Research on Irrigation Decision-Making for Xinjiang Cotton Based on Genetic Algorithm and Reinforcement Learning

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Abstract. To improve water use efficiency and cotton yield in the field cotton planting of Changji, Xinjiang, this paper proposes an intelligent irrigation decision-making scheme based on genetic algorithms and reinforcement learning. The 2023 cotton planting data were used to validate the accuracy of the CROPGRO-Cotton model. After ensuring the crop model's ability to simulate field conditions, a decision-making model based on DSSAT and genetic algorithms was proposed. Reinforcement learning was then used to optimize the crossover and mutation rates of the genetic algorithm. The experimental results show that the irrigation strategy based on DSSAT and genetic algorithms significantly improved both water use efficiency and cotton yield. After optimization with reinforcement learning, both water use efficiency and yield were further improved. The optimal irrigation decision, as simulated, involved 10 irrigations and a total irrigation amount of 454mm, with a cotton yield and water use efficiency of 6266 kg·hm^{-2} and 1.26 kg·m^{-3}, respectively. Compared to the field experiment with the same irrigation amount and the genetic algorithm, the cotton yield was 596 kg·hm^{-2} and 22 kg·hm^{-2} higher, respectively. This study provides new theoretical insights and practical value for cotton irrigation decision-making in the Changji region of Xinjiang.

Keywords: Genetic Algorithm; Reinforcement Learning; DSSAT Model; Irrigation System; Subsurface Drip Irrigation

1 Introduction

Xinjiang, recognized as China's largest cotton-producing region, accounts for over 90% of the nation's total cotton output. However, this region is situated in the northwest of China and falls within arid and semi-arid zones, which are characterized by relatively

X. Li et al. (eds.), *Proceedings of the 2025 International Conference on Agriculture and Resource Economy (ICARE 2025)*, Advances in Biological Sciences Research 4
https://doi.org/10.2991/978-94-6463-746-5_9

limited water resources. Cotton is a crop that requires substantial amounts of water, necessitating significant irrigation to promote optimal growth and development. To address the demands of cotton production while also conserving water resources, film underground drip irrigation technology has been widely implemented in Xinjiang [1]. However, farmers responsible for making irrigation decisions often tend to over-irrigate. Coupled with the region's hot and evaporative climate conditions, this practice results in an agricultural irrigation water utilization efficiency of less than 40% in Xinjiang [2]. Consequently, there is an urgent need to explore effective deficit irrigation strategies for cotton cultivation in this area.

Traditional field experiments are not only time-consuming and costly, but the results obtained often lack general applicability [3]. Crop models, which leverage mathematical analysis and computer technology, assist agricultural producers and researchers in making informed scientific decisions. They enhance crop yields and economic benefits while simultaneously reducing resource waste. These advantages have positioned crop models as a promising new research direction for replacing traditional field experiments in agricultural decision-making.

Bai Z.T et al. [4] used the DSSAT (Decision Support System for Agrotechnology Transfer) crop model to simulate and found that cottonseed yield peaked at its highest level when combined with 100% ETc and 300-120-90 $kg \cdot hm^{-2}$ (N-P2O5-K2O) nutrient inputs, while WP, PFPN, and fiber quality were all improved. Alibabaei K et al. [5] trained a deep learning network (Deep Q-Network) using DSSAT as the reinforcement learning (RL) environment. The trained Q network can automatically learn to avoid water waste at the beginning of the season and plant stress at the end of the season.

There have been numerous studies on crop modeling utilizing the DSSAT model for cotton crops across various regions, both domestically and internationally. However, there is a relative scarcity of research that integrates the DSSAT model with optimization algorithms specifically for cotton deficit irrigation in Xinjiang. The optimal frequency and volume of irrigation during the cotton growing period remain ambiguous. Consequently, this study leverages weather and soil data from Changji, Xinjiang to first investigate the effects of different water-saving scenarios on yield and Water Use Efficiency (WUE) under deficit irrigation conditions. Secondly, the optimal values of two key hyperparameters in genetic algorithms—crossover rate (Pc) and mutation rate (Pm)—usually need to be manually adjusted by researchers， and previous studies have not considered the impact of Pc and Pm on crop yield and water use efficiency. Therefore, this study aims to enhance the stability of the genetic algorithm population and achieve the goals of water conservation and increased yield by using the Q-learning algorithm from reinforcement learning to optimize these hyperparameters. This provides new theoretical insights and practical value for irrigation decision-making in the Changji region of Xinjiang. Finally, based on the aim of improving water use efficiency and seed cotton yield in Changji, Xinjiang, we decode and analyze the optimal number of irrigation events as well as irrigation volumes throughout the cotton growth period using an optimized genetic algorithm.

2 Materials and Methods

2.1 Establishment of Crop Model Databases

2.1.1 Meteorological Data

This study collected meteorological data from ECMWF (www.ecmwf.org) at 87.3°E, 44.2°S, as shown in Figure 1. The weather data used for yield prediction includes rainfall (mm), solar radiation (MJ·m⁻²), maximum temperature (°C), and minimum temperature (°C) for the year 2023.

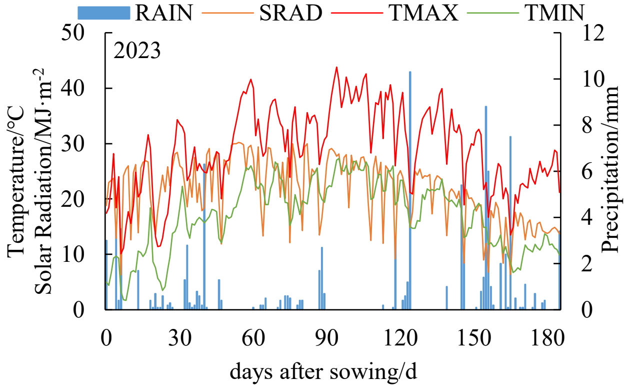

Fig. 1. Weather data for the cotton growing season in 2023.
Note. 1. RAIN: Precipitation; SRAD: Solar Radiation;
TMAX: Maximum Temperature; TMIN: Minimum Temperature.

2.1.2 Soil Data

Before seeding in the field, soil samples were taken by auger sampling method for layering and the physical properties and initial conditions of soil from 0 to 100cm depth were determined. The detailed data is shown in Table 1.

2.1.3 Field Management Data

The cotton variety planted in the experimental field was "Zhong Mian 113", which was sown on April 23, 2023. The field experiment was set up with 3 groups of water-saving irrigation treatments and 1 group of conventional irrigation control treatment. Each treatment was set up with 3 replications. The irrigation method was subsurface drip irrigation. T1, T2, and T3 implemented 10%, 15%, and 20% water-saving treatments, respectively, based on the control treatment of CK. The detailed design is shown in Table 2.

2.2 Calibration and Validation of Crop Models

2.2.1 Model Evaluation Metrics

To ensure that the model effectively simulates field experiments, this study employs three evaluation metrics: the normalized root mean square error (n$RMSE$), the consistency index (d), and the coefficient of determination (R^2). These indicators are utilized to assess the accuracy of crop model simulations. The corresponding formulas are as follows:

$$\text{n}RMSE = \frac{\sqrt{\sum_{i=1}^{n} \frac{(S_i - O_i)^2}{n}}}{\overline{O}} \tag{1}$$

$$\text{d} = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} \left(|S_i - O_i| + |O_i - \overline{O}|\right)^2} \tag{2}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n} (O_i - \overline{O})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n} (S_i - \overline{S})^2 \sum_{i=1}^{n} (O_i - \overline{O})^2}} \right)^2 \tag{3}$$

In the formula, S_i represents the simulated value, O_i represents the measured value, and $\overline{O}$ is the average of the observed values. When $nRMSE \le 10\%$, it indicates that the simulated value has very good precision; when $10\% \le nRMSE \le 20\%$, it indicates that the simulated value has good precision; when $20\% \le nRMSE \le 30\%$, it indicates that the simulated value has average precision. When $nRMSE \ge 30\%$, it indicates that the simulated value has poor precision [6]. When d's value is closer to 1, it indicates that the consistency effect is better, and when d > 0.6, it indicates that the consistency effect is good [7]. When R^2's value is closer to 1, it indicates that the fitting degree is better, and when $R^2 > 0.5$, the simulation results are considered acceptable [8].

Table 1. Field experiment design.

Irrigation date	Field experiment plan			
	CK	T1	T2	T3
2023-04-25	45	40	38	36
2023-06-09	52	47	44	41
2023-06-19	37	33	31	30
2023-06-29	37	33	31	30
2023-07-09	45	41	38	36
2023-07-14	37	33	31	30
2023-07-21	60	54	51	48
2023-07-28	52	47	44	41
2023-08-04	52	47	44	41
2023-08-11	45	41	38	36
2023-08-18	45	41	38	36
2023-08-25	30	27	26	24
Irrigation amount(mm)	537	484	454	429
Yield($kg \cdot hm^{-2}$)	6110	5469	5670	4875

Table 2. Soil Physical Characteristics.

Soil depth (cm)	Clay (%)	Silt (%)	Sand (%)	Bulk density ($g \cdot cm^{-3}$)	Wilting point ($cm^3 \cdot cm^{-3}$)	Field capacity ($cm^3 \cdot cm^{-3}$)	Saturated water content ($cm^3 \cdot cm^{-3}$)
0-10	2.91	16.89	80.2	1.062	0.072	0.186	0.565
10-20	3.08	17.86	79.06	1.251	0.080	0.223	0.422
20-30	2.73	16.99	80.28	1.300	0.091	0.216	0.392
30-40	3.07	19.44	77.49	1.252	0.103	0.219	0.421
40-60	3.02	18.91	78.07	1.252	0.102	0.206	0.421
60-80	2.66	17.22	80.12	1.266	0.102	0.236	0.412
80-100	2.68	17.78	79.54	1.245	0.093	0.221	0.426

2.2.2 Calibration and Validation of Cotton Variety Parameters

In this experiment, the historical yield data from previous years' field trials was used to calibrate the crop model parameters of DSSAT, and the validation was conducted using the observed data on growth period and yield from the 2023 field experiment with deficit irrigation. The parameter calibration of cotton variety was carried out using the GLUE (Maximum Likelihood Estimation) tool provided by the DSSAT model, with a total of 20000 runs. The simulation values and observed values are shown in Table 3. The $nRMSE$ values of the simulated flowering date, maturity date, and seed cotton yield are 1.31%, 2.26%, and 6.89%, respectively, all of which are less than 10%, indicating that the calibration results are excellent. The d value and R^2 value of the simulated yield are 0.885 and 0.816, respectively, indicating that the consistency of the calibration results is very good and can be used for the next steps of the research.

2.3 The Construction and Solution of Genetic Algorithm Irrigation Decision Model

2.3.1 Construction of the Decision Model

Trying different irrigation schemes to find a better one for improving cotton yield and water use efficiency can be regarded as an optimization problem. Considering that genetic algorithms have strong global search capabilities, they are introduced to address the optimization problem of increasing cotton yield and water use efficiency. The decision model construction process is divided into the following steps, as shown in Figure 2.

1) Population initialization and fitness calculation: Initialize the population size to 100, consisting of different irrigation schemes. Manually set Pc=0.8 and Pm=0.5. Use the DSSAT48 model to simulate each initial individual, and the simulated yield values are directly used as the fitness values for the genetic algorithm. The fitness calculation is as shown in Equation 4.

$$\mathrm{F} = \max Y\left(x\right) = \max D\left(x\right) \tag{4}$$

In this equation, Y represents the yield output by DSSAT simulating a set of irrigation schemes, and x represents the set of irrigation schemes. D represents the crop model in DSSAT.

2) Water-saving constraints and selection operations: When applying water-saving constraints (such as CK usage restrictions of 0%, 10%, 15%, and 20%), if an individual's water usage exceeds the expected value, it is considered non-optimal and eliminated, regardless of its fitness value. After elimination, new individuals are added to maintain the population size, and their fitness values must be recalculated. The "parent" is then selected using a roulette wheel method, where higher yield individuals have a greater selection probability. Supplemented individuals must comply with water-saving constraints, satisfying equation (5).

$$0 \le I_i \le \left(CK \times \left(1 - S\right)\right) / T \tag{5}$$

In this formula, S represents the water-saving rate, T represents the number of irrigation times, and CK represents the field control experiment under normal conditions.

3) Interaction between crop model and genetic algorithm: In step 2, the selected "parent" individuals are crossed with others in the population, followed by a multi-point mutation operation. The new population is updated in the COX management file of DSSAT using a Python script, and the yield and other information are simulated. This process facilitates interaction between the crop model and the genetic algorithm, completing one iteration of the optimization.

4) Optimize the crossover and mutation operators: Follow the steps in Section 2.3.2 to optimize the crossover and mutation operators using Q-learning.

Table 3. Comparison between simulated and observed values of cotton growth period and yield in 2023.

Year	Treatment	Flowering Date		Maturity Date		Cottonseed Yield	
		Sim. (d)	Obs. (d)	Sim. (d)	Obs. (d)	Sim. ($kg \cdot hm^{-2}$)	Obs. ($kg \cdot hm^{-2}$)
Validation of Crop Model	CK	76	75	162	157	6332	6110
	T1	76	75	160	157	5671	5469
	T2	76	75	159	157	5088	5670
	T3	76	75	157	157	4458	4875

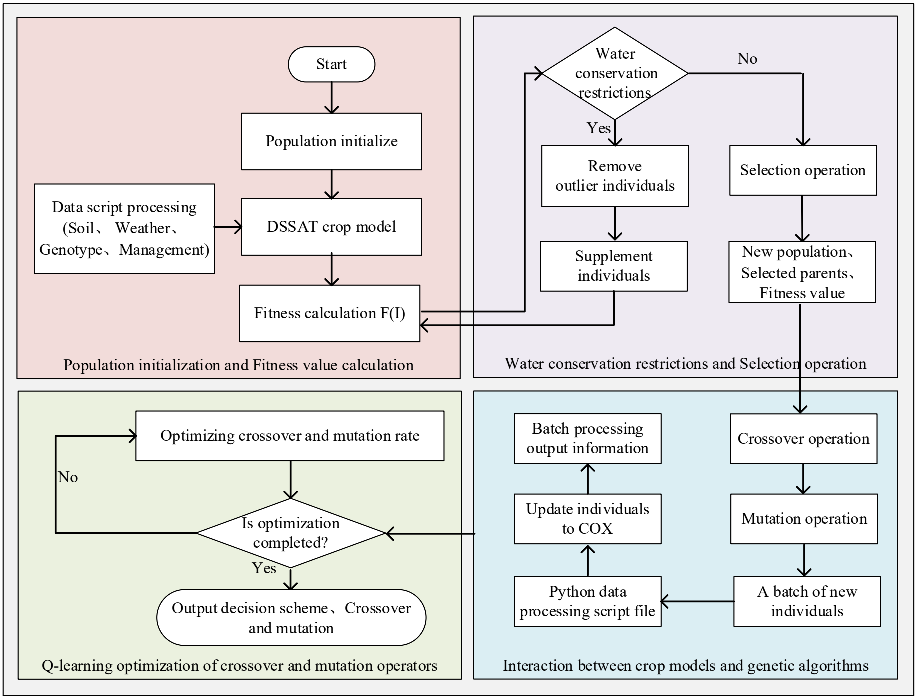

Fig. 2. Optimization flowchart of irrigation decision-making.

2.3.2 Q-learning algorithm optimizes Pc and Pm

An excessively large or small Pc and Pm can affect the stability of the Genetic Algorithm (GA) population. Therefore, this study uses the Q-learning algorithm to dynamically adjust these parameters to enhance the robustness of the decision model. The study uses all the steps of GA interaction with DSSAT as the Q-learning environment, and the environment also includes the process of changing Pc and Pm. The Q-learning algorithm is executed for 10 rounds, with a sampling length of 50 for each round. Combining Figure 3, the process of optimizing Pc and Pm using Q-learning mainly includes the following steps.

1) Initialize the Q-table: The Q-learning algorithm first initializes state∈[0-19], action∈[0-9], policy π(a|s) and initializes a Q-table (20x10) consisting of states and actions, with all initial values set to 0.

2) Optimizing Pc and Pm: The Agent will select an action based on its policy π in the current state. The Environment optimizes and adjusts Pc and Pm based on the Agent's selected action (a_t) and state (s_t), and sends the adjusted Pc and Pm into the DSSAT-GA to execute a genetic algorithm. In which Pc varies between 0.5 and 1, and Pm varies between 0.1 and 0.3. Then, the Agent transfers to the next state (s_{t+1}) and receives the real-time reward (R_t) for the current state. Pc and Pm are calculated by formulas (6) and (7), and the reward function is defined by formula (8).

$$Pc = R(0.5 + 0.05 \times a, 0.5 + 0.05 \times (a + 1)) \tag{6}$$

$$Pm = R(0.1 + 0.01 \times s, 0.1 + 0.01 \times (s + 1)) \tag{7}$$

$$\mathrm{Re}\,ward = fit(t + 1) - fit(t) \tag{8}$$

In this formula, R represents the generation of a random floating-point number within the real number range, and a represents an action, while s represents a state. "fit" is the fitness value for the GA, which is the yield simulated by DSSAT.

3)Update Q-table: In step 2, the real-time reward R_t at time t and the state s_{t+1} at time t+1 were obtained, and then the Q-values were updated in the Q-table. The Q-value update is calculated by formula (8).

$$Q(s_t, a_t) = Q + a[R_t + \gamma \times \max Q(s_{t+1}, a_t) - Q] \tag{9}$$

In this equation, Q denotes the previous value prior to the update, while R_t signifies the immediate reward received after executing an action. The parameter γ represents the discount factor, which is set at 0.1, and α indicates the learning rate, assigned a value of 0.8. Additionally, s_t refers to the current state, and a_t corresponds to the action selected by the Agent based on an ε-greedy policy at that specific time. Finally, $maxQ(S_{t+1}, a_t)$ represents the maximum Q value achievable by taking the chosen action in the subsequent state.

4)Loop Condition: Verify whether the Q-value has stabilized and is no longer exhibiting significant changes, or if the predetermined sampling limit (episode * length = 500) has been reached. If neither condition is met, proceed to repeat steps 2 and 3 for further optimization until either the algorithm converges or the episode count is fulfilled.

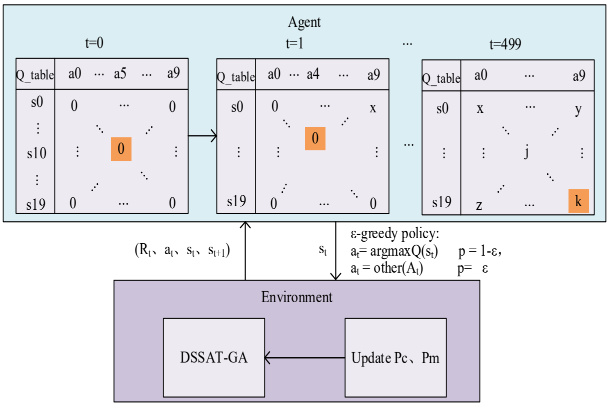

Fig. 3. Q-learning optimizing genetic algorithm's Pc and Pm.

Note. 1. The DSSAT-GA module is responsible for managing the interaction between GA and DSSAT.

Table 4. Simulation results of different design schemes using genetic algorithms.

Treat-ment	Water restrictions	Irrigation times	Irrigation amount (mm)	ET (mm)	Yield (kg.hm^{-2})	WUE (kg.m^{-3})	Pc	Pm
				GA-DSSAT				
G1	0%	12	528	519	6397	1.23	0.80	0.50
G2	10%	11	479	510	6347	1.24	0.80	0.50
G3	15%	11	454	494	6244	1.26	0.80	0.50
G4	20%	10	429	471	5850	1.24	0.80	0.50
				O-GA-DSSAT				
Q1	0%	12	530	520	6404	1.23	0.73	0.17
Q2	10%	11	483	512	6365	1.24	0.74	0.22
Q3	15%	10	454	496	6266	1.26	0.88	0.21
Q4	20%	10	429	463	5892	1.27	0.76	0.18

GI1: [29, 21, 42, 47, 51, 38, 56, 35, 52, 37, 60, 60]	QI1: [34, 31, 28, 57, 25, 51, 51, 44, 58, 41, 58, 52]
GI2: [0, 22, 43, 45, 52, 58, 51, 52, 27, 47, 55, 27]	QI2: [1, 20, 42, 50, 60, 29, 55, 57, 58, 32, 46, 33]
GI3: [1, 6, 34, 57, 35, 55, 46, 42, 40, 59, 49, 30]	QI3: [0, 0, 39, 51, 48, 36, 37, 58, 59, 55, 41, 30]
GI4: [0, 4, 41, 7, 49, 30, 54, 53, 37, 55, 40, 39]	QI4: [0, 0, 16, 46, 57, 36, 33, 45, 58, 46, 49, 43]

Note. 1. Irrigations with a water volume less than 5mm are not considered as a single irrigation.

Note. 2. GI1-GI4 and QI1-QI4 represent the irrigation quantity statistics for each irrigation process in the G1-G4 and Q1-Q4 decision schemes.

2.4 Results and Analysis

2.4.1 Cenario Simulation

After calibrating and validating the genetic parameters of cotton varieties, this study designed a water-saving irrigation experiment based on the optimization of crossover rate and mutation rate using Q-learning, referred to as Q-GA-DSSAT. As shown in Table 4, the experimental design implemented water-saving restrictions of 0%, 10%, 15%, and 20% irrigation amounts based on CK, resulting in a total of four treatments. To ensure the persuasiveness of the experiment, this study also conducted an ablation experiment with the same water-saving restrictions based on Q-GA-DSSAT (removing the Q-learning optimization module from Q-GA-DSSAT), referred to as GA-DSSAT, which also included four treatments.

2.4.2 The Impact of Different Irrigation Conditions on Yield

As shown in Figure 4, different water-saving rates or irrigation totals have different effects on yield. With the increase of water-saving rate, the yields of T1, T2, and T3 are 5469 kg hm^{-2}, 5670 kg hm^{-2}, and 4875 kg hm^{-2}, respectively. These field water-saving experiments had significantly lower yields than the control experiment CK with a yield of 6110 kg hm^{-2}, showing a water-saving yield reduction phenomenon. In the GA-DSSAT experiment at water-saving rates of 0%, 10%, and 15%, the yields of G1, G2, and G3 are 6397 kg hm^{-2}, 6347 kg hm^{-2}, and 6244 kg hm^{-2}, respectively. It can be seen that the yields optimized by the decision model are significantly higher than the yield of the control experiment CK, showing a water-saving yield increase phenomenon. Compared with the CK experiment with the same amount of water in the field, the yields of T1, T2 are 287 kg hm^{-2} and 878 kg hm^{-2} higher, respectively. When the water-saving rate reaches 20%, the yield of G4 is only 260 kg hm^{-2} lower than CK, but is 975 kg hm^{-2} higher than the yield of T3 with the same amount of water.

In the Q-GA-DSSAT experiment, the yields of Q1, Q2, Q3, and Q4 at water-saving rates of 0%, 10%, 15%, and 20% are 6404 kg hm^{-2}, 6365 kg hm^{-2}, 6266 kg hm^{-2}, and 5892 kg hm^{-2}, respectively. They are 294 kg hm^{-2}, 896 kg hm^{-2}, 596 kg hm^{-2}, and 1017 kg hm^{-2} higher than the yields of the CK experiment with the same amount of water, and slightly higher than the yields of the GA-DSSAT experiment with the same amount of water.

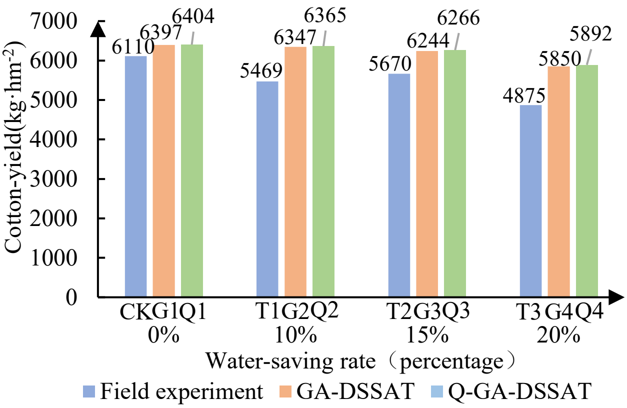

Fig. 4. Comparison of yield between different models and field experiments.

As shown in Table 4, no matter how much water-saving is achieved, the experiment always shows a pattern: the effect of GA-DSSAT is always better than that of field experiment, slightly worse than that of Q-GA-DSSAT, and both GA-DSSAT and Q-GA-DSSAT experiments achieve the goal of water-saving and yield increase at water-saving rates of 0%, 15%, and 20%. At a water-saving rate of 20%, the yield is slightly lower than that of CK, but the water use efficiency (WUE) is improved.

2.4.3 Analysis of Optimal Irrigation Schedule

To achieve dual optimization of yield and water use efficiency, the study conducted a field water-saving irrigation experiment and utilized the GA-DSSAT and Q-GA-DSSAT models for the simulation and optimization of irrigation strategies. The experimental results indicated that all three different experiments achieved optimal irrigation effects at a water-saving rate of 15%. When comparing the three optimal irrigation schemes, it was further found that the scheme recommended by the Q-GA-DSSAT model performed the best in comprehensively considering yield and water use efficiency. This is because the Q-GA-DSSAT model not only possesses the global search capability of GA-DSSAT but can also dynamically adjust suitable Pc and Pm based on changes in the water-saving rate, enabling the population to perform crossover and mutation operations more effectively—capabilities that the field experiment does not have.

Given that crops have different water requirements at different stages of growth, the decision-making algorithm in this study is able to identify these critical differences and automatically allocate a reasonable irrigation amount based on the crop's water sensitivity at each growth stage. This can be verified by analyzing the Q3 scheme separately. As shown in Table 5: No irrigation was conducted during the seedling stage (the first and second irrigation) because in Xinjiang Changji region, where the seeding period is in April, after the snow has just melted, the temperature is not high and the evaporation is small, the soil moisture content is relatively abundant, and the soil moisture can meet the crop's growth needs. During the budding stage (the third to fifth irrigation), the cotton plant grows faster, rainfall decreases and the temperature gradually rises, and the soil moisture evaporation increases, so appropriate irrigation is needed to promote cotton growth. During this period, the water consumption calculated by the algorithm accounts for about 19.82% of the total water consumption. During the flowering and boll-forming stage (the sixth to tenth irrigation), it is the most vigorous growth stage of cotton, and the cotton plant grows mainly by reproductive growth. Its stems, branches, and leaves will grow to the maximum, and its flowering and boll formation will reach the peak of nutrient absorption. During this period, the water consumption calculated by the algorithm is about 64.53% of the total water consumption. During the podding stage (the eleventh and twelfth irrigation), the water consumption is reduced compared to the flowering and boll-forming stage, and watering is needed to prevent the leaves from yellowing prematurely to increase boll weight and fiber content. During this period, the water consumption calculated by the algorithm is about 15.63% of the total water consumption. The Q3 decision-making scheme reduces the number of irrigation times from 12 to 10 and automatically allocates the water used during the seedling stage to other growth stages where water demand is more sensitive.

Table 5. Water consumption during the growing season.

Growth Stage (d)	Water consumption (mm)	Water consumption proportion(%)	Irrigation times
seedling	0	0	0
budding	90	19.823	2
flowering	293	64.537	6
boll-opening	71	15.638	2
total	454	100	10

3 Discussion

Under the condition that the irrigation time is determined, with the aim of increasing crop yield and conserving water, the optimal irrigation regime for the Changji region of Xinjiang was obtained through optimization using genetic algorithms. It is readily observable that when the total irrigation amount of the two experiments, GA-DSSAT and Q-GA-DSSAT, is between 430mm and 480mm, the increase in yield is considerable; when it is between 480mm and 530mm, the increase in yield is relatively small. This indicates that for cotton, an overly large total irrigation amount does not significantly increase the yield but instead wastes more water resources. Through analysis, it may be that the irrigation frequency is too high, the cotton plants grow too vigorously, and the vigorous vegetative growth in the early stage delays reproductive growth and cotton maturation [9]. Therefore, to achieve the goals of increasing yield and conserving water, the irrigation quota and the number of irrigations need to be controlled within a certain range [6].

Through the comparison of GA-DSSAT and Q-GA-DSSAT experiments, it is easy to find that the irrigation frequency is reduced from 12 times to 10-11 times in the range of 430mm-480mm of irrigation volume. In fact, distributing seedling water or partial water use to other growth stages can achieve the effects of seedling drought training and increased yield, which is similar to the research results [10] that high seedling water deficit or certain drought stress can improve cotton yield. By comparing the G1, G2, G3, G4 experiments of GA-DSSAT and the Q1, Q2, Q3, Q4 experiments of Q-GA-DSSAT, the latter has a slight advantage in yield. This shows that the former experiment, which performs cross and variation operations with fixed values, will have slow convergence and fall into a local optimal solution [11] , while the latter optimizes the genetic algorithm through Q-learning to adaptively adjust the ways of Pc and Pm, and jumped out of the local optimal solution to evolve the population towards higher yield. By comparing the Q1, Q2, Q3, Q4 schemes, it can be seen that Scheme Q3 performs the best in considering the comprehensive performance of yield and water use efficiency. Therefore, it is recommended to choose the Q3-scheme of the Q-GA-DSSAT model, which is a combination of 10 irrigation times and irrigation quota of 454mm, as the irrigation system for cotton subsurface drip irrigation in Xinjiang Changji area. This scheme ensures crop yield while improving water use efficiency, showing its comprehensive advantages.

4 Conclusion

After calibrating and validating the DSSAT-CROPGRO-Cotton model, the irrigation volume was automatically adjusted by combining the crop model with a genetic algorithm to achieve a rational decision under the same irrigation time as the field experiment. In order to increase the robustness of the genetic algorithm, the Q-learning algorithm was used to optimize the crossover operator and mutation operator of the genetic algorithm. The optimization results show that the yield increases significantly within the irrigation total of 430mm-480mm, and the growth slows down within the irrigation total of 480mm-530mm; when the irrigation total is 15% of the actual field water use, the G3 scheme obtained by the genetic algorithm (GA-DSSAT) and the Q3 scheme obtained by the Q-GA-DSSAT algorithm optimized by Q-learning both perform better in terms of yield and water use efficiency. However, the cotton yield obtained by the genetic algorithm optimized by Q-learning is higher than that of the pure genetic algorithm, which shows that the genetic algorithm population can evolve towards higher yield and water use efficiency by using the dynamic adjustment method of cross rate and mutation rate through Q-learning. Finally, the irrigation regime for cotton under drip irrigation in Xinjiang Changji was determined as the Q3 scheme: 10 irrigations during the growing period and an irrigation total of 454mm.

Acknowledgment

This study was funded by the "National Key Technology Research and Development Program of the New Generation Artificial Intelligence" (Project No. 2022ZD0115801). This funding has supported our in-depth research and exploration in the field of smart agriculture, promoting the development and application of relevant technologies. We sincerely appreciate this support and look forward to achieving greater progress in our future research.

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