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Automatic water-saving irrigation technology for farmland based on PSO-ELM algorithm and micro control unit

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In response to the significant waste of agricultural irrigation resources and the inaccuracy of water demand predictions, this study aims to develop an automated irrigation system that can reduce fluctuations in water volume and enable precise control. Against the backdrop of current water scarcity and low agricultural water efficiency, improving irrigation precision is of great significance for ensuring food security and promoting sustainable agricultural development. This study combines particle swarm optimization algorithm with extreme learning machine and integrates it into a microcontroller to construct a new intelligent irrigation system. This technology can solve the problem of inaccurate crop water demand predictions in existing technologies and promote the transformation of intelligent agriculture from empirical to data-driven. This technology uses a LoRa based wireless sensor network to collect data and is controlled by a microcontroller. The particle swarm algorithm optimizes the initial parameters of the extreme learning machine, improving the accuracy with which it predicts farmland water demand. The results showed that the proposed method had the lowest root mean square error value, with an average of only 0.1025, indicating that the algorithm had the most accurate irrigation prediction effect. The automatic water-saving irrigation technology proposed in this study required less water compared to traditional irrigation techniques, with a minimum water consumption of 3015 m³/hm² and a maximum water consumption of only 5268.3 m³/hm². The system's accuracy in predicting crop irrigation water demand could reach over 98%. The method proposed in this study can accurately control irrigation water. It can also maximize irrigation water conservation. This brings new research directions for the knowledge system of automated water-saving irrigation technology in farmland. It also provides new technical ideas for the development of intelligent agricultural irrigation technology.

KEYWORDS

automatic irrigation, combining algorithms, extreme learning machine (ELM), micro control unit, particle swarm optimization (PSO), water-saving agriculture

1 Introduction

Although China is a sizable agricultural nation, there are disparities in the allocation of water resources both in space and time. Although agricultural irrigation water (IW) consumption accounts for 61.2% of total water consumption (WC), its effective utilization coefficient is only 0.559. This is significantly lower than the range of

0.7–0.8 observed in industrialized nations (Uddin and Dhar, 2020; Attri et al., 2022). Developing water-saving irrigation technology is crucial for alleviating water scarcity, reducing waste, and improving agricultural water use efficiency. The rise of smart agriculture has created new opportunities for upgrading irrigation systems with technologies such as the Internet of Things and artificial intelligence (Zhao et al., 2023). However, the current coverage rate of efficient, water-saving irrigation technology is relatively low. It is mostly concentrated in plains with superior conditions, which results in problems such as low irrigation efficiency, serious water resource waste, and high investment costs in vast areas. This is especially true in the central and western regions, where water resources are scarce (Pervaiz et al., 2022). Existing automated irrigation systems rely heavily on simple threshold control. They lack the ability to accurately predict crop water requirements, which makes it difficult for them to adapt dynamically to complex and changing environmental factors (Manoharan, 2021). Particle swarm optimization (PSO) and extreme learning machine (ELM), as efficient optimization and prediction tools, have demonstrated great potential in successful applications in fields such as energy load and financial forecasting. In view of this, this study aims to address the problems in farmland irrigation, overcome the shortcomings of existing farmland irrigation technologies, reduce the WC rate of farmland irrigation. Moreover, it designs an energy-saving and high-precision farmland IW consumption control system. This study will design automatic irrigation technology for farmland by combining microcontroller technology with PSO and ELM. The research expects that the PSO-ELM algorithm can significantly improve the performance of automatic irrigation technology in farmland and reduce water resource waste. The innovation of this study lies in combining two neural network algorithms to predict the irrigation amount of irrigation equipment. The application of this combination algorithm can not only save costs, but also be applicable to international irrigation standards.

This study mainly includes five sections. The first section primarily discusses the current state of IW resource utilization in farmland, existing research progress, and gaps. It also clarifies the theoretical and practical significance of this study. The second section primarily reviews the progress of applying domestic and foreign farmland irrigation technology and machine learning to agricultural irrigation. It also summarizes current research gaps. The third section is the methods and materials section. This section mainly introduces the hardware design of the automatic irrigation system for farmland and the calculation methods related to crop water demand. It also introduces the principle and implementation path of the PSO-ELM algorithm. The fourth section is the results section, which verifies the research effectiveness through experiments. The fifth section is for discussion and conclusion, summarizing the results of this study and pointing out the limitations and future prospects of the research.

2 Literature review

The issue of farmland WSI system design has been widely noticed and discussed by scholars at home and abroad. Zhao (2022) found that the WSI system could be combined with the

IoT to achieve intelligent control. Therefore, the study proposed a design of WSI system based on IoT. The design was centered on wireless sensor network (WSN) sensor node design and coverage computation. The results showed that the system could perform smart irrigation in a timely and accurate manner. Ramkumar et al. (2021) found that water supply was being wasted in Indian farms. Based on this, the research suggested a technique to use IoT to automate the irrigation system in an attempt to save time and water. The findings demonstrated that farmers could more effectively regulate how much water was used for crop and livestock production. Water scarcity was a major danger to agriculture's sustainable development, according to research by Yang et al. (2022). On the basis of this, the study suggested a WSI application that included guidelines for agricultural water conservation. The findings demonstrated a considerable rise in the agricultural IW's effective usage coefficient. Zhou et al. (2022) found that the development of WSA was not only important for farmers to increase production and income, but also for the protection of water resources. Therefore, the study designed a stepped water price control system. The results showed that the system could greatly promote the sustainable development of WSA in China. Zha et al. (2022) found that WSA started earlier in Europe and achieved certain results. Therefore, a learning software for irrigation WSA was designed to improve information sharing. The results showed that the software played an important academic significance in the protection of water resources as well as the development of WSA.

The application of automatic control technology combined with machine learning in agricultural irrigation can greatly develop intelligent irrigation and improve water production efficiency. Ifriza and Sam'an (2021) found that rural water use was often limited by the flow of water from reservoirs, which led to an unbalanced distribution of rural water use systems. The study proposed a combination of correlation based feature selection (CFS) and an improved binary PSO method for optimizing irrigation management of agricultural reservoirs to address this issue. The results showed that the accuracy of the proposed method was 91.84%, much higher than similar algorithms. Veerachamy and Ramar (2021) (Veerachamy and Ramar, 2022) found that IoT in the agricultural sector could continuously provide agricultural information to the world, but lacked warnings about the irrigation needs of farmland. Therefore, the study first used neural networks to cluster the recommended irrigated farmland by agricultural experts, and then proposed an optimized PSO algorithm for predicting irrigation conditions. The results showed that the proposed method could accurately determine the irrigation demand and location based on soil moisture, temperature, wind speed, and other conditions in the agricultural field through the IoT. Behzadipour et al. (2023) found that the implementation of intelligent irrigation and adjustment of irrigation systems was crucial in today's agricultural systems. Therefore, a combined model of measuring farmland air humidity through sensors and processing leaf images to adjust the microcontroller of the intelligent irrigation system was proposed. The results showed that the proposed model reduced the IW consumption by 11% compared to the previous year, demonstrating significant water saving benefits. To make the evaluation of IW use efficiency evaluation indicators more comprehensive and scientific, Dong et al. (2020) constructed a

TABLE 1 Comparison of advantages and disadvantages of automatic water-saving irrigation methods for farmland mentioned in the literature review section.

Reference	Method corresponding author	Advantage	Shortcoming
Zhao (2022)	Zhao (2022)	Through wireless sensor networks, real-time data such as soil moisture and meteorological information can be obtained to adjust irrigation rates in a timely manner and ensure that crops receive appropriate moisture	The stability and reliability requirements for IoT technology and sensor nodes are high, and any technical failure may affect irrigation efficiency
Ramkumar et al. (2021)	Ramkumar et al. (2021)	Automated irrigation systems can reduce water waste, improve agricultural production efficiency, and save farmers' time and energy	Automation systems rely on stable power supply and have high requirements for power infrastructure
Zhou et al. (2022)	Zhou et al. (2022)	It plays a positive role in the sustainable development of water-saving agriculture and is beneficial for long-term protection and management of water resources	The design of tiered water pricing may raise fairness issues, especially for farmers in poorer areas who may face certain burdens
Zha et al. (2022)	Zhang et al. (2022)	By designing tiered water pricing, farmers and farm owners can be incentivized to conserve water and optimize irrigation strategies	The implementation of tiered water pricing requires cooperation and management from the government and relevant regulatory departments, with high management costs and complexity

new optimization model for evaluation indicators, which took the indicator of irrigation machine driver pressure state influence correspondence and information significance difference as the evaluation benchmark. The results showed that the proposed model provided a simpler and more convenient index optimization system for the study of IW use efficiency evaluation indicators. Zhao (2022) further investigated the design of a WSI system based on IoT to address the serious problem of water waste in automatic farmland irrigation. At the same time, a WSI system structure model combining wireless sensors was built, and the farmland irrigation system was tested by wireless signals. The results showed that the system proposed by the research could perform intelligent irrigation in a timely and accurate manner. The comparison of the above literature methods is shown in Table 1.

The inclusion criteria for literature are as follows: (1) The research topic is agricultural automation and water-saving irrigation technology. It involves intelligent algorithms, the Internet of Things, and microcontroller applications. (2) The publication period is from 2021 to 2025. (3) The source is a peer-reviewed journal article. (4) Clear experimental data or validation results for method comparison are provided. The exclusion criteria are as follows: (1) Grey literature such as government reports, enterprise technology white papers, and unpublished dissertations. (2) Irrigation research in non-agricultural fields. (3) Literature that only describes theory without empirical verification. In conclusion, researchers from both domestic and foreign institutions have put forth a multitude of optimization strategies for the implementation of automatic WSI technology in agricultural settings. However, there has been a paucity of scholars who have employed neural network algorithms for the purpose of IW control prediction. Based on this, a field automatic WSI technology combining microcontroller technology with PSO and ELM is studied and designed. The two neural network algorithms are combined for predicting the irrigation amount of WSI devices.

The contribution of the methods proposed by the research to the existing relevant knowledge system is mainly reflected in the following aspects: (1) The research provides a new technological

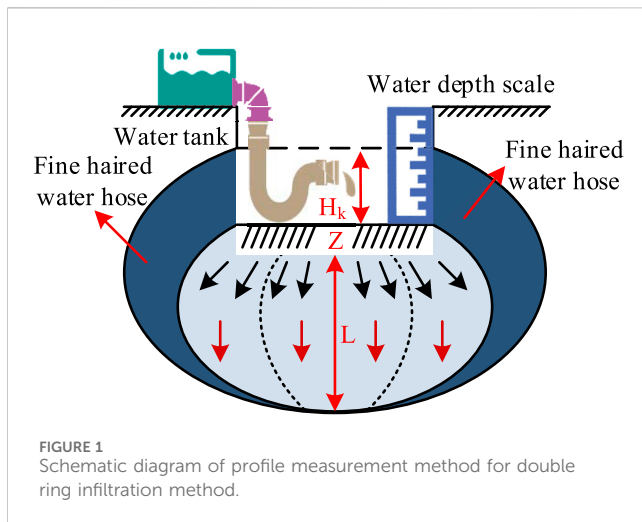
solution for WSI of farmland by integrating microcontroller technology, PSO, and ELM. This interdisciplinary technology integration helps promote the development of intelligent agricultural technology, especially in improving irrigation efficiency and water resource utilization. (2) The optimized algorithm can be used as part of an intelligent irrigation control system to reduce manual intervention and increase the level of automation in irrigation management through automatic control and intelligent decision making. (3) The research results can serve as a part of the intelligent agricultural technology system, promote the transformation of agriculture from “empirical” to “precise” development, and provide new impetus for accelerating agricultural modernization. (4) The efficacy of the algorithm is validated through simulation experiments in this study, thereby bridging the gap between theoretical research and practical applications. The transformation and implementation of scientific research outcomes is facilitated, and tangible technical solutions for the domain of farmland irrigation are provided.

3 Methods and materials

The study addresses the issues of automated WSI system in agricultural fields. Firstly, for the selection of network sensors for the irrigation system is explained and the experiment finally selects long range radio (LoRa) as the transmission network. Then the influencing factors of crop water demand are calculated to facilitate the control variables. This is the basis for the proposal of the PSO-ELM combined control algorithm and the explanation of its operation logic.

3.1 Circuit MCU design for automatic WSI technology in farmland

Before implementing automatic irrigation technology for agricultural crops, several key issues need to be addressed to ensure the effectiveness and sustainability of the technology.



First, it is necessary to understand and study the growth habits and water requirements of agricultural crops at different stages of growth. The control of IW usage also relies on understanding soil moisture. If the soil moisture meets the standard, only a small amount of irrigation or no irrigation is needed. Otherwise, it is necessary to control the amount of water used for plant irrigation. Under different weather conditions, the volatilization of soil moisture in agricultural crops varies. The study introduces the Penman Monteith formula to calculate crop evapotranspiration, as shown in Equation 1.

$$ET_c = K_c ET_0 \quad (1)$$

In Equation 1, ET_0 represents the CET. K_c is crop growth coefficient. The study set K_c to 1.05. ET_c represents the crop's water evapotranspiration during crop growth. From this, the actual amount of water irrigated can be deduced and calculated as shown in Equation 2.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

In Equation 2, γ represents the average value of surrounding temperature for crop growth. G represents the natural wind speed in a radial direction of 2 m. G represents the soil heat below the crop plant. R_n represents the net radiation in a normal environment. Δ represents the slope of air temperature and water pressure in the time dimension. T stands for moment. Water evaporation from the soil is closely related to IW use, so the study introduced the double ring percolation method to measure water infiltration in the soil. The profile measurements of this method are shown in Figure 1.

In Figure 1, the study sets the diameter of the inner ring of the measurement ground plane to 0.25 m, while the diameter of the outer ring is 0.5 m, and the measurement depth is 0.5 m in both cases. However, the centers of the inner ring and the outer ring overlap, and they are both rooted into the soil at a depth of 0.1 m. When the height of the water level in the outer ring H_k reaches 0.1 m, irrigation is not required. The two-ring infiltration method, on the other hand, observes WC once every 5 min and transmits the changes to the observation terminal via sensors. The infiltration rate is calculated as shown in Equation 3.

$$V = \frac{Qn^*10}{t_n S} \quad (3)$$

In Equation 3, V represents the infiltration rate of soil moisture (mm/min). Qn represents the amount of IW required by the crop (mL). t_n represents the point in time between observations of irrigation. S represents the area covered at the time of irrigation. Accordingly, it can be deduced that the infiltration coefficient of the double ring percolation method is calculated as shown in Equation 4.

$$K = \frac{Qn^*10}{t_n S} \times \frac{L}{H_k} \quad (4)$$

In Equation 4, K represents the infiltration coefficient. H_k represents the outer ring water table line. L represents the depth of the irrigation tool into the soil. The infiltration coefficients of IW at different temperatures are inconsistent. The irrigation infiltration coefficients at different temperatures is extrapolated from Equation 4 and calculated as shown in Equation 5.

$$K_{10} = \frac{K_t}{0.7 + 0.03t} \quad (5)$$

In Equation 5, K_{10} represents the irrigation infiltration coefficient at a temperature of 10 °C. K_t represents the infiltration coefficient at a temperature of t . t represents the water temperature. Knowing the soil moisture evaporation as well as the irrigation infiltration coefficient, the irrigation time point can be predicted. The study projected uniform irrigation time is calculated as shown in Equation 6.

$$T = \frac{0.1 \cdot a \cdot d (RH_1 - RH_0)}{ET_c + 60K_t} \quad (6)$$

In Equation 6, RH_1 represents the average soil moisture of the farmland to be irrigated. RH_0 represents the suitable soil moisture required for crop growth in the farmland. a represents the depth of soil cover. d represents the soil capacity weight per Gram of cubic centimeter. In summary, the study to control the amount of water used for irrigation of farmland crops, then the circuit system of automatic WSI technology for farmland can be further designed. However, WSI technology for farmland involves the operational experience of growers and the need to accurately grasp the growth of crops in irrigated farmland. Traditional crop growth observation techniques still rely on manual inspection, which is inefficient and costly (Shi, 2021). Automatic WSI technology for farmland relies on computers and information terminals to record and monitor crop growth, control soil moisture and irrigation volume. It is possible to increase the efficiency of observations and reduce costs by choosing the right sensors to monitor soil moisture, weather conditions, etc. WSN is a distributed sensor network, with sensors at its periphery that can perceive and inspect the external world. WSN sensors communicate wirelessly, allowing for flexible network settings. The location of devices can be changed at any time, and connections to the internet can be wired or wireless. Research has chosen LoRa as the signal transmission network for agricultural areas, and agriculture urgently needs low-power and low-cost sensors. LoRa is well suited for such scenarios, and its transmission logic is shown in Figure 2.

After confirming the signal sensors covering farmland, it is necessary to use micro control unit (MCU) technology as the

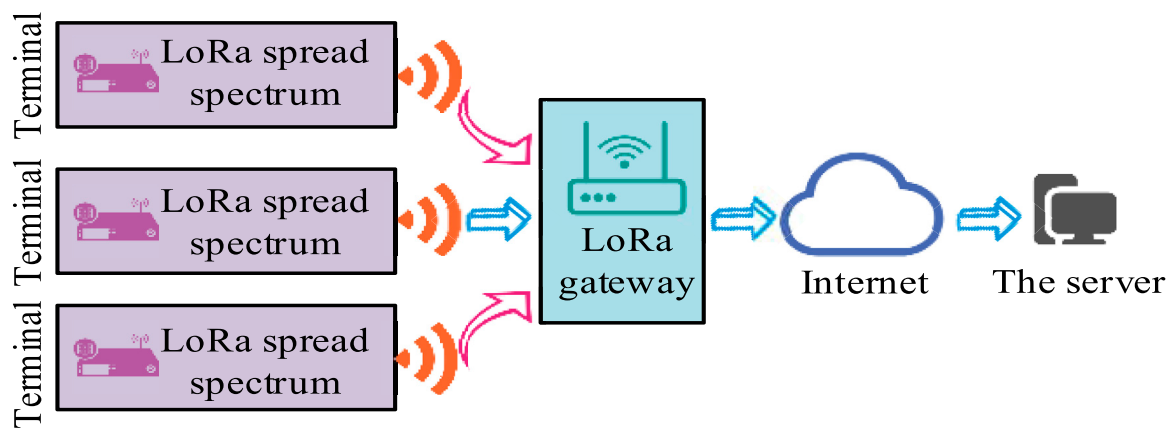


FIGURE 2
Schematic diagram of LoRa network transmission logic.

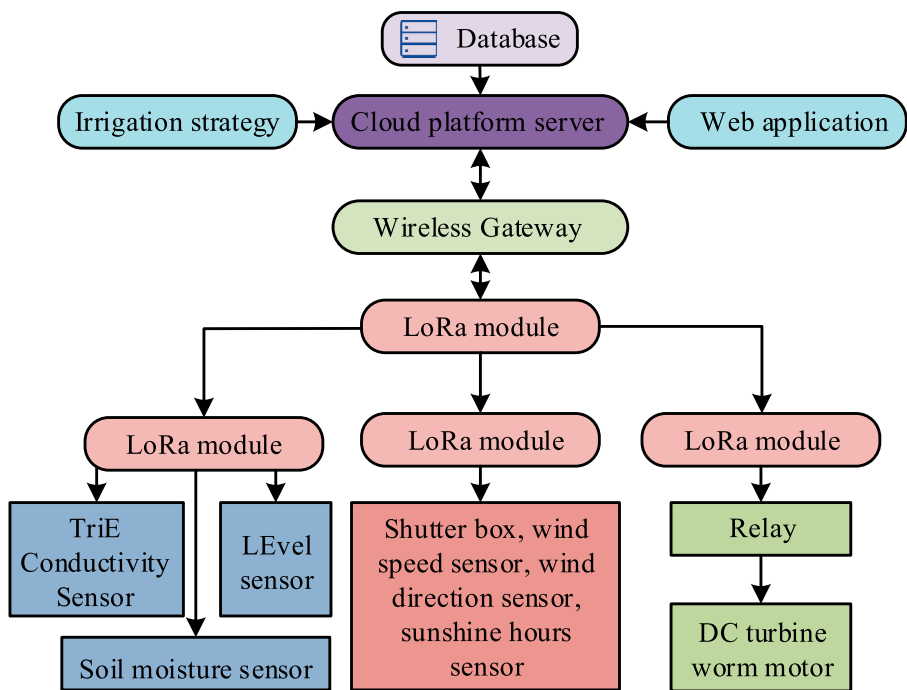


FIGURE 3
Schematic diagram of the hardware architecture of the agricultural WSI system designed for research.

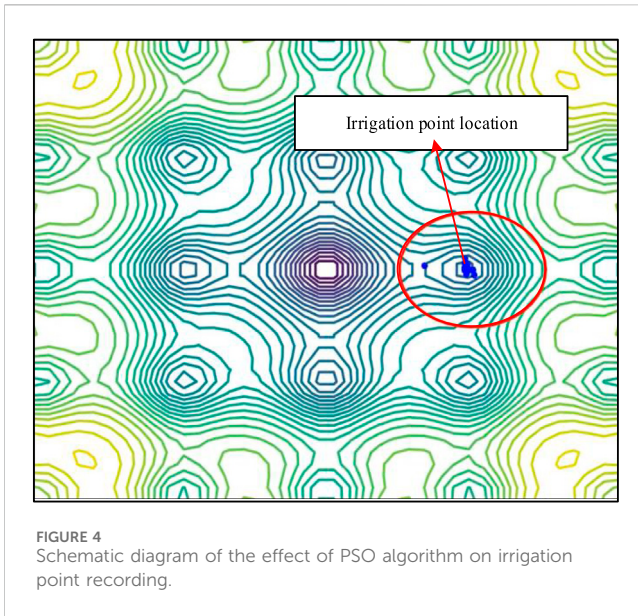
control terminal to control the circuit. MCU is a portable product with high integration, small size, high reliability, strong control function, low voltage, low power consumption, and easy production. The application fields of MCU are very extensive, such as smart meters, real-time industrial control, communication devices, navigation systems, household appliances, etc. The hardware architecture of the WSI system for farmland research and design is shown in Figure 3.

In Figure 3, the power supply module is involved to drive the power supply to control the operating voltage of all the sensors in the irrigation system. In addition to this, the study considers the atmospheric pressure, natural wind speed, sunlight light intensity

and natural humidity in the air environment. Therefore the optimization system such as louver box, soil moisture sensor and light sensor are added to the irrigation system.

3.2 Predictive irrigation technology based on PSO-ELM algorithm for crop water use in farmland

After the hardware configuration planning of the automatic WSI technology in farmland is completed, it is also necessary to consider the accuracy of the irrigation system in controlling the amount of



IW demanded by farmland crops. Based on this, the study introduces PSO to effectively solve the water demand projection of the irrigation space. PSO is a stochastic search technique that first requires the initialization of all particles and their positions and velocities to imitate the foraging behavior of flocks of birds and collective intelligence (Liu et al., 2021; Camacho-Villalón et al., 2021; Demir and Sahin, 2023). At the outset of the calculation, the study normalizes all water data to ensure the algorithm's generalizability and accelerate the convergence speed of the algorithmic learning process. The normalization equation is shown in Equation 7.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (7)$$

Equation 7 represents the linear normalization function. Among them, X_{norm} represents the normalized data, X represents the original data, X_{max} represents the maximum value (MaxV) of the dataset, and X_{min} represents the minimum value (MinV) of the dataset. Once the data normalization process is complete, it is essential to establish the historical best pBest of the particles as the current position and the best particle in the population as the current gBest. Subsequently, it is essential to calculate the fitness function values for each particle in each iteration. It is assumed a flock of birds foraging, with m birds forming a group in a D -dimensional space, the position of the i th bird is calculated as shown in Equation 8.

$$Xi = (x_i^1, x_i^2, \dots, x_i^D) \quad (8)$$

In Equation 8, Xi represents the location of the i th bird, or the location of the i th plant irrigated. From this, it can be inferred that the point position of the crop in the irrigated area is calculated as shown in Equation 9.

$$Pi = (p_i^1, p_i^2, \dots, p_i^D) \quad (9)$$

In Equation 9, Pi represents the point in the irrigated crop where the most accurate amount of water is used. Based on Equation 9 the

irrigation rate can be deduced as the average appropriate water use of the irrigation system, which is calculated as shown in Equation 10.

$$V_i = (v_i^1, v_i^2, \dots, v_i^D) \quad (10)$$

In Equation 10, V_i represents the irrigation rate of the i th plant. In summary, the irrigation rate at different points and the irrigated area points can be deduced and calculated as shown in Equation 11.

$$v_i^d = w v_i^d + c_1 r_1 (p_i^d - x_i^d) + c_2 r_2 (p_g^d - x_i^d) \quad (11)$$

In Equation 11, v_i^d represents the irrigation rate at different points. r represents the transformed random number in the interval 0–1. p_g^d represents the point position with the smallest adaptation value for the whole irrigation area. Figure 4 illustrates the impact of the PSO algorithm suggested in the study on the recording of irrigation sites.

However, the PSO algorithm also has drawbacks in that it cannot optimize the collected point data in the implicit layer, and it can confuse and overlap with the recorded data, which affects the accuracy of irrigation prediction. To enhance the irrigation system's computational accuracy and learning speed, the study presents the ELM method, which is based on the PSO algorithm. The novel feature of the ELM algorithm is that it significantly decreases computation because the connection weights between the implicit and input layers can be set randomly and do not need to be modified repeatedly (Bandewad et al., 2023). The second is that the connection weights do not need to be adjusted iteratively and can be solved at once by solving a system of equations. The study assumes a neural network with L hidden points. Its expression is shown in Equation 12.

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = o_j, j = 1, 2, \dots, N \quad (12)$$

In Equation 12, g represents the required connection weights for ELM. X_j represents the activation equation. β_i represents the output weights. b_i represents the position of the i th implicit point. N represents either sample and W_i represents the inner product. If the error in the output weights needs to be controlled, Equation 13 is obtained.

$$\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) = t_j, j = 1, 2, \dots, N \quad (13)$$

The nodes of the single-layer implicit neural network can be derived from Equation 13, which is calculated as shown in Equation 14.

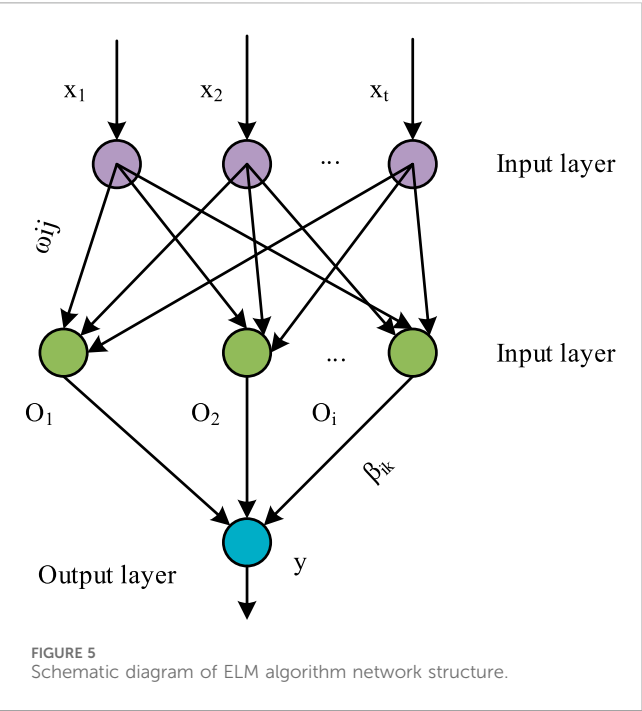
$$\|H(W_i^A b_i^A - T)\| = \min_{W, b, \beta} \|(W_i, b_i) \beta_i - T\| \quad (14)$$

In Equation 14, T represents the hidden node output. T represents the desired output value. From this the minimum loss function of ELM can be calculated as shown in Equation 15.

$$E = \sum_{j=1}^N \left(\sum_{i=1}^L \beta_i g(W_i \cdot X_j + b_i) - t_j \right)^2 \quad (15)$$

In Equation 15, E represents the minimization loss function. The weights of single layer implicit neural network are calculated as shown in Equation 16.

$$\beta = H + T \quad (16)$$



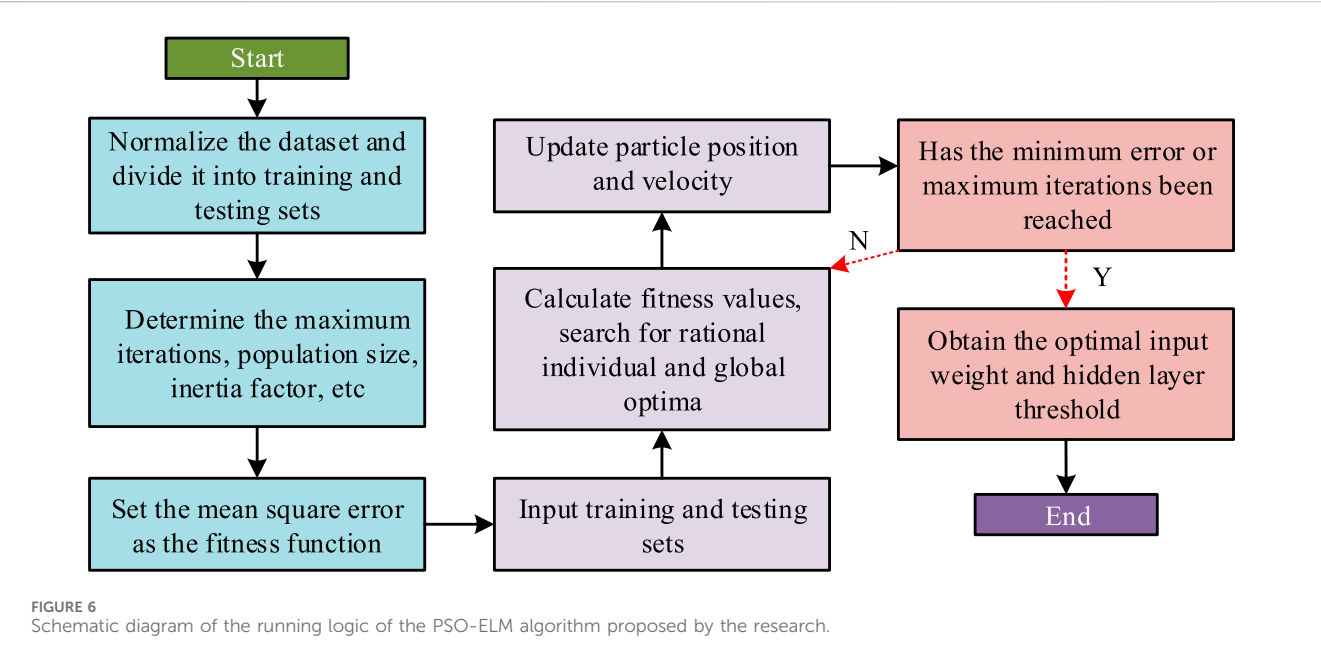
According to Equation 16 the MinV as well as the unique value can be measured accurately. Combining the aforementioned requirements, Figure 5 depicts the ELM algorithm’s network topology.

The final project builds an intelligent automatic WSI system for farming based on the PSO-ELM algorithm, combining the benefits of the two algorithms. The PSO-ELM algorithm constructed by the study firstly needs to normalize the collected historical data of IW use, and then set the training set and test set. Immediately after that, an implicit node restriction needs to be applied to the input data set of the ELM. It is then subdivided into the output layer, as well as the

need to set restrictions on the number of training iterations, IW particle intervals for the PSO algorithm. The study adopts mean squared error (MSE) as the regression evaluation index and calculates the single crop water requirement as the optimization benchmark to adjust the global particles. The study then investigates the final optimal parameter that can be obtained by comparing the error minimization records for the number of iterations. This parameter will be applied as a representative index in the irrigation system. In summary, the operation logic of the PSO-ELM algorithm proposed by the study is shown in Figure 6.

3.3 Experimental design and evaluation methods

This study uses data from two sources. The first source is a historical dataset of major farmland ecological sites in northern China from 2003 to 2025, published by the China Meteorological Science Data Center. The second source is real-time data collected by a sensor network deployed in a wheat-maize rotation experimental field in the North China Plain. The historical dataset has a data volume of approximately 1.2 GB and includes over 400000 valid daily records. Each record contains 14 original characteristic variables, including average temperature, maximum temperature, minimum temperature, average relative humidity, average wind speed, sunshine hours, precipitation, and reference crop evapotranspiration calculated using the Penman Monteith formula. Meteorological data is collected once a day. To match irrigation decision-making needs, soil moisture data is generated through virtual sensors at a frequency of once every 30 min. Moreover, its daily average is calculated and included in the dataset. During the 120 days experimental period, the real dataset deploys 5 soil moisture sensors and 1 micro meteorological station in each experimental field, collecting over 17000 valid data records. In the experiment, data cleaning, feature selection, and dataset



partitioning are required. First, quality control is applied to the raw data to eliminate outliers that are clearly beyond the physical range. For a small number of missing values, time series linear interpolation is used to fill in. Then, based on the principles of agricultural hydrology, characteristics directly related to crop water demand are selected. These characteristics include temperature, humidity, wind speed, sunshine, and soil moisture. The Pearson correlation coefficients between all preliminary characteristics and actual IW requirements are calculated, and characteristics with correlation coefficients below 0.1 are excluded. Thus, eight characteristics are determined for the model input, including average temperature, daily maximum temperature, average relative humidity, average wind speed, sunshine hours, previous day soil moisture, cumulative precipitation, and reference crop evapotranspiration. Finally, the 7:3 ratio is divided into training and testing sets.

After completing data preprocessing, to fairly evaluate the performance of PSO-ELM, the study selects backpropagation neural network (BPNN), wavelet neural network (WNN), and standard extreme learning machine (ELM) as baseline models for comparison. The comparative indicators include prediction error RMSE, MAE, as well as goodness of fit R^2 and actual water-saving effect. To avoid the limitations of traditional voting counting methods, this study used effect size analysis to quantify the performance differences between PSO-ELM and various baseline models. This was done by calculating Cohen's d and combining it with an independent sample t -test to verify the statistical significance of the differences ($\alpha = 0.05$). This ensured the statistical robustness of the model comparisons. To address the issue of incomparability caused by dataset heterogeneity, time scale differences, and differences in indicator dimensions, this study standardizes all indicators. For error indicators such as RMSE and MAE, the min max scaling method is used to convert them to the $[0, 1]$ interval to eliminate the influence of dimensionality. To account for variations in data types and time periods, these standardized metrics must be further converted into z -scores. All data should be uniformly transformed to a common baseline for description, ensuring fair comparisons across different scenarios. To enhance the objectivity of experimental quality evaluation, this study uses inter rater reliability for testing. Two researchers with agricultural intelligent algorithm backgrounds independently verifies the accuracy of experimental data input and the accuracy of evaluation index calculation. Subsequently, Cohen's kappa coefficient is used to quantify consistency, with a kappa coefficient of 0.92, indicating excellent consistency.

4 Results

To verify that the proposed PSO-ELM algorithm can improve the WSI system, the experiment firstly analyzes the error of the algorithm and compares the R^2 value, so as to prove the effectiveness and advantages of the algorithm. Second, the PSO-ELM algorithm is combined with the WSI system to carry out experiments to compare the results of monitoring soil moisture and sunshine hours, which are the indicators of irrigation impact. Finally, the WC and crop output of the technology are compared.

4.1 Impact analysis of PSO-ELM algorithm on automatic WSI technology in farmland

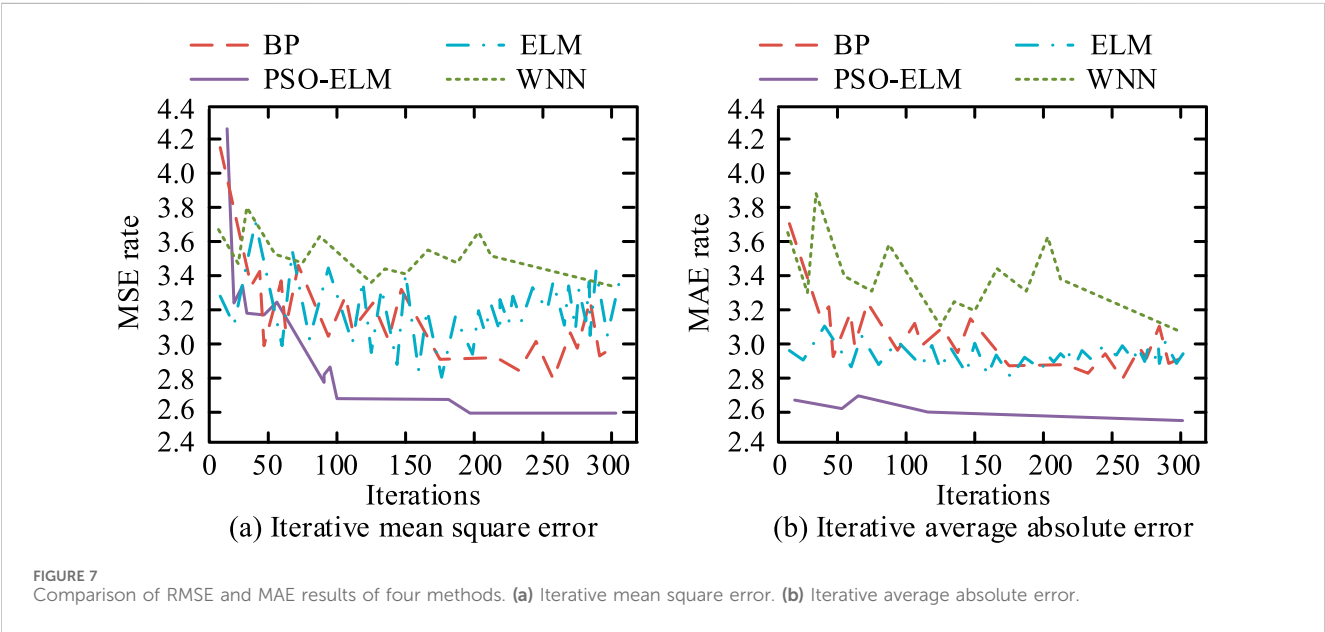
To ascertain whether the PSO-ELM algorithm and microcontroller proposed by the research can enhance the efficacy of automatic WSI technology in agricultural settings, a series of experiments are conducted. First, in order to determine the optimal values of population size, iteration times, and inertia weights in the proposed algorithm, this study designs ablation experiments. By holding other parameters constant and altering the target parameter's value, the optimal parameter combination is selected through comparing the model's RMSE, MAE, and R^2 values on the test set, as well as the accuracy of water demand forecasts. ELM has 30 hidden layer nodes, activation function Sigmoid, and regularization coefficient 0.01. The results are shown in Table 2.

In Table 2, when the population size is 10, the RMSE is 0.186, which is the maximum. R^2 is the smallest at 0.921. The insufficient number of particles at this time results in inadequate coverage of the search space. This makes it difficult to find the optimal initial parameters for ELM. As the population size increases, particle diversity improves, search accuracy improves, RMSE decreases, and R^2 increases. However, when the population size exceeds 30, RMSE increases. The reason is that too many particles lead to computational redundancy and are prone to oscillations around local optimal values. This results in comprehensive performance and computational efficiency. When the number of iterations is 50, the RMSE is 0.215, which is the maximum. At this point, the particles have not fully explored the parameter space. When the number of iterations gradually increases to 300, RMSE continues to decrease and R^2 increased, indicating that increasing the number of iterations promotes parameter optimization. When the number of iterations is 400, the RMSE decreases by only 0.001. This indicates that the performance improvement is relatively small, but the iteration time increases significantly. When the inertia weight is 0.07, the RMSE is the smallest at 0.103 and the R^2 is the largest at 0.986, indicating a balance between global and local search. Overall, it can be determined that the optimal population size is 30, the optimal number of iterations is 300, and the optimal inertia weight is 0.7. Then, the PSO-ELM algorithm is used to analyze the error in determining irrigation demand. The experiment introduced BPNN, WNN, and single ELM method. The comparison results are shown in Figure 7.

In Figure 7a, the MSE of the proposed PSO-ELM algorithm under study reduces with the increase in the iterations and the curve shows a decreasing state. The maximum of the MSE appears before 50 iterations with a value of 4.3. Its error curve stabilizes when it is iterated up to 100 times. The minimum occurs in the interval of 200–300+ iterations with a value of 2.6. This indicates that the calculation error of PSO-ELM algorithm tends to stabilize with the increase of irrigation demand. The MSE curve of the WNN algorithm is at the top, indicating that the error is large and the algorithm has a poor impact. The MaxV of the root mean squared error (RMSE) for WNN is 4.19 and the MinV is 3.4. In Figure 7b, the mean absolute error (MAE) of the proposed PSO-ELM algorithm of the study reduces with the increase in the iterations, and the curve shows an overall flat decreasing state. This indicates that the proposed method has the lowest error and overall performance is relatively stable. The maximum MAE occurs in the interval of

TABLE 2 Ablation experiment.

Parameter	Parameter values	RMSE	MAE	R2	Prediction accuracy (%)
Population size	10	0.186	0.152	0.921	90.5
	20	0.112	0.091	0.978	97.2
	30	0.108	0.088	0.981	97.5
	40	0.115	0.093	0.976	96.8
	50	0.132	0.105	0.965	95.3
Iteration count	50	0.215	0.178	0.896	88.2
	100	0.142	0.118	0.952	93.5
	200	0.110	0.090	0.979	97.3
	300	0.102	0.082	0.987	98.1
	400	0.101	0.081	0.988	98.2
Inertia weight	0.4	0.156	0.125	0.945	92.8
	0.5	0.132	0.108	0.963	95.1
	0.6	0.115	0.095	0.975	96.7
	0.7	0.103	0.083	0.986	97.9
	0.8	0.128	0.102	0.969	95.7



50–100 iterations, with a value of 2.7. Its error curve stabilizes after 100 iterations, and the minimum occurs in the interval of 250–300+ iterations, with a value of 2.3. The MAE curve of the WNN algorithm remains at the top, indicating that the mean absolute error between the algorithm’s predicted and true values is large and the algorithm has little impact on the irrigation system. The MaxV of the RMSE of WNN is 3.9 and the MinV is 3.1. The above data proves that the research’s proposed combined algorithm has smaller calculation errors than other similar algorithms. It has a minimum mean square error of 2.6 and 2.3, respectively, which

greatly improves the irrigation system. The experiment employs the PSO-ELM and WNN algorithms to predict evapotranspiration of crops. These algorithms exhibit a notable discrepancy in error, thereby further substantiating the merits of the proposed algorithm. The test results are shown in Figure 8.

In Figure 8a, the maximum phase of predicted volatilization of evapotranspiration by the proposed method of the study appears between 0–50 days and 400–450 days, with a high value of 9.6 mm. However, the minimum phase of volatilization occurs between 248 and 276 days, with a value of –1.8 mm. The actual

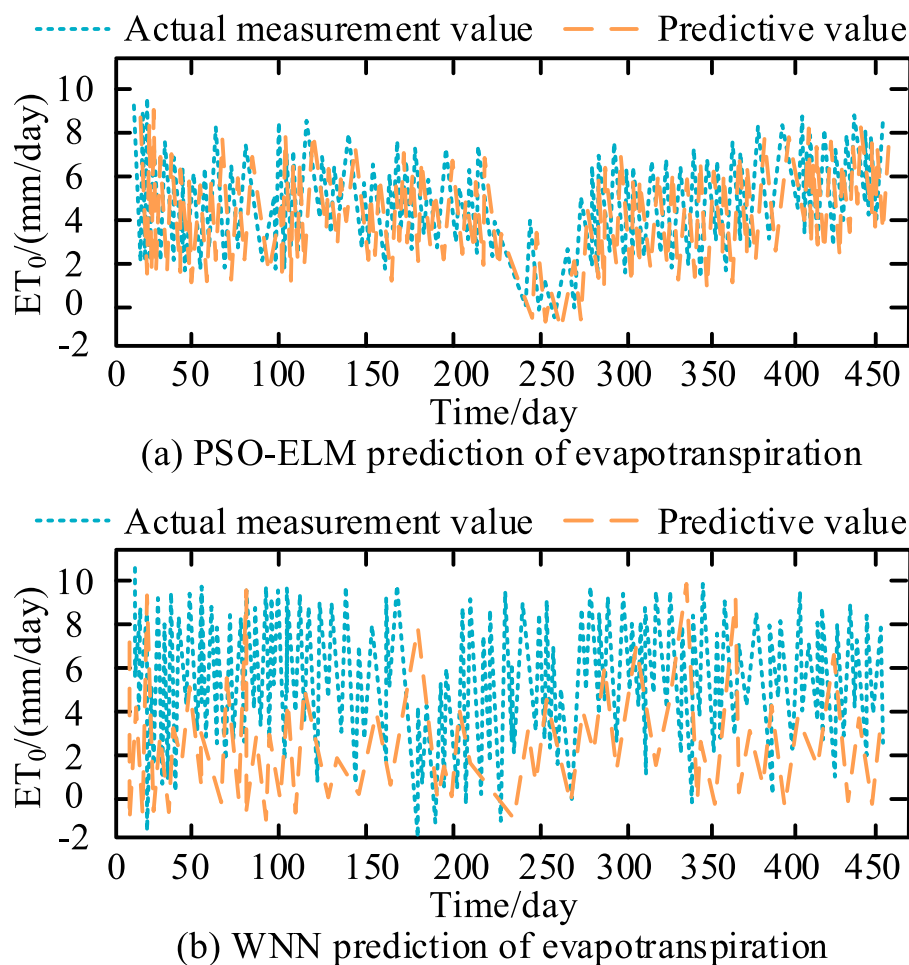


FIGURE 8
Comparison of two methods for predicting crop evapotranspiration. (a) PSO-ELM prediction of evapotranspiration. (b) WNN prediction of evapotranspiration.

volatilization is in line with the range of predicted volatilization peaks and troughs, with a maximum of 9.5 mm and a minimum of -1.9 mm. Peak and troughs are in agreement with the prediction of the data both differed by 0.1 mm. It can be clearly seen from Figure 8a that the predicted volatility curve is close to the actual volatility curve, indicating that the PSO-ELM algorithm can accurately predict crop evapotranspiration. In Figure 8b, the prediction results of CET by the WNN algorithm differs greatly from the actual evapotranspiration results. The maximum stage of evapotranspiration predicted volatilization occurs between 0 and 50 days, which is as high as 9.9 mm. However, the minimum stage of volatilization occurs between 200 and 250 days, with the value of -2 mm. The MaxV of actual volatilization is 10 mm, and the MinV is -1.9 mm. This indicates that the method does not enhance the performance of the irrigation system. In general, the predictive performance of the PSO-ELM algorithm is superior, with a maximum difference of only ± 0.1 mm from the actual volatilization amount. It can provide decision-making reference for saving IW. The experiment concludes with a comparison of the R^2 and RMSE results of the four methods as a means of verifying

that the proposed algorithm of the study is able to locate the point of the crop to be watered faster. The results are shown in Figure 9.

In Figure 9a, the RMSE value of the proposed method of the study is the lowest with a mean value of only 0.1025 . It suggested that the PSO-ELM algorithm is the most accurate for irrigation prediction. The BPNN algorithm has the largest RMSE value of 5.0410 . The RMSE value of ELM algorithm is second only to the value of the algorithm proposed in the study with a mean value of 0.6078 . The mean value of RMSE of WNN algorithm is 0.7577 . In Figure 9b, the higher value of R^2 represents that the result is closer to the accurate value. The PSO-ELM algorithm has the largest R^2 value of 0.9876 . The BP algorithm has the smallest R^2 value of 0.7889 . The R^2 values of WNN and ELM are in the middle of the range of 0.9188 and 0.8652 , respectively. In summary, the PSO-ELM algorithm proposed in the study can greatly enhance the performance of the automatic irrigation system. It is able to control irrigation accurately and at the same time predict the factor variables rationally. The algorithm can provide strong technical support for the accuracy and energy saving of irrigation technology.

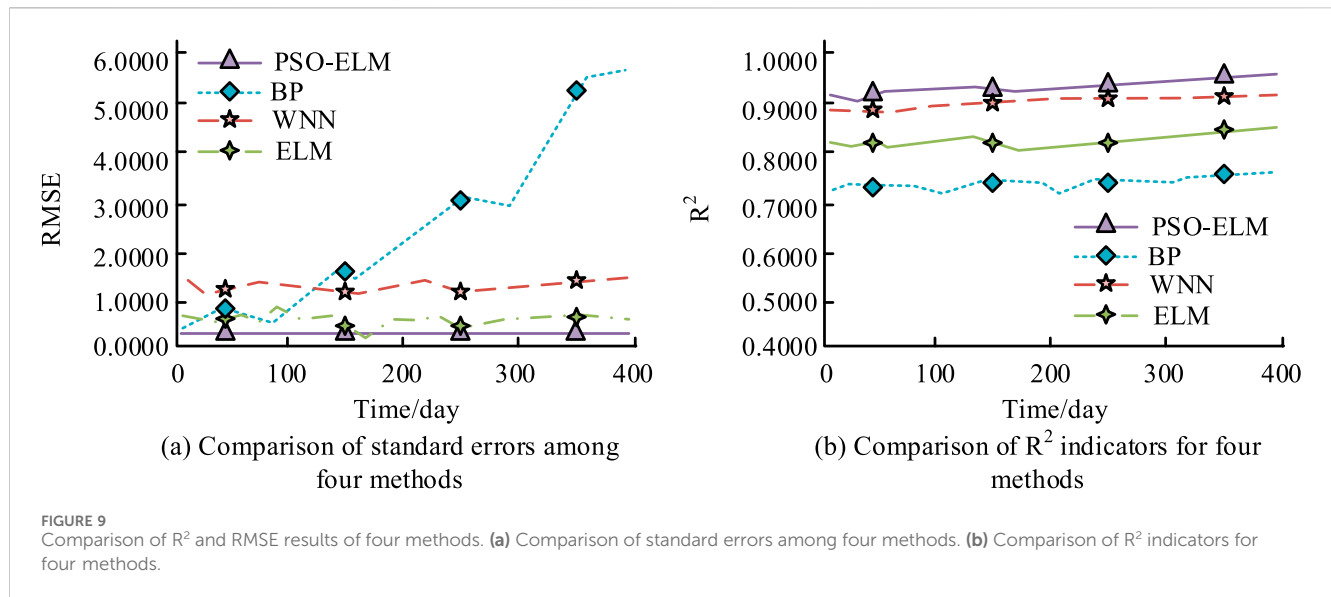


TABLE 3 Partial data of test set.

Time/day	Average temperature/°C	Daily maximum temperature/°C	Average relative humidity/%	Average wind speed m/s	Daily minimum temperature	Sunlight hours1
1	21.7	33.2	45	6.5	13.6	11
2	20.8	29.3	70	6.0	10.6	6.4
.....	—	—	—	—	—	—
3599	25.6	30.8	69	2.1	25.6	11.2
3600	24.3	30.6	82	3.1	24.3	9.5

4.2 Experimental analysis of automatic WSI technology for farmland based on PSO-ELM algorithm and MCU

In order to verify that the PSO-ELM combination algorithm proposed in the study has more accurate water control for farmland irrigation, the climate conditions of a certain irrigation plain are referred to as the data for the test set, and simulation experiments are conducted. Due to the limited geographical location of the experiment, a static application is chosen. At the outset of the experiment, it is hypothesized that dynamic applications necessitate a dynamic data simulation system capable of updating and responding to farmers' inputs in real time. This is to ensure that the application can reflect changes and demands in the real world at runtime. The final experiment uses Matlab R2019b software to simulate and calculate the irrigation model. The experimental observation period is 3600 days, involving the climate conditions, average wind speed, soil moisture, etc. of the plain. The training set data is sourced from the National Meteorological Science Center <http://data.cam.cn>. The test set data is shown in Table 3.

The experiment randomly selects 7 days of observation data to test the performance of the smart self-service WSI system on farmland. The irrigation impact indicators soil moisture as well as sunshine hours of these 7 days observation data are also

compared. The monitoring results and measured results are shown in Figure 10.

In Figure 10a, the irrigation system based on PSO-ELM algorithm proposed by the study is more accurate in monitoring the sunshine hours. Among them, the monitoring results on days 3, 6, and 7 are consistent with the measured results. The longest sunshine hours occur on day 7 with 14.5 h. The shortest sunshine hours occur on day 2 with 1.00 h, and the measured hours are 1.05 h, with a difference of only 0.5 h. This indicates that the proposed algorithm is able to accurately control the sunshine information in the actual monitoring of the farmland. It is very useful for the control of soil moisture as well as the WC of plant irrigation. In Figure 10b, the proposed irrigation system based on PSO-ELM algorithm can accurately control the soil moisture in the farmland. The monitoring results on days 1, 2, 3, and 6 is consistent with the measured results. The highest value of soil moisture retention occurs on day 3 with a value of 89.5%. The lowest value of soil moisture retention occurred on day 4 with a value of 87.7% and the measured moisture is 87.0% with a difference of 0.7%. This shows that the proposed method can control the soil moisture in the farmland to be irrigated, which can provide an accurate reference for the water supply of the WSI system. At the end of the experiment, the crop yield and WC of the irrigated plain are analyzed, and simulation experiments are conducted by combining

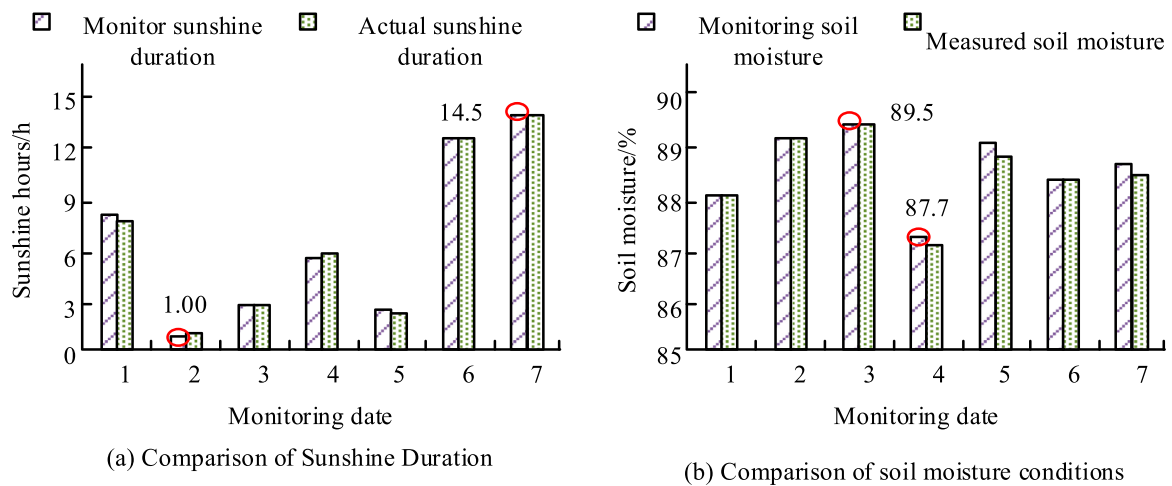


FIGURE 10 Comparison of sunshine count and soil moisture using the method proposed by the research. (a) Comparison of Sunshine Duration. (b) Comparison of soil moisture conditions.

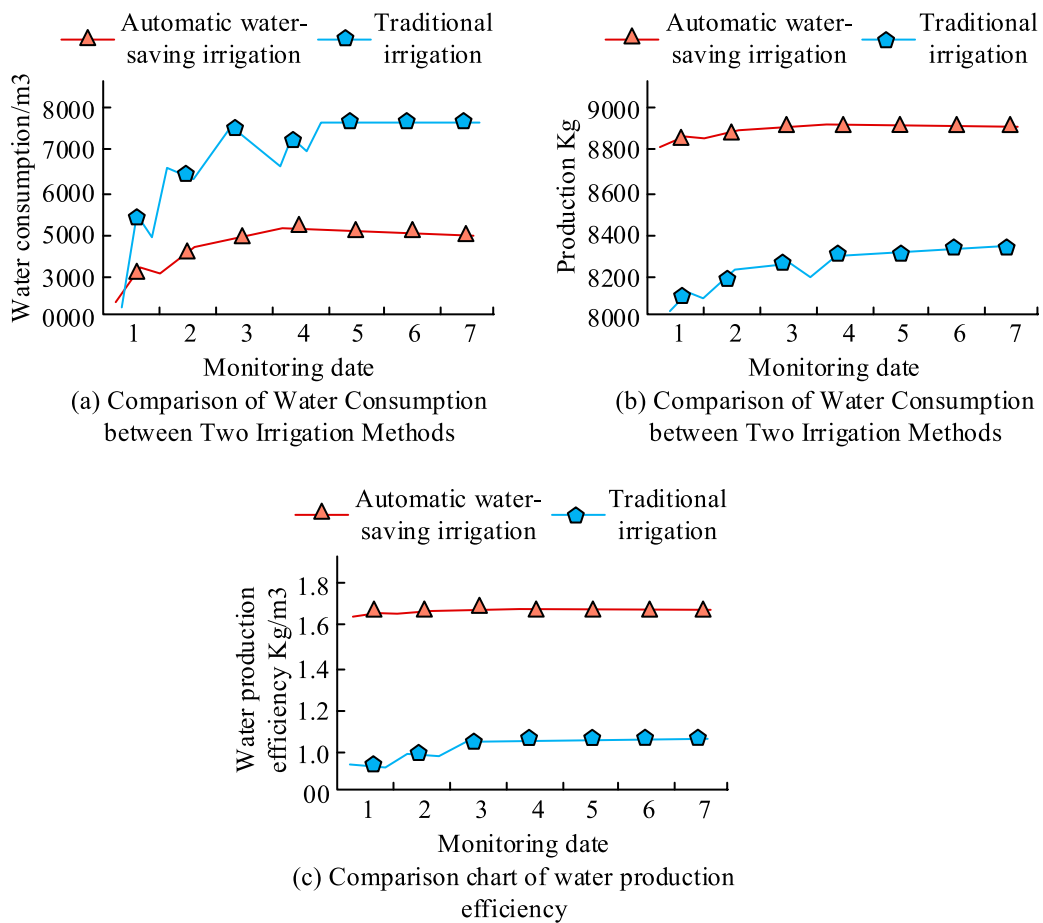


FIGURE 11 Comparison of production efficiency between traditional irrigation methods and research methods. (a) Comparison of Water Consumption between Two Irrigation Methods. (b) Comparison of Water Consumption between Two Irrigation Methods. (c) Comparison chart of water production efficiency.

TABLE 4 Performance comparison of different irrigation systems in real scenarios.

Evaluation metrics	Total irrigation water consumption (m ³ /hm ²)	Crop yield (kg/hm ²)	Water productivity (kg/m ³)
Conventional irrigation methods	6985.4 ± 345.2	8125.6 ± 285.4	1.16 ± 0.08
Automatic irrigation system based on microcontroller and PSO-ELM	4326.8 ± 198.7	8765.3 ± 192.1	2.03 ± 0.11
<i>t</i>	25.67	9.89	38.45
<i>p</i>	<0.05	<0.05	<0.05

traditional methods of artificial irrigation with the methods proposed in the research. The results are shown in Figure 11.

In Figure 11a, the proposed automatic WSI technique for farmland based on PSO-ELM algorithm is studied with less WC. The maximum WC of the traditional irrigation method appears on day 3 with a value of 7647.1 m³/hm². The minimum WC of the irrigation system proposed by the study appears on day 1 with a value of 3015 m³/hm². The maximum WC appears on day 4 with a value of 5268.3 m³/hm². In Figure 11b, the difference in crop yield between the two irrigation methods is also large. The maximum crop yield of the irrigation system mentioned in the study is 8840.5 kg/hm². However, the maximum crop yield under the conventional irrigation method is only 8260.5 kg/hm² and the minimum yield is 8009.3 kg/hm². In Figure 11c, the water productivity varies between the two irrigation methods. The MaxV of water production efficiency of the irrigation system proposed by the study is 1.68 kg/m³. Whereas, the water production efficiency of the conventional irrigation method is lower with a value of 1.06 kg/m³. The above data shows that the irrigation system with the control algorithm proposed by the study is able to use less IW. This produces more crop volume and higher water supply efficiency, which is a better overall performance than traditional irrigation methods. This method can greatly achieve the effect of WSI, and plant irrigation. To further verify the effectiveness of the microcontroller-based automatic irrigation system using the PSO-ELM algorithm, a 120-day field experiment was conducted in a wheat-maize rotation area in northern China. The experiment is divided into a control area and an experimental area, each with an area of 1 ha. The control area adopts conventional irrigation methods, while the experimental area deploys the proposed automatic irrigation system. During the experiment, the total IW consumption, crop yield, and water productivity are recorded. The results are shown in Table 4.

As shown in Table 4, the total IW consumption of the proposed system is 4,326.8 ± 198.7 m³/hm², which is significantly lower than that of conventional irrigation methods. The proposed system can save 38.1% of water, which is a statistically significant difference ($p < 0.05$). The crop yield of the proposed system is 8765.3 ± 192.1 kg/hm², while the crop yield of conventional irrigation methods is 8125.6 ± 285.4 kg/hm². Compared with conventional irrigation methods, the proposed system increases yield by 79%, with a significant difference ($p < 0.05$). The water productivity of the proposed system is 2.03 ± 0.11 kg/m³, which is much higher than that of conventional irrigation methods. There is a significant difference between the two ($p < 0.05$). The above results indicate that the proposed system can adapt to real fluctuations in agricultural environments, proving its effectiveness and reliability in practical applications.

5 Discussion and conclusion

With the advancement of science and technology, China's automatic IW-saving technology for farmland is also tending toward intelligent development, but there are also problems such as high water demand, high WC rate and high labor cost. To solve these problems, it is necessary to study how to accurately control IW consumption and improve water efficiency. Therefore, the study proposed an automatic WSI algorithm for farmland that combined microcontroller technology with the PSO-ELM algorithm. The results showed that the maximum mean square error of the PSO-ELM algorithm proposed by the research occurred before 50 iterations, with a value of 4.3 and a MinV of 2.6. The MaxV of the MAE index was 2.7 and the MinV was 2.3. This indicated that the combined algorithm proposed by the research had small calculation errors and could accurately irrigate according to irrigation needs and environmental characteristics, which greatly improved the entire irrigation system. In addition, the automatic WSI technology for farmland proposed by the research required less water, with a minimum WC of 3015 m³/hm² and a maximum WC of 5268.3 m³/hm². The accuracy of predicting the IW demand for crops using the irrigation system proposed by the research could reach over 98%. This study validates the effectiveness and enormous potential of data-driven methods that combine intelligent optimization algorithms and embedded hardware to solve complex problems in the optimization of agricultural systems. At the same time, it provides multiple insights for the development path of intelligent agriculture. For agricultural technology promotion and policymakers, the importance of investing in agricultural IoT data infrastructure has been emphasized. Forward looking investment is needed in agricultural IoT data infrastructure. Data insights should be transformed into fair water-saving incentive policies. For agricultural engineers and data scientists, it reveals the necessity of interdisciplinary collaboration. The deep integration of advanced algorithms with reliable hardware requires full consideration of the complexity of the agricultural environment. It also requires consideration of the limitations of equipment computing power and the usage habits of farmers. The integration of computational intelligence tools provides agronomists and producers with an opportunity to quantify and model traditional planting experience. This shifts irrigation decisions from experience-driven to data-driven. However, this study still has some limitations. Although LoRa technology is an ideal choice for this system because of its low power consumption and ability to communicate over long distances, complex terrain in rural farmland environments may obstruct and attenuate signals,

leading to unstable communication when the technology is deployed. The hardware cost of deploying a large number of sensor nodes, the maintenance cost in the later stage, and the requirement for farmers' technical literacy will also have an impact on its promotion. At the same time, the system's economic feasibility has not been thoroughly analyzed. The initial cost of a complete automatic irrigation system, including sensors, microcontrollers, actuators, communication modules, and software development, is relatively high. The investment payback period between it and the long-term benefits brought by water-saving and income increase is still unclear. For small-scale farmers with weaker capital capacity, this is the core consideration in deciding whether to adopt this technology. Therefore, future research will optimize network topology, introduce relay nodes to enhance the robustness of LoRa networks in complex environments, and explore low-cost, open-source hardware solutions to reduce deployment costs. In addition, long-term and large-scale field trials will be conducted to quantify the comprehensive benefits of the system in terms of water conservation, yield increase, and labor savings. Detailed cost-benefit analysis will be conducted to provide clear economic feasibility reports for farms of different operating scales. Explore sustainable business models based on services. Examples include government or cooperative investment in building cloud platforms and infrastructure, as well as farmers using services through leasing or pay-as-you-go. These models lower the initial investment threshold for small farmers and improve the accessibility and scalability of technology.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HJ: Methodology, Validation, Conceptualization, Data curation, Resources, Writing – original draft, Writing – review and editing, Visualization, Formal analysis. DS: Methodology, Validation, Conceptualization, Data curation, Resources, Writing – original draft, Writing – review and editing, Visualization, Formal

analysis. CZ: Methodology, Validation, Conceptualization, Data curation, Resources, Writing – original draft, Writing – review and editing, Visualization, Formal analysis.

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