RESEARCH ARTICLE

Construction and Application Performance of a Smart Farm Technology System for Plateau Cold-Season Vegetables: A Case Study in Huangzhong District, Qinghai Province, China

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Abstract

Open-field vegetable production in the cold plateau regions of Northwest China faces labor shortages, extensive management, meteorological risks, and inefficient use of agricultural inputs. Taking a 6.67 ha smart farm in Huangzhong District, Xining, Qinghai Province, China, as a case study, this study developed a four-tier smart agriculture system comprising perception, transmission, platform, and application layers. The system integrates agricultural Internet of Things (IoT) monitoring, BeiDou Navigation Satellite System (BDS)-based intelligent machinery, precision water and fertilizer management, and a big-data decision-making platform, all adapted to plateau conditions. Field trials and operational data from a complete production season showed that the system increased labor productivity and output per unit area by 18.2% and 11.7%, respectively, while reducing labor cost per unit area by 16.3%. The irrigation water use coefficient reached 0.82, pesticide use efficiency increased to 43.5%, and annual net income increased by 18 000 CNY ha^{-1}. These results demonstrate that the locally adapted system improves production efficiency, resource utilization, and economic performance, providing a practical framework for smart agriculture in Northwest China and other high-altitude cold regions.

Keywords: plateau cold region, open-field vegetables, smart farm, IoT-based sensing, precision water and fertilizer management, intelligent agricultural machinery, Northwest China.

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1 Introduction

Digital and smart agriculture constitute the core pathway of China's agricultural modernization. The 14th Five-Year Plan for National Agricultural and Rural Informatization, issued by China's Ministry of Agriculture and Rural Affairs, explicitly calls for the deep integration of new-generation information technologies—such as the Internet of Things (IoT), big data, and artificial intelligence (AI)—into agricultural production, so as to improve the precision and intelligence of farming operations [1–3]. Benefiting from abundant sunshine, a large diurnal temperature range, and low pest and disease pressure, the spatial pattern of vegetable production in China has been continuously shifting toward western plateau regions in recent years, with the cold plateau areas of Northwest China gradually emerging as an important supply base for summer and autumn cold-season vegetables [4], and their industrial development has become a pillar for rural revitalization and income growth in the region [5]. Constrained by geographical conditions and prevailing production modes, open-field vegetable production on the plateau has long faced three core problems. First, there is a structural shortage of agricultural labor: the outmigration of young and middle-aged rural workers has pushed labor costs up year by year, resulting in acute labor constraints in transplanting, field management, and harvesting [6]. Second, extensive production management: water and fertilizer application relies largely on experience, and over-irrigation and over-fertilization are widespread, causing resource waste and posing a risk of agricultural non-point source pollution [7]. Third, weak disaster response capacity: meteorological hazards such as strong winds, low temperatures, and hail occur frequently on the plateau, whereas under the traditional model early warning lags behind and control is largely reactive, often leading to substantial yield losses [8].

Smart farms enable precise sensing, intelligent decision-making, and automated execution throughout the production process, offering an effective pathway to overcoming the above constraints. Internationally, precision agriculture started early in countries such as the United States, Israel, the Netherlands, and Germany, where mature technology systems have been established and applied at scale in variable-rate fertilization, intelligent plant protection, and autonomous operation of agricultural machinery [9–11]. These solutions, however, are generally designed for large-scale contiguous farms; their high equipment purchase and maintenance costs and strong dependence on consolidated arable land and stable infrastructure make them difficult to transfer directly to China's plateau regions, where smallholder-based fragmented management predominates. In China, research on agricultural IoT, intelligent equipment, and big-data platforms has advanced rapidly in recent years [12, 13], and numerous demonstration applications have been carried out in scenarios such as smart management of greenhouse vegetables and precision cultivation of field crops [14]. Nevertheless, existing work has focused mainly on the eastern plains and facility agriculture, and studies specifically targeting cold-season open-field vegetables on the plateau remain scarce. In particular, integrated technical solutions adapted to special habitats characterized by high altitude, low temperature, strong ultraviolet radiation, and undulating terrain are lacking, and evident shortcomings persist in equipment durability, model adaptability, and system cost-effectiveness [15].

This paper takes the open-field vegetable smart farm located in the Modern Agriculture Industrial Park of Huangzhong District, Xining City, Qinghai Province, China as the research object. Aiming at the intelligent upgrading of the entire production process, it constructs a plateau-adapted smart farm technology system, carries out customized optimization of crop models, intelligent equipment, and management workflows, and quantitatively evaluates the application performance. The study follows the technical route of "demand investigation—scheme design—system deployment—field trials—performance evaluation—model formulation", and finally summarizes a replicable and scalable construction model for smart farms producing open-field vegetables on plateaus, with a view to providing a practical reference for Northwest China and other high-altitude cold-season vegetable production regions.

2 Site Description and Overall Design

2.1 Site Baseline Conditions

The study area, Huangzhong District (approximately 36.5°N, 101.6°E), is located in the eastern agricultural region of Qinghai Province in northwestern China, in the transition zone between the Qinghai–Tibet Plateau and the Loess Plateau, at an average elevation of 2200–2800 m (Figure 1). It features a plateau continental climate, with an annual mean temperature

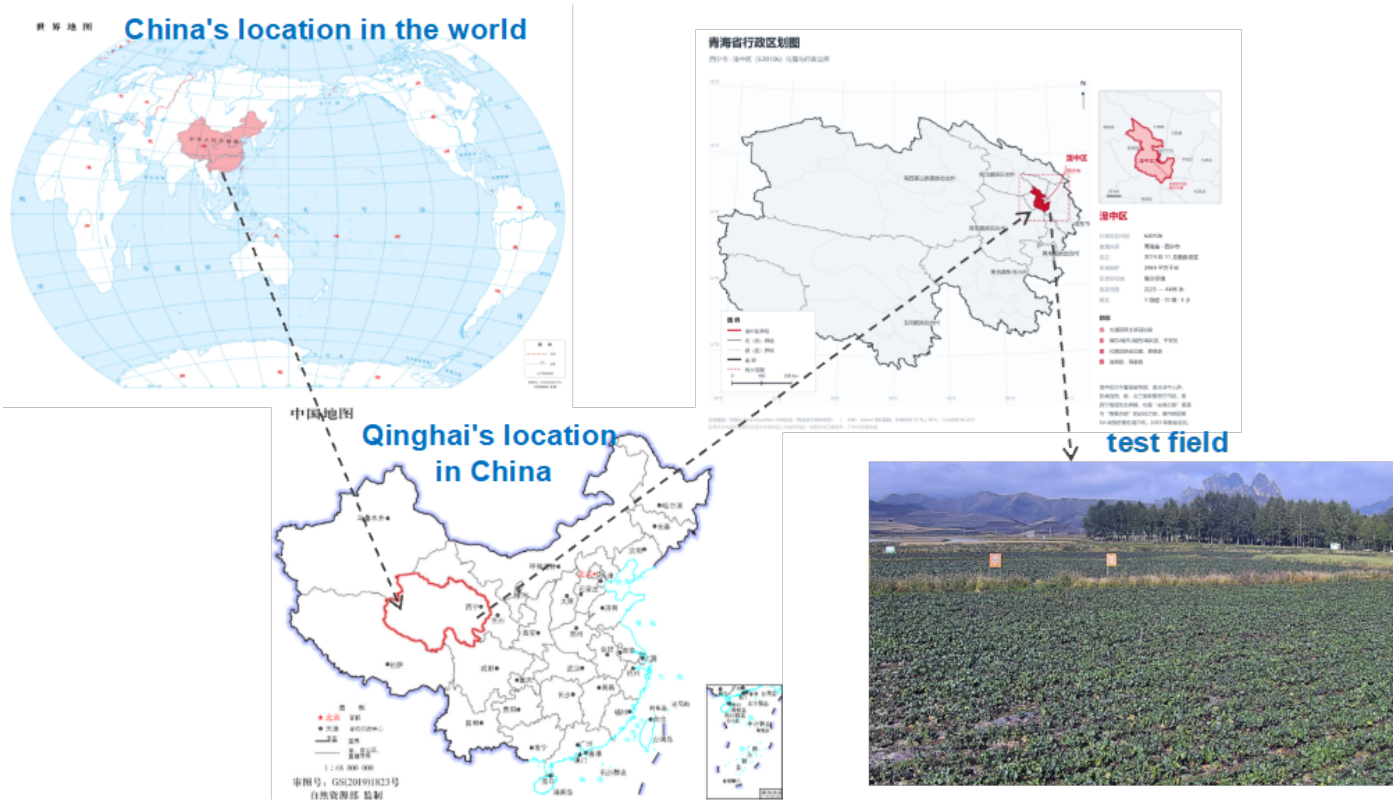

Figure 1. Location of the experimental field.

of 5.6 °C, annual sunshine duration of more than 2500 h, diurnal temperature differences of 12–15 °C, and a frost-free period of 110–130 d, making it highly suitable for the growth of cool-climate vegetables such as cabbage (*Brassica oleracea* var. *capitata*), baby cabbage (baby Chinese cabbage, *Brassica rapa* subsp. *pekinensis*), flowering Chinese cabbage (*Brassica rapa* var. *parachinensis*), and lettuce (*Lactuca sativa*), whose products are characterized by superior quality, good taste, and a low incidence of pests and diseases. The Huangzhong District Modern Agriculture Industrial Park was approved for establishment in May 2024, with greenhouse vegetables and plateau cold-season vegetables as its leading industries. Its vegetable sown area has remained stable at more than 7300 ha, with an annual output close to 300 000 t and an annual output value exceeding 2 billion CNY. Covering 10 townships including Lanlongkou and Xibao and 118 administrative villages, the park is an important vegetable production and supply base in Qinghai Province. The smart farm was sited in the core open-field vegetable production area of the park, covering 6.67 ha, with the main cultivars being the dominant varieties of plateau summer vegetables. The plots are relatively flat and contiguous, providing the basic conditions for smart upgrading.

2.2 Overall System Architecture

Following a layered design concept, the smart farm adopts a four-tier technical architecture consisting of the perception layer, transmission layer, platform layer, and application layer, thereby realizing full-chain closed-loop management from field data acquisition to intelligent decision execution. Perception layer: as the data source of the smart farm, it comprises outdoor weather stations, soil moisture monitoring stations, intelligent pest monitoring and forecasting lamps, crop growth monitoring devices, on-board sensors on agricultural machinery, and flow meters of the fertigation system. It is responsible for the comprehensive acquisition of four categories of data—meteorological, soil, crop, and equipment—providing the basic data support for decision-making at upper layers. In response to the plateau environment, all sensing devices adopt an industrial-grade design featuring a wide operating temperature range, ultraviolet resistance, and protection against wind and sand, ensuring stable operation at high altitude [15, 16]. Transmission layer: it is responsible for the aggregation and transmission of sensed data using a hybrid scheme of "Long Range (LoRa) wireless local area network + 4G wide area network", which effectively resolves the problems of inconvenient power supply and difficult cabling in the field and remains stable in areas with weak signal coverage (details in Section 3.1) [16]; as 5G networks gradually extend to rural areas, this architecture can smoothly evolve toward higher-bandwidth 5G transmission, further enhancing real-time control capabilities [17]. Platform layer: serving as the "brain" of the smart farm, it is deployed on cloud servers and comprises three core components, namely a data middle platform, a model library, and an algorithm engine. The data middle platform performs the cleaning, normalization, storage, and management of multi-source heterogeneous data; the model library integrates crop growth models, disaster warning models, water and fertilizer decision models, and yield prediction models; and the algorithm engine provides intelligent computing capabilities such as image recognition, data mining, and trend prediction. The platform adopts a microservice architecture that supports flexible expansion of functional modules and multi-terminal access [10, 13]. Application layer: it delivers services to different users, including the production management system, intelligent agricultural machinery system, big-data visualization platform, and mobile client. Production managers can view field data in real time, remotely control equipment, and receive warning information through both computer and mobile terminals, while administrative departments can grasp the overall production situation of the park through visualization screens to support industrial decision-making [10, 11].

2.3 Objectives

Centered on four core objectives—cost reduction, efficiency improvement, quality enhancement, and environmental sustainability—the smart farm aims to establish a demonstration model for the smart production of open-field vegetables on plateaus. Precision production: precise management and control of environmental monitoring, water and fertilizer application, and plant protection operations are achieved, with a marked increase in water, fertilizer, and pesticide use efficiency and unified, controllable production standards [7]. Reduced labor requirements: physically demanding operations such as tillage, ridging, plant protection, and transport are mechanized and automated, substantially reducing labor input and alleviating labor constraints [6, 18]. Digitalized management: data from the entire production process can be recorded, traced, and analyzed, shifting management decisions from experience-driven to data-driven [3, 10]. Significant benefits: labor productivity is increased by more than 15%, production cost per unit area is reduced by more than 10%, and output per unit area is increased by more than 10%, generating a strong demonstration and diffusion effect.

3 Construction of the Core Technology Framework for the Smart Farm

3.1 Multi-Dimensional Agricultural IoT Sensing System

Guided by the principles of scientific deployment, full coverage, and high data accuracy, the park has established a field monitoring network integrating multi-dimensional observations of meteorology, soil moisture, pest occurrence, and crop growth. This network is supported by a data transmission architecture comprising low-power LoRa terminals, edge gateways, and a cloud platform, enabling all-weather, three-dimensional sensing and reliable data backhaul of both the production environment and crop growth status (Figure 2).

Meteorological monitoring: one integrated outdoor weather station is deployed in the core area, measuring six indicators including air temperature and humidity, wind speed and direction, rainfall, and light intensity, at a sampling frequency of once per hour, with an accuracy conforming to agrometeorological observation standards. The device adopts a wide operating temperature range design of $-40\,°C$ to $85\,°C$ and its wind speed sensor tolerates a maximum wind speed of 60 $m\,s^{-1}$, making it adaptable to extreme weather on plateaus. An embedded disaster warning model provides graded early warnings for hazards such as strong winds, low-temperature frost damage, and heavy rainfall within the next 24 h, thereby guiding proactive prevention and control [8, 16]. Soil moisture monitoring: one monitoring station is deployed every 2 ha, with frequency domain reflectometry (FDR) sensors buried at four soil depths and calibrated in situ using the soil auger method to measure volumetric soil water content and temperature. The stratified measurement captures the vertical distribution of soil moisture, avoiding the interference of surface soil wetting–drying fluctuations in irrigation decisions; irrigation thresholds are set according to crop root distribution, enabling moisture-based irrigation [19]. Pest monitoring: one intelligent pest monitoring and forecasting lamp is installed in the core area. It combines light attraction with pheromone attraction and integrates a high-definition camera and an AI recognition algorithm to automate the entire workflow of pest trapping, drying, identification, and counting. After transfer learning on local samples of cabbage white butterfly (*Pieris rapae*), aphids (Aphididae), and diamondback moth (*Plutella xylostella*), the recognition accuracy exceeds 90%. The system records pest population density on a daily basis and, once the control threshold is exceeded, automatically issues an alert and recommends green control measures, replacing manual field scouting [20, 21]. Crop growth monitoring: two high-definition crop growth monitoring stations are deployed, each equipped with a 360° pan–tilt–zoom (PTZ) camera. Through image segmentation and vegetation index calculation combined with growth models, the system evaluates crop phenological progress and vigor. Periodic aerial surveys by remote-sensing unmanned aerial vehicles (UAVs) generate field-wide growth heat maps, identifying weak-growth zones and guiding site-specific topdressing and field management, thereby reducing the resource waste caused by uniform fertilization [12]. To address

Figure 2. Multi-dimensional agricultural IoT monitoring devices.

the challenges posed by widely dispersed plateau farmland, difficult power supply and cabling, and weak mobile signal coverage in certain areas, all field terminals are powered by solar panels combined with lithium batteries and operate in a scheduled sampling and intermittent transmission mode. The average operating current is below 50 mA, and a single full charge supports more than 15 d of continuous operation under rainy or overcast conditions, making the terminals well suited to off-grid field deployment. Communication is based on LoRa wireless technology, which offers long transmission range, low power consumption, and strong penetration capability. A single gateway accommodates up to 64 terminals and provides a coverage radius of up to 2 km in open terrain, meeting the requirements of farms spanning tens of hectares. Each gateway integrates an edge computing module that performs on-site cleaning of anomalous data to reduce unnecessary uploads, and connects to the cloud platform through the 4G network with a high-gain antenna. Local data caching and resumable transmission after connection loss are supported, ensuring the continuity of data transmission in areas with poor signal coverage [15, 16]; in areas where 5G signals are available, the gateway can transmit data via a 5G module, substantially increasing transmission bandwidth and response speed [17].

3.2 Intelligent Agricultural Machinery and Full-Process Operation Management

To cover the complete production chain of open-field vegetables—tillage, sowing, field management, harvesting, and transport—three categories of intelligent equipment, centered on high-precision positioning provided by the BeiDou Navigation Satellite System (BDS), are deployed: unmanned tractors, targeted spraying robots, and UAV-based inspection and unmanned transport systems, thereby enabling automated, precise, and labor-reduced field operations.

Unmanned tractor: a 140 hp (≈104 kW) wheeled unmanned tractor equipped with a BeiDou real-time kinematic (RTK) high-precision positioning module has been introduced. In combination with implements for rotary tillage, ridging, film mulching, and seeding, it performs unmanned operations across multiple production stages (Figure 3). The BDS-RTK positioning accuracy reaches ±2.5 cm, with a straight-line operation deviation of less than 3 cm and an adjacent-pass error of below 5 cm [12]. The system incorporates a path-planning algorithm that automatically generates optimal routes according to field shape and working width. Its turning algorithm has been specifically optimized for the irregular plots and narrow headlands characteristic of plateau farmland, achieving a minimum turning radius of less than 4 m and thus adapting well to local small fields. Field applications demonstrate that its operational efficiency is 32% higher than that of manual driving and that it supports continuous 24 h operation. The resulting ridges are straight and uniform, providing favorable conditions for subsequent crop growth and mechanized management [14].

Targeted spraying robot: a four-wheel-drive (4WD) targeted spraying robot has been developed for

Figure 3. Rotary tillage operation performed by the unmanned tractor.

Figure 4. Precision field operation of the targeted variable-rate spraying robot.

open-field vegetable production on plateaus, involving breakthroughs in three key technologies (Figure 4): (1) a battery-electric, high-payload 4WD drive-by-wire chassis with independent suspension on all four wheels, providing a maximum payload of 300 kg and a gradeability of 30°, which adapts to unpaved field surfaces and undulating terrain; (2) a precise turning and row-entry technique for narrow headlands that integrates BDS with vision-aided positioning, achieving a row-entry deviation of less than 5 cm; and (3) a deep-learning-based target recognition and pulse-width modulation (PWM) variable-rate spraying technique enhanced by an illumination-adaptive module, which improves recognition accuracy under the intense direct and backlit lighting conditions typical of plateau environments, enabling spraying only when a target is detected and halting it otherwise, thus avoiding ineffective application between rows. Under the conventional knapsack spraying mode, the baseline pesticide utilization rate in the experimental area was 31.6%. Following precision application using the targeted spraying robot, the pesticide utilization rate increased to 43.5%, representing a relative increase of 37.7%. Meanwhile, the pesticide application rate per unit area decreased by more than 30%. The robot covers 2.0 ha per working day, equivalent to the workload of 6–8 workers, while also reducing operators' risk of pesticide exposure [22, 23].

UAV inspection and unmanned transport: one integrated automatic UAV dock has been deployed, enabling unattended take-off, landing, charging, flight, and data upload throughout the entire process. Managers can remotely formulate inspection plans, and the UAV operates along preset routes, covering 13.3 ha in a single flight with centimeter-level aerial imagery resolution. After mosaic reconstruction and analysis on the platform, the imagery can rapidly identify missing seedlings and broken ridges, uneven growth, and pest- or disease-affected zones, and generate distribution maps of problem locations; inspection efficiency is more than 10 times that of manual scouting (Figure 5). In addition, two battery-electric unmanned transport robots are configured for the in-field transfer of vegetables after harvest. Using light detection and ranging (LiDAR)–vision fusion navigation for obstacle avoidance, they can travel autonomously on unstructured field roads, automatically avoid obstacles, and support cooperative multi-vehicle scheduling. Each unit has a maximum payload of 1000 kg, a full-load travel speed of 5 $\mathrm{km\,h^{-1}}$, and an endurance of 7–8 h. They replace manual handling and small farm vehicles for field transfer, effectively alleviating labor pressure during the harvest period [24, 25].

Figure 5. Fully automated UAV inspection and unmanned transport system: (a) UAV dock with UAV; (b) unmanned transport robot.

3.3 Intelligent Fertigation System for Precision Water and Fertilizer Management

Pursuing the goal of "supply on demand and precision control", the intelligent fertigation system uses the head control unit, the field pipe network, and end effectors as its hardware foundation. Its core is a dynamic decision-making mechanism of "crop water requirement model + soil moisture correction", and through deep integration with the IoT monitoring system and the smart management and control platform it forms a closed-loop control workflow, realizing fully automated and traceable irrigation and fertilization.

System composition and hardware configuration. The system consists of three parts: the head control unit, the field pipe network, and end effectors (Figure 6). The head control unit is equipped with one multi-channel intelligent fertigation machine with three fertilizer suction channels, achieving a fertilization accuracy of $\pm 2\%$ and supporting real-time monitoring and automatic adjustment of electrical conductivity (EC) and pH; it can adjust the acidity and alkalinity of the nutrient solution in response to the alkaline water quality typical of plateaus, thereby improving fertilizer uptake efficiency. A two-stage filtration scheme combining a sand–gravel filter and a disc filter is adopted to prevent impurities in groundwater with high sand content from clogging the emitters. The field pipe network adopts a layout of buried polyethylene (PE) main pipes combined with surface drip lines, and is divided into 10 independently controlled irrigation zones according to plot shape and planting row spacing. Pressure-compensating emitters are used, achieving a flow uniformity above 95% and ensuring uniform discharge even under undulating terrain. Each zone is equipped with flow and pressure sensors that automatically detect and give alarms for pipeline leakage, clogging, and other faults [26].

Figure 6. Intelligent fertigation system for precision water and fertilizer management.

Crop water and nutrient requirement dynamic decision model. Abandoning the traditional fixed-schedule irrigation mode, the system calculates the daily reference crop evapotranspiration ($\mathrm{ET_o}$, $\mathrm{mm\,d^{-1}}$) from real-time weather station data and multiplies it by the crop coefficient (K_c, dimensionless) to obtain the theoretical crop water requirement, i.e., the crop evapotranspiration $\mathrm{ET_c} = K_\mathrm{c}\,\mathrm{ET_o}$, which is then corrected in real time using soil moisture measurements: irrigation is appropriately reduced when the soil water content exceeds 70% of field capacity and supplemented promptly when it falls below 60%, so that soil moisture is maintained within an optimal range [13, 27]. Fertilization follows the target yield method: by integrating soil nutrient test results with the nutrient uptake patterns of each growth stage, a whole-growth-period "basal fertilizer + topdressing" program is formulated, and nutrients are injected proportionally at each irrigation event, realizing "small doses, high frequency, supply on demand". The crop coefficients and nutrient uptake parameters for each growth stage were calibrated based on two years of field trial data for baby cabbage and flowering Chinese cabbage, producing a localized water and fertilizer decision model whose decision accuracy is 21.3% higher than that of the generic model [13, 28].

Closed-loop automatic control workflow. The fertigation system is deeply integrated with IoT monitoring and the smart management and control platform, forming a complete closed loop of "data acquisition—intelligent decision-making—instruction delivery—automatic execution—feedback archiving": the weather station and soil moisture sensors acquire environmental data and upload them to the platform in real time; the decision model automatically calculates the daily irrigation amount and fertilizer amount based on cultivar, growth stage, weather, and soil moisture data, and generates an irrigation schedule; the platform issues instructions to the fertigation machine and the field solenoid valves, and the equipment executes them automatically without manual operation; flow and pressure sensors transmit execution data back in real time, and the system automatically records the time, water volume, and fertilizer amount of each irrigation and fertigation event, forming a traceable production archive. This model replaces the traditional practice of manually opening valves and applying fertilizer based on experience, achieving irrigation timing accurate to the minute and application amounts accurate to the liter. The irrigation water use coefficient of the system reaches 0.82, saving more than 35% of water and 25% of fertilizer compared with conventional flood irrigation [7, 26].

3.4 Integrated Smart Farm Management and Control Platform

The Huangzhong integrated smart agriculture management and control platform is the core of the smart farm. It adopts a browser/server (B/S) architecture and is built on a geographic information system (GIS), integrating the resource data of the park in the form of a "single map" to achieve full-element, full-process visualized management. The platform consists of six functional modules and a big-data analytics and decision engine, providing unified support for production management and business decision-making.

Functional modules. The platform core comprises six modules: (1) park overview, presenting the overall profile, industrial distribution, construction achievements, and key indicators of the industrial park, with support for electronic map zooming and site querying; (2) environmental monitoring, displaying real-time data from IoT devices with support for historical query, trend analysis, and anomaly alarms; (3) crop growth, integrating crop monitoring and UAV inspection data to display the phenological progress, growth distribution, and growth trends; (4) disaster warning, integrating meteorological and pest and disease warnings, displaying them by severity level and pushing control recommendations, thereby making disaster prevention and mitigation proactive; (5) intelligent equipment, providing unified management of intelligent agricultural machinery, fertigation equipment, and UAVs, with support for remote control, status monitoring, and operation statistics; and (6) production management, covering farm operation planning, personnel, inputs, and quality traceability to achieve full-process digitalized management [3, 10].

Big-data analytics and decision support. The platform incorporates a big-data analytics engine that performs deep mining of multi-source data to provide three types of support. Production decision-making: based on crop growth models and historical data, it predicts maturity dates and yields to guide harvest scheduling and sales planning, and predicts high-incidence periods according to pest and disease occurrence patterns so that control measures can be deployed in advance [11, 13]. Market decision-making: a supporting agricultural product price analysis system uses web crawling and adaptive information extraction to collect vegetable price and supply–demand data from China's major agricultural product wholesale markets, establishes a multi-region, multi-cultivar price database, and forecasts price trends for the next 7–15 d through a hybrid prediction model, helping growers arrange market timing and cultivar structure rationally [11]. Visualized presentation: a big-data visualization screen is installed in the park's control center to intuitively present key indicators and real-time data in the form of charts, heat maps, and dashboards, providing a visualization medium for park management, demonstration, and outreach [29].

4 Discussion

Compared with existing studies, the novelty of the technology system constructed in this paper is reflected mainly in three aspects. First, at the level of system coordination, it overcomes the limitation of conventional smart farms in which subsystems are built independently and information is fragmented. By opening up the data and business channels among IoT sensing, intelligent agricultural machinery, fertigation management, and the integrated management platform, a complete closed loop of "data acquisition—analysis and decision-making—precise execution—effect feedback" is formed, so that soil moisture data can directly trigger automatic irrigation, pest warnings can automatically dispatch plant protection operations, and machinery operation records are archived synchronously, significantly reducing the cost of redundant construction and data redundancy. Second, at the level of model localization, in response to the climatic characteristics of cold plateau regions, namely high altitude, low accumulated temperature, large diurnal temperature range, and strong ultraviolet radiation, two years of field positioning trials were conducted to recalibrate the growth cycle, water and fertilizer requirements, and accumulated temperature thresholds of the main cultivars including baby cabbage, cabbage, and flowering Chinese cabbage; the temperature and photoperiod coefficients of generic crop models were revised, bringing the phenological prediction error within 3 d and improving water and fertilizer decision accuracy by 21.3% over the generic model, thereby fundamentally alleviating the poor adaptability of plain-area generic models under plateau conditions. Third, at the level of machinery–agronomy integration, by unifying the standard planting ridge spacing at 60 cm, calibrating tractor power for plateau conditions, optimizing the parameters of rotary tillage and ridging implements, and promoting multi-machine joint operations, the intelligent equipment is genuinely embedded into local agronomic workflows, which is also a key constraint accounting for the low implementation rate of similar projects in plateau regions. As noted in the Introduction, the mature precision-agriculture systems of the United States, Israel, the Netherlands, and Germany [9–11] generally target large-scale contiguous farms and are difficult to transfer directly to China's plateau regions, whereas related Chinese research has concentrated largely on the eastern plains and facility agriculture [12–14]. At the scale of a 6.67 ha demonstration base, this paper adopted a modular and tailorable combination of low-cost equipment together with localized decision models. The system reduced labor input per unit area from 420 to 345 person-days ha^{-1}, raised the irrigation water use coefficient from 0.55 to 0.82, and cut fertilizer and pesticide application by 25% and 30%, respectively, while achieving an 18.2% increase in labor productivity, an 11.7% increase in output per unit area, an increase in the premium-grade product rate from 70% to 85%, and an additional annual net income of 18 000 CNY ha^{-1} (Table 1). These results indicate that in ecologically fragile and economically underdeveloped high-altitude cold regions, smart agriculture technologies can likewise deliver synergistic economic, ecological, and social benefits. The findings provide a quantitatively validated example for the digital transformation of cold-season vegetable production regions in Northwest China, and may offer a technical reference for other high-altitude cold agricultural regions, such as the Andean highlands, the East African highlands, and the southern foothills of the Himalayas, subject to the single-site, single-season limitation of the present study.

In this study, labor productivity was defined as the economic output of vegetable cultivation per unit of labor input, reflecting the improvement in labor-use efficiency achieved by the smart farming system. It was calculated as follows:

$$LP = \frac{V}{L}, \tag{1}$$

where LP denotes labor productivity, V is the output value of marketable vegetable yield per unit area, and L is the labor input per unit area, expressed in person-days ha^{-1}. Marketable yield refers to the actual quantity of vegetables harvested in the field that met the requirements for market sale.

Table 1. Summary of the performance indicators reported for the 6.67 ha smart farm.

Indicator	Baseline	Smart farm	Change
Labor input (person-days ha^{-1})	420	345	$-17.9\%^{*}$
Labor productivity	—	—	$+18.2\%^{\dagger}$
Output per unit area	—	—	$+11.7\%^{\dagger}$
Labor cost per unit area	—	—	$-16.3\%^{\dagger}$
Irrigation water use coefficient	0.55	0.82	$+0.27^{*}$
Fertilizer application	—	—	$-25\%^{\dagger}$
Pesticide application	—	—	$-30\%^{\dagger}$
Pesticide use efficiency	—	43.5%	+37.7%
Premium-grade product rate	70%	85%	+15 percentage points
Additional annual net income (CNY ha^{-1})	—	—	$+18\,000^{\dagger}$

*Absolute values measured directly in field trials.
†Absolute baseline and smart farm values are not disclosed due to commercial sensitivity; relative changes are derived from farm accounting records for the complete 2024 production season.
Labor productivity (LP) was calculated as $LP = V/L$, where V is output value per unit area and L is labor input per unit area (person-days ha^{-1}).

5 Conclusions

Addressing the production bottlenecks of open-field vegetables in China's cold plateau regions, this paper constructed and validated a smart farm technology system adapted to the plateau environment. The main conclusions are as follows. (1) The four-tier architecture of "perception layer—transmission layer—platform layer—application layer", together with the integration of four core modules, namely IoT-based four-condition monitoring (meteorology, soil moisture, pest occurrence, and crop growth), BDS-based intelligent agricultural machinery, precision management of integrated water and fertilizer application, and a big-data decision-making platform, can be stably implemented in plateau open-field vegetable production scenarios; closed-loop management and control enabled by multi-system coordination is the key to its efficient operation. (2) Localized adaptation of crop models and deep machinery–agronomy integration are central to achieving technical effectiveness: the localized model keeps the phenological prediction error within 3 d and improves water and fertilizer decision accuracy by 21.3% relative to the generic model, outperforming the directly transplanted generic solution. (3) Operation of the 6.67 ha demonstration base over one complete production season increased labor productivity by 18.2%, increased output per unit area by 11.7%, raised the irrigation water use coefficient from 0.55 to 0.82, and generated an additional annual net income of 18 000 CNY ha^{-1} (Table 1), delivering synergistic economic, ecological, and social benefits and forming a replicable and scalable construction paradigm for smart farms producing cold-season vegetables on plateaus. Future research will proceed in three directions: first, expanding vegetable cultivars and trial sites, accumulating multi-year continuous observation data, and continuously iterating crop growth models and intelligent decision algorithms to enhance model generalizability and prediction accuracy; second, extending digital management and control to post-harvest sorting, cold-chain logistics, and branded marketing, so as to build a smart system covering the entire industrial chain; and third, developing low-cost and lightweight supporting equipment together with subscription-based service models, to lower the initial investment and adoption threshold for small and medium-sized growers. As the strategic value of agricultural resources in high-altitude cold regions becomes increasingly prominent under global climate change, this model may be applicable in Northwest China and in ecologically similar regions along the Belt and Road, providing sustained technical support for the digital and green transformation of plateau specialty agriculture.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

Jianbo Shen served as an Editor-in-Chief of the *Digital Intelligence in Agriculture* at the time of manuscript submission. To ensure the integrity of the peer-review process, Jianbo Shen was not involved in the editorial handling, peer review, or decision-making process for this manuscript, which was handled independently by another editor. Changxian Zhou, Xinxin Feng, and Pengcheng Luan are affiliated with the Nongxin Technology (Beijing) Co., Ltd., Beijing 100097, China; Shuang Chen is affiliated with the Beijing Hangtian Fengyi Information Technology Co., Ltd., Beijing 100094, China. The authors declare that these affiliations had no influence on the study design, data collection, analysis, interpretation of the results, or decision to publish. The authors declare that they have no other competing interests.

AI Use Statement

The authors declare that no generative AI was used in the preparation of this manuscript.

Ethical Approval and Consent to Participate

Not applicable.

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