seeding depth control systems. Price and Gaultney [8] and Mouazen et al. [9] both designed online soil moisture measurement instruments using near-infrared spectroscopy, enabling dynamic real-time detection of soil moisture during field operations to guide corn seeding.

Soil electrical conductivity is a commonly used parameter for evaluating soil productivity. Measurement typically employs the four-electrode current-voltage method. In recent years, domestic researchers have begun developing vehicle-mounted soil electrical conductivity detection systems. Yang Wei et al. [10] and Yang Wenqi [11] both developed vehicle-mounted rapid detection systems for field soil electrical conductivity based on this principle, which can quickly predict the distribution trend of soil leachate electrical conductivity to provide reference for seeding operations. International research on vehicle-mounted soil electrical conductivity sensors began earlier, with several commercial products now available, notably the EM38-MK2 from Geonics Limited [12] and the Veris 3150 from Veris Technologies [13]. A vehicle-mounted rapid detection system for field soil electrical conductivity is shown in Figure 2 [Figure 2: see original paper].

Soil organic matter is another key indicator for evaluating soil fertility. Using soil organic matter information to guide variable-rate seeding is a common practice. International research on soil organic matter sensors has achieved in-depth results, with some products already commercialized. Ess [14] from Purdue University designed a soil organic matter sensor based on photoelectric principles, which determines organic matter content based on the principle that different organic matter contents result in different reflected spectral bands. Precision Planting' s SmartFirmer sensor [15] simultaneously emits and receives X-rays, visible light, and radio waves, analyzing the characteristics of these three light types to obtain soil organic matter content information. Domestic research on vehicle-mounted soil organic matter sensors remains limited, with most studies focusing on model development and portable rapid detection instruments. For example, Tang Haitao et al. [16] and Xie et al. [17] used near-infrared spectroscopy technology with different characteristic wavelength extraction algorithms for specific conditions to build soil organic matter content prediction models, providing theoretical basis for online prediction. Cui Yulu et al. [18] designed a portable soil organic matter detector based on spectroscopic principles, achieving a correlation coefficient R^2 of 0.891 between instrument measurements and standard values.

Although various sensor types exist for monitoring soil environmental information, current limitations in sensor installation space and data response delay during seeding operations make simultaneous detection of multiple soil parameters difficult. Moreover, the lack of support from historical yield data and current meteorological information prevents online soil sensors from making comprehensive seeding decisions. Consequently, variable-rate seeding based on prescription maps remains the most commonly used approach. Regarding prescription map generation for variable-rate seeding, the United States has developed a mature commercial service system, with companies like CASE, Topcon, and Ag Leader providing numerous technical services for prescription decision-making and generation. Compared with developed countries, domestic research on variable-rate seeding decision-making is still in its infancy, with most studies focusing on seeding rate control based on forward speed [19,20]. Research emphasis has been placed on control systems rather than seeding decision-making, resulting in relatively low adoption rates of real-time sensor-based variable-rate seeding control systems abroad.

2.2.2 Precision Fertilization Information Perception and Prescription Decision-Making

Precision fertilization involves multiple key technologies, including information perception, prescription decision-making, and precise control. Extensive research has been conducted worldwide on crop nitrogen diagnosis, with several representative sensors commercially available for obtaining crop nutrition information. These include the GreenSeeker (660 nm, 780 nm) developed by Oklahoma State University and N-tech Company, and the RapidSCAN CS-45 (670 nm, 730 nm, and 780 nm) developed by Holland Company. Yang Guijun et al. [21], Sun Hong et al. [22], and Lin Weipan et al. [23] developed crop growth monitoring instruments, including the CropSense (650 nm, 810 nm) for crop vigor monitoring, a dual-band (650 nm, 850 nm) active light source chlorophyll content detection sensor, and the portable three-band (660 nm, 730 nm, 815 nm) crop growth monitor CGMD303, which can obtain Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Fractional Vegetation Cover (FVC), and chlorophyll content. Jiao Leizi et al. [24] and Zhou Peng et al. [25] used laser-induced technology to measure soil nitrogen and near-infrared spectroscopy to detect soil nutrients, respectively.

In terms of precision fertilization decision-making methods, Oklahoma State University researchers Lukina et al. [26] and Raun and Walsh [27] developed the Nitrogen Fertilization Optimization Algorithm (NFOA). Shi et al. [28] corrected the fertilization model based on nitrogen content during variable-rate fertilization decision-making using the GreenSeeker sensor, dividing target fertilization rates into 12 levels according to NDVI values for layered application. Cao et al. [29] established variable-rate fertilization decision models for rice and corn in Northeast China using data from multiple spectral sensors.

2.2.3 Precision Pesticide Application Information Perception and Prescription Decision-Making

The core of precision pesticide application is obtaining information on pest, weed, and disease variations within small field areas and applying variable-rate technology for on-demand application. Real-time pest, weed, and disease information acquisition technologies mainly include spectroscopy-based, image-based, and spectral imaging methods, suitable for pre-emergence weed control, inter-row weed control, and in-row weed control, respectively. For spectroscopy-based methods, commercial weed sensors such as WeedSeeker and Weed IT are available internationally [30]. For image-based methods, visual navigation products like Autopilot, CamPilot, and Robocrop have been developed abroad. For hyperspectral imaging methods, Pan Ranran et al. [31] combined chemometric methods to classify and identify weeds in rapeseed. Disease identification has also yielded numerous results: Zhou Qiaoli et al. [32] identified tomato leaf diseases using an improved lightweight convolutional neural network MobileNetV3; Reddy and Rekha [33] implemented automatic leaf disease detection using a Deep Leaf Disease Prediction Framework (DLDPF) based on transfer learning; Bravo et al. [34] conducted early diagnosis of wheat yellow rust using spectral reflectance data; and Liu et al. [35] classified four grades of rice panicle disease using BP neural networks. Based on pest, weed, and disease detection, machine learning algorithms such as random forest and artificial neural networks are employed to establish crop growth status diagnosis models and pesticide application prescription decision models, integrating multi-source data and knowledge rules to generate field-scale pesticide application prescriptions.

In summary, regarding information perception and intelligent decision-making technologies for field unmanned farms, international research on online perception technologies for key seed, fertilizer, and pesticide information is more systematic, with multiple commercial online perception sensors available for precision application decision-making. Domestic research primarily focuses on integrated application of foreign sensors, limiting adaptability in sensor combination and decision models. Chinese research teams have independently developed some soil and crop sensors and conducted preliminary studies on precision fertilization and pesticide application decision models for different crops in various regions. With improvements in sensor technology and decision models, domestically developed sensors will play a greater role in precision operations.

2.3 Unmanned Farm Precision Operation Technology and Equipment

Precision operations involve the precise application of agricultural inputs such as seeds, seedlings, fertilizers, and pesticides to specific locations according to agronomic requirements or prescription decisions. These operations mainly include precision seeding/transplanting, precision fertilization, and precision spraying.

2.3.1 Precision Seeding/Transplanting Technology and Equipment

"Success depends 70% on seeding and 30% on management." Precision seeding/transplanting is a critical link in crop production, aiming to ensure uniform spatial distribution of crop plants to reduce competition for light, heat, water, and nutrients among plants [36,37]. Field precision seeding/transplanting mainly includes three forms: single-grain precision hill-drop seeding, quantitative uniform drilling, and transplanting.

(1) Single-grain precision hill-drop seeding is the process of planting single seeds into soil at uniform plant spacing, stable seeding depth, and consistent row spacing, primarily for crops such as corn, soybean, and cotton that require single-grain precision seeding. To achieve unmanned seeding operations, key components of conventional mechanical seeders—including metering devices, seed tubes, depth control mechanisms, downforce control, and covering/repression mechanisms—have been intelligently upgraded. Companies like Precision Planting and Kverneland represent the international advanced level in single-grain precision hill-drop seeding, achieving motor-driven control of metering devices, intelligent stepless

adjustment of seeding depth, hydraulic/pneumatic downforce regulation, operation quality monitoring, and other functions. Precision Planting' s SmartFirmer (Figure 3 [Figure 3: see original paper] (a)) enables real-time monitoring of moisture, temperature, and organic matter content in the seed furrow; SmartDepth (Figure 3 (b)) allows rapid stepless adjustment of seeding depth via motor control through human-machine interaction terminals; VDrive (Figure 3 (c)) achieves precise control of metering devices through circumferential motor drive; DeltaForce (Figure 3 (d)) enables rapid detection of downforce on seeding units and real-time hydraulic control; WaveVision (Figure 3 (e)) is a seed metering detection sensor with strong penetration and high dust resistance; and Speedtube (Figure 3 (f)) achieves smooth and orderly seed delivery from the metering device to the seedbed using a partitioned conveyor belt [38]. Based on motor-driven metering devices and satellite positioning technology, Kverneland has achieved precise control of seed lateral and longitudinal positioning, enabling variety seeding [39]. China has also conducted pioneering research on seeder intelligent upgrades. He et al. [40-42] explored motor-driven metering technology using DC motors to drive metering devices, achieving a single-grain rate of 98.4% under high-speed seeding conditions of 12 km/h, and investigated prescription map-based variable-rate seeding technology.

In seeding detection, researchers have explored various sensors including machine vision, photoelectric, capacitive, and piezoelectric types, with photoelectric sensors forming the mainstream product [43-46]. Fu Weiqiang et al. [47] and Gao Yuanyuan et al. [48] used pin sensors to detect downforce on seeding units and employed hydraulic and pneumatic methods to regulate downforce, achieving qualified seeding depth indices of 90.37% and 98.91%, respectively. To achieve smooth seed transport from metering devices to the seedbed, Liu et al. [49] designed a partitioned conveyor belt-type secondary seed delivery device that maintains high-quality seeding operations even at 14 km/h.

(2) Quantitative uniform drilling is the process of uniformly distributing seeds at consistent depth according to required seeding rates, primarily for wheat and direct-seeded rice. The basic requirements are accurate seeding rates, uniform distribution, and consistent depth. Drills are classified as mechanical or pneumatic based on seed delivery method. Mechanical drills primarily use external fluted roller metering devices as the main seed distribution component, while pneumatic drills mainly use air-seeders for seed distribution, typically on large seeders. Amazone' s Cataya series drill (Figure 4 [Figure 4: see original paper] (a)) is a combined tillage and seeding machine using external fluted roller metering devices for rapid calibration and high-precision control with a seeding rate error of 1%. The Avant series drill (Figure 4 (b)) is equipped with a pneumatic centralized metering device for uniform seed distribution, and combined with intelligent human-machine interaction terminals, can achieve section control functions. Domestic drills with external fluted roller metering devices operate on the same principle as foreign products but lag in reliability and

operational precision. For pneumatic centralized metering devices, Lei Xiaolong et al. [51] optimized the design of a wheat-rapeseed compatible pneumatic centralized metering device using gas-solid two-phase coupling methods, achieving row-to-row consistency variation coefficients below 4% for rapeseed and 5% for wheat, with total discharge stability variation coefficient and seed damage rate below 1.0% and 0.1%, respectively. Zhang Xiaohui et al. [52] designed a pneumatic centralized metering system with discharge stability variation coefficients as low as 1.01%-1.19%, demonstrating good wheat seeding performance. Additionally, China' s unique wide-precision wheat seeding technology is widely applied due to its excellent seed-saving and yield-increasing effects, primarily achieved through optimized design of seed tubes and distributors for wide uniform seed distribution.

(3) Transplanting involves inserting age-appropriate crop seedlings into soil at required planting depth and spacing. Field operations mainly refer to rice transplanting, with the basic requirement of ensuring seedlings are "shallow, straight, uniform, and aligned." Currently, mainstream transplanters are Japanese brands including Kubota, ISEKI, and Yammar (Figure 5 [Figure 5: see original paper]). In recent years, Chinese transplanters have achieved breakthrough developments, with domestic products from companies like Suzhou Jiufu, World, and Xingyueshen gradually achieving localization. These machines enable multi-level adjustment of operating parameters including hill spacing, transplanting depth, lateral seedling pickup frequency, and longitudinal seedling pickup depth, accommodating different varieties and seedling sizes.

2.3.2 Precision Fertilization Operation Technology and Equipment

Precision fertilization involves the precise application of chemical fertilizers through field operation equipment, accurately controlling the precise amount and location of fertilizer application. The operation process can be divided into fertilization rate calibration, precision fertilization control, and intelligent fertilization monitoring.

Fertilization rate calibration aims to determine the amount of fertilizer applied per revolution of the applicator, with calibrated results serving as the basis for precision fertilization control. To conduct calibration quickly and efficiently, Yuan Wensheng et al. [53] designed a closed-loop rapid fertilization rate calibration device based on load cells, using the difference between load cell measurements and target fertilization rates as input to adjust the drive motor speed of the fertilizer shaft until the target rate is achieved, thereby calculating the per-revolution fertilization amount.

Precision fertilization control combines target fertilization rates, calibrated rates, and forward speed to achieve precise control of fertilizer shaft rotation speed for accurate application. Meng Zhijun et al. [54] designed a hydraulic motor-based fertilization system achieving precise fertilization control with an error of 3%. Fu Weiqiang et al. [55] developed a CAN bus-based hydraulic fertilization control system with a total fertilization control error of 10%. Professor Liu Gang's team at China Agricultural University [56,57] designed a precision fertilizer discharge control system based on dual variables of discharge opening size and shaft rotation speed, achieving a fertilization control accuracy of 97.6% at an operating speed of 7 km/h. Precision fertilization control can be applied to both uniform and variable-rate fertilization, with uniform fertilization being the current primary method in China.

Variable-rate fertilization adjusts application ratios and amounts according to spatial distribution of soil nutrients, crop nutrient requirements, and target yields. International variable-rate fertilization products have been developed. CASE IH designed the Advanced Farming Systems (AFS) precision agriculture geographic information system, which can store prescription maps generated by AFS software in variable controllers to control variable-rate fertilization operations on its ST820 variable-rate fertilization seeder (Figure 6 [Figure 6: see original paper] (a)). French company KUHN's Axis series mounted variable-rate spreader is equipped with the EMC control system for automatic adjustment of spreading rates, enabling efficient variable-rate spreading by real-time adjustment of spreading disc opening and angle (Figure 6 (b)). Zhang et al. [58] designed a lag time detection system and used a plane coordinate-based lag distance compensation method to reduce lag time, with experimental results showing this method can effectively reduce lag distance for variable-rate applicators.

Intelligent fertilization monitoring uses fertilization sensors and satellite speed positioning to achieve operation statistics and fault warning functions. Wang Dake et al. [59] designed a wireless fertilization measurement system that accurately warns of empty fertilizer boxes and blocked/empty fertilizer tubes. Yang Liu et al. [60] used infrared photoelectric sensors to detect blocked/empty fertilizer tubes and encoders to measure fertilizer shaft rotation speed for calculating application rates, enabling real-time monitoring and fault warning. Chen Jincheng et al. [61] designed a layered fertilization machine operation monitoring system that achieves precise operation area statistics with an error of 0.05%.

2.3.3 Precision Pesticide Application Operation Technology and Equipment

The core of precision pesticide application lies in obtaining information on pest, weed, and disease variations within small field areas and employing efficient spraying and variable-rate application technologies for on-demand treatment.

Currently, hyperspectral and visible light technologies are mainstream for pest, weed, and disease identification in farmland, having essentially achieved identification functionality. Sun Wenbin et al. [62] proposed a shallow crop disease identification model based on visible spectroscopy and improved attention mechanisms, designing a new attention module SMLP and crop disease identification model SMLP_{ResNet}, achieving disease identification rates of 86.93% and 99.32% on the AI Challenger 2018 and Plant Village datasets, respectively. Tronthmanna et al. [63] noted that multi-feature fusion technology has improved weed identification accuracy and stability to some extent, such as combining LiDAR with spectral imaging to understand crop information comprehensively from both horizontal and vertical vegetation structures. Cao et al. [64] proposed using diverse data devices including hyperspectral, near-infrared, and LiDAR combined with transfer learning algorithms, data augmentation methods, and deep learning networks to achieve precise identification of crop pests and diseases. However, due to complex and variable field conditions such as lighting and crop overlap, these technologies still face challenges in practical application.

Mainstream precision spraying still relies on uniform application across entire fields, primarily implemented through trailed/mounted boom sprayers, self-propelled boom sprayers, and aerial application equipment. International companies such as France's KUHN and Denmark's HARDI have developed advanced precision sprayers capable of functions including chemical addition, spraying, mixing, and tank cleaning. Advanced technologies including nozzle adjustment, boom control, variable-rate application, and intelligent monitoring are widely applied, enabling precise pesticide spraying across entire fields. KUHN' s SprayKit [65] integrates spraying equipment with weeding equipment to achieve fusion of mechanical and chemical control. HARDI' s MEGA series [66] introduces the SmartCom array platform for sprayer monitoring, diagnosis, and control, improving operation efficiency and accuracy.

Domestic research has extensively investigated these technologies. Chen et al. [67] developed a height stability sliding mode control system based on air suspension to improve boom height variation caused by liquid reduction in self-propelled sprayers. Zhang Chunfeng et al. [68] studied the impact of return flow ratio on pipeline pressure fluctuations in target spraying systems, providing support for further optimization of target spraying devices. Jeon et al. [69] used ultrasonic sensing technology to measure plant canopy-to-nozzle distance to assist variable-rate spraying, with experiments showing that optimizing the relative position between ultrasonic sensors and nozzles can improve distance measurement accuracy. Wei et al. [70] developed a Pulse-Width-Modulation (PWM)-based variable-rate spraying system where droplet diameter variation does not exceed 10% when adjusting spray flow from maximum to minimum. Wen et al. [71] constructed a fluid dynamics model that can accurately reproduce droplet drift and deposition during spraying by quadrotor drones, providing a good theoretical research foundation for plant protection drone studies.

Chinese enterprises have developed numerous products with independent intellectual property rights suited to China' s national conditions, gaining high domestic recognition. Driven by huge market demand, electric multi-rotor plant protection drones have rapidly developed in China as the main aerial plant protection machinery, becoming an effective supplement to ground sprayers for operations in tall crops, paddy fields, and hilly mountainous areas. Advanced technologies such as one-key takeoff, autonomous path planning, precision spraying control, automatic obstacle avoidance, and terrain-following flight are rapidly iterating and being promoted on plant protection drones.

Comprehensive research on precision operation technologies both domestically and internationally shows that monitoring and control technologies for precision operations have been extensively studied and applied in mature products worldwide. However, the inability to quickly, accurately, and cost-effectively obtain field prescriptions for seeds, fertilizers, and pesticides, and the lack of data and theoretical foundations for accurately developing real-time sensor-based decision models, represent bottlenecks limiting the development of precision operation technologies and breakthrough points for future innovation.

2.4 Autonomous Driving Technology for Unmanned Farms

2.4.1 Autonomous Driving Environment Perception Technology

Autonomous driving environment perception serves autonomous navigation of agricultural machinery, primarily including perception of field boundaries, crop rows, and field obstacles.

Field boundary perception detects artificially or naturally formed boundaries during tillage operations, which is crucial for determining start rows, turning points, and end rows for autonomous driving and defining the operational scope. Common detection methods include high-precision Global Navigation Satellite System (GNSS) positioning, remote sensing methods, and vehicle-mounted visual information detection. Currently, the most widely used method in autonomous driving is pre-positioning detection using GNSS, while large-area boundary extraction based on remote sensing images and real-time detection using vehicle-mounted sensors remain in the research stage [72-75]. Liu Dong et al. [76] obtained farmland multispectral data using UAVs and employed the Otsu threshold method for farmland segmentation based on NDVI value differences across regions. Zhang et al. [77] used UAV-mounted image and GNSS positioning sensors to stitch complete farmland maps. Wang Qiao et al. [78] and Qiao Yujie et al. [79] used image processing methods based on grayscale jumps between inside and outside farmland pixels to detect headland boundaries, achieving detection accuracy rates above 96% for headland appearance and above 92% for headland boundary lines. Kan Tao and Gu Bin [80] invented a farmland boundary detection method and device that obtains detection images, performs first interference reduction processing to obtain primary images, conducts secondary interference reduction processing on headland boundaries to obtain secondary images, and generates farmland boundary graphics.

Crop row perception forms the basis for determining each operational path for autonomous agricultural machinery. For autonomous operations in non-cropped scenarios such as tillage and seeding, crop rows are primarily determined using high-precision GNSS positioning data to generate operational row lines. For crop row perception during seedling-stage field management, real-time perception based on vehicle-mounted sensors such as cameras is mainly employed. Jiang Guoquan et al. [81,82] used a wheat row detection algorithm based on image feature point extraction and particle swarm clustering of feature points, achieving a recognition rate of 95%. Meng Qingkuan et al. [83] proposed a corn centerline detection method based on linear correlation coefficient constraints, with a maximum lateral deviation of 7 cm at 1.2 m/s speed. Wang Qiao et al. [84] clustered multiple corn seedling-stage crop row lines using characteristic parameters including vertical spacing, trend angle, and coverage width, fitting them with least squares method. Choi et al. [85] proposed a method using the morphological characteristic that leaves typically converge toward the central stem region to identify the central area of rice plants. Hu et al. [86] proposed a method for identifying rice crop rows using LiDAR data, with maximum parallelism of 45 mm and maximum median deviation of 7 mm. Zhai et al. [87] proposed a multi-crop-row detection algorithm based on binocular vision, with detection accuracy greater than 92.78%. Gasparino et al. [88] proposed a corn row detection method fusing camera and 2D LiDAR data, with 64.02% of errors within 5 cm.

Obstacle perception is fundamental to safe autonomous agricultural machinery operations. Common obstacle detection sensors include vision, LiDAR, millimeter-wave radar, infrared cameras, and ultrasonic detectors. In recent years, obstacle detection based on vision and LiDAR has become a research hotspot with continuously improving accuracy. Yang and Noguchi [89] used omnidirectional stereo vision to reconstruct human positions in the scene for pedestrian detection in fields, with obstacle detection mean square error less than 0.5 m. Li et al. [90] used deep learning convolutional neural networks to detect pedestrians in different postures in rice harvesting environments, achieving an average processing speed of 32.2 frames/second and an average obstacle detection success rate of 96.6%. Shang Yehua et al. [91] proposed a 3D LiDAR point cloud-based field obstacle detection method using Euclidean clustering, achieving an average detection rate of 96.11% for field pedestrians within 30 m. Lang Lang et al. [92] used LiDAR technology for farmland terrain reconstruction, designing a vehicle-mounted farmland terrain reconstruction system with projection area approximation between reconstructed and original terrain point cloud data exceeding 93% before and after leveling. Zeng et al. [93] studied a semantic segmentation method for sparse 3D point clouds in trellis-structured apple orchards based on geometric features, creating canopy density and depth maps with segmentation accuracies of 88.6%, 82.1%, and 94.7% for trellis lines, support poles, and trunks, respectively. Rovira-Mas et al. [94] used a stereo camera to detect people standing in fields, demonstrating effective obstacle detection within 0.3-2.9 m range with decreasing accuracy as vehicle-obstacle distance increases. Yin et al. [95] used a 3D camera with a 2D histogram-based clustering algorithm to back-project obstacle pixels onto the ground plane for image segmentation and real-time pedestrian detection in fields, achieving average positioning errors of 5.6 cm under static conditions and 7.1 cm under moving conditions.

2.4.2 Unmanned Agricultural Machinery Path Planning Methods

Unmanned agricultural machinery path planning, based on known map environments and constrained by one or more conditions (such as non-operational travel distance or minimum total working time), achieves complete coverage of target areas and plans overall operation routes [96-98]. Path planning algorithms vary according to different objectives, but all aim to maximize land utilization in minimum time. The planning process considers two main aspects: full-coverage path planning for operational areas and headland turning path planning.

Full-coverage path planning for operational areas has two primary approaches: one where the operator defines initial paths that are continuously translated to achieve full coverage, and another using specific patterns such as shuttle, spiral, or contour methods under particular field conditions [99,100].

In recent years, full-coverage operations have been widely studied and applied in tillage, spraying, fertilization, and harvesting due to advantages over manual operation in reducing path repetition and improving operation quality and efficiency [101]. For example, Luo Chengming et al. [102] from Huazhong Agricultural University proposed a full-coverage path planning algorithm for rapeseed combine harvesters that reduced non-operational path length. However, due to complex field environments and mostly irregularly shaped fields, full-coverage path planning faces issues such as high repetition rates and incomplete coverage. Additionally, agricultural machinery operations must consider optimal paths, obstacle avoidance, and specific scenarios such as detouring, making single algorithms insufficient. Domestic and international researchers have optimized full-coverage path planning algorithms by combining multiple methods [103]. Khan et al. [104] proposed an online boustrophedon motion combined with bidirectional proximity search algorithm with optimized backtracking for complete coverage path planning in unknown areas. Liu et al. [105] proposed a heuristic template combined with greedy criterion backtracking mechanism for full-coverage path planning.

For headland turning and maneuvering path planning needs, researchers have designed and optimized local path algorithms based on implement kinematic characteristics and field features to achieve optimal headland turning effects. Yuan Jiahong [106] designed five turning modes for rice transplanters, selecting appropriate modes based on relationships between operating spacing and minimum turning radius. Wang and Noguchi [107] proposed the Circle-back turning method and designed an environmentally adaptive headland path planning and control method with optimization objectives including row alignment accuracy, headland width, and non-operational travel distance. This method significantly improved turning efficiency and row alignment accuracy for unmanned tractors. Zhai Weixin et al. [108] designed a path planning method based on block nested operation patterns, effectively solving issues including adaptability to quadrilateral fields, unmanned agricultural machinery adaptability, and complete field operation path planning.

2.4.3 Path Tracking Control Technology

With planned operation paths, automatic navigation systems for agricultural machinery obtain vehicle status information—including position, heading, speed, and acceleration—through real-time sensor data collection. Using kinematic or dynamic modeling combined with selected path tracking control algorithms, the system calculates and obtains motion control parameters such as vehicle speed and steering wheel angle to enable automatic tracking of planned trajectories. Path tracking performance directly affects operation quality and efficiency. Current path tracking methods for agricultural machinery automatic navigation mainly include PID algorithms, Model Predictive Control (MPC) algorithms, and pure pursuit algorithms [109].

The PID algorithm is a feedback error-based control method that does not require modeling of the controlled object and offers good performance with simple principles. For example, Nagasaka et al. [110] from Japan's National Agriculture Research Center designed a proportional controller using lateral deviation and heading deviation between the agricultural vehicle' s current pose and desired path as inputs, solving wheel steering angles to achieve straight-line tracking. However, PID control parameters are significantly affected by external conditions and vehicle status, with time-consuming parameter adjustment processes that impact operation efficiency. Single PID control cannot meet autonomous driving operation requirements. To address this bottleneck, many scholars have studied improved PID controllers for trajectory tracking. Netto et al. [111] designed a PID control method incorporating feedback mechanisms and visual navigation, demonstrating good tracking performance on high-curvature paths. Al-Mayyahi et al. [112] proposed a fractional-order PID controller based on particle swarm optimization, using the sum of squared tracking errors as the fitness evaluation function to solve for optimal controller parameters and improve algorithm robustness.

Model Predictive Control (MPC) algorithms achieve control objectives by predicting current models and implementing rolling optimization and feedback correction [113]. In recent years, domestic and international scholars have designed and optimized agricultural machinery path tracking control algorithms based on MPC combined with actual operating conditions, improving path tracking accuracy to some extent [114]. For example, Zhang Wanzhi et al. [115], based on PID path tracking control algorithms, designed a linear time-varying model predictive control path tracking algorithm to further improve automatic tracking accuracy for agricultural vehicles. This method linearizes and discretizes the nonlinear kinematic model of agricultural vehicles, using system control increments as state variables in the objective function and converting target function solving into a constrained quadratic programming problem to achieve optimized control.

The pure pursuit algorithm has been widely applied in agricultural machinery autonomous driving path tracking due to its simplicity and ease of implementation. This algorithm uses geometric relationships to calculate the arc path the agricultural machinery needs to travel to reach a specified position, thereby obtaining vehicle motion control parameters to achieve path tracking. However, agricultural machinery operations involve complex environments with positioning deviations and fluctuations, making geometric path adjustments difficult in traditional geometric model-based tracking control. In response, scholars have optimized pure pursuit system algorithms. Wang et al. [116] proposed an improved pure pursuit model for agricultural machinery path tracking using speed-adaptive preview distance, effectively improving navigation accuracy during high-speed operations.

2.4.4 Crop Row Alignment and Boundary Alignment Control Technology

Rice and wheat harvest boundary alignment control is a special scenario for autonomous driving systems during crop harvesting. Since row-following is generally unnecessary during rice and wheat harvesting, the main operational path involves aligning the harvester head boundary with crop boundaries. Current research on harvest boundary alignment control mainly includes harvest boundary detection and automatic alignment control. Crop row perception during harvesting primarily uses image and 2D LiDAR detection. Wu et al. [117] determined candidate points based on color characteristics between harvested and unharvested areas, proposing an improved random Hough transform algorithm for harvest line detection that effectively detects straight lines within 200 ms processing time. Zhao et al. [118] used 2D LiDAR with neighborhood mean differential and Otsu edge detection algorithms to obtain rice harvest boundaries, achieving average static lateral errors of $±$12 cm and dynamic lateral errors of $±$25 cm. Zhang et al. [119] proposed a machine vision-based rice/wheat harvest edge detection method using polynomial fitting for straight and curved boundaries, with average harvest boundary positioning error of 2.84 cm. Jiang et al. [120] proposed a navigation path curve extraction method using depth images, with field tests showing average boundary point detection accuracy of 99.0% and average processing time of 45 ms per frame. Automatic alignment control during harvesting primarily uses dynamics model-based control. Snider et al. [121] designed a pure pursuit controller based on GNSS positioning information. Coen et al. [122] simplified the vehicle to a two-wheel kinematic model and calculated wheel steering angles based on Ackermann steering geometry for row-following control. Zhao Teng [123] designed a PI controller for rice/wheat alignment harvesting based on boundary detection by 2D LiDAR and tracked harvester steering models. Wang Lihui et al. [124] used particle swarm-based fuzzy control algorithms based on GNSS positioning information for tracked harvester navigation control.

2.4.5 Master-Slave Agricultural Machinery Cooperative Control Technology

With the rapid development of agricultural mechanization, multi-machine cooperative operations have gradually become a development trend to improve field operation efficiency, reduce energy consumption, and minimize labor requirements [125,126]. Research on multi-machine cooperative operations began in the early 21st century internationally [125,126], with China starting similar research around 2010, focusing mainly on multi-machine cooperative path planning and master-slave cooperative control.

Multi-machine cooperative path planning improves the execution efficiency of cooperative systems, enabling multi-machine cooperative operation scheduling management within regional farmland. For example, Li et al. [127] proposed an intelligent scheduling method for multi-machine cooperative operations based on NSGA-III and improved ant colony algorithms, outputting accurate scheduling plans with deployment information. Gong Jinliang et al. [128] proposed a cooperative operation strategy for agricultural robot groups targeting overall optimal group performance, improving the repetition rate of total traversed area. Yao Jingfa et al. [129] considered conflicts between combine harvester turning and operations, proposing a path optimization algorithm (Improved Genetic Algorithm, IGA) with comprehensive optimization objectives of total operation time and duration, reducing total operation time and duration. Qin et al. [130] proposed a master-slave instruction-based orchard map multi-robot cooperative navigation system, achieving maximum absolute lateral errors of 24.9 cm for spraying robots and 29.7 cm for refilling robots, meeting the automatic navigation requirements for traditional orchard spraying machine group collaborative tasks. Zhang et al. [131] developed a path planning and tracking algorithm for agricultural master-slave robot systems, where the master machine completes harvesting, tillage, and planting operations while the slave machine follows the master to perform transportation and refueling auxiliary work.

Master-slave cooperative operation technology precisely controls spacing maintenance, speed following, and attitude following between master and slave machines. It is a multi-objective optimization control problem widely applied in tillage, seeding, and harvesting operations. In recent years, extensive research has been conducted on master-slave agricultural machinery cooperative operations. Shojaei et al. [132] designed an adaptive leader-follower neural network controller based on saturated observers for multi-tractor cooperative control. Moorehead et al. [133] used a remote monitoring terminal to manage two autonomous tractors, using radar and cameras to guide tractors along row centers. Zhang et al. [134] developed an intelligent agricultural vehicle master-slave system where the slave vehicle follows the master vehicle at given lateral and longitudinal offsets. Noguchi et al. [126] proposed “GO-TO” and “FOLLOW”operation modes for agricultural machinery cooperative operation systems, achieving master-slave cooperative operations. Zhang et al. [135] developed a leader-follower system enabling two robots to cooperate in completing straight-line walking, tracking, and headland turning operations. Luo et al. [136] used dual-vehicle steering angle and speed control laws to solve the problem of two vehicles not traveling on the same straight line in master-slave cooperative mode. Li et al. [137] designed an agricultural machinery automatic navigation system consisting of one master and one slave machine, controlling the slave vehicle' s lateral and heading deviations based on master-slave position information for following control. Mao et al. [138] used the Cloth Simulation Filter (CSF) and Random Sample Consensus (RANSAC) algorithms to obtain path points and employed pure pursuit algorithms to track these points, solving the problem of discontinuous turning in master-slave navigation mode. Bai Xiaoping' s team [139,140] combined feedback linearization theory and sliding mode control theory to design harvester group formation maintenance and path tracking control laws, achieving high-precision tracking operations for agricultural machinery.

After nearly 30 years of research, breakthroughs have been achieved in key autonomous driving technologies including environment perception, navigation and obstacle avoidance, path planning, and multi-machine coordination both domestically and internationally. Various unmanned operation equipment has been created for the entire production process of paddy and upland crops from tillage to harvest, with application demonstrations conducted. However, current autonomous driving for unmanned agricultural machinery primarily follows preplanned routes for navigation tracking and cannot yet achieve navigation and obstacle avoidance control based on real-time sensor information. Future unmanned agricultural machinery will develop toward higher intelligence levels for autonomous unmanned operation, with core technologies including perception of unstructured farmland environments, autonomous path planning and navigation obstacle avoidance, and multi-machine autonomous coordination becoming critical challenges that need to be addressed.

2.5 Unmanned Operation Equipment

Unmanned operation equipment refers to the collective term for mobile equipment used throughout the entire production process of field unmanned farms. Its development benefits from the rapid application and promotion of Internet of Things, big data, cloud computing, and artificial intelligence technologies in agricultural intelligent equipment and robotics. It now basically covers the entire unmanned production process from crop tillage, planting, management to harvest, enabling fully automatic, comprehensive, high-quality, and efficient completion of essential agricultural production activities.

Land preparation is the foundation of all agricultural production links in field unmanned farms. Unmanned land preparation equipment refers to the use of autonomous driving tractors or robots with sufficient power sources to carry plows, subsoilers, rotary tillers, and combined tillage implements for field unmanned land preparation operations, possessing functions such as path planning, path tracking, tillage depth detection, and implement control. Among these, using unmanned tractors mounted with subsoilers for upland subsoiling achieves field navigation operation errors of 2 cm and automatic steering steady-state errors of 0.23°, ensuring good operation quality and high efficiency [116]. Figure 7 [Figure 7: see original paper] shows the unmanned land preparation equipment developed by the Research Center of Intelligent Equipment, Beijing Academy of Agriculture and Forestry Sciences.

Seeding/transplanting, fertilization, and spraying are important components of the planting and management stages in field unmanned farms. Unpowered precision seeding/transplanting, fertilization, and spraying implements combined with unmanned tractors form unmanned operation equipment for seeds, seedlings, fertilizers, and pesticides. Self-propelled implements equipped with autonomous driving systems and automatic control devices are transformed into unmanned operation equipment through unmanned modifications, enabling unmanned precision application of agricultural inputs in fields. This equipment typically features rapid and precise adjustment of application rates, automatic precision application, residual amount detection and refill warnings, operation quality monitoring, and remote data transmission functions. Some unmanned operation equipment equipped with prescription maps can achieve variable-rate unmanned operations, transforming traditional extensive input models, improving operation precision and fertilizer/pesticide utilization rates, and enabling real-time monitoring of operation process data. Figure 8 [Figure 8: see original paper] shows the unmanned seeding and spraying equipment developed by the Research Center of Intelligent Equipment, Beijing Academy of Agriculture and Forestry Sciences.

Crop harvesting is the final and decisive stage of unmanned operations. Self-propelled harvesters equipped with autonomous driving systems, automatic control devices, and unmanned modifications, combined with modified supporting grain carts, can achieve unmanned precision harvesting of field crops. These systems possess functions including crop row perception, obstacle detection, path planning, path tracking, crop row alignment, boundary alignment, master-slave coordination, and header control. Figure 9 [Figure 9: see original paper] shows the unmanned harvester developed by the Research Center of Intelligent Equipment, Beijing Academy of Agriculture and Forestry Sciences. Field test results show operation path tracking accuracy of $±$2.5 cm, automatic headland turning and alignment with crop boundaries with alignment error of 10 cm, and automatic control of key operation components such as threshing and cleaning systems.

Material replenishment is a critical yet weak link in achieving full-process unmanned agricultural machinery operations. Current material replenishment during machinery operations mainly relies on manual labor and simple machinery, involving high labor intensity and low replenishment efficiency. Existing material replenishment methods and equipment cannot meet the operational requirements for unmanned agricultural machinery replenishment. Future development should combine the replenishment needs for seeds, fertilizers, pesticides, and fuel during unmanned operations to develop unmanned replenishment mobile platforms suitable for different material transportation, and integrate modular unmanned material replenishment equipment to achieve unmanned automatic replenishment of seeds, fertilizers, pesticides, and fuel in field unmanned farms.

In summary, current research and development of unmanned agricultural machinery equipment primarily focuses on single-machine intelligent control technologies such as autonomous driving and precision operations, with insufficient research on multi-machine coordination and master-implement operation coordination. Single-machine control also faces challenges, as current autonomous driving primarily follows pre-planned routes for navigation tracking and cannot yet achieve navigation and obstacle avoidance control based on real-time sensor information. Future unmanned agricultural machinery equipment will develop toward higher intelligence levels for autonomous unmanned operation, with core technologies including perception of unstructured farmland environments, autonomous path planning and navigation obstacle avoidance, and multi-machine autonomous coordination becoming critical challenges that need to be addressed.

2.6 Unmanned Farm Management and Control Platform

Currently, major international agricultural machinery companies have developed remote monitoring platforms for agricultural machinery. Onboard terminals installed on machinery transmit real-time operation position, working status, and conditions to monitoring platforms for comprehensive monitoring, management, and remote services. For example, German company CLAAS' s TELEMATICS system can access machine performance parameters, electronic data, and operation data for remote fault repair and intelligent operation and maintenance services [141]. CASE IH' s AFS Connect system can remotely monitor fleet status and location, manage operation data, share fault information, and perform remote diagnosis and alarm processing, providing proactive services for farmers' agricultural production [142]. John Deere's remote information processing collaboration system JDLink features machinery monitoring, fault diagnosis, electronic fencing, and shared maps and AB lines, building a relatively complete operation management and service system covering its agricultural machinery products [143]. AGCO' s FUSE smart farming system enables decision-making on seeding and fertilization rates and statistical analysis of fuel consumption for farm machinery, and can plan operation routes to reduce turning times, compaction, and time consumption, improving agricultural machinery operation efficiency [144]. The European farm management platform 365FarmNet features farm management, soil nutrient information collection, prescription map generation, crop rotation, and variety planning functions, providing customized, convenient, and intelligent agricultural services [145].

With the rapid development of "Internet+" information agriculture, China has built multiple service systems adapted to domestic agricultural production models in agricultural machinery monitoring and scheduling platforms (AMMSP), gradually developing in-depth research using information technologies such as the Internet of Things to construct multiple operational monitoring service systems, achieving remote monitoring and scheduling of agricultural machinery operations and improving operation quality and intelligent equipment levels [146]. For example, the Research Center of Intelligent Equipment, Beijing Academy of Agriculture and Forestry Sciences established a remote monitoring service platform for agricultural machinery operations, achieving real-time monitoring of operation position, working conditions, and images, as well as monitoring and statistical accounting of operation area, bale count, and quality parameters, fertilization rates, seeding rates, and spraying rates. The platform has been promoted and applied across 27 provincial-level administrative regions, serving 150 million mu (10 million hectares) of cultivated land [147]. The Chinese Academy of Agricultural Mechanization Sciences established a precision operation platform for agricultural mechanization that can obtain real-time information on agricultural machinery operation conditions, position, and time, and conduct statistical analysis of operation area to meet remote monitoring and management needs [148]. Harbin Institute of Technology built an intelligent agricultural machinery management system that can provide monitoring services for various operation types including subsoiling, seeding, harvesting, and straw returning [149]. Lovol Heavy Industry Co., Ltd. released the iFarming smart agriculture solution for cluster precision operation services and remote operation and maintenance needs of agricultural machinery equipment, building an intelligent cloud service platform for agricultural machinery equipment that enables refined operation management throughout the entire agricultural production process from tillage, seeding, planting, plant protection, harvesting to grain drying and storage. The system serves more than 200,000 agricultural machines [150].

In summary, major international agricultural machinery enterprises have widely utilized new-generation information technologies such as big data, cloud computing, and mobile Internet to build agricultural intelligent decision-making and management platforms based on intelligent services and digital applications. These platforms provide users with full lifecycle management, monitoring, and operation and maintenance services for agricultural machinery equipment, as well as intelligent farm production management services, improving farm production efficiency and economic benefits. After years of development, China has built multiple service systems adapted to domestic agricultural production models for agricultural machinery operation monitoring, achieving operational deployment and providing effective support for efficient agricultural machinery operation supervision. However, current agricultural machinery operation monitoring technology is mainly used for supervision, lacking efficient analysis and decision-making models and mature service technologies in farm management, precision operation decision-making, agricultural machinery fleet task allocation and scheduling, and remote interaction. This represents the main technical challenge currently facing China’ s unmanned farm management platforms and a key technology to be addressed in the future.

3 Case Study of Unmanned Farm Technology Construction

Taking the maize unmanned farm constructed by the Research Center of Intelligent Equipment, Beijing Academy of Agriculture and Forestry Sciences in Gongzhuling City, Jilin Province as an example, this section elaborates on the composition and application of the maize unmanned farm.

3.1 Construction Content of the Unmanned Farm

The Gongzhuling unmanned farm is located in the Jilin Provincial Agricultural Science and Technology Demonstration Park, south of National Highway 102 in Gongzhuling City, Jilin Province, covering an area of 67 hectares (1,000 mu), including a core area (dryland) of 23 hectares (350 mu).

The maize unmanned farm consists of three components: an information perception system, intelligent agricultural machinery equipment, and a management and control cloud platform.

3.1.1 Information Perception System The system comprises an integrated sky-ground observation and data perception system including UAV remote sensing equipment, field comprehensive monitoring stations, and IoT measurement and control systems. It can automatically monitor farm environmental and crop growth information and transmit data to the intelligent agricultural machinery management system.

UAV remote sensing equipment was deployed for farmland plot and crop information collection and monitoring, providing basic data on plot boundaries and crop growth for farm production management and unmanned agricultural machinery operations. The collected farmland plot information is shown in Figure 10 [Figure 10: see original paper].

Additionally, the unmanned farm deployed field comprehensive monitoring stations and IoT monitoring systems for real-time collection of soil fertility, soil temperature and moisture, atmospheric temperature and humidity, solar radiation, and other maize growth environmental information, as well as leaf age and other growth status information, providing data support for farm production management. Insect, soil, and meteorological observation stations are shown in Figure 11 [Figure 11: see original paper], with collected maize growth and insect distribution data shown in Figure 12 [Figure 12: see original paper].

3.1.2 Intelligent Agricultural Machinery Equipment To meet the demands of efficient and precise operations in unmanned farms, existing tractors and matching implements, plant protection machines, harvesters, and grain carts were unmannedly modified by installing autonomous driving systems, precision operation control devices, and remote monitoring terminals. Through data sharing and command interaction with the unmanned farm cloud platform, unmanned operations for maize tillage, planting, management, and harvesting were achieved.

As shown in Figure 13 [Figure 13: see original paper], unmanned tractors can carry subsoilers, straw returning machines, and other implements for unmanned land preparation operations, achieving functions such as autonomous path planning, real-time operation status monitoring, real-time operation effect photography and upload, and automatic implement lifting.

Unmanned tractors coupled with electrically-driven seeders and integrated with high-precision satellite positioning systems, navigation control systems, precision seeding control systems, operation path planning systems, and network communication systems can achieve master-slave cooperation to complete unmanned seeding operations. The maize unmanned seeding operation scenario is shown in Figure 14 [Figure 14: see original paper].

In the plant protection stage, UAVs equipped with multispectral cameras were used to collect field crop information. Machine vision algorithms were employed to analyze crop growth and nutrient information, generating leaf nitrogen content distribution maps (Figure 15 [Figure 15: see original paper]) and determining fertilization rates. Visible-light cameras collected farmland environmental images to analyze and obtain maize pest and disease information for pesticide prescription map generation. The management and control cloud platform system then transmitted fertilization and pesticide prescription maps to ground operation terminals, with unmanned plant protection machines implementing precision variable-rate application. Unmanned high-clearance boom sprayers were used for precision variable-rate spraying, achieving functions including autonomous operation path planning, high-precision path tracking, automatic headland turning, automatic forward speed regulation, integrated boom lifting and folding control, emergency obstacle avoidance, and remote control. These capabilities reduce phytotoxicity, lower labor costs, and improve high-clearance sprayer utilization, providing key technical equipment for plant protection operations in maize unmanned farms.

Unmanned harvesters integrated operation information detection systems, automatic navigation systems, obstacle detection systems, and intelligent harvest operation control systems to achieve unmanned maize harvesting operation status and condition monitoring, autonomous driving, automatic obstacle avoidance, and automatic operation control functions. Harvesting efficiency was improved by 3-4 times, providing strong support for unmanned maize harvesting in the farm.

3.1.3 Unmanned Farm Cloud Platform The unmanned farm cloud platform mainly includes four components: a basic geographic information management system for unmanned farms, a remote monitoring and control system for unmanned agricultural machinery, an intelligent agricultural machinery precision operation management system, and an unmanned agricultural machinery operation display system. The farm basic geographic information management system provides basic geographic information support for unmanned agricultural machinery precision operations through centimeter-level digital mapping and processing at the field scale. The remote monitoring and control system for unmanned agricultural machinery provides services such as farm tillage, planting, management, and harvesting operation supervision, condition monitoring, front-backstage interaction, and operation management. The intelligent agricultural machinery precision operation management system and database mainly provide basic agricultural data maintenance management, variable prescription management, agricultural machinery operation parameter sharing, and agricultural machinery operation quality supervision services for precision operations. The unmanned agricultural machinery operation display system provides a basic platform for daily system operation and maintenance, operational services, and demonstrations. Figure 16 [Figure 16: see original paper] shows the unmanned farm cloud platform for Gongzhuling City.

3.2 Socioeconomic Benefit Analysis

Against the backdrop of continuously decreasing global agricultural labor forces, increasing labor costs, and rising agricultural production inputs, unmanned farms provide effective technical support for modern agricultural development. Addressing the strategic needs of developing modern agriculture, Gongzhuling City in Jilin Province constructed a full-process unmanned production farm for maize, achieving unmanned operations for maize tillage, planting, management, and harvesting, which greatly improved maize production efficiency and reduced labor input. Taking the maize harvesting stage as an example, unmanned harvesters can operate 24 hours continuously, increasing harvesting speed by 3-4 times. The 67-hectare maize field can be harvested in 3-5 days, saving 50-60 laborers. In other stages, unmanned seeders not only save labor but also enable precision and section control seeding, effectively avoiding repeated operations at headlands, improving operation quality, and reducing seed input. In conclusion, the construction and application of the maize unmanned farm in Gongzhuling City represent a typical case of deep integration between modern science and technology and agriculture. As a representative of advanced productive forces in agriculture, unmanned farm technology promotes the transformation and upgrading of agricultural machinery equipment and the transformation of modern agricultural production methods, generating significant social and economic benefits.

4 Development Prospects for Unmanned Farms

Global agricultural production faces common issues including continuous reduction of agricultural practitioners, high labor costs, and poor operation quality of traditional machinery. Questions of who will farm, how to farm, and even unmanned farming in the future represent important challenges for global agriculture. With deep integration of modern information technology and agricultural production, the role and benefits of unmanned farms in agricultural production are becoming increasingly evident. Key unmanned farm technologies represented by autonomous navigation are already changing or will change modern agricultural production methods.

Marked by agricultural machinery autonomous navigation, China has conducted nearly 20 years of research on key unmanned farm technologies. During this period, China’ s agricultural machinery autonomous driving systems have experienced a challenging development process of learning, development, catching up, and surpassing foreign technologies, forming autonomous navigation product series with independent intellectual property rights and breaking the long-term monopoly of foreign products. In recent years, leading Chinese agricultural machinery enterprises have successively developed unmanned agricultural machinery products including unmanned tractors, unmanned plant protection machines, unmanned harvesters, and unmanned grain carts, conducting extensive application practices in maize, wheat, rice, and other field crop production. These efforts have initially formed unmanned farm prototypes adapted to domestic agricultural production models.

(1) Compared horizontally with international unmanned farm technologies, China’ s unmanned farm technologies are generally lagging. In terms of intelligent decision-making for agricultural machinery operations and precision operation control, China lacks sufficient agricultural production data and data dimensions, and lacks effective data analysis and utilization. Moreover, China’ s vast territory creates significant differences in crop types between north and south, with crop growth environments and agronomic requirements showing spatial and temporal variations. These factors result in a shortage of mature agricultural machinery operation decision models in China, with limited model universality. Overall, China remains in the research and development stage in precision seeding and variable-rate fertilization control, precision spraying control, and efficient, high-quality harvesting operation control, representing a gap compared with international advanced levels. This is also the direction for future development of unmanned farm technologies in China.

(2) As a new production method, unmanned farm technology is not yet fully mature technically, with common issues including lack of multi-modal information fusion perception models for unstructured farmland environments and poor autonomy of unmanned agricultural machinery equipment. Future unmanned farm technology research will mainly focus on core technology areas including perception of unstructured farmland environments, autonomous driving of agricultural machinery in complex and variable farmland environments, autonomous task allocation and path planning for unmanned agricultural machinery, and autonomous cooperative operation control of unmanned agricultural machinery groups. These technologies are both challenging and represent the most competitive technological commanding heights in the future. China is basically on the same starting line as international counterparts in these fields, representing the most likely areas for China to surpass international technologies in the future.

(3) The development of unmanned farms in China needs to target the major

demands of agricultural modernization and rural revitalization strategies, breakthrough bottleneck and 短板 technologies for unmanned farms, and create unmanned agricultural machinery equipment suitable for China’ s agricultural production. This will achieve the transformation from human labor to machines, from human brains to computers, and from imports to autonomous development. Through extensive promotion and application of technology products, China can accelerate improvement of its agricultural production predicament, enhance agricultural production efficiency and benefits, lead modern agricultural development, and become a world agricultural power at an early date.

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