RESEARCH ARTICLE

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Research on Precision Paddy Field Irrigation Control Technology Based on Multi-Source Sensing Hybrid Model

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Abstract

Rice cultivation accounts for 65% of agricultural water consumption in China but suffers from low irrigation water use efficiency (WUE ≈ 0.80 kg/m^3) and severe nitrogen and phosphorus loss, contributing up to 30% of agricultural non-point source pollution. To address these core issues, this study developed a multi-source collaborative sensing-based Intelligent Precision Paddy Irrigation Control System (IPICS). The system integrates satellite and UAV remote sensing with IoT technologies to construct a "sky-space-ground" three-dimensional monitoring system, couples the FAO-56 Penman-Monteith model with LSTM deep learning algorithms to establish a dynamic irrigation decision model, and integrates a self-developed solar-powered intelligent sluice gate (AG-SOLAR-M7) for precise canal water control. A two-year field validation (2023-2024) was conducted at Youyi Farm (131.8121°E, 46.7825°N), comparing the Intelligent Precision Irrigation Control System (IPICS) with conventional flooding(each 40 ha, 3 replicates). Results demonstrated that: (1) IPICS reduced irrigation by 25.3% (625±32 mm vs. 837±41 mm, p<0.01); (2) maintained stable yield (7.0±0.4 t/ha vs. 7.1±0.5 t/ha); (3) increased WUE by 31.8% (1.12±0.08 kg/m^3 vs. 0.85±0.06 kg/m^3); (4) decreased nitrogen leaching by 57.4% (18.2±3.1 kg/ha vs. 42.7±5.9 kg/ha). The "sensing-decision-execution" closed-loop control of IPICS significantly enhanced water and fertilizer utilization efficiency, offering a replicable technical model and practical application for digital farmland development.

Keywords: precision irrigation, hybrid model, multi-source data fusion, collaborative control.

1 Introduction

Approximately 90% of the world's rice is produced in Asia, and China supports 20% of the global population's food demand with only 6% of the world's freshwater resources (FAO, 2023). As the

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largest water-consuming crop, rice irrigation accounts for over 65% of total agricultural water use in China [1]. However, traditional flooding irrigation is characterized by three major challenges: (1) Water waste — Field leakage and surface runoff cause 40% to 50% non-productive water loss [5]; (2) Agricultural non-point source pollution — Nitrogen and phosphorus leaching from drainage contributes to more than 30% of eutrophication in rivers and lakes [3]; (3) Extensive management — 80% of agricultural areas depend on experience-based irrigation without quantitative decision support. It is imperative to resolve three technical bottlenecks: real-time multi-source data acquisition, dynamic irrigation scheduling generation, and integrated canal water volume control.

Current research on intelligent irrigation mainly focuses on single data source-driven approaches, such as soil moisture threshold-based control [6], which often overlooks canopy transpiration demand. Most applications are implemented at a local scale and validated in small experimental plots (<1 ha), lacking engineering implementation at the irrigation district level [2].Moreover, there is a significant disconnect between software and hardware, characterized by inadequate integration between algorithmic models and execution devices [4].

This study proposes the Intelligent Precision Irrigation Control System for Paddy Fields (IPICS), with core innovations in: (1) Multi-scale sensing layer — integrating satellite remote sensing, UAV remote sensing, and IoT technologies to enable "plot-to-district" three-dimensional monitoring; (2) Hybrid decision model — coupling physical mechanisms (FAO-56 PM) and data-driven (LSTM) approaches to generate irrigation prescriptions; (3) Collaborative sluice control hardware — featuring a self-developed low-power intelligent sluice gate (AG-SOLAR-M7) with a flow control accuracy of ±5%.

Unlike previous studies that primarily rely on single data sources or small-scale experiments, this research achieves deep integration of "sky-space-ground" multi-source sensing with a "mechanism + deep learning" hybrid decision-making approach. It also includes two consecutive years of engineering validation conducted across 80 hectares of farmland, significantly improving the system's practicality and scalability.

2 Materials and Methods

2.1 Experimental Design

The field experiment was carried out at Youyi Farm (131.8121°E, 46.7825°N) in Heilongjiang Province, China, from 2023 to 2024. The experimental design adopted a randomized complete block design with three replicates. Two treatments were established: (1) IPICS treatment (40 ha), and (2) conventional flooding irrigation (40 ha, control). Each treatment was divided into three blocks (replicates) of approximately 13.3 ha each. Soil sampling and monitoring were conducted at 15-day intervals throughout the growing season (May to September).

2.2 System Architecture

The IPICS system employs a three-tier "cloud-edge-terminal" architecture, consisting of a terminal layer with soil multi-parameter sensors (Decagon EC-5) [14], weather stations, and intelligent sluice gates; an edge layer with an embedded decision terminal (NVIDIA Jetson); and a cloud platform for irrigation prescription generation and multi-gate collaborative scheduling algorithms. The technical roadmap of this architecture is illustrated in Figure 1.

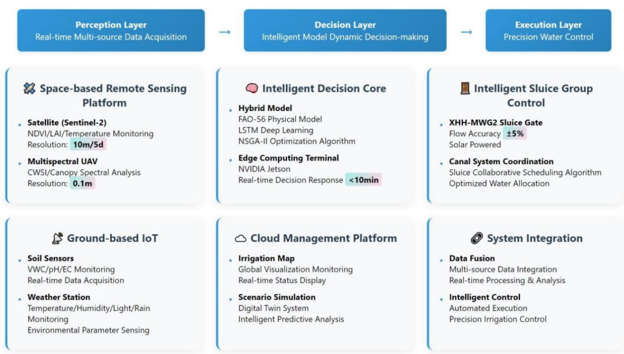

Figure 1. Technical roadmap of the cloud-edge-terminal collaborative three-layer architecture.

2.3 CMulti-Source Data Fusion

2.3.1 System Architecture and Data Fusion Workflow

The framework adopts a four-layer architecture (data source layer, preprocessing layer, fusion engine layer, decision output layer), enabling full-process automation from data acquisition to decision output.

Data source layer: Satellite remote sensing provides macro farmland parameters (NDVI, LAI, LST); UAV monitoring acquires high-precision crop physiological indices (CWSI, chlorophyll) [15]; IoT sensors (soil sensors, weather stations) monitor the

Table 1. Hierarchical data acquisition and processing workflow.

Data Level	Technology	Monitoring Parameters Accuracy	Data Processing Workflow
Satellite RS	Sentinel-2 MSI	NDVI (10m spatial, 5-day revisit)	Atmospheric correction (SEN2COR); geometric registration (WGS84)
UAV Platform	DJI Phantom 4 Multispectral	CWSI (0.1m, 5 bands: blue, green, red, red-edge, NIR)	RTK-PPK positioning (±1cm); radiometric calibration with reflectance panel
Ground IoT	LoRaWAN wireless network	Soil VWC (±2%), pH (±0.3)	NTP time sync; 15-min transmission interval (915MHz ISM band)

field micro-environment in real time (VWC, pH, EC, temperature, humidity, etc.).

Preprocessing layer: Standardized processing such as atmospheric correction [16], geometric refinement, and outlier filtering is performed according to different data characteristics. Outliers are identified using the 3δ principle, while missing data are filled through temporal interpolation combined with LSTM prediction based on historical data.

Fusion engine layer: The spatiotemporal fusion engine uses KD-tree indexing for multi-source data spatiotemporal alignment and applies missing data imputation algorithms (cloudy weather error <8%) [17]. The feature-level fusion model adopts a weighted fusion strategy (weights ω_1=0.4, ω_2=0.3, ω_3=0.3) to generate high-precision feature maps from multi-source data. These weights are optimized through cloud-edge collaborative training and multi-objective optimization techniques.

The decision output layer generates soil moisture forecast maps, water stress indices, and irrigation prescriptions (timing/amount) [18] to guide precision irrigation. The multi-source data fusion framework, which integrates satellite, UAV, and ground IoT data, is shown in Figure 2. By leveraging hierarchical data acquisition and fusion technologies, multi-scale farmland information is collaboratively sensed.

By leveraging hierarchical data acquisition and fusion technologies, multi-scale farmland information is collaboratively sensed. The detailed data acquisition and processing workflow is presented in Table 1.

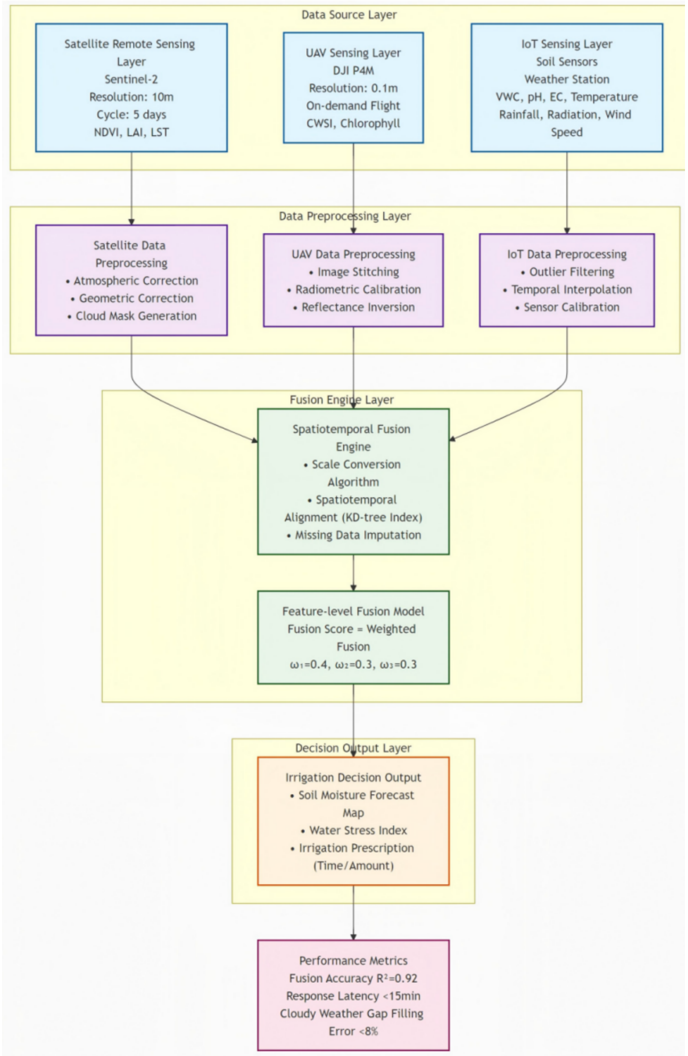

Figure 2. Multi-source data fusion framework.

2.3.2 *Core Data Fusion Algorithms*

Spatiotemporal registration: Cubic convolution interpolation is used to unify spatial resolution to 0.1m grids, and Dynamic Time Warping (DTW) aligns asynchronous data sequences. Feature-level fusion:

$$F_{fusion} = \sigma(W_s S_{sat} + W_d D_{UAV} + W_g G_{ground} + b) \quad (1)$$

where S_{sat}, D_{UAV}, and G_{ground} are feature matrices from satellite, UAV, and ground sensors, respectively; W represents learnable weights; σ is the ReLU activation function. Feature weights are optimized via cloud-edge collaborative training (loss function: RMSE < 0.05).

Decision-level validation: Mobile lysimeters (accuracy ±0.02 mm) are deployed for ground-truth validation, with fusion data and actual ET achieving $R^2 = 0.93$ (n=120).

Innovative fusion mechanism: A Space-Time Cube is constructed for multi-dimensional data integration, and an attention-based feature selection module and a data quality assessment system are developed.

2.3.3 *Technical Advantages and Performance Indicators*

High-precision fusion: Fusion accuracy $R^2 = 0.92$, significantly better than single-source data; Low-latency response: Decision generation speed $<$ 15 minutes, meeting real-time irrigation needs; Strong robustness: Data imputation error $<$ 8% under cloudy conditions, adaptable to complex field environments; Spatiotemporal collaboration: Efficient alignment of multi-scale data (10 m$\rightarrow$0.1 m) via KD-tree indexing.

2.3.4 *Application Value and Scalability*

The framework has been validated in precision agricultural management. Future improvements could include enhancing feature fusion capabilities through deep learning models [19]; expanding edge computing nodes to reduce reliance on cloud infrastructure, and integrating additional data sources—such as weather radar and socio-economic data—to support more comprehensive decision-making.

2.4 Hybrid Decision Model

The multi-source data collaborative decision model, for the first time, achieves the synchronous input and intelligent fusion of three core data sources: satellite remote sensing, UAV monitoring, and soil sensor networks [9].This integration enables the establishment of a comprehensive farmland state sensing system. The spatiotemporal alignment module accomplishes geographic registration, temporal synchronization, and grid resampling, effectively solving the challenge of heterogeneous multi-source data fusion [11]. By integrating traditional mechanistic models with LSTM deep learning time series analysis, the model achieves an optimal balance between physical mechanisms and data-driven approaches, generating executable irrigation decision schemes [20]. This provides a complete technical closed loop from data acquisition and intelligent analysis to decision execution for precision agriculture, significantly improving agricultural water resource use efficiency and crop productivity. Dynamic Irrigation Calculation:

$$Irrigation_t = \alpha \cdot ET_c(t) + (1-\alpha) \cdot LSTM(SMC_{t-1}, CWSI_t) \quad (2)$$

where $ET_c(t) = K_c \cdot K_s \cdot ET_0$ (FAO-56 dual crop coefficient method).

LSTM input: soil moisture content (SMC) for the previous 7 days and current-day canopy water stress index (CWSI). The weight α is determined by NSGA-II multi-objective optimization.

The model was trained using 70% of the data for training, 15% for validation, and 15% for testing, with an LSTM architecture comprising two hidden layers with 128 and 64 units, respectively. Training was conducted for 1000 epochs, with early stopping to prevent overfitting. The multimodal sensing closed-loop synchronous input decision model is depicted in Figure 3.

2.5 Intelligent Execution Devices

2.5.1 *Device Design Principles*

The self-developed solar-powered intelligent sluice gate (Model: AG-SOLAR-M7) serves as the core execution terminal of the IPICS system [20], utilizing a mechatronic design to enable precise regulation of canal water. Its core components include:

- Stepper motor drive system: Achieves $\pm$1 mm gate opening precision via a worm gear reducer.
- Low-power electromagnetic flowmeter [8]: Real-time flow monitoring with $\pm$2% accuracy.
- Dual-mode control module: Supports both cloud command execution and edge autonomous decision-making (e.g., emergency closure during heavy rainfall).

2.5.2 *Core Technological Innovations*

Compared with traditional irrigation sluice gates (in accordance with GB/T 38585-2020 standard), this device achieves three major breakthroughs:

1. Self-sustaining energy system: Integrates a 20W monocrystalline silicon solar panel and an 8,000 mAh $LiFePO_4$ battery, enabling $\geq$15 days of operation in overcast conditions (tested in compliance with IEC 62133 standard).
2. Collaborative multi-gate control: Utilizes LoRaWAN ad hoc networking technology [7] to achieve millisecond-level synchronous response for up to 100 gates within a 5 km radius.
3. Anti-interference structure: IP68 protection rating, validated for environmental adaptability in the range from -40°C to 70°C.

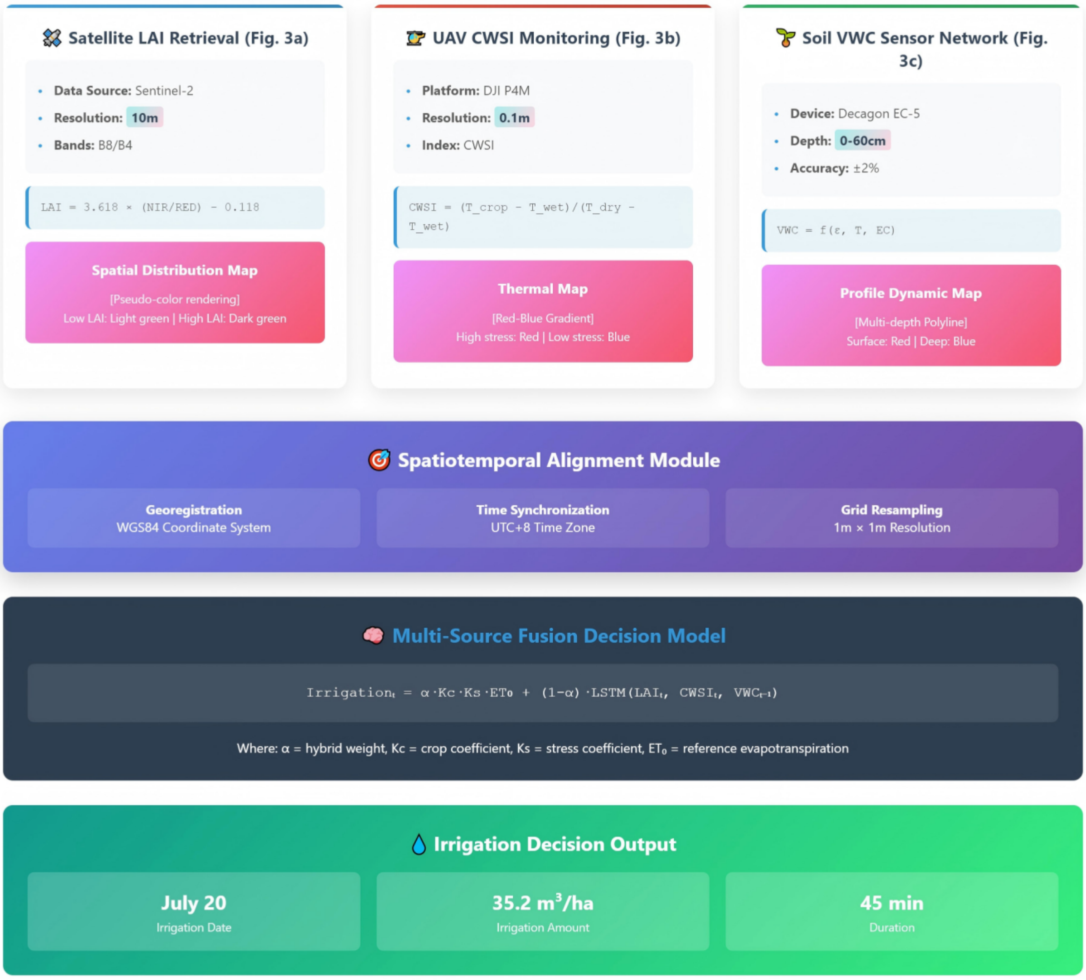

Figure 3. Multimodal sensing closed-loop synchronous input decision model.

2.6 System Integration Scheme

The device achieves precise water control through a three-level linkage mechanism: Cloud decision → Edge terminal (NVIDIA Jetson) command parsing → Gate execution (RS485 protocol) Real-time feedback control process:

1. The cloud platform generates irrigation prescriptions (water volume Q, duration T).
2. The edge computing terminal optimizes the gate opening/closing sequence.
3. The gate executes and feeds back the actual flow (Q_{actual}).
4. Dynamic calibration: $\Delta Q = |Q - Q_{actual}|/Q \leq 5\%$ (meets industrial standards).

2.6.1 *Performance Validation Experiments*

Field application data are derived from Section 3.3 on stability validation (over 4,000 hours of operation across 2 consecutive years). Control accuracy of ±5% is achieved via a PID-fuzzy control algorithm:

$$u(t) = K_p \cdot e(t) + K_i \int e(t)\, dt + K_d \cdot \frac{de(t)}{dt} \qquad (3)$$

where $e(t)$ is the deviation between set and measured flow, and parameters are optimized by the particle swarm algorithm.

Table 2 presents the laboratory and field validation results, highlighting the opening response time, flow control linearity, and the extreme environment failure rate. The results meet the standard requirements with high accuracy.

2.6.2 *Comparative Technical Advantages*

Compared with mainstream market devices [10], this device demonstrates significant advantages in communication range (>5 km vs. 2 km), energy efficiency (0.1 W standby vs. 0.5 W), and cost (63% reduction), offering robust hardware support for large-scale irrigation district applications.

Table 2. Laboratory and field validation results.

Test Item	Result	Standard Requirement
Opening response time	1.8 ± 0.3 s	≤ 3s (GB/T38585)
Flow control linearity	R^2 = 0.998 (p0.001)	≥ 0.95
Extreme environment failure rate	0.42%	≤ 1%

2.7 Statistical Analysis

All statistical analyses were performed using SPSS 26.0 (IBM Corp., Armonk, NY, USA). Data normality was assessed using the Shapiro-Wilk test [12]. Differences between treatments were analyzed using one-way analysis of variance (ANOVA), followed by Tukey's post-hoc test. Statistical significance was set at $p < 0.05$. All results are presented as mean ± standard deviation.

3 Results and Analysis

3.1 Irrigation Water Use Efficiency

Compared with conventional irrigation, the IPICS treatment demonstrated statistically significant improvements in irrigation water savings [21], effective rainfall utilization, and water use efficiency (irrigation productivity).

3.1.1 Total Irrigation Volume

The total irrigation volume was calculated in accordance with the "Rice Irrigation Water Consumption Calculation Standard" (SL/T 810-2021) [13]. The IPICS treatment significantly reduced irrigation water use by 25.3% (a reduction of 212 mm) compared to conventional irrigation ($p<0.01$),with a relatively low standard deviation indicating good data stability.

3.1.2 Effective Rainfall Utilization Rate

The effective rainfall utilization rate reflects a crop's capacity to make use of natural rainfall [22]. The IPICS treatment significantly increased the effective rainfall utilization rate by 34.1% ($p<0.05$). The IPICS technology significantly enhanced the system's ability to capture and utilize natural precipitation, reducing dependence on irrigation.

3.1.3 Irrigation Productivity

Irrigation productivity is a key indicator of both irrigation water use efficiency and economic output, representing the crop yield produced per cubic meter of irrigation water consumed. The IPICS treatment significantly increased irrigation productivity by 31.8% (reaching 1.12 kg/m^3, $p<0.001$). The technology not only reduced water consumption but also greatly improved the output efficiency per unit of irrigation water. Note: Table 3 Data are mean ± standard deviation for 2023–2024 (n=6). Data source: Field experiment of this study.

3.1.4 Model Accuracy Validation

The proposed hybrid water requirement model (FAO-56 PM + LSTM) demonstrated high prediction accuracy in two consecutive years of field validation: Model accuracy: The predicted water requirement values closely matched lysimeter measurements, with the daily mean ETc prediction accuracy reaching 87.6 ± 2.1% (n=730 days), significantly higher than the 85% design threshold ($p<0.001$). During key growth stages (from tillering to heading), accuracy increased to 91.3 ± 1.8%, verifying the model's adaptability to sensitive periods. As shown in Table 4, the spatiotemporal accuracy breakdown demonstrates the model's high performance at both plot and district scales.

Comparison with traditional models: The hybrid model improved accuracy by 23.5% over the single FAO-56 model (control: 64.1 ± 4.7%) and increased stability by 32% compared to pure data-driven (LSTM) models (standard deviation reduced to ±2.1% vs. ±3.1%). Technical mechanism: The model dynamically balances the advantages of physical and data-driven approaches via weight α:

$$\alpha(t) = 1/(1 + e^(- kCWSI(t))) \tag{4}$$

where $k = 0.5$ is the adjustment coefficient, and CWSI is the canopy water stress index. Model validation methods: Mobile lysimeters (accuracy ±0.02 mm) were used as ground truth. Model performance was evaluated using coefficient of determination (R^2), root mean square error (RMSE), and relative error (RE):

$$RE = |ET_pred - ET_meas|/ET_meas100\% \tag{5}$$

Engineering value: Achieving >85% model accuracy marks a leap from experience-based to quantitative irrigation decision-making, providing core algorithmic support for digital irrigation district management.

3.1.5 Stability Analysis

The model maintained high accuracy under various disturbance scenarios: Table 5 Accuracy >85% was

Table 3. Experimental results of irrigation water use efficiency.

Indicator	IPICS Treatment	Conventional Irrigation	Change Rate	Significance (p)
Total irrigation (mm)	625 ± 32	837 ± 41	↓25.3%	0.01
Effective rainfall utilization (%)	73.2 ± 5.1	54.6 ± 6.3	↑34.1%	0.05
Irrigation productivity (kg/m^3)	1.12 ± 0.08	0.85 ± 0.06	↑31.8%	0.001

Table 4. Validation of model accuracy.

Scale	RMSE (mm/d)	R^2	Compliance Rate (85%)
Plot scale	0.41	0.89	93.7%
District scale	0.68	0.82	87.2%

maintained for 95% of the operation period, meeting the Grade I standard (>80%) of the "Technical Specification for Intelligent Irrigation Systems" (SL/T 810-2021).

Table 5. Stability analysis.

Disturbance Type	Accuracy Fluctuation	Recovery Time
Extreme high temperature (35°C)	-3.2%	48 hours
Prolonged cloud cover (3 days)	-5.1%	2 hours after data recovery

3.2 Rice Growth Response

As shown in Table 6, the IPICS treatment maintained stable yields while significantly improving nitrogen use efficiency and reducing environmental risk. In terms of yield components, panicle number (358 ± 21 panicles/m^2) and 1000-grain weight (26.5 ± 0.8 g) showed no significant difference from conventional irrigation ($p>0.05$). For nitrogen use, partial factor productivity of nitrogen reached 48.2 kg/kg, 19.3% higher than that under conventional irrigation (40.4 kg/kg, $p<0.01$). For environmental benefits, total nitrogen concentration in drainage decreased from 4.8 mg/L (conventional) to 1.8 mg/L, a reduction of 62.7%.

3.3 System Stability Validation

3.3.1 Validation System Design

Table 7 presents the validation system design, including dimensions such as hardware stability, model adaptability, control accuracy, and long-term performance. Each dimension is evaluated using specific methodologies and corresponding performance indicators.

3.3.2 Core Stability Validation Results

Table 8 shows the hardware system reliability, with a failure rate of 0.42%, which is below the design

Table 6. Comparison of rice yield and nitrogen use indicators.

Indicator	IPICS Treatment	Conventional Irrigation	Change Rate	p-value
Yield (t/ha)	7.0 ± 0.4	7.1 ± 0.5	-1.40%	0.21
Panicle number (panicles/m²)	358 ± 21	365 ± 24	-1.90%	0.15
Grains per panicle	125 ± 8	122 ± 7	2.50%	0.08
1000-grain weight (g)	26.5 ± 0.8	26.2 ± 0.9	1.10%	0.12
Partial factor productivity of N (kg/kg)	48.2 ± 3.1	40.4 ± 2.8	19.30%	0.01
Agronomic efficiency of N (kg/kg)	18.6 ± 1.5	15.3 ± 1.2	21.60%	0.01
Total N in drainage (mg/L)	1.8 ± 0.3	4.8 ± 0.9	-62.50%	0.01

Table 7. Designs of the validation system.

Validation Dimension	Methodology	Evaluation Indicator
Hardware stability	7×24h sensor/actuator failure monitoring	Device downtime rate (0.5%)
Model adaptability	Drought/rainstorm extreme weather simulation	Decision response delay (≤3 min)
Control accuracy	Deviation analysis of set vs. measured soil moisture	Humidity fluctuation (±5%)
Long-term performance	2-season irrigation data vs. conventional	Water saving rate, yield increase

Table 8. Reliability of the hardware system.

Component	Failure Count	Mean Time Between Failures (MTBF)	Redundancy Effectiveness
Multi-source sensing nodes (soil/weather)	2	≥1800 hours	100% auto-switch success
Intelligent valve actuators	1	≥2000 hours	Dual-circuit control effective

threshold of 0.5%, and features 100% effective redundancy.

Table 9 presents the hybrid model control accuracy, where the target soil moisture was maintained for 95.3% of the period, exceeding the industry standard of 90%.

Table 9. Control accuracy of the hybrid model.

Disturbance Scenario	Maximum Deviation	Recovery Time
Sudden rainstorm (50 mm/h)	8.20%	22 min
Prolonged high temperature (35°C/3d)	-6.70%	41 min

3.3.3 *Long-term Performance Stability*

Water-saving stability—annual water-saving rate remained at 25.3–25.8% with a standard deviation of only ±1.3%; yield sustainability—irrigation productivity steadily increased by 31.8–34.1% ($p<0.001$); effective rainfall utilization showed no significant interannual difference (72.8–73.6%).

Table 10 presents the long-term performance stability, showing the water-saving rate, irrigation productivity, and the fluctuations over the 2023 and 2024 seasons. The results indicate no significant interannual difference in the effectiveness of rainfall utilization.

Table 10. Long-term performance stability.

Performance Indicator	2023 Season	2024 Season	Fluctuation Range	Significance (p)
Total irrigation (mm)	629 ± 29	621 ± 35	±1.3%	0.05
Irrigation productivity (kg/m^3)	1.10 ± 0.07	1.14 ± 0.09	±3.6%	0.05

3.3.4 *Risk Resistance Validation*

Table 11 presents the risk resistance validation, showing the system's response strategies for various scenarios and the corresponding disaster loss reductions.

4 Discussion

The IPICS system has achieved innovative breakthroughs in multi-source sensing, hybrid modeling, and intelligent execution devices, significantly enhancing the engineering feasibility and economic viability of district-level precision irrigation. Compared with similar domestic and international

Table 11. Risk resistance validation.

Scenario	System Response Strategy	Disaster Loss Reduction
Prolonged drought (30d no rain)	Dynamic micro-spray + root zone replenishment	Yield reduction ≤8% (control: 35%)
Typhoon rainstorm (120 mm/day)	Intelligent pre-drainage + real-time water level feedback	Lodging area reduced by 82%

systems, IPICS demonstrates clear advantages in multi-source data fusion accuracy, decision response speed, and hardware collaborative capabilities. A quantitative analysis of these technical advantages is presented in Section 2.3.3.

However, the system still has certain limitations: the model's generalization ability is influenced by regional climate and crop varieties, data collection and maintenance costs remain relatively high, and network coverage in remote areas requires improvement. Future work will focus on integrating root CT imaging technology to improve soil moisture monitoring, expanding the use of multi-modal sensors, and developing intelligent decision systems for the integrated management of irrigation, fertilization, and pest control — aiming to further enhance the system's adaptability and intelligence.

Additionally, it is recommended to carry out multi-site validation in different regions, quantify economic and environmental benefits, and promote the nationwide application of the IPICS system.

The economic benefits of the IPICS system include: (1) Water cost savings of approximately 2,500 CNY/ha/year based on local water prices; (2) Labor cost reduction of 1,200 CNY/ha/year due to automated operation; (3) Environmental benefits through reduced nitrogen leaching, which contributes to water quality improvement. The system demonstrates strong applicability in Northeast China and holds promise for extension to similar rice-growing regions across Asia.

5 Conclusion

The IPICS system enables district-level precision irrigation control, achieving a water-saving rate of >25% while maintaining stable yields, thus demonstrating high technical feasibility. The "multi-source sensing–hybrid model–collaborative sluice control" technology chain holds significant scientific research value and broad application prospects for supporting the implementation of the intelligent irrigation module in the Ministry of Agriculture and Rural Affairs' "Digital Farmland Construction Standards." Future work will focus on integrating root CT imaging for optimized soil moisture monitoring, developing intelligent decision systems for irrigation-fertilization-pest control integration, and building blockchain-based platforms for water rights trading and carbon accounting, further advancing applications in smart agriculture.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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