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Article

Research on irrigation and drainage optimization strategy combining hydrological model and data mining technology

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Abstract: With the deepening of the integrated development of agriculture, the precision of intelligent irrigation and drainage is increasingly required. In this paper, in the research of optimizing irrigation and drainage strategies, a virtual platform is used to realize the running simulation of hydrological model and model the hydraulic characteristic parameters in it. At the same time, the optimal parameters of the model are predicted and adjusted by combining data mining technology to build a water and fertilizer irrigation intelligent decision-making system to improve the utilization rate of water resources. After prediction and testing, the system adjusts the soil water content parameter downward in the first half of this year, so that the coincidence rate between the predicted water diversion and the actual water diversion is more than 95%, the irrigation water utilization rate is greatly improved, and the soil drainage is more in line with the actual situation.

Keywords: hydrological modeling; data mining techniques; parameter adjustment; irrigation drainage; intelligent decision making

1. Introduction

At present, the rapid development of social economy, so that the quality and technical level of water conservancy engineering has also been effectively enhanced, and water conservancy engineering to a certain extent and promote social and economic development [1-2]. Accompanied by the continuous development of water conservancy engineering and drainage business, in the analysis of the moisture status of farmland and the change rule of regional water conditions, irrigation and drainage put forward higher requirements, not only to effectively promote animal husbandry and agricultural production, for the rational use of water resources to lay a good foundation for the development of water resources, but also more to play an important role in defending against droughts and floods in the regulation of the disaster [3-6].

At present, global warming has led to changes in precipitation patterns, extreme dry and early events occur frequently, resulting in hydrological disorders, and many areas are in serious water shortages, coupled with the existing irrigation and drainage facilities and other aspects of aging, not only resulting in the quality of the entire irrigation and drainage system and the efficiency of the downward trend, but also reduces the ability to prevent disasters [7-10]. The traditional irrigation strategy is based on diffuse irrigation channel water transmission process due to leakage and evaporation loss of large amounts of water resources, and irrigation efficiency is low, but also easy to lead to excessive or insufficient local water; at the same time, long-term excessive irrigation so that the salts with the water rising accumulation of the surface, triggering salinization; excessive extraction of groundwater leading to water table decline, ground subsidence and other problems [11-14]. In addition, agriculture accounts for seventy percent of global water use, but the effective utilization of water is less than fifty percent [15]. Therefore, optimizing irrigation and drainage strategies is not only related to the advantages and disadvantages of water resources utilization to a certain extent, but also reflects whether the actual production of water conservancy projects plays an important role and benefits.

With the development of smart agriculture, more intelligent equipment is put into the irrigation and drainage system to monitor the hydrological environment and provide a scientific basis for dynamic irrigation and drainage decision-making [16-17]. Traditional irrigation and drainage strategies based on experience gradually expose defects, while hydrological models are based on mathematical and statistical principles and hydrological theories, and mathematical relationships describing hydrological processes are established by processing and analyzing hydrological data [18]. For example, runoff models, evaporation models and rainfall models are able to provide long-term mean values, frequency distributions, and other statistical characteristics of hydrological variables through quantitative description of hydrological processes, which provide a basis for the design and strategic planning of irrigation and drainage systems [19-21]. However, a single hydrological model results in biased observations due to the simplified model structure and the exclusion of parameters such as topographic features and abrupt characteristics [22]. The data mining technology can mine the hidden laws from a large amount of monitoring data for analysis and prediction, break through the limitations of hydrological models, and collaborate to support the optimization of irrigation and drainage decision-making.

The core content of irrigation and drainage work is to solve the water condition in a certain area with the help of irrigation and drainage engineering measures, etc., and the irrigation channel system mainly undertakes the work of water transportation and distribution tasks to discharge the excess water [23-24]. Optimization studies of hydrological models in irrigation and drainage have shifted from traditional hydrological models to intelligent algorithm empowerment. Literature [25] constructed a simulation-optimization model for optimal irrigation scheduling of crops based on the AquaCrop model and optimization model, and analyzed the optimal irrigation scheduling of wheat under uncertain conditions (hydrological situation, crop price, etc.). Literature [26] proposed an integrated hydrological-irrigation optimization modeling system based on a distributed hydrological model to optimize rice irrigation strategy by using the initial reservoir level at the beginning of crop planting and different maximum water releases. Literature [27] used the Soil and Water Assessment Tool (SWAT) model to simulate irrigation schedules under different hydrological scenarios in arid regions of the basin, and introduced hierarchical analysis and gray correlation analysis to output the optimal irrigation strategy. Literature [28] combined a nonlinear algorithm and a support vector machine regression model to form a two-layer model, which optimized planting structure and irrigation water use and predicted drainage to achieve better irrigation and drainage in irrigated areas. Literature [29] constructed a genetic algorithm (GA)-based optimization model for an irrigation network channel system, which reduced leakage losses, evapotranspiration, and total water demand by scientifically designing the water supply time and flow allocation of the system to improve water utilization.

In addition, literature [30] combined the simulation of physical movement process of water-salt equilibrium in the field and GA to formulate a synergistic optimization model of irrigation and drainage considering groundwater hydrology in arid farmland, and issued an optimization plan for monthly irrigation and drainage, which led to an 8% increase in the efficiency of irrigation and drainage system and maintained the optimal level of groundwater. Literature [31] developed an optimization model based on multi-objective GA to optimize water allocation and planting structure selection in an irrigation and drainage network in a region, which effectively reduced water consumption and increased net profit. Literature [32] constructed a regional irrigation water use optimization model by combining an agro-hydrological model and a non-dominated sorting GA with the objectives of minimizing irrigation water use and maximizing crop yields, and achieved an increase in irrigation benefits through multi-level collaboration among farmland, irrigation district and irrigation basin in consideration of the climate change context. Literature [33] proposed a novel GA-based MIKE URBAN model for simulating and optimizing the drainage efficiency of an integrated irrigation and drainage network, based on infiltration well overflow capacity experiments, which enabled minimization of annual irrigation and drainage costs. Literature [34] developed a simulation optimization model through system dynamics and Powell's algorithm to successfully optimize the cost effectiveness, drainage capacity and drainage salinity of irrigation and drainage network by optimizing the crop cropping pattern.

The application of data mining techniques in the field of irrigation and drainage involves the prediction and evaluation of parameters related to irrigation and drainage decisions, as well as the early warning of management risks. For example, literature [35] used various data mining tools for regional runoff prediction in a climate change environment and combined with a generalized atmospheric-oceanic circulation model to predict future temperature and precipitation in the region, with the best prediction being made by a support vector machine. Literature [36] combined data on groundwater characteristics, temperature, humidity, and evapotranspiration rate in a region, and introduced data mining techniques to predict the effective rainfall and crop water demand in the region to avoid regional irrigation and drainage exceeding the limits. Literature [37] used data mining techniques to mine weather forecast data (temperature, humidity, and precipitation) and constructed a water transport model to predict soil moisture and determine soil status for irrigation control. Literature [38] predicted the water level in the watershed through data mining techniques based on gradient descent algorithm and K-mean algorithm, the prediction results have reduced error compared to traditional statistical methods, which helps in calculating the amount of water available in the watershed in the future. Literature [39] proposed a combination of a data mining model and thermal infrared images to estimate the daily evapotranspiration of crops in irrigated areas, which facilitates scientific irrigation decision making for optimizing water resource management. Literature [40] classified remotely sensed data with the help of data mining tools such as neural networks, support vector machines and decision trees, and mined the hidden trends in the data to realize the prediction of flood hazards, which provided data support for irrigation and drainage decision-making and risk warning systems. Literature [41] evaluated the performance of three data mining algorithms in predicting the groundwater quality class, and based on the predicted results, a groundwater salinity hazard map was drawn, which informed the risk of irrigation and assisted in irrigation risk early warning decisions.

In this paper, we invert each hydraulic characteristic parameter of soil within a fully distributed hydrological model to simulate the irrigation and drainage process during the growing period of crop planting in terms of infiltration, evapotranspiration, vertical seepage, and horizontal operation of water. The actual irrigation and drainage data were used as inputs to build a water and fertilizer irrigation parameter model. Using data mining technology, the parameters are not reasonable enough to be analyzed and adjusted. By the three steps of data input, data mining and parameter adjustment, the construction of water and fertilizer irrigation intelligent decision-making system is finally completed to optimize the irrigation and drainage strategy of the irrigation area.

2. Design of Intelligent Decision-making System for Water and Fertilizer Irrigation under Data Mining and Model Simulation

2.1. Hydrologic model simulation design

Model simulation is carried out within a fully distributed hydrological model, which is generally a hydrological model with physical mechanisms that can simulate vertical hydrological processes such as evapotranspiration, infiltration, and vertical seepage from the soil layer, as well as horizontal hydrological processes such as slope catchment and loamy flow, which are involved in hydrological processes such as irrigation and drainage.

Taking RHESSys as an example, the simulation methods for each hydrological process are as follows:

2.1.1. Infiltration

The amount of water infiltrating into the soil from the water layer was calculated in the RHESSys model based on the Philip's infiltration formula.

$$Q_{t,\inf ilt} = It_p + S_p\sqrt{t_d - t_p} + K_{sat_s}(t_d - t_p)\ if\ t_d > t_p \tag{1}$$

$$Q_{t,\inf ilt} = It_d\ if\ t_d < t_p \tag{2}$$

where $Q_{t,infilt}$ is the infiltration volume (mm); I and t_p are the intensity and ephemeral time of the precipitation input; and K_{sat_s} is the saturated hydraulic conductivity of the wetting peak. S_p is the water absorption, calculated using Manley's formula:

$$S_p = \sqrt{2}K_{sat_s}0.76\varnothing_{ae} \tag{3}$$

where $\varnothing_{ae}$ is the inlet pressure as a soil input parameter.

The waterlogging time t_d is calculated using the Green-ampt approximation:

$$t_d = K_{sat_s}0.76\varnothing_{ae}\frac{\varnothing - \theta_0}{I\left(1 - K_{sat_s}\right)} \tag{4}$$

where $\varnothing$ is the porosity; θ_0 is the initial soil water content.

2.1.2. Evaporation

In RHESSys it is possible to calculate water surface evaporation, soil evaporation and evaporation intercepted by vegetation, transpiration from the stomatal layer, and evaporation and transpiration rates are calculated using the Penman-Montein formula.

1) Soil evaporation

Soil evaporation is limited by energy and air-driven limitations, and the maximum evaporation rate is a function of soil parameters at a given soil moisture. The potential evaporation rate is used to represent the limitation of soil evaporation by soil moisture and can be calculated using the Eagleso method:

$$pot_{qexfil} = \left[S^{\frac{1}{2b}} \sqrt{\frac{8\bar{\varnothing} \cdot \bar{K}_{sat}\varphi_{ae}}{3(1+3b)(1+4b)}} \right] \tag{5}$$

where b is the pore size index; $\bar{\varnothing}$ and $\bar{K}_{sat}$ are the mean values of porosity and saturated hydraulic conductivity above the groundwater layer below the soil layer, respectively; and S is the relative soil humidity, calculated by dividing the unsaturated layer water content by the potential water content of the saturated layer.

The energy of soil evaporation and air drive were calculated using the Penman-Monteith equation. Soil surface conductance was determined based on empirical functions of rhizosphere soil water content and diffusion impedance.

2) Evapotranspiration from vegetation canopies

The evapotranspiration from each canopy layer includes evaporation of canopy retained water and evapotranspiration from the stomatal layer. The rates of evapotranspiration were both calculated using the standard Penman-Monteith equation.

Evapotranspiration rates are calculated separately for precipitation and nonprecipitation periods of the day, with water vapor deficit adjusted accordingly, precipitation calendar time is an input to the model, and aerodynamic impedance is used with the corresponding aerodynamic impedance for each canopy stratum. Evapotranspiration was calculated for each canopy stratum for each day using the formula:

$$\begin{aligned} E = \min\Big[\theta_l, E_{pot}\left(vpd = 0; gs = gs_{nonvas}\right)\left(D_{drain}\right) \\ + E_{pot}\left(vpd = \overline{vpd}; gs = gs_{nonvas}\right)\left(D_{day} - D_{drain}\right)\Big] \end{aligned} \tag{6}$$

where θ_l is the present moment intercepted storage; D_{drain} is the intraday precipitation calendar time; D_{day} is the theoretical sunshine duration; $\overline{vpd}$ is the average daily water vapor deficit; and gs is the canopy conductance.

2.1.3. Vertical leakage

Vertical leakage from the rhizosphere to the unsaturated layer and from the unsaturated layer to the saturated layer can be expressed in RHESSys.

Vertical leakage between soil layers is limited by the amount of water held in the field and also by the vertical unsaturated hydraulic conductivity between soil layers. Vertical leakage does not occur when the water content of the soil layer is less than the field holding capacity; vertical leakage from the upper soil layer to the lower soil layer occurs when it is greater than the field holding capacity.

The formula for calculating vertical seepage is as follows:

$$Q_{seepage} = \begin{cases} \min\left[K_{unsat}(z)dT, \theta_{upper} - \theta_{fc}\right] & if\ \theta_{upper} < \theta_{fc} \\ 0 & if\ \theta_{upper} > \theta_{fc} \end{cases} \tag{7}$$

where $Q_{seepage}$ is the amount of vertical seepage; $K_{unsat}(z)$ is the vertical unsaturated hydraulic conductivity between soil layers; θ_{upper} denotes the water content of the upper soil layer; and θ_{fc} is the amount of water held in the field.

2.1.4. Horizontal transport of moisture

Horizontal transport of moisture in slope and loamy mid-streams is modeled using an explicit confluence model, based on the DHSVM confluence method. The confluence model assumes that the saturated flow $q(t)_{a,b}$ from the a cell to the b cell can be calculated using the following equation:

$$q(t)_{a,b} = Tr(t)_{a,b} \tan \beta_{a,b} \omega_{a,b} \tag{8}$$

$$Tr(t)_{a,b} = \int_{-\infty}^{z_{sat}} K_{sat_0} \exp^{-\frac{s}{m_s}} dz \tag{9}$$

where $q(t)_{a,b}$ denotes the outflow from space cell a to downstream cell b, $\omega_{a,b}$ is the width of the flow line between space cell a and b; $\beta_{a,b}$ is the local slope. In the calculation formula, the streamline width of the space cell is certain; for a grid, the streamline width is 0.55 times the grid, and for an irregular grid, the streamline width is the length of the junction of the two grids.

2.2. Application of Data Mining Techniques in Irrigation and Drainage

2.2.1. Parametric modeling of water and fertilizer irrigation

Soil moisture content in the farmland and crop growth state of water demand to reach a state of equilibrium, is the best state of farmland water and fertilizer irrigation. Crops on water and fertilizer demand has a certain regularity, in the normal growth process, the amount of water and fertilizer required for crops to reach the optimal growth state is defined as crop water demand. The amount of water evaporation and dissipation of farmland soil can be expressed as

$$ET = I + P + \Delta W - R - S \tag{10}$$

where ET denotes the amount of soil moisture evapotranspiration loss; I denotes the amount of irrigation water; P denotes the amount of precipitation; ΔW denotes the soil moisture content, R denotes the amount of soil moisture runoff; and S denotes the value of net flux at the lower boundary of the soil.

The evaporative water loss of the crop during the same period of time in the same state of crop growth can be expressed as

$$EP = \frac{0.4\Delta \cdot R_n + \gamma \cdot \dfrac{900}{T+273} \cdot U_2 \cdot (e_n - e_d)}{\Delta + \gamma \cdot (1 + 0.34U_2)} \tag{11}$$

where EP denotes the amount of crop water lost through evaporation; R_n denotes the surface radiative flux; e_n denotes the value of saturated water pressure; e_d denotes the value of actual water pressure; U_2 denotes the surface wind speed; Δ denotes the ratio between the value of saturated water pressure and the temperature; γ denotes the dryness and wetness constants; and T denotes the average temperature.

2.2.2. Water and Fertilizer Function Implementation

After simulating and calculating the relevant data of the water and fertilizer irrigation parameter model through the data mining technology, we can find the parameter that best meets the needs of crop and soil changes and make adjustments. Afterwards, the water-fertilizer integrated machine can precisely control the water and fertilizer in the irrigation process, automatically adjust according to the different states of crop growth and different environments, and quickly and accurately mix the water and fertilizer and automatically irrigate. Figure 1 is the structure of water and fertilizer irrigation machine. The control system requires good environmental adaptability and anti-interference, and its parameters mainly include water and fertilizer concentration, irrigation time and irrigation duration. The water and fertilizer concentration is adjusted by different system EC values, and the soil moisture information and crop growth state information detected by the sensing technology is compared with the crop growth database to adjust the irrigation time and duration to ensure that the soil moisture and fertilizer required by the crop growth state can meet the current crop growth state.

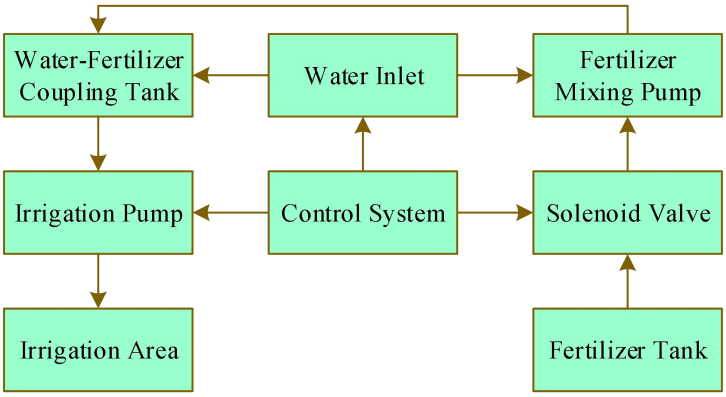

Figure 1. Structural Diagram of Water-Fertilizer Integrated Machine.

Figure 2 shows the working principle of water-fertilizer coupler. Under the action of solenoid valve and fertilizer mixing pump, the fertilizer enters the water-fertilizer coupling tank through the pipeline, dilutes to the required concentration, and the irrigation pump carries out the irrigation of the water-fertilizer coupling liquid, and the irrigation time and the length of the irrigation are adjusted through the control system.

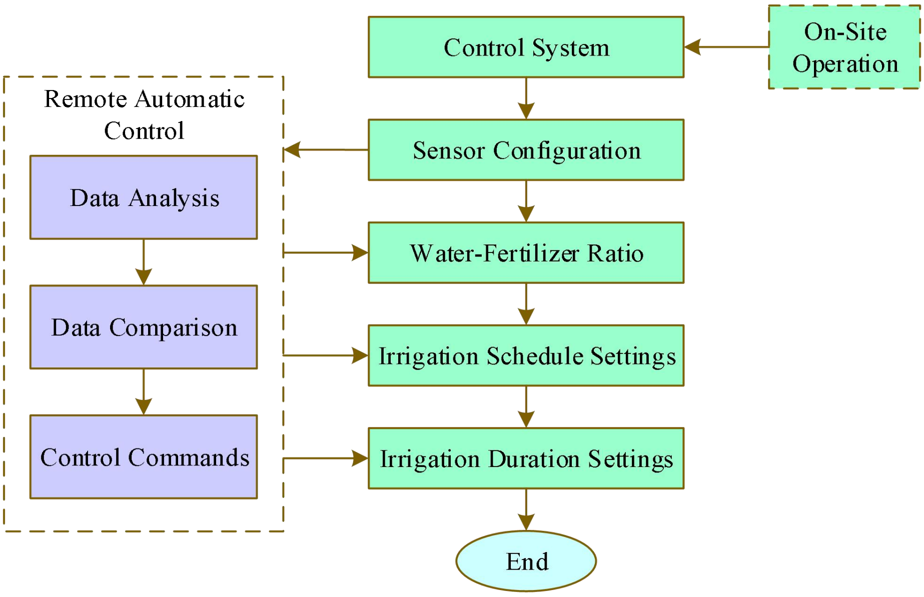

Figure 2. The working principle of the water and fertilizer integration machine.

The water and fertilizer machine has two working modes, one is on-site control and the other is remote control based on the knowledge database data comparison. The hardware of the two modes of work is the same, only the application of the work process is different, the field control data can be visualized through the display or hardware system, remote control mode through the implementation of the collection of data and knowledge database to analyze and compare.

2.3. Intelligent decision-making system design for water and fertilizer irrigation

In the design process of water and fertilizer irrigation decision-making system, the number of input and output nodes of the system is determined, the model initialization is completed, and the training sample dimension is used to determine the affiliation function.

Between the growth process water demand and soil water holding capacity, crop water content and theoretical demand constitutes multi-node input data, through the iteration after the acquisition of irrigation water, the input and output data are formatted to obtain the decision-making system raw data, namely

$$y = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{12}$$

Where y is the formatted system data; x is the original data; $x_{\min}$ is the minimum input data; $x_{\max}$ is the maximum input data. Figure 3 shows the algorithm flow of water and fertilizer irrigation intelligent decision-making system.

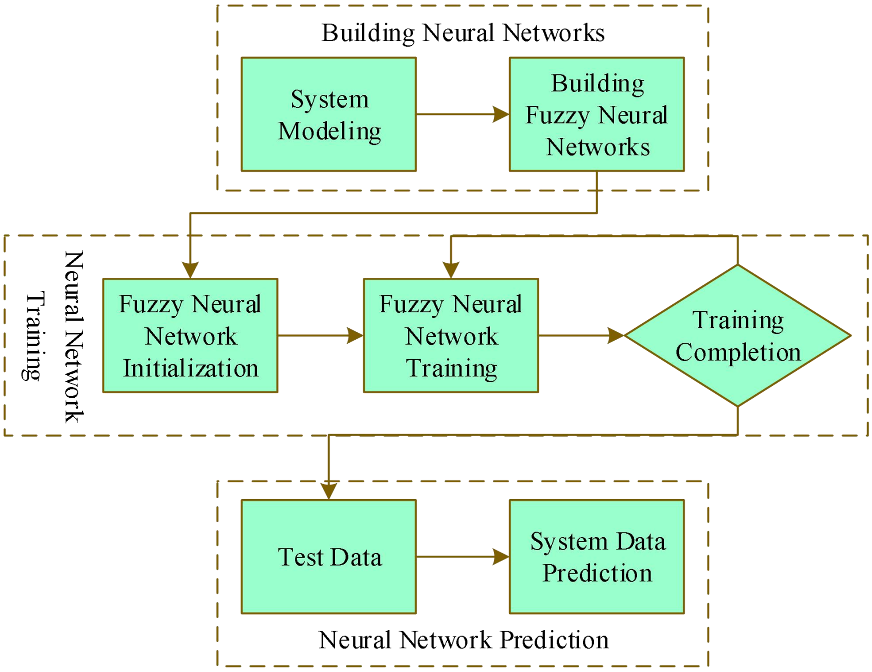

Figure 3. Intelligent Decision-making System for Water and Fertilizer Irrigation.

The design process of the intelligent decision-making system for water fertilizer irrigation includes the design of the system platform, the selection of the system architecture, the design of the system functions and the design of the database. Intelligent decision-making system for water fertilizer irrigation requires strong practicality and convenient operation, and at the same time, it is able to carry out intelligent operation of the agricultural production process and meet the actual production needs in the process of use. Therefore, in the use of data mining technology for water fertilization irrigation intelligent decision-making system design, the requirement to follow the system has a high degree of practicality, according to the actual needs of the system expansion, at the same time has a high degree of compatibility, the system is easy to operate, has a high degree of data security. Figure 4 shows the overall structure of the water and fertilizer irrigation intelligent decision-making system.

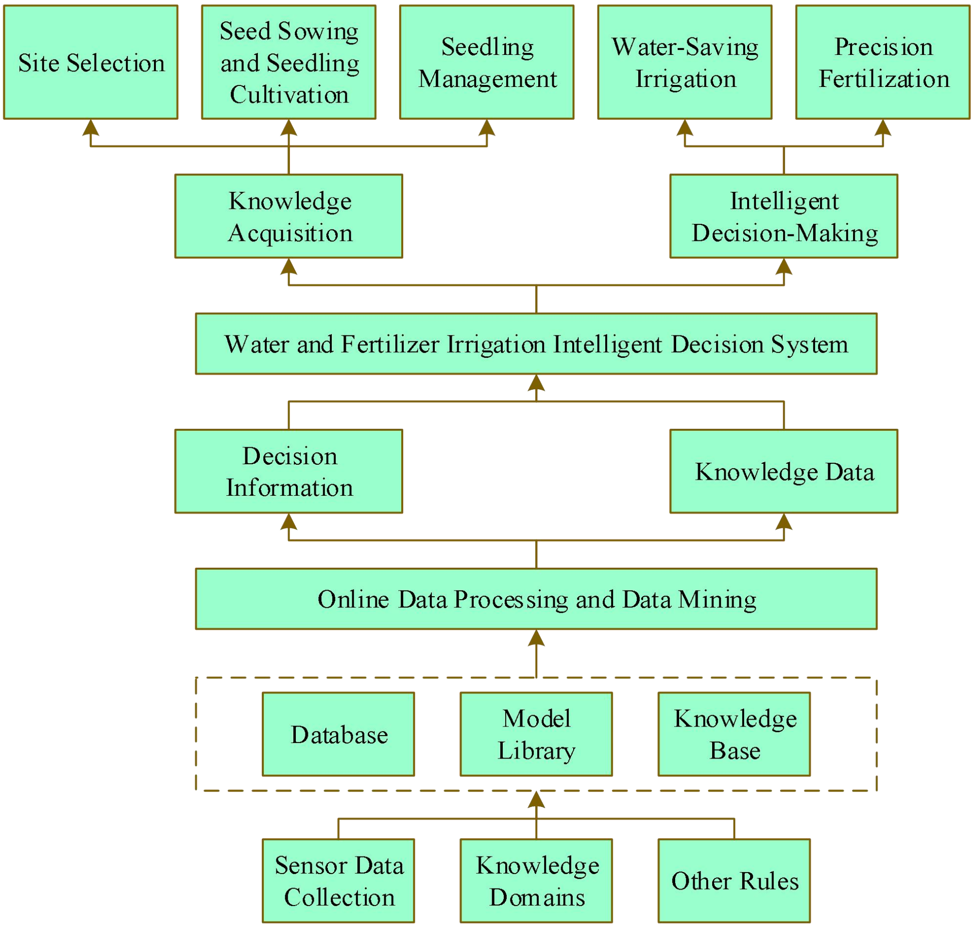

Figure 4. Structure of the intelligent decision-making system.

3. Optimization of irrigation and drainage strategies practice and results analysis

3.1. Learning Data Inputs and Irrigation Model Parameter Sensitivity Tests

3.1.1. Irrigation water requirements

In order to ensure the usability of the intelligent decision-making system for water and fertilizer irrigation based on data mining technology, it is necessary to ensure that the actual input node data and so on are correct and the hydrological model simulation process is responsive in the data learning and hydrological model simulation. In this paper, the data related to the irrigation water demand of cash crops and month-by-month water diversion in 2021-2024 in the south bank irrigation district of H River Basin are used as input data to analyze the parameter sensitivity and value of hydrological model to ensure that the simulation process is scientific and reasonable. Table 1 shows the irrigation water demand from 2021 to 2024 in the South Bank Irrigation District of River H. The irrigation water demand for the whole year from 2021 to 2024 is 357.65, 360.07, 361.42 and 359.42 m^3/mu, respectively, and the irrigation water demand of cash crops is relatively stable in each year with a certain planting area. At the same time, the irrigation water demand in the fixed months of January-December each year is not much different because the changes in climate and planting timing are also almost the same.

Table 1. The irrigation water demand from 2020 to 2024(m^3/hectare).

Month	Year			
	2021	2022	2023	2024
1	26.19	26.37	26.49	26.31
2	29.22	29.54	29.76	29.49

3	30.04	30.29	30.41	30.24
4	34.45	34.61	34.73	34.56
5	36.18	36.36	36.48	36.37
6	30.94	31.12	31.24	31.04
7	29.37	29.54	29.66	29.42
8	28.10	28.28	28.54	28.23
9	30.82	31.09	31.21	31.04
10	27.85	28.03	28.15	27.98
11	26.39	26.58	26.37	26.53
12	28.10	28.26	28.38	28.21
Total	357.65	360.07	361.42	359.42

3.1.2. Monthly water diversions

Table 2 shows the month-by-month water diversions in the South Bank Irrigation District of the H River Basin for the years 2021-2024. Considering soil evaporation and local irrigation practices, the month-by-month water diversions in the area for 2021-2024 will be more than the actual irrigation water requirements. The total diversions of 382.77, 384.76, 391.82, and 403.17 m^3/mu are the same as the water demand, and the fixed-month diversions for 2020-2024 tend to be the same.

Table 2. Monthly water withdrawal volume from 2020 to 2024(m^3/hectare).

Month	Year			
	2021	2022	2023	2024
1	28.43	28.51	29.02	30.02
2	31.36	31.58	32.67	33.41
3	31.97	32.37	32.92	32.95
4	36.49	36.65	37.29	38.27
5	38.13	38.44	38.79	40.08
6	32.98	33.16	33.75	34.75
7	31.35	31.58	32.18	33.13
8	30.44	30.32	31.05	31.94
9	32.76	33.13	33.71	34.76
10	29.99	30.07	30.66	31.69
11	28.63	28.62	28.81	30.24
12	30.24	30.33	30.97	31.93
Total	382.77	384.76	391.82	403.17

3.1.3. Model Parameter Sensitivity and Validation of Values

The soil irrigation situation was simulated in the hydrological model based on the actual situation of water demand and diversion. The 10 parameters in the hydrological model that have a large impact on runoff were selected and analyzed and evaluated by sensitivity analysis method to ensure that the corresponding hydrological characteristics of the model would change with the parameter changes. Table 3 shows the model parameter sensitivity and values. p-value indicates the significance of parameter sensitivity, the absolute value of p-value of the 10 parameters is not more than 0.10, and quite close to 0.00, which indicates that these 10 parameters of the model are more sensitive, and they can well respond to the changes of hydrological conditions in the actual water-fertilized irrigation process. This provides a good carrier for the in-depth application of data mining technology.

Table 3. Model parameter sensitivity and values.

Parameters	Meaning	T	P	Range of values	Value
CN2	Runoff curve number	-30.29	0.00	-0.71-0.43	-0.25
GW-DELAY	Groundwater delay days	18.33	0.00	0.00-594.00	50.49
ESCO	Soil evaporation compensation factor	-10.80	0.00	-0.46-0.38	0.05
SOL-AWC	Soil effective moisture content	8.92	0.01	-0.41-0.53	0.26
SOL-K	Soil saturated permeability coefficient	-9.24	0.03	-0.37-0.47	0.10
GH-K2	Main river hydraulic conductivity	4.17	0.00	-0.03-459.19	243.85
GW-REVAR	Groundwater re-evaporation coefficient	-0.53	0.05	0.04-0.31	0.06
SOL-BD	Soil bulk density	0.86	0.06	1.64	1.64
SURLAG	Surface runoff lag time	0.94	0.07	3.92	3.92
ALPHA-BNK	River embankment α factor	-0.07	0.00	0.00-1.28	0.57

3.2. Optimization of soil irrigation and drainage strategies under data mining

3.2.1. Inversion results of hydraulic characteristic parameters

Data mining technology was utilized in the hydrological model to invert the hydraulic characteristic parameters of each layer and predict the changes of soil water content in each layer according to the laws obtained from mining. Comparing the prediction results with the measured results, the usability of the data mining technology and the practicality of the intelligent decision-making system for water and fertilizer irrigation are examined. The residual water content θr, saturated water content θs, and saturated hydraulic conductivity Ks are based on actual measurement, the pore connectivity parameter l is taken as 0.45, and only the empirical parameters α and n are inverted.

Table 4 shows the inversion results of hydraulic characteristic parameters of each soil layer. In the process of inversion, as the depth of the soil layer deepens from 0-25 cm to 105-120 cm, the empirical parameters α and n increase continuously. α increases from 0.021 cm^{-1} to 0.074 cm^{-1}. n increases from 1.093 to 1.452. The results of the parameter inversion more accurately reflect the changes of the soil hydraulic characteristics. In order to better utilize the data mining technique for soil water content prediction and comparison, observation points were set up at 25, 35, 45, 55, and 65 cm in the irrigation area on the south bank of the H River basin. The accuracy of the data mining technique was evaluated by comparing the measured values with the simulated predicted values.

Table 4. Inversion results of soil hydraulic characteristic parameters.

Layer depth/cm	θ_r cm³/cm³	θ_s cm³/cm³	α cm^{-1}	n	K_s cm/d	l
0-25	0.084	0.502	0.021	1.093	48.49	0.45
25-50	0.084	0.502	0.043	1.214	54.87	0.45
50-75	0.084	0.547	0.052	1.275	40.21	0.45
75-90	0.084	0.547	0.059	1.309	34.50	0.45
90-105	0.084	0.596	0.067	1.367	21.09	0.45
105-120	0.084	0.596	0.074	1.452	18.36	0.45

3.2.2. Prediction of soil water content by layer

Through data mining techniques and input soil data, a model of water fertilization and irrigation parameters is constructed. When different soil depths were used as inputs, the parameters were continuously adjusted to realize the prediction of water content of soil at other depths. Table 5 shows the comparison between the predicted and measured results of soil water content in each layer. Taking the measured soil water content of 25 cm as the input quantity, the variation ranges of the parameters R^2, RMSE/%, and RPD of the water-fertilizer-irrigation parameter model for 35, 45, 55, and 65 cm were predicted to be 0.684-0.873, 1.038%-1.093%, and 2.986-3.028, respectively.Similarly, using the measured soil water content of 35, 45, 55, and 65 cm as the inputs, the parameter variations of the other predictive models can be obtained. From the results of comparison between predicted and measured, the predicted water content parameters are smaller than those of measured water content. The reason for this is that considering the actual evaporation, the system will actively increase the amount of water diversion to meet the complex soil water and fertilizer irrigation demand in the case of a smaller water content parameter.

Table 5. Comparison between predicted and measured moisture content.

Soil depth	Prediction of water content layer depth	Predicted value			Measured value		
		R^2	RMSE/%	RPD	R^2	RMSE/%	RPD
25	35	0.873	1.093	3.028	0.914	1.112	3.039
	45	0.769	1.074	3.019	0.812	1.093	3.023
	55	0.701	1.045	3.003	0.742	1.064	3.014
	65	0.684	1.038	2.986	0.725	1.057	2.997
35	25	0.901	1.203	2.765	0.942	1.222	2.776
	45	0.745	1.124	2.609	0.786	1.143	2.622
	55	0.698	1.109	2.551	0.739	1.128	2.562
	65	0.671	1.098	2.502	0.712	1.117	2.513
45	25	0.910	1.300	2.475	0.951	1.319	2.486
	35	0.882	1.277	2.463	0.923	1.296	2.474
	55	0.753	1.209	2.402	0.794	1.228	2.413
	65	0.702	1.186	2.399	0.743	1.205	2.401
55	25	0.914	1.308	2.310	0.955	1.327	2.321
	35	0.890	1.299	2.297	0.931	1.318	2.308

	45	0.762	1.251	2.283	0.803	1.273	2.294
	65	0.711	1.222	2.270	0.752	1.241	2.281
65	25	0.920	1.314	2.252	0.961	1.333	2.263
	35	0.894	1.300	2.241	0.935	1.319	2.252
	45	0.770	1.242	2.200	0.811	1.261	2.211
	55	0.723	1.209	2.104	0.764	1.228	2.115

3.2.3. Evaluation of system simulation results

Based on the simulation results of the predicted and measured parameters, the effectiveness of data mining techniques in hydrological modeling was verified. Next, the soil water content of each layer of cash crops in this irrigation area in 2025 was obtained by simulating and predicting using soil water and fertilizer irrigation data from previous years to optimize the irrigation and drainage strategies. Table 6 shows the optimization results of soil water content parameters for each layer in 2025. Figure 5 shows the overlap between the predicted and measured soil water content of each layer in the first half of 2025. After the optimization of soil water content parameters, compared with the predicted parameters of previous years, the parameter values of 2025 are increased, i.e., the amount of reserved water diversion is reduced, so that the actual amount of water diversion is just enough to meet the irrigation demand and reduce waste. And the coincidence rate between the predicted value of irrigation and drainage and the measured value of actual water demand after system optimization exceeded 95% in all layers of soil, reaching a maximum of 99.81%. It indicates that the irrigation strategy adjustment using the water and fertilizer irrigation intelligent decision-making system has practical value for improving the irrigation water use rate and reducing the difficulty of soil drainage.

Table 6. Optimized results of moisture content parameters for each layer of soil.

Parameters / Soil depth/cm	R^2	RMSE/%	RPD
25	0.905	1.502	2.510
35	0.892	1.433	2.446
45	0.764	1.394	2.371
55	0.729	1.303	2.282
65	0.711	1.285	2.159

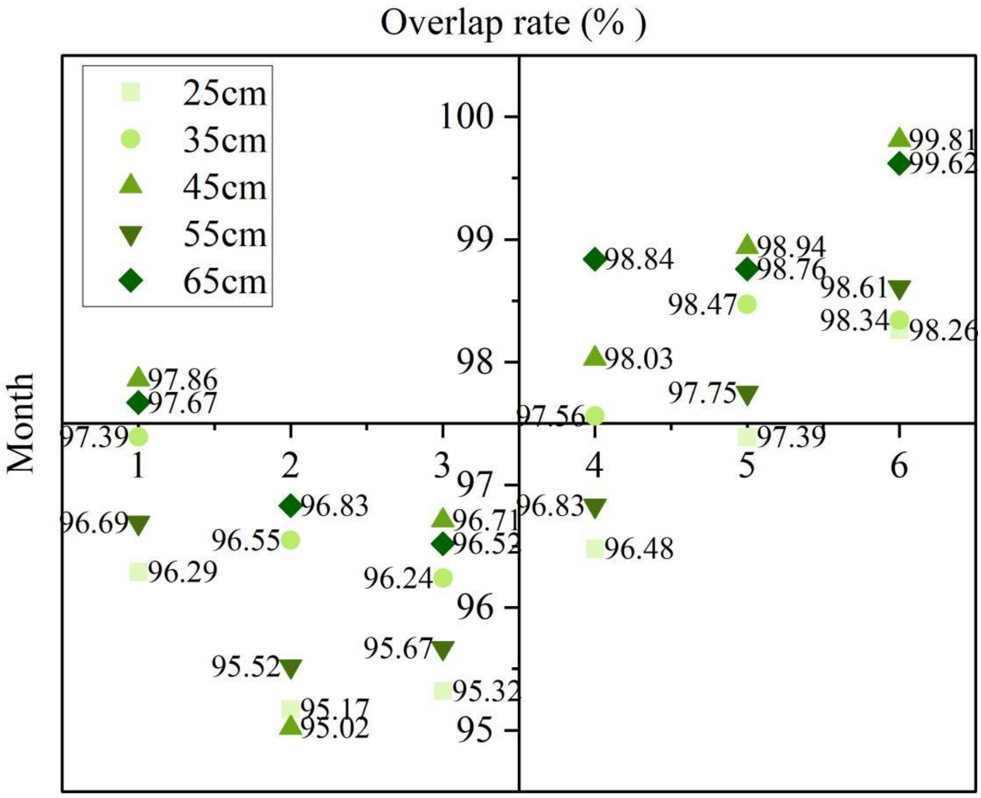

Figure 5. Coincidence rate between the predicted values and the measured values.

3.3. Comparison of water utilization rate before and after the application of intelligent decision-making system

From July to September 2025, the application of the water and fertilizer irrigation smart decision-making system was tested in the irrigation district on the south bank of the H River Basin. Table 7 shows the results of water utilization comparison before and after the application of water and fertilizer irrigation smart decision-making system. The water utilization rate of smart irrigation was substantially improved over traditional irrigation. The amount of single irrigation was reduced by 37.46%, the water use coefficient was improved by 40.98%, the annualized water saving was significantly increased by 1210%, the irrigation timeliness was optimized by 50.59%, and the water use efficiency of the soil was improved by 68.15%. The system effectively adjusts soil water demand parameters by using data mining techniques and hydrological model simulation, and realizes the optimization of irrigation and drainage strategies and the optimal use of water resources.

Table 7. Utilization rate of water resources before and after the system application.

Evaluation indicators	Traditional irrigation	Intelligent Irrigation	Improvement percentage
Single irrigation volume (m^3/peracre)	70.23	43.92	-37.46%
Water utilization coefficient	0.61	0.86	40.98%
Annual water-saving volume (m^3/peracre)	0.09	109	1210%
Irrigation timeliness rate (%)	60.21	90.67	50.59%
Water use efficiency (%)	50.83	85.47	68.15%

4. Conclusion

In this paper, the improvement of irrigation and drainage strategies was realized through hydrological model simulation and data mining. After establishing an intelligent decision-making system for water and fertilizer irrigation, three water content parameters were adjusted in the irrigation district on the south bank of the H river basin. There was almost agreement (up to 99.81%) between the system's predicted water diversion and the actual water demand. The indicators of irrigation timeliness and water use efficiency also realized a significant improvement. Intelligent irrigation decision-making makes up for the limitations of traditional irrigation, which is of great benefit for expanding the scale of cash crop cultivation, reducing labor costs, and improving water utilization.

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