Multi-objective optimal allocation of regional water resources based on slime mould algorithm

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Abstract

The slime mold algorithm (SMA) is applied to optimize the allocation of water resources in Wuzhi. The cost of using mathematical methods to optimize an engineered water allocation problem is enormous, and heuristic algorithms have become reliable and effective optimization tools. In this study, a multi-objective water resources optimal allocation model integrating social, economic and environmental objectives is constructed for the study area, and SMA equipped with fast convergence and accurate search is applied to optimize the problem. Water allocation schemes for the region in 2025 and 2030 were obtained, and the distribution results were independently analyzed from both the demand and supply sides. The results show that the total water distribution in 2025 and 2030 are about 323 million m^3 and 346 million m^3, and the water deficit ratios are 2.90% and 6.95%, respectively. From the perspective of regional development, the water dispatched in the region still is less than the water demand and the optimized water resource allocation plan can guide the development of the region.

1 Introduction

Water, an irreplaceable natural resource, is an essential material for human survival. Although water is renewable and two-thirds of the earth is covered by water, the amount of fresh water available to humans is highly limited, accounting for only

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2.5% of total global water consumption. According to UNESCO, water resources, predominantly fresh water, are the paramount resource for human beings, cross-cutting all societal, economic and environmental special events. As the basic living condition for the survival of all individuals living on the planet we live in, it is not only a limiting or a catalyst factor for any social and technological development, but also a probable source of suffering or welfare, conflict or cooperation. Due to the increasing and expanding of water resources consumption in cities, the contradiction between supply and demand is increasingly prominent in many countries and regions with the development of the world economy. Over the past decade, population growth, food production, climate change and other factors have led to moderate to severe water shortages in various sectors around the world [1, 2]. It is reported that more than 4 billion people live with severe water shortage for at least one month every year [3]. Water is a pivotal natural resources to control the ecological environment and a strategic economic resource constituting the comprehensive national strength of a country. As a process of human redistribution and distribution of water resources, optimization of water resources allocation is a crux to achieving sustainable utilization of water resources. Excellent allocation of water resources can not only produce a satisfactory effects on the ecosystem, but also is conducive to establishing the balance between supply and demand of water to promote the sustainable population of economy, technology and society [4, 5]. On the contrary, unscientific allocation of water resources may lead to the decline of the ecosystem and the deterioration of the ecology and affect the normal evolution of society. It can lead to conflicts between the water sectors if water resources in an area, especially in water-scarce areas, are not appropriately allocated. [6, 7].

In order to reconcile the balance between water use and water conservation, many scholars have long been studying the allocation of water resources to achieve sustainable urbanization growth.

In the 1960s, Maas et al. [8] invoked systems analysis and optimization theory to introduce water resources planning, which symbolized the birth of the first model to study regional water resources allocation and laid the foundation for applying systems analysis to optimize water resources allocation. In 1982, the USA held a conference entitled "Multi-objective Analysis of Water Resources," which focused on the application of multi-objective decision-making technology in the water resources allocation [9]. In 1995, Watkins et al. [10] developed a joint operational model of water resources to address the risks and uncertainties present in water resources planning models.

Optimal allocation of water resources is a meaningful effort to achieve sustainable use of water resources, and its main task is to allocate water resources to the industrial and agricultural sectors, the irrigation water sector and the domestic water sector. Single-objective planning is widely used in many studies to resolve water resource allocation conflicts among various departments caused by competitive water use [11–17]. In the early days of research, methods such as dynamic programming and game theory were applied to construct water resources allocation models. However, some mathematical optimization methods are difficult to get close to reality due to the complexity of water resources allocation problems, and it is challenging for a single objective function model to provide a sustainable

water distribution plan [18]. As a result, the study of water allocation models has gradually evolved into a new research direction, and many researchers have extended their ideas to multi-objective planning. For example, Zhong et al. [19] proposed a multi-objective decomposition model for the optimal operation of water resources according to the demand indicators of users in the research area. Roozbahani et al. [20] advanced a multi-objective model covering technological, economic, social and environmental aspects, in which competing stake holders share the water resources of the basin. Combining opportunity constraints, fractional objectives and multi-objective planning, Ren et al. [21] developed a multi-objective stochastic fractional objective planning model and applied the model to the allocation of water resources among industries. Li [22] suggested an intuitive fuzzy multi-objective nonlinear programming model to help alleviate the water shortage problem under dry and wet conditions in irrigation areas and adopted multi-objective nonlinear programming technology to obtain a balanced water distribution scheme. Banihabib et al. considered the uncertainty of water resources and economic parameters in the basin and formulated a fuzzy multi-objective heuristic model for water allocation to provide optimal planting patterns under uncertainty.

To fit the practical problem, the allocation of water resources is modeled as a hierarchical and complex problem with multiple sources, multiple elements, multiple users and multiple objectives. [23]. It is difficult to get the result quickly without an effective optimization algorithm. With the intensification of water resources allocation model research, various mathematical techniques are applied to water resources for optimal allocation [24–27]. However, some mathematical optimization methods have local optimal traps. As the scale of the problem increases, the solved process becomes increasingly cumbersome and complex, which dramatically increases the cost of solving the problems. Fortunately, with the exploration of heuristic optimization algorithms, the optimization technique has become a practical tool for solving optimization problems after mathematical optimization techniques [28–30]. There are some classical algorithms, including genetic algorithm (GA) [31], ant colony optimization (ACO) [32, 33] and particle swarm optimization algorithm (PSO) [34], and recent algorithms such as gray wolf algorithm [35], moth-flame optimization algorithm [36] and aquila optimizer (AO) [37, 38].

Benefiting from the proposal and progress of the heuristic optimization algorithms, the optimization technology has become a powerful means to complex large-scale engineering problems. Nowadays, intelligent algorithms have been widely used in different branches of science and engineering [39, 40]. Beskirli et al. [41] used tree seed algorithm (TSA) and the modified tree seed algorithm (MTSA) to optimize the application of energy demand prediction in Turkey and completed the estimation of the energy needed for national economic activities. Essa et al. [42] used the Harris Hawks optimizer, an optimizer proposed by simulating the hunting behavior of Harris Hawks, to determine the optimal parameters of artificial neural networks for improving the accuracy of traditional networks in predicting solar stationary output. Chauhan et al. [33] improved the probability of the ant colony algorithm getting a better initial population by improving the initialization method, and applied m-ACO to optimize the parameters of PID controller for coupled tank

system. Chauhan et al. [43] completed cluster head selection in heterogeneous wireless sensor networks with diversity-driven multi-parent evolutionary algorithm with adaptive non-uniform mutation.

Similarly, intelligent algorithms have been used to solve the optimal allocation model of water resources at the beginning of the 21st century. In 2000, GA [31, 44] was implemented into the multi-objective analysis model of uncertain water resources optimal allocation. In 2014, Zhang et al. [45] built a model system framework with multiple objectives considering sewage reuse supply and demand, cost and profit and pollutant trade-off. Then, the NSGA II algorithm applicable to complex problems was applied to the experiments. In 2020, Chen et al. [46] employed PSO to the multi-objective model of urban water resources allocation, and the water distribution scheme obtained by the method effectively mitigated urban water conflict. Godwin et al. [47] generated the genetic algorithm to establish a water resource allocation model to fairly distribute available water to all sectors, and the Kano River irrigation scheme produced the optimal fair water release. There can be no doubt that optimization techniques have been widely used in water resource allocation and water management strategic decisions [48–53]. In summary, the study of mathematical models and heuristic algorithms for water allocation has received increasing attention in order to ensure the sustainable development of water resources.

Consequently, this paper introduces the slime mold algorithm (SMA) [54], a newly proposed heuristic optimization algorithm, to complete the optimization of regional water resources. SMA has satisfactory global exploration and development capabilities, and its advantages can be attributed to several aspects: Adaptive weights ensure rapid convergence and jump out of local optimal traps; vibration parameters can improve the accuracy of search agents; the generation of new individuals will make full use of historical information to make better decisions; a variety of position update methods ensure the adaptability of the early and late searches. Hence, SMA has been proposed recently and applied in some fields. For example, Zubaidi et al. [55] used SMA to optimize an artificial neural network model to predict urban water demand. Vashishtha et al. [56] investigated the opposition-based slime mold algorithm to find the optimal parameters of the extreme learning machine (ELM). Chauhan et al. [57] proposed a hybrid algorithm that makes full use of the development and exploration capabilities of SMA and arithmetic optimizer algorithm (AOA) by crossing and merging them.

This paper investigates the application of SMA in the regional water resources optimal allocation. The framework is applied to a study area to complete the allocation optimization of regional water resources in 2025 and 2030 with known data. When dealing with the problem, a simple weight combination of targets is avoided and the optimization ability of SMA is efficiently utilized. Combined with the optimization strategy of large-scale systems, the sub-objectives are first optimized one by one. Then a comprehensive target of optimal allocation is calculated using the optimization results. Finally, the comprehensive goal is used as the fitness function of SMA and optimized. The allocation of water resources at different target years in the study area provides data reference for the future utilization of water resources and the development of the region.

The rest of this paper is composed of a hierarchy as follows: First, Sect. 2 introduces the multi-objective model of regional water resources allocation and the method used to study the problem. Second, the research area is described and the initial data used in the research work is given in Sect. 3. Then, the experimental results are given and elaborated in detail in Sect. 4. Section 5 provides a comprehensive analysis and discussion of the experimental results, and gives suggestions for improvement in the allocation of water resources in the study area. Finally, the study of this paper is summarized in Sect. 6.

2 Method

2.1 Mathematical model

2.1.1 Objective functions

The optimization of the regional water resources allocation model with sustainable development features aims to maximize the synthetical performance of society, economy and ecology. Hence, this study takes society, economy and ecology as the goals to construct a multi-objective allocation model of regional water resources and pursues the synthetical benefits of the three when solving the model. Table 1 lists the expression and meaning of parameters or variables involved in the objectives.

Objective 1 (Social objective): Eq. (1) expresses the social benefits:

$$Min f_1(x) = \sum_{k=1}^{K} \sum_{j=1}^{J(k)} \left[D_j^k - \sum_{i=1}^{I(k)} x_{ij}^k \right] \tag{1}$$

Scientific and reasonable distribution of water resources can maintain social stability, ensure the steady development of society and coordinate the contradiction between water departments. Since the social benefit is a quantity that is difficult to visualize, the amount of water shortage is used to measure social stability in this study. In detail, the more the allocation of water resources can meet the demand of users, the better the social stability can be guaranteed. Therefore, the minimum water shortage in the formula Eq. (1) can reflect the maximum social benefits brought by water resources.

Objective 2 (Economic objective): Eq. (2) expresses the economic benefits:

$$Max f_2(x) = \sum_{k=1}^{K} \sum_{j=1}^{J(k)} \sum_{i=1}^{I(k)} (b_{ij}^k - c_{ij}^k) \, x_{ij}^k \alpha_i^k \beta_{ij}^k \omega_k \tag{2}$$

An excellent water resource allocation plan can directly bring better economic benefits, which represent the economic growth that water resources can bring to the region after being allocated to users. Therefore, maximizing the target is expected to seek the allocation scheme that maximizes economic benefits. In Eq. (2), the water

Table 1 Parameters of objectives

	Parameter	Description
Common	K	The number of subareas in the study area is expressed as K which depends on the actual problem.
	$I(K)$	The number of water sources in subarea k.
	$J(K)$	The number of water users in subarea k.
	x_{ij}^k	The volume ($\times 10^4\ m^3$) of water allocated from the water source i to the user j in the subarea k.
Social	D_j^k	The water demand ($\times 10^4\ m^3$) of user j in subarea k.
Economic	b_{ij}^k	The unit water supply benefit coefficient ($yuan/m^3$) of water source i to user j in subarea k.
	c_{ij}^k	The unit water supply cost coefficient ($yuan/m^3$) of water source i to user j in subarea k.
	ω_k	A positive integer used to represent the weight of subarea k.
	α_i^k	The coefficient reckoned from the order in which subregion k are supplied by water source i.
	β_j^k	The water equity coefficient of user j in subarea k.
Ecological	d_j^k	The content of important pollutants in the water discharged by user j in subarea k.
	ρ_j^k	The emission modulus of user j in subarea k.

supply cost coefficient c_{ij}^k and benefit coefficient b_{ij}^k are related to local water price and the economic benefits that water resources can provide, respectively.

The water supply sequence coefficient α_i^k reflects the water supply priority of the water source i in the subarea k. The higher priority the water source has, the larger value number is. And its calculation method can refer to the formula Eq. (3).

$$\alpha_i^k = \frac{1 + I(k) - n_i^k}{\sum_{i=1}^{I(k)}(1 + I(k) - n_i^k)} \tag{3}$$

where $n_i^k = 1, 2, ..., I(k)$ denotes the order of water source i in subarea k to provide water resources to users (the integer 1 indicates that the source supplies water first).

Similarly, the water equity coefficient reflects the demand degree of user j in the subarea k for water. The greater degree demand users have, the larger value number is. Its calculation method can refer to formula Eq. (4).

$$\beta_j^k = \frac{1 + J(k) - n_j^k}{\sum_{j=1}^{J(k)}(1 + J(k) - n_j^k)} \tag{4}$$

where $n_j^k = 1, 2, ..., J(k)$ denotes the order of water used by user j in subarea k (the integer 1 indicates that the user is supplied with water first).

Objective 3 (Ecological objective): Eq. (5) expresses the ecological benefits:

$$Min\, f_3(x) = \sum_{k=1}^{K} \sum_{j=1}^{J(k)} d_j^k \rho_j^k \sum_{i=1}^{I(k)} x_{ij}^k \tag{5}$$

The distribution and utilization of water resources need to take into account environmental issues. The waste water discharged by each user will carry a certain amount of pollutants. Minimizing the accumulation of pollutants is an important measure to ensure an excellent ecological condition. Therefore, minimizing the value is used in the formula to reflect the maximization of ecological benefits.

2.1.2 Constraint conditions

The optimal allocation of water resources is limited by the following conditions:

Water availability constraints:

$$\sum_{j=1}^{J(k)} x_{ij}^k \le O_i^k \tag{6}$$

where O_i^k denotes the available water supply of headstream i in subsegment k.

Water demand constraints:

$$L_j^k \le \sum_{i=1}^{I(k)} x_{ij}^k \le H_j^k \tag{7}$$

where L_j^k and H_j^k signify the lower bound and upper bound of water demand of user j in subarea k, respectively. The water supply afforded by the water source to users in the subarea shall not be lower than the lower limit of water consumption, nor higher than the upper limit of water consumption [5]. Generally, $L_j^k = 0.9D_j^k$ and $H_j^k = D_j^k$.

Water delivery capacity constraints:

$$x_{ij}^k \leq Q_{ij}^k \tag{8}$$

where Q_{ij}^k denotes the maximum water delivery capacity of water source i to user j in subarea k. Under normal circumstances, $Q_{ij}^k = min\{O_i^k, D_j^k\}$.

Non–negative constraints:

$$x_{ij}^k \geq 0 \tag{9}$$

Inequality (9) represents that water distribution volume must not be negative.

2.2 Slime mold algorithm

2.2.1 The mathematical principle

The SMA, a meta-heuristic algorithm proposed in 2020 [54], is inspired by the behavior and morphological changes of Physarum polycephalum in the process of diffusion and foraging. It exhibits fast convergence speed and strong optimization ability in dealing with optimization problems. This section describes the mathematical principle of the SMA and the formulas Eq. (10) - Eq. (15) [54] involved in the algorithm principle. For the meaning of the parameters and variables involved in the formulas, please refer to Table 2.

$$\overrightarrow{X(t+1)} = \begin{cases} \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(\overrightarrow{W} \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)} \right), & r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X(t)}, & r \geq p \end{cases} \tag{10}$$

$$a = arctanh\left[-\left(\frac{t}{max\_t} \right) + 1 \right] \tag{11}$$

$$p = tanh \mid S(i) - DF \mid \tag{12}$$

$$\overrightarrow{W(SmellIndex(i))} = \begin{cases} 1 + r \cdot log\left(\frac{bF - S(i)}{bF - wF} + 1 \right), & condition \\ 1 - r \cdot log\left(\frac{bF - S(i)}{bF - wF} + 1 \right), & others \end{cases} \tag{13}$$

$$SmellIndex = sort(S) \tag{14}$$

Table 2 Parameters of SMA

Parameter	Description
t	Iteration counter.
$\vec{X}$	The location of slime mold biological front-end.
$\overrightarrow{X_b}$	The optimal biological front-end position generated by all iterations before the current iteration process.
A, B	Two randomly selected individuals of slime mold.
$\overline{W}$	The weight of slime mold.
r, rand	A random number selected from the interval [0,1].
$S(i)$	The fitness value of individual, i represents the index of the individual in a population.
DF	The best fitness value in the iterative process.
$\overrightarrow{vc}$	A variable that decreases from 1 to 0 with the number of iterations.
$\overrightarrow{vb}$	A random variable in the range [-a,a] where the value of a is calculated by the following formula Eq.(11).
SmellIndex	The result sequence after the fitness list is sorted (according to the ascending rule in the minimum value problem).
bF, wF	The best and worst fitness value found in the iterative process, respectively.
z	An experience value variable.
UB, LB	The boundaries of the search range, representing the upper and lower bounds, respectively.

When the slime mold is foraging, it determines the location of food based on the concentration of food odor in the air and then spreads to the food. When the slime mold vein approaches food, a biological oscillator in the vein produces propagating waves that control the flow of cytoplasm in the vein and the slime mold can secrete enzymes to digest the food it surrounds. The following formula Eq. (10) is proposed to simulate such approximation behavior.

Need to add that, the *condition* in the formula Eq. (13) signifies the first half of the population. In addition, the original author determined a random number z from the plentiful experimental results and showed that it can help slime mold obtain food sources with higher concentration better when z is less than 0.03. In combination with the above principle formulas, the modified formula for a slime mold to update location was given (see Eq. (15)).

$$\overrightarrow{X'(t+1)} = \begin{cases} rand \cdot (UB - LB) + LB, & rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{vb} \cdot \left(\overline{W} \cdot \overrightarrow{X_A(t)} - \overrightarrow{X_B(t)} \right), & r < p \\ \overrightarrow{vc} \cdot \overrightarrow{X(t)}, & r \geq p \end{cases} \quad (15)$$
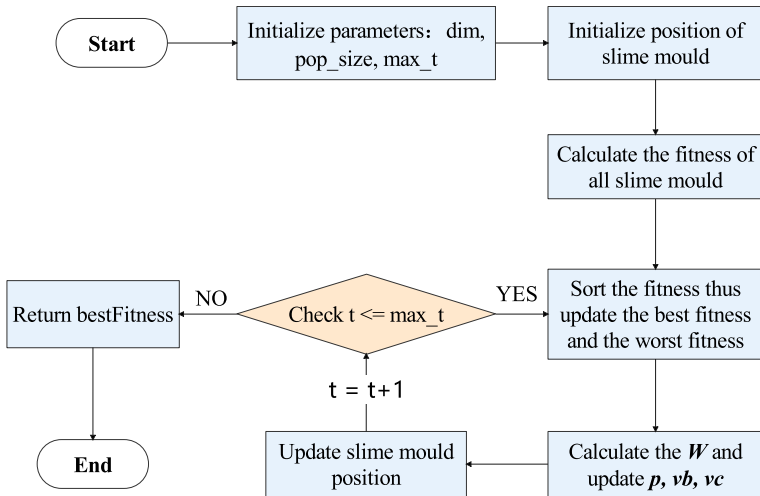
Fig. 1 Flowchart of SMA

According to the mathematical mechanism of the algorithm, the pseudo-code of the SMA can be constructed and given (Algorithm 1) [54], and the flowchart of the algorithm can be drawn (Fig. 1).

Algorithm 1 Pseudo-code of the SMA

1: Initialize parameters: dim, pop_size, max_t
2: Initialize position of slime mould;
3: **while** $t \leq max\_t$ **do**
4:     Calculate the fitness value of all slime mould;
5:     Sort the fitness thus update the best fitness and the worst fitness;
6:     Calculate the W and update p, vb, vc;
7:     Update position of slime mould;
8:     $t = t + 1$;
9: **end whilereturn** bestFitness;

2.2.2 Simulation experiment

It is a common strategy to evaluate the performance of an algorithm with a set of benchmark mathematical functions [36]. In order to demonstrate the superiority of the SMA, some unimodal ($f_1 - f_5$) and multimodal ($f_6 - f_9$) test functions of standard benchmarks are selected and listed in Table 3 [58–60]. Unimodal functions have only one global optimum and no local optimum, so they are suitable for benchmark testing of algorithms, while multimodal functions have multiple local optima, so it is helpful to test the global searching ability of algorithms [36].

Table 3 Test functions

Function	Dim	Range	f_{min}
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]$	0
$f_2(x) = \sum_{i=1}^{n} (\sum_{j=1}^{i} x_j)^2$	30	$[-10, 10]$	0
$f_3(x) = max_i\{|x_i|, 1 \le i \le n\}$	30	$[-100, 100]$	0
$f_4(x) = \sum_{i=1}^{n} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	$[-30, 30]$	0
$f_5(x) = \sum_{i=1}^{n} ix_i^4 + random[0, 1]$	30	$[-128, 128]$	0
$f_6(x) = \sum_{i=1}^{n} -x_i sin(\sqrt{|x_i|})$	30	$[-500, 500]$	$-418.9829*Dim$
$f_7(x) = \sum_{i=1}^{n} [x_i^2 - 10cos(2\pi x_i) + 10]$	30	$[-5.12, 5.12]$	0
$f_8(x) = -20exp\left[-0.2(\frac{1}{n}\sum_{i=1}^{n} x_i^2)^{0.5}\right]$ $-exp\left[\frac{1}{n}\sum_{i=1}^{n} cos(2\pi x_i)\right] + 20 + e$	30	$[-32, 32]$	0
$f_9(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos(\frac{x_i}{\sqrt{i}}) + 1$	30	$[-600, 600]$	0

Table 4 Parameters for algorithms

Algorithm	Pop size	Iterations	Parameters setting
GA	30	1000	Pc=0.5, Pm=0.01
PSO	30	1000	c1=2, c2=2, vMax=6
GWO	30	1000	a=[2,0]
MFO	30	1000	b=1.0
SMA	30	1000	z=0.03

In order to verify the performance of the SMA, the representative and latest algorithms, which are summarized in Table 4, are chosen to conduct optimization on the test functions in Table 3. For each algorithm, 30 search agents were used and 1000 iterations were carried out. Parameters related to the algorithms are shown in Table 4. The convergence curves for each function iterated 1000 times using all the algorithms are summarized in Fig. 2 and each subplot represents a test function. It can be seen from the figure that SMA can always find a better solution than other algorithms, which indicates that SMA has better global search ability and faster convergence. Moreover, the run results of the functions (f_2, f_4, f_6 and f_8) are listed in Table 5 to give a numerical representation of SMA performance. From the convergence value, SMA can search for more accurate values than other algorithms. In terms of running time, SMA is only slower than GA, but has faster convergence speed than other algorithms. As a consequence, SMA is applied to the optimal allocation of regional water resources based on its excellent performance.
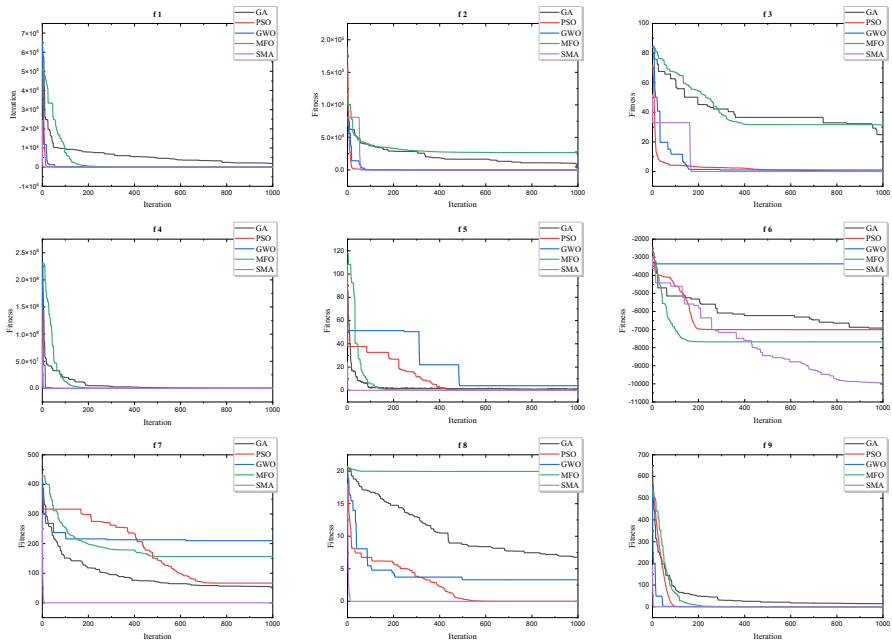
Fig. 2 Summary diagram of simulation curves

2.3 Technique process

Although the allocation of regional water resources is a multi-objective problem, each objective is still independent. In order to make full use of the independent optimization ability of each objective, the following steps are adopted to allocate the water resources in the research region and the detailed framework is shown in Fig. 3.

(1) According to the mathematical model of water resource allocation, we use the following code to represent a group of water resources allocation schemes.

$$X^* = \begin{pmatrix} X_1 \\ \vdots \\ X_k \end{pmatrix}, k = 1, ..., K \tag{16}$$

$$X_k = \begin{pmatrix} X_{k,1} \\ \vdots \\ X_{k,i} \end{pmatrix}, i = 1, ..., I(k) \tag{17}$$

Table 5 Simulation results of several functions

Function	Algorithm	Iterations	Convergency value	Time (s)	Stable generation *
f_2	GA	1000	9459.32	17.77	980
	PSO	1000	1.45	59.32	423
	GWO	1000	39.95	61.88	246
	MFO	1000	26679.00	55.85	597
	SMA	1000	0.00	26.20	63
f_4	GA	1000	253396.87	12.31	826
	PSO	1000	27.21	52.62	784
	GWO	1000	440.09	55.72	305
	MFO	1000	125.65	49.73	990
	SMA	1000	29.00	20.49	16
f_6	GA	1000	− 6917.30	6.80	941
	PSO	1000	− 7002.27	48.92	457
	GWO	1000	− 3365.98	51.60	0
	MFO	1000	− 7677.52	45.18	249
	SMA	1000	− 9949.00	16.43	906
f_8	GA	1000	6.79	10.55	983
	PSO	1000	0.00	50.92	583
	GWO	1000	3.31	53.81	503
	MFO	1000	19.96	47.65	70
	SMA	1000	0.00	18.04	13
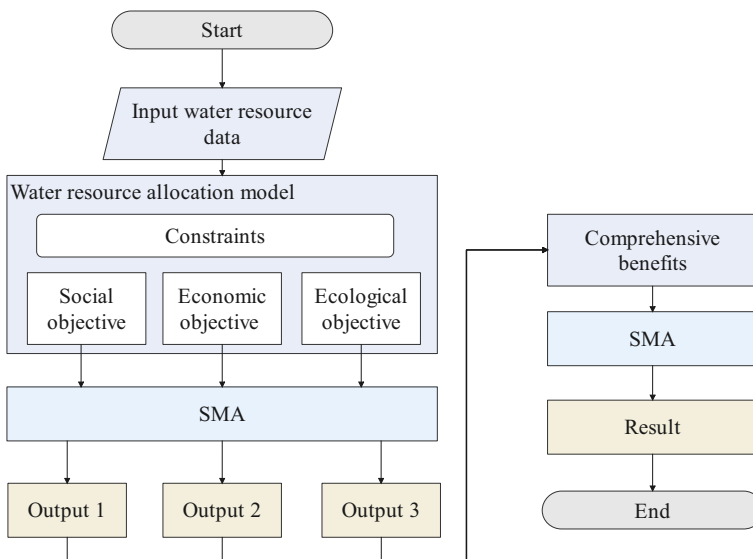
Fig. 3 Framework for optimal allocation of water resources using SMA

$$X_{k,i} = \begin{pmatrix} x_{k,i,1} \\ \vdots \\ x_{k,i,j} \end{pmatrix}, j = 1, ..., J(k) \tag{18}$$

(2) The SMA algorithm is used to optimize social, economic and ecological benefits and output the optimized water resource allocation scheme $X_q^*, q = 1, 2, 3$ (q indicates the objective index).

(3) The scheme is used to calculate the value of each objective, and the comprehensive benefits are constructed through the following formula Eq. (19).

$$F = \sum_{q=1}^{3} \lambda_q \left(\frac{f_q(x) - \min \left\{ f_q(X_m^*), m = 1, 2, 3 \right\}}{\max \left\{ f_q(X_m^*), m = 1, 2, 3 \right\} - \min \left\{ f_q(X_m^*), m = 1, 2, 3 \right\}} \right) \tag{19}$$

where λ_q represents the importance of objective q in regional development, which is determined according to the development goals of the studied region and $\sum_{q=1}^{3} \lambda_q = 1$.

(4) Optimize the comprehensive benefit objective F and output optimization scheme.
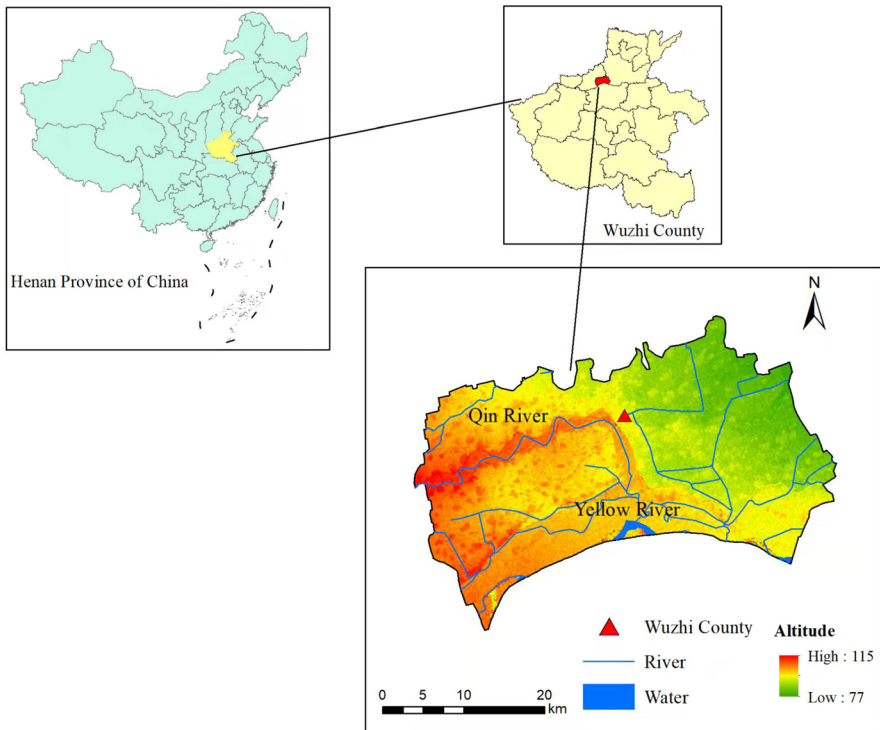

Fig. 4 Geographical map of Wuzhi County, Henan Province, China

Table 6 The volume ($\times 10^4\ m^3$) of water supply sources

Target year	Surface				Ground water	Reclaimed
	Qin river	South-to-North Water Diversion	Yellow river	Other surface		
2025	1000	1200	16936	576	7260	5380
2030	2700	1200	16936	1440	4840	7500

Table 7 The volume ($\times 10^4\ m^3$) of water demand users

Target year	Domesticity	Agriculture	Industry	Tertiary industry	Ecology
2025	3464.58	13204.54	13579.40	643.08	2417.65
2030	3988.65	12153.26	15512.63	2452.08	3071.82

3 Study area and data

Wuzhi County (34°57′N-35°10′N, 113°10′E-113°40′E) (see Fig. 4) is located in the northwestern part of Henan Province in China. It is affected by the continental monsoon climate of warm temperate so that it has an average annual temperature of 14.4 °C, annual precipitation of 575.1 mm and a frost-free period of 211 days. The county with high terrain in the west and low terrain in the east covers an area of about 805 square kilometers. Being located in the middle and lower reaches of the Yellow River, it belongs to the confluence area of the Yellow River and the Qin River, and the South-North Water Transfer Central Project can provide water resources. Radiated by the core area of the Zhengzhou metropolitan area in 2019, its regional Gross Domestic Product (GDP) increased by 7.9% year-on-year, and the total amount jumped to the top of the six counties for the first time. Wuzhi County invested in and implemented 59 "Three Great Remolding" projects, and built and operated the county e-commerce service center, which promoted a year-on-year increase of 20.3% in revenue from the tertiary industry.

As the region is building a modern economic system, the exploitation and usage of natural resources are proliferating to accommodate economic development. Improper allocation of natural water resources may lead to conflicts between supply and demand, and incompatibility between economic growth and water resources development. A scientific and reasonable water resources allocation plan in the region can elevate the capacity factor of water resources in the region, take into account current and long-term interests and achieve coordinated development in many aspects of the region. Therefore, the area was selected as a research area based on the actual situation to provide a reference for allocating water resources.

The primary water sources in the study area include the Qin River, the South-to-North Water Transfer, the Yellow River, other surface water, groundwater and reclaimed water, among which the Qin River, the South-to-North Water Diversion,

Table 8 Model parameters from the demand side

j	User	b_{ij}^{k} [*1]		c_{ij}^{k} [*2]	β_j^{k} [*3]	d_j^{k} [*4]	ρ_j^{k}
		2025	2030				
1	Domesticity	0.0500	0.0500	2.35	0.33	400	0.80
2	Agriculture	0.0026	0.0045	0.40	0.07	200	0.20
3	Industry	0.0182	0.0250	2.90	0.20	300	0.30
4	Tertiary industry	0.2000	0.1538	3.60	0.13	500	0.80
5	Ecology	0.0500	0.0500	2.35	0.27	0 [*5]	0 [*5]

[*1] $10^4 yuan/m^3$. Since the urban ecological environment is closely related to the lives of residents, the values of b_{i1}^{k} and b_{i5}^{k} are the same.

[*2] $yuan/m^3$. c_{ij}^{k} is determined by the water price and tax collection standards in the area.

[*3] With reference to the importance of each water sector in the area, the order of each water sector is: domesticity, ecology, industry, tertiary industry and agriculture.

[*4] Take Chemical Oxygen Demand (COD) as a reference indicator for pollutants in sewage, mg/L.

[*5] Ecological water does not participate in the calculation of sewage discharge

Table 9 Model parameters from the supply side

i	Supplier	α_i^k
1	Qin River	0.24
2	South-to-North Water Diversion	0.19
3	Yellow River	0.14
4	Other surface water	0.28
5	Groundwater	0.10
6	Reclaimed	0.05

the Yellow River and other surface water belong to surface water. The primary water users are domesticity, agriculture, industry, tertiary industry and ecology. Based on these realities, the values of K, I and L in the model can be obtained, that is, $K = 1$, $I = 6$ and $J = 5$. Taking 2017 as the base year, the quota method is used to predict the water availability of water supply sources and the water demand of the water sector for target years [61]. The water availability statistics (Table 6) and water demand statistics (Table 7) can be obtained.

On the basis of the actual situation of each water source in the area and the importance of water use by each water sector, the order of water supply is determined as: other surface water, Qin River water, South-to-North Water Diversion, Yellow River water, groundwater and reclaimed water, and the order of degree for using water is determined as: domesticity, ecology, industry, tertiary industry

and agriculture. According to the actual situation and combined with statistical data, the parameters in the allocation model of regional water resources in the district can be determined [61], and they are summarized in Tables 8 and 9. Since people-oriented is the cornerstone of social development, the research gives priority to ensuring social benefits and second pays attention to economic and ecological benefits and the parameters in comprehensive benefit are set as $\lambda_1 = 0.5, \lambda_2 = 0.3, \lambda_3 = 0.2$.

4 Results

Based on the above content, the majorization of water resources allocation in the region takes advantage of the SMA to accomplish the assignment, and this section is a circumstantial description of the results.

Figures 5 and 6 show the optimization curves of SMA for different target years. To start with, the SMA is used to independently optimize the three goals (social, economic and ecological) and then get the corresponding results. In the next place, the comprehensive objective is optimized by combining with these geographic results. In the figures, the vertical axis represents the fitness value of the target (objective function value) and the horizontal axis represents the number of iterations. As shown in the figures, the gradual stabilization of the curve means that the objective converges gradually with the iterative process. The curve converges rapidly in the early stage of iteration, and the fluctuation amplitude decreases in the late stage of iteration, indicating that the algorithm has found a great solution.
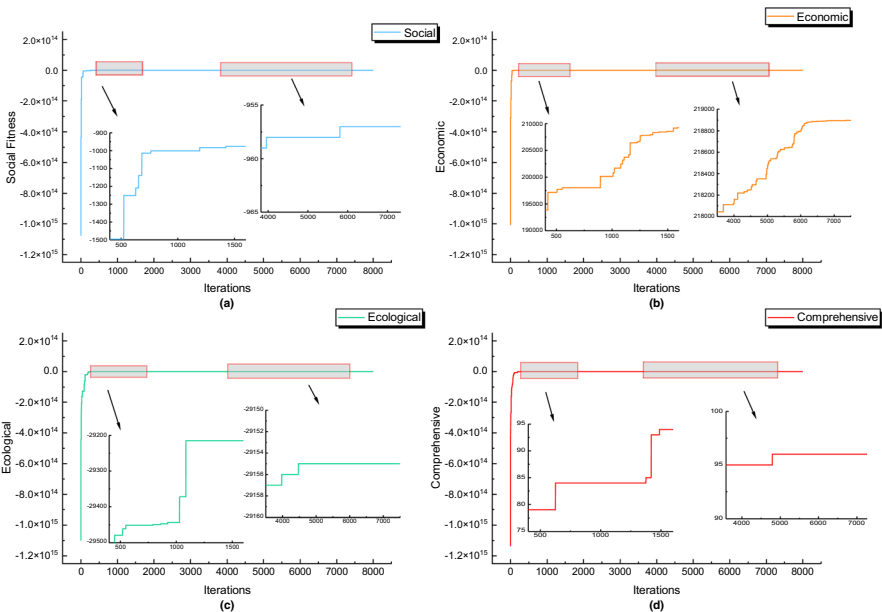

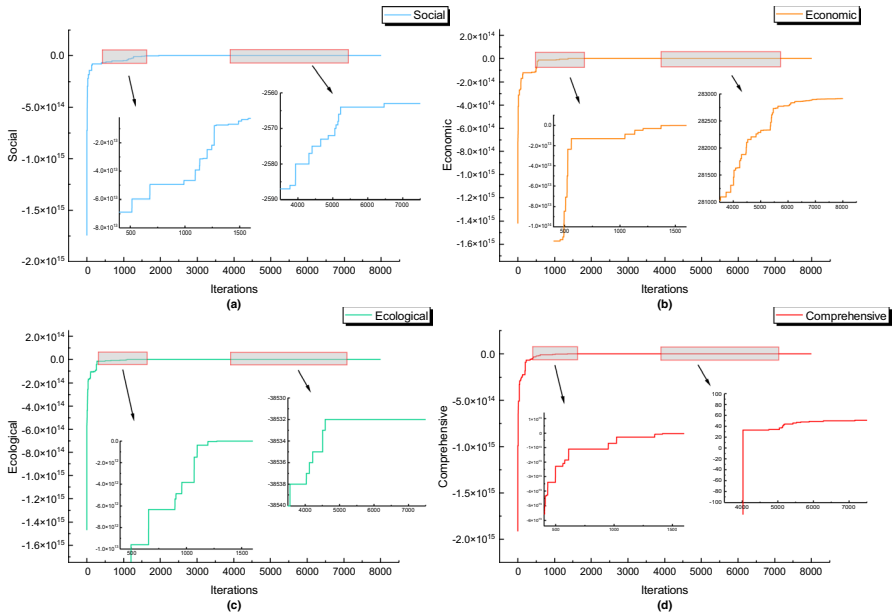**Fig. 5** Iterative curves of slime mold algorithm based on 2025 data

Fig. 6 Iterative curves of slime mold algorithm based on 2030 data

Table 10 Result of optimal allocation of regional water resources ($10^4 m^3$)

Target year	Supplier	Domesticity	Agriculture	Industry	Tertiary industry	Ecology
2025	Qin river	0.00	17.10	363.33	619.31	0.10
	South-to-North Water Diversion	0.00	0.00	24.44	1.07	1173.87
	Yellow river	3464.58	12973.70	59.15	0.00	437.50
	Other surface water	0.00	0.00	0.00	0.42	574.22
	Ground water	0.00	0.00	7256.64	0.00	0.00
	Reclaimed water	0.00	0.00	5359.40	16.92	0.00
	Total	3464.58	12990.80	13062.96	637.72	2185.69
2030	Qin river	2665.35	28.05	0.00	2.58	2.87
	South-to-North Water Diversion	1189.58	0.00	6.86	0.00	0.03
	Yellow river	4.43	47.42	13896.72	1.20	2984.57
	Other surface water	0.00	0.45	3.20	1427.27	4.26
	Ground water	0.00	3730.27	179.66	921.54	0.36
	Reclaimed water	129.29	7236.26	14.62	99.23	20.19
	Total	3988.65	11042.45	14101.06	2451.82	3012.28

In the experiment, the solutions that do not conform to the constraint conditions were punished by a penalty constant (be set as 10^{10}). Consequently, it can be demonstrated from the curves that all the solutions obtained after iteration meet
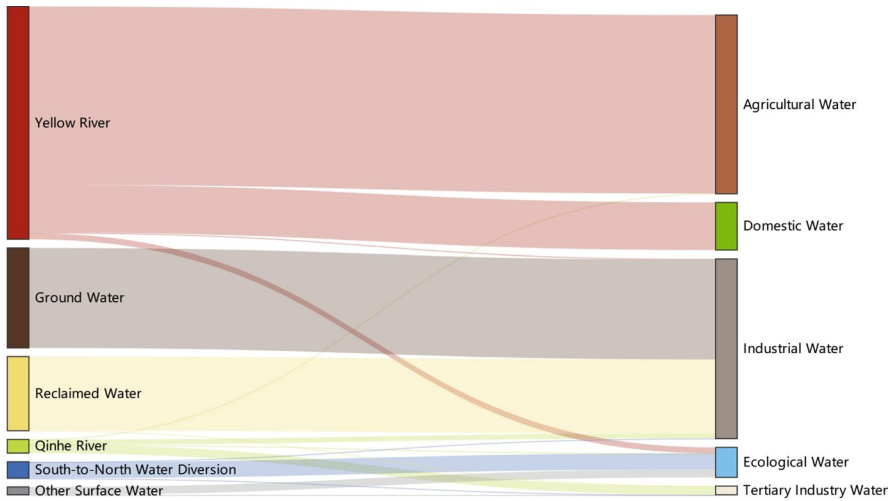
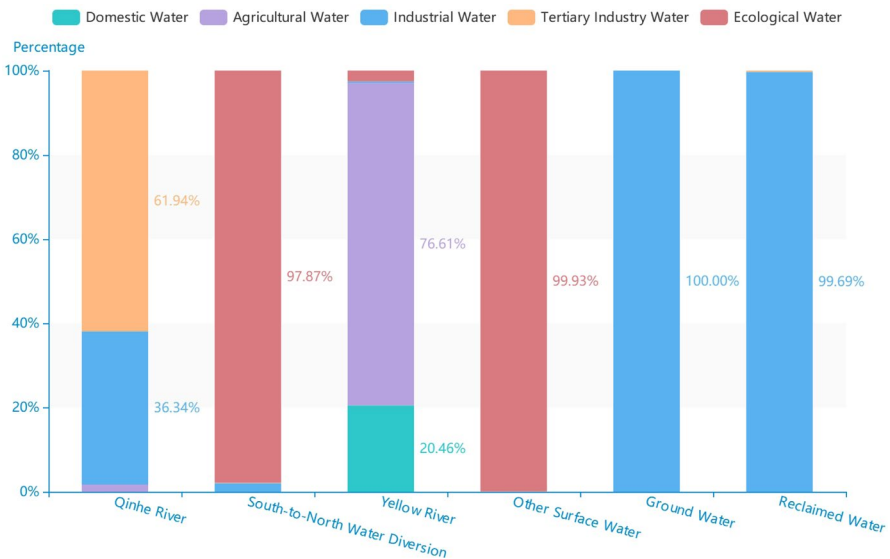**Fig. 7** The sankey diagram of water flow in 2025

Fig. 8 The bar chart of supply side water distribution ratio in 2025

the constraint conditions. The optimal allocation of regional water resources in the area is displayed in Table 10, and the data in the table are visualized from different aspects as in Figs. 7, 8, 9, 10, 11 and 12.

Figures 7, 8 and 9 visualize the distribution results based on 2025 data. Fig. 7 in which the flow and direction of water resources were described shows the Sankey diagram of water resources flowing from water source to users. The
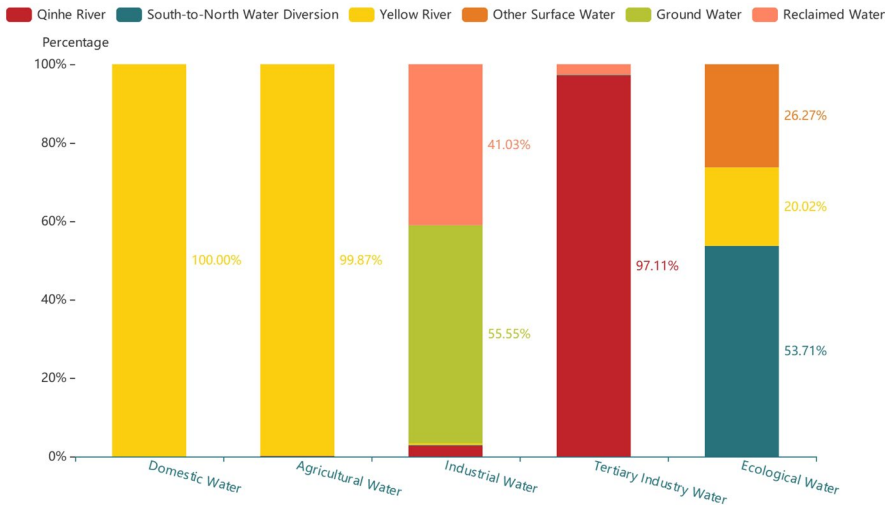
Fig. 9 The bar chart of demand side water distribution ratio in 2025
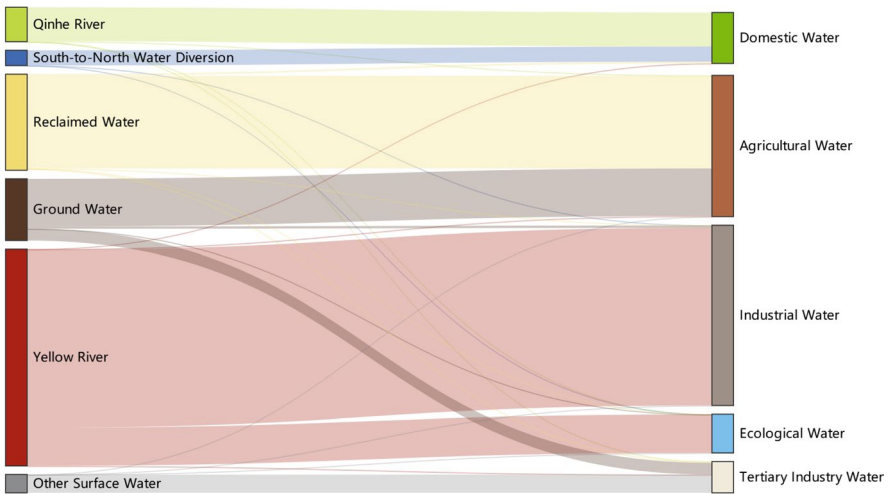

Fig. 10 The Sankey diagram of water flow in 2030

rectangles on the left of the Sankey diagram represent the water suppliers and the right rectangles represent the users. The length of the rectangle and the width of the branches correspond to the amount of water. For example, the Yellow River supplies the most water so the rectangle representing the Yellow River on the left is the longest. At the same time, the Yellow River supplies the most water to the agricultural sector, so it has the largest branch width. The value in Fig. 8 is a bar chart of water resources allocation from the supply side, each item of which exhibits the ratio of the water allocated to each user to the total water supply of
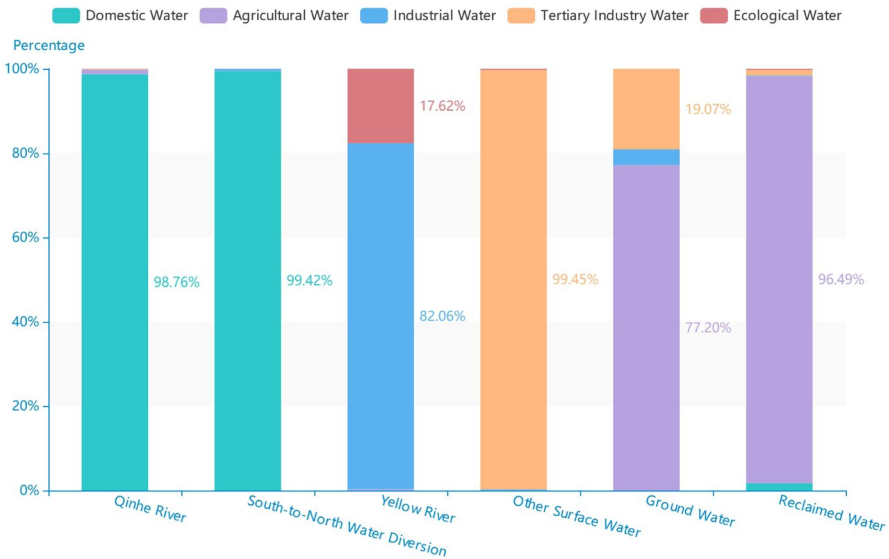
Fig. 11 The bar chart of supply side water distribution ratio in 2030
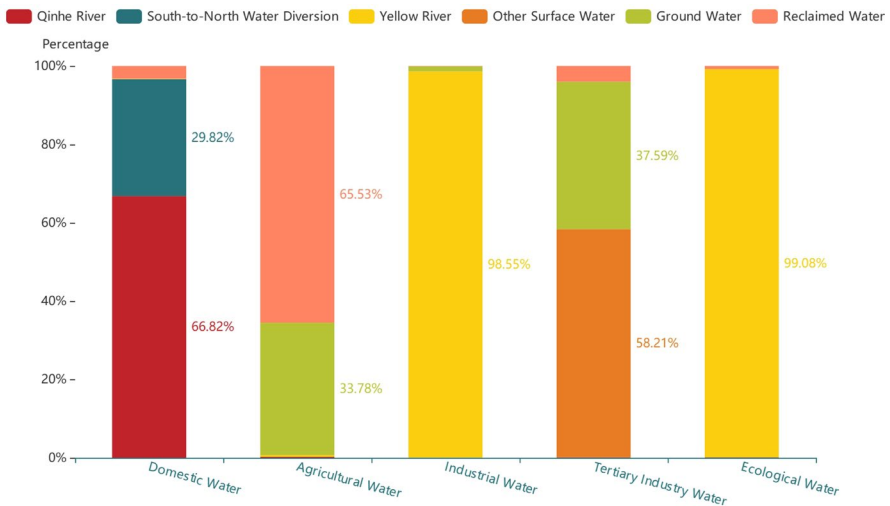

Fig. 12 The bar chart of demand side water distribution ratio in 2030

the source. In the figure, different colors are used to represent different users. The horizontal axis lists the supplier and the vertical axis lists the proportion value, which represents the percentage of the total amount of water provided by the supplier to the water users. For example, 61.94% of the water in Qinhe is supplied to the tertiary industry. Figure 9 displays a bar chart of the water resources allocation ratio on the demand side, where the value represents the ratio of water from

each water source to the total water consumption of the user. Different colors are used to represent different suppliers. The horizontal axis represents water users and the vertical axis represents the proportion value. All domestic water is supplied from the Yellow River, so the column representing domestic water is yellow and the value is 100%.

From the perspective of suppliers (Fig. 8), the water supply structures of groundwater, reclaimed water and other surface water are all unitary. 100% of groundwater and 99.69% of regenerated water are supplied to industry, while almost all other surface water (99.93%) is used for ecological water. Unlike the former, the water supply structures of the Yellow River and the Qin River are more complicated. Most of the South-to-North Water Transfer Project (97.87%) is used as a supplement to compensate for the shortage of ecological water, and a little is allocated to the industrial sector. On the side of demand (Fig. 9), the sources of water consumption for different users are significantly different. The results show that almost all domestic water all agricultural water are sourced from the Yellow River. The water used by the tertiary industry is mainly from the Qin River. For industrial water, the supply of groundwater to industry and the total supply of other water sources account for about half of the total. The water resources used for the ecological environment come from the comprehensive water transportation of the long-distance water transfer of the South-to-North Water Diversion Project, the Yellow River and other surface waters.

Similarly, Figs. 10, 11 and 12 are visualizations of the configuration results based on 2030. Compared with the results of water resources allocation in 2025, what has changed in the configuration structure is that the Yellow River water distribution of water resources transformation is the most prominent in 2030. The distribution of a large amount of Yellow River water has been transformed from the original supply to the agricultural sector to the supply to the industrial sector. At the same time, agriculture has become the main user of groundwater and reclaimed water. The conclusion that can be seen from Fig. 11 is that 96.49% of reclaimed water and 77.20% of ground water flow to the agricultural sector. From the perspective of the water sector, the primary source of industrial and ecological water is the Yellow River water. Among the total water consumption of ecological environment and industrial water, the Yellow River water accounts for 99.08% and 98.55%, respectively. In addition, domestic water, agricultural water and tertiary industry water consumption all come from the aggregation of multiple water sources.

5 Discussion

The water resource allocation in Wuzhi is optimized by SMA. It completes the output of multi-objective function optimization results with given constraints. In order to understand the characteristics of water resources utilization in the region, the results are statistically output and analyzed. In accordance with the water demand and water distribution schemes, the balance analysis of water resources supply and demand in the region is carried out, and the results are summarized in Table 11, where the water shortage ratio of each user in different years can be visualized as a bar graph (see Fig. 13)

Table 11 Balance between supply and demand in different target years

Target year	User	Water demand (10^4m^3)	Water supply (10^4m^3)	Supply ratio (%)	Water deficit (10^4m^3)	Deficient ratio (%)
2025	Domesticity	3464.58	3464.58	100.00	0.00	0.00
	Agriculture	13204.54	12990.80	98.38	213.74	1.62
	Industry	13579.40	13062.96	96.20	516.44	3.80
	Tertiary industry	643.08	637.72	99.17	5.36	0.83
	Ecology	2417.65	2185.69	90.41	231.96	9.59
	Total	33309.25	32341.75	97.10	967.50	2.90
2030	Domesticity	3988.65	3988.65	100.00	0.00	0.00
	Agriculture	12153.26	11042.45	90.86	1110.81	9.14
	Industry	15512.63	14101.06	90.90	1411.57	9.10
	Tertiary industry	2451.82	637.72	99.99	0.26	0.01
	Ecology	3071.82	3012.28	98.06	59.54	1.94
	Total	37178.44	34596.26	93.05	2582.18	6.95
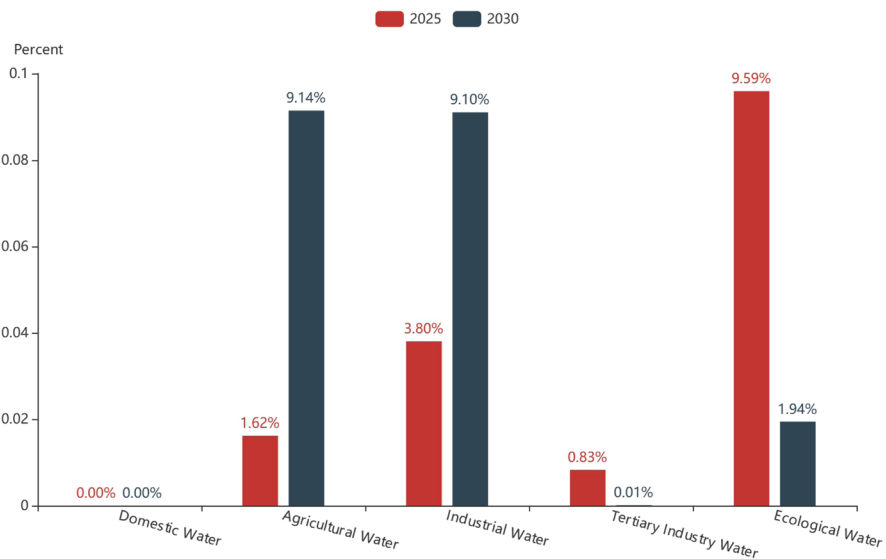
Fig. 13 The bar chart of water deficient ratio at different levels

First of all, it can be seen combining the result of the 2025 and the bar chart that other sectors have different degrees of water shortage when the domestic water supply is met. Among them, the water shortage ratios of agricultural water, industrial water and tertiary industry water are all present at a relatively low level, which are 1.62%, 3.80% and 0.83%, respectively. On the contrary, ecology

will become the primary water shortage sector in 2025 with a higher water shortage rate. In terms of the water resources allocation plan in 2025, the total water allocation is $32341.75 \times 10^4 m^3$ and the water deficient is $967.50 \times 10^4 m^3$, which accounts for 2.90% of the total water demand. On top of that, as can be seen from the water resources allocation plan for 2030, the water shortage ratio of ecological water can be reduced to 1.94%. Although the water used for ecological environment has been improved, agriculture and industry both appear high water shortage ratios. Basically consistent with 2025, domestic water and ecological water can also get water security. The water resource allocation plan for 2030 indicates that the water supply at the target year is $34,596.26 \times 10^4 m^3$ which results in a water shortage rate of 6.95%. On the whole, the high proportion of water shortage indicates that the water shortage in the area is severe.

As the area is in the stage of development, the water demand is bound to increase with the development of the county. According to the result, the water demand in 2030 increases by $3869.19 \times 10^4 m^3$ compared with 2025, while the increase in total available water supply is only $2224 \times 10^4 m^3$. What can be inferred is that the increase in water supply in the county is lower than water demand, which leads to an increase in the water shortage ratio. From the perspective of the current situation of water resources development and the structure of water supply, it can be intuitively found that the water resources in this area are in a state of shortage, and there are urgent problems need to be solved in the distribution of water resources. In consequence, this research paying attention to the comprehensive benefits of society, economy and environment while guaranteeing domestic water in view of the current situation of the region has carried out reasonable water resources optimized allocation to ensure the supply of water resources to adapt to the regional development and enhance the water utilization efficiency.

The sector with the largest water shortage in 2025 is ecological water, implying that the region is developing its economy and overall strength at the expense of the environment. In 2030, the main water shortage sectors are agriculture and industry, while the environment is improved. The change of configuration structure shows that the development focus of the region is transforming. Moreover, environmental conditions are closely related to regional development. If the environment can be protected during development and progress, good comprehensive benefits can be brought to the region.

In addition to formulating a reasonable water resources allocation scheme, Wuzhi county should take some other measures as far as possible to bridge the gap between water resources supply and demand. For example,

a) Jointly dispatch water resources and supply water by quality. Wuzhi County can jointly dispatch water resources from different water sources according to the regulation and storage capacity of surface water storage projects and underground aquifers. In addition, it is also a significant measure to coordinate the water balance between industries and departments. In the procedure of water resources allocation, domestic water should be given priority while agricultural and industrial production water should be satisfied as much as possible. The requirements of different departments for water supply assurance ratio and water quality are so

different that implementing water supply with different quality is a reliable measure to solve the regional water shortage effectively.

b) Develop virtual water resources to lift the carrying capacity of water resources. Virtual water, a kind of water contained in products in the form of "virtual," is the water required to manufacture products and services, also known as embedded water [62]. The total volume of international virtual water trade was 567 cubic kilometers in 2007, accounting for about 22% of the global agricultural fresh water extraction [63]. For Wuzhi, low water consumption products in the region can be exchanged for high water consumption products produced in other water-rich watersheds. The approach, transferring virtual water resources in and out, reasonably lifts the carrying capacity of regional water resources.

c) Develop reclaimed water reuse projects and attach importance to ecological environment protection. Reclaimed water reuse, a project to save water resources and reduce environmental pollution, means to use various means to treat industrial waste water at different depths to meet the water quality standards required by the process. Wuzhi can not only recycle reclaimed water by ecological construction and water quality assurance technology, but also try to encourage reclaimed water reuse by preferential water and supply policy.

In order to seek regional development, the county should firmly seize the new opportunities of contemporary water resources governance revitalization strategy, and focus on solving the problem of "water bottlenecks" that restrict high-quality economic development. Smooth rivers, ecological health, and harmony between people and water are necessary for the long-term development of the region.

6 Conclusion

In this study, Wuzhi County of Henan Province in China, which has rapid economic development, was selected as the research area, and the SMA was used to allocate regional water resources. Taking the comprehensive performance of social benefits, economic benefits and environmental benefits as the overall goal in the regional water allocation model, the water resources in 2025 and 2030 in the region are rationally allocated.

To start with, the water sources in this area are divided into four categories according to the actual situation: surface water (the Qin River, the Yellow River and other surface water), reclaimed water, transferred water and ground water. And water users are classified into five classifications: agricultural water, industrial water, ecological water, domestic water and tertiary industry water. Then, water resources allocation schemes are presented on account of the data of water demand and supply in different target years. Finally, this study comprehensively analyzed the allocation of water resources from different perspectives. The analyses show that the current water resources of the county which is developing rapidly are still lacking, and the situation may not be able to adapt to the development rate. The experimental results give the optimal water resources allocation scheme with comprehensive benefits under the condition of not increasing the total amount of water resources. Moreover,

it is worth doing that some appropriate comprehensive measures are put forward in view of the development status, hoping to improve the situation of a shortage of water resources.

In terms of water resources allocation, we introduce SMA with fast convergence and accurate search ability into solve the regional water resources allocation problem. In order to make full use of the excellent decision-making ability and historical record adaptability of SMA algorithm, the treatment and solution of the regional water resource allocation problem can be summarized as follows:

(1) In the model of regional optimal allocation of water resources, we choose three objectives which include not only artificial ecosystem (social and economic benefits), but also consider natural ecosystem (ecological benefits).
(2) We select the SMA with fast convergence, strong self-decision ability, accurate search ability and great adaptability as the algorithm to solve the optimization problem.
(3) On the one hand, we unify the three objectives and develop the comprehensive benefits, which can consider the fair distribution of benefits among different beneficiaries. On the other hand, we use SMA to maximize the advantages of SMA in engineering problems by conducting independent optimization experiments on sub-objectives and using the independent results to construct comprehensive objectives.
(4) In the analysis of the results, we get the regional water resources situation and a more scientific allocation plan by thoroughly analyzing the supply side and the demand side of the allocation plan. It can help the region to carry out a more reasonable allocation of water resources.

In general, the study shows that it is reasonable and feasible to apply slime mold algorithm to optimize the allocation scheme of regional water resources. The optimal allocation scheme of regional water resources is analyzed in all aspects, and the conclusion is drawn that the research region is short of water resources. In this case, the allocation of water resources is carried out to ensure the maximum comprehensive benefits. The process and method of the work can put forward the water resources allocation scheme that can maximize the comprehensive benefit of regional development under the background of limited water resources and it can be extended to solve and analyze the water resources situation in other regions. It is worth noting that this research only applies to the optimization of water resources allocation schemes at the regional level. Since the allocation of water resources in the basin involves more natural factors such as flood season and non-flood season, water quality and so on, the applicability of the process to the allocation and management of water resources in the basin has not been verified. In the future, we will try to study the river basin optimal water allocation model and apply the method to solve it. Second, we will consider establishing a unified data set and objective function of water resources to improve the regional optimal allocation of water resources.

Although water is renewable, it is also extremely precious. Here, we call on humanity to pay attention to the rational use of water resources and focus on water

resources management and protection. We firmly believe that we can take advantage of intelligent algorithms to effectively solve most optimization problems and innovate methods to find a more ecological, economical and reasonable allocation solution in water allocation problems. In the future, we will continue to study models and methods for water resources allocation, and explore the broad applications of intelligent algorithms.

Data Availability The datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Disclosures The authors declare that there is no conflict of interest.

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