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System Dynamics-Multiple Objective Optimization Model for Water Resource Management: A Case Study in Jiaxing City, China

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Abstract: Predicting and allocating water resources have become important tasks in water resource management. System dynamics and optimal planning models are widely applied to solve individual problems, but are seldom combined in studies. In this work, we developed a framework involving a system dynamics-multiple objective optimization (SD-MOO) model, which integrated the functions of simulation, policy control, and water allocation, and applied it to a case study of water management in Jiaxing, China to demonstrate the modeling. The predicted results of the case study showed that water shortage would not occur at a high-inflow level during 2018–2035 but would appear at mid- and low-inflow levels in 2025 and 2022, respectively. After we made dynamic adjustments to water use efficiency, economic growth, population growth, and water resource utilization, the predicted water shortage rates decreased by approximately 69–70% at the mid- and low-inflow levels in 2025 and 2035 compared to the scenarios without any adjustment strategies. Water allocation schemes obtained from the "prediction + dynamic regulation + optimization" framework were competitive in terms of social, economic and environmental benefits and flexibly satisfied the water demands. The case study demonstrated that the SD-MOO model framework could be an effective tool in achieving sustainable water resource management.

Keywords: water resource management; system dynamics; multi-objective optimization; dynamic regulation; feedback

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1. Introduction

Water is an important resource, supporting life, economies, and healthy ecological environments [1]. In the past several decades, rapid population and economic growth and the accelerated expansion of cities have led to widespread water scarcity [2–4]. This has also raised problems such as water quality degradation and environmental vulnerability [1]. Meanwhile, growing user demands have intensified competition for water resources, resulting in water resource instability [5]. The imbalance between water supply and demand requires innovative water management methods to coordinate the sustainable development of water resources within society, the economy, and the environment [6].

Water flows from a natural cycle to a social cycle through precipitation and water withdrawal, and it has complex relationships with social, economic, and environmental systems [7,8]. It being inherently necessary in production and human lives promotes the J-shaped growth of water demand [9]. To meet the exploding demand, there are widespread efforts to increase water availability (e.g., building dams, pumping groundwater, trading virtual water), but the problem of water scarcity has not been solved [10] because

of population growth [11]. In order to avoid an indefinite vicious cycle, demand-curbing strategies such as water-saving agriculture, industrial structure optimization, gradient water price, and water-saving appliances have been widely explored [12–14]. Moreover, water resource management often involves complex driving forces and constraints. The interactions between them are not completely linear. System dynamics (SD) is a useful method to deal with high-order, nonlinear, multi-feedback, complex, and uncertain system problems [15]. It has been widely applied to the systematic management of water resources on basin [16], regional [17], and urban scales [18,19]. In water resource management, the SD model has not only been used to simulate internal processes of water resource systems but also to evaluate the impacts of population growth, industrial development, and other factors associated with water resource decision making [20–22]. Certain water resource decisions with single or combined goals have been made previously based on the results of SD model simulations [16,23]. However, the parameters of the SD model remain constant, whereas policy packages may change during the simulation [24]. Thus, feedback mechanisms to dynamically adjust the parameters are concerned in the decision making.

Feedback mechanisms provide an important theoretical basis for dynamic management and can be divided into positive and negative feedback according to the adjustment direction. Positive feedback makes the system locally unstable, whereas negative feedback makes the system oscillate or reach an equilibrium [25]. In water management, the difference between the real and ideal states of a system can be regarded as "the amount of action that needs to be taken" [14]. Dynamic feedback considers the system state and forms an adaptive management strategy which provides valuable insights to cope with the increasing uncertainty, complexity, and system interaction in water management [26].

Optimal allocation of water resources is another important task in water resource management. Influenced by social, environmental, and political factors, water stakeholders have conflicts in terms of regions, generations, users, and benefit objectives [27]. As it is difficult for stakeholders to reach an agreement on their own, the authority in the basin or region must make fair and reasonable water resource allocations [28]. In most cases, the stakeholders are required to compromise to achieve maximum group benefits and balance conflicting interests [29]. Multi-objective optimization (MOO) is a common method to solve such a problem but many studies have focused on optimizing the solution algorithms [30–32] rather than on the dynamic change of supply and demand constraints. The combination of SD and MOO in a simulation-based optimization framework (SD-MOO) has been proposed to generate effective boundaries. The framework has been applied to supply chain management [33,34], but is rarely reported in water resource management.

Based on these considerations, this study incorporated dynamic adjustment into the SD-MOO modeling framework which included three functional modules: water supply and demand prediction, feedback-based dynamic adjustment, and MOO-based allocation. The integrated model not only optimized the macro policy package to minimize the gap between supply and demand, but also made full use of the SD simulation results to ensure that water allocation proceeded within realistic limits. In the following sections, we first introduce the overall framework of the SD-MOO model and the detailed structure of each module. Then, we take Jiaxing City as a case study to illustrate how the three functions are realized. Finally, deficiencies in the case study and several improvement directions of the model are discussed.

2. Methodology

The SD-MOO model framework for water resource management consists of three functional modules: water supply and demand prediction, dynamic adjustment, and water optimal allocation (Figure 1). With respect to water supply and demand, the complex interactions among population, economy, environment and water are visualized by a flow diagram (Figure 2) and quantitatively described by the formulae in Table S1. The water

shortage rate (*WSR*) is defined as “the percentage of simulated supply and demand gap in total water demand” and was selected to evaluate the gap between the water supply and demand in the framework.

$$WSR = \left(1 - \frac{\sum_{i=1}^3 WS_i}{\sum_{j=1}^4 WD_j} \right) \times 100\% \quad (1)$$

where WS_i means the water supplied from source i (1, 2, and 3 represent surface water, diversion water, and reclaimed water, respectively), and WD_j denotes the demand of user j (1, 2, 3, and 4 represent agriculture, industry, domestic, and environment, respectively).

The validated SD model was used to predict future *WSR*. A negative *WSR* indicates that the total water demand of region can be met, and water resources can support the local population, economic development and ecosystem stability. When the *WSR* was positive, meaning the water demand was not satisfied, various management strategies were tested to regulate *WSR* in the “dynamic adjustment” module. The prediction results of water supply and demand or the results after dynamic adjustment were used to serve as the boundary or constraints of the water optimal allocation model.

Prediction and dynamic adjustment were operated on the system dynamics platform Vensim DSS Version 6.4 (<https://vensim.com/>). The water optimal allocation was modeled and solved in a General Algebraic Modeling System (GAMS).

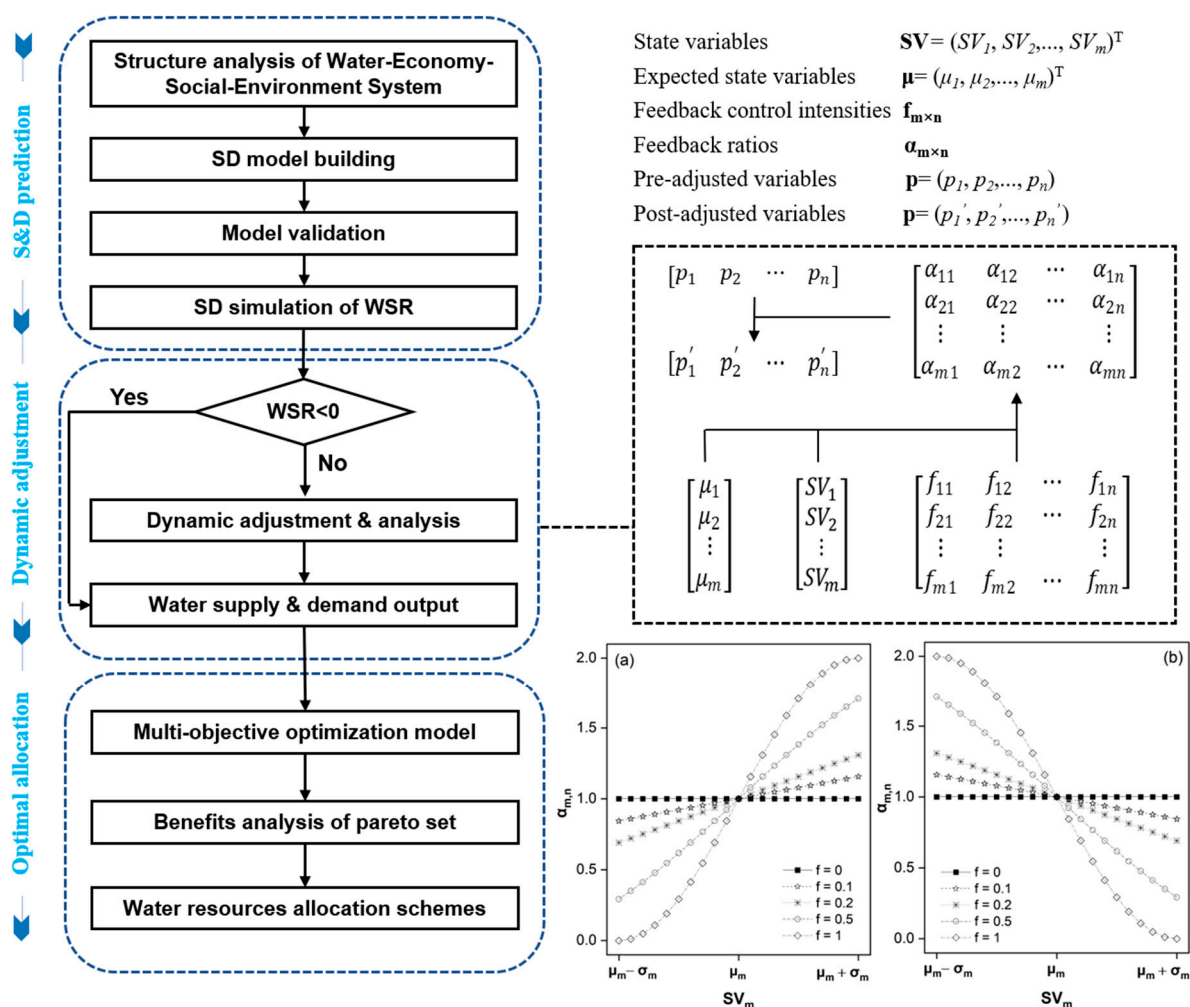


Figure 1. Framework of the system dynamics-multiple-objective optimization SD-MOO model. (a) Positive feedback diagram; (b) negative feedback diagram.

2.1. System Dynamics (SD) Model

System dynamics is a combination of qualitative and quantitative research methods, which can comprehensively simulate the structure of various complex systems and analyze the internal relationships of the system [15]. The structure of a system brings about observable and predictable behaviors [26]. The models with system dynamics of water supply and demand are established based on causal loop diagrams (Figure 2), and the relationships between variables are described by first-order differential equations with a time lag.

As a natural water supplier, surface water significantly correlates with precipitation and is uncertain owing to the specific climatic and hydrological conditions [35]. The supply of surface water was directly determined by hydrological condition and surface water utilization rate. Inter-basin, or cross-regional water diversion projects have become important ways to alleviate regional water scarcity [36,37]. The dispatching of water from a water source area to an intake area is controlled by the total annual of water diversion [38]. As a supplement to water resources, reclaimed water which derives from wastewater treatment plants has become an active water source in many regions [39–41].

Water users are usually divided into agricultural, industrial, domestic, and environmental users and the efficiency of production-oriented water use in agriculture, industry, and the urban public is compatible with GDP growth and technological improvement. The agricultural, industrial and urban public water demand can be further calculated by the production scale (e.g., farmland irrigation area, amount of livestock, and fishpond area) or gross output value of agriculture and industry. The urban and rural domestic water demand are affected by two factors: the change in per capita water quota caused by water-saving equipment and water usage habits and the distribution of the urban and rural population caused by population growth and urbanization. The environmental water demand refers to urban green land irrigation water, determined by the green land area and water quota for green land. Detailed SD equations are provided in Table S1.



Figure 2. System flow diagrams of (a) the water supply and demand prediction module and (b) the dynamic adjustment module based on feedback. Red fonts indicate the policy adjustable variables.

The SD model needs to be calibrated and validated before application. The mean relative error (*MRE*), coefficient of determination (R^2), and Nash-Sutcliffe efficiency coefficient (*NSE*) were adopted to evaluate model performance. *MRE* represents the overall deviation degree and direction of the simulated value from the observed value; R^2 characterizes the fitness of the two sets of data, and *NSE* measures the credibility of the model [42]. The evaluation statistics parameters were computed as follows:

$$MRE = \frac{\sum(V_s - V_o)}{\sum V_o} \quad (2)$$

$$R^2 = \left(\frac{\sum(V_s - \bar{V}_s)(V_o - \bar{V}_o)}{\sqrt{\sum(V_s - \bar{V}_s)^2 \sum(V_o - \bar{V}_o)^2}} \right)^2 \quad (3)$$

$$NSE = 1 - \frac{\sum(V_s - V_o)^2}{\sum(V_o - \bar{V}_o)^2} \quad (4)$$

where V_s and V_o represent the simulated and the observed values of variables; \bar{V}_s and \bar{V}_o are the mean values of the corresponding variables.

2.2. Dynamic Adjustment Based on Feedback

Seemingly perfect policies may fail due to unexpected challenges in their implementation. Triggering built-in policy adjustments by monitoring indicator changes is useful to prevent policy failures [43]. The key to applying this policy adjustment in an SD model is to define feedback functions between system state and regulatory metrics.

Feedback functions are designed to either exacerbate the deviation (positive feedback) or resist the interference (negative feedback) as responses to the signal. Suppose the current status of the system can be expressed as an m -dimensional vector $\mathbf{SV} = (SV_1, SV_2, \dots, SV_m)^T$ and its theoretical expected state is $\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_m)^T$. Tracing from state variables down to underlying logic along the causal loop, each state variable is affected by the adjustable variable $\mathbf{p} = (p_1, p_2, \dots, p_n)$, which is a time-varying table function or constant. When SV_m deviates from its expected value μ_m , the difference between them will be mapped to the feedback ratio $\alpha_{m,n}$ by feedback functions, further changing p_n to p'_n as follows:

$$p'_n = p_n \times \prod_{m=1}^M \alpha_{m,n} \quad (5)$$

The following characteristics are required for the feedback functions [44]: (i) when SV_m reaches its expected value μ_m , the feedback ratio $\alpha_{m,n}$ is equal to 1, which means p_n does not need to be adjusted; (ii) $\alpha_{m,n}$ monotonously and nonlinearly increases (positive feedback) or decreases (negative feedback) with the state variable SV_m ; (iii) $\alpha_{m,n}$ has upper and lower bounds, and (iv) $\alpha_{m,n}$ is affected by the feedback control intensity $f_{m,n}$ (insets (a) and (b) in Figure 1). Two reconstructed sine functions, Equations (6) and (7), are designed to calculate the feedback ratio $\alpha_{m,n}$ of the positive and negative feedback mechanisms, respectively:

$$\alpha_{m,n} = 1 + \sin\left(\frac{\pi}{2} \times \frac{SV_m - \mu_m}{\sigma_m} \times f_{m,n}\right) \quad (6)$$

$$\alpha_{m,n} = 1 - \sin\left(\frac{\pi}{2} \times \frac{SV_m - \mu_m}{\sigma_m} \times f_{m,n}\right) \quad (7)$$

where σ_m is the maximum distance between the state variable SV_m and its expected value μ_m . The feedback intensity $f_{m,n}$ varies in the range of [0, 1] to maintain monotonicity of the feedback functions.

It can be interpreted that the feedback forms a logical closed loop of $\mathbf{SV} \rightarrow \boldsymbol{\alpha} \rightarrow \mathbf{P} \rightarrow \mathbf{SV}$. Feedback control intensity f is the "controller" which can be artificially changed, and its value reflects the decision-maker's sensitivity to the system state.

2.3. Water Allocation Based on Multi-Objective Optimization

Water scarcity and the contradiction between supply and demand urge water management authorities to make water allocation plans that have maximum social, economic, and environmental benefits [45,46]. In water optimal allocation model, the social benefit objective (F_1) can be expressed in terms of the minimum WSR in the region (Equation (8)), whereas the economic benefit objective (F_2) is represented by the lowest sum of the water fees generated by different water allocation paths (Equation (9)). Water use is accompanied by waste generation. The environmental benefit objective (F_3) is recognized as the minimum discharge of chemical oxygen demand (COD) within the region (Equation (10)).

$$\min F_1(X) = \left(1 - \frac{\sum_{i=1}^3 \sum_{j=1}^4 x_{ij}}{\sum_{j=1}^4 WD_j}\right) \times 100 \quad (8)$$

$$\min F_2(X) = \sum_{j=1}^4 \sum_{i=1}^3 x_{ij} \times y_{ij} \quad (9)$$

$$\min F_3(X) = \left(\sum_{i=1}^3 x_{i1} \times k_1 \times c_1 + \sum_{i=1}^3 x_{i2} \times k_2 \times c_2 \right) \times 0.01 \quad (10)$$

where the decision variable x_{ij} is the amount of water allocated from source i to user j (10^8 m^3); y_{ij} is the cost coefficient of x_{ij} (yuan/ m^3); k_1 and k_2 are the discharge coefficients of domestic sewage and industrial wastewater, respectively, and c_1 and c_2 are the mean COD concentrations of domestic sewage and industrial wastewater (mg/L), respectively.

The water supply and demand predicted by the SD model and optimized by the dynamic adjustment served as constraints in the optimal allocation model. The amount of water supplied by each source should not exceed its available water WS_i (Equation (11)). The amount of water allocated to each user should ensure the minimum water demand (greater than $WD_{j,min}$) but avoid water waste (less than $WD_{j,max}$) (Equation (12)). In addition, the decision variable should be non-negative (Equation (13)).

$$\sum_{j=1}^4 x_{ij} \leq WS_i, \forall i \quad (11)$$

$$WD_{j,min} \leq \sum_{i=1}^3 x_{ij} \leq WD_{j,max}, \forall j \quad (12)$$

$$x_{ij} \geq 0 \quad (13)$$

After compiling and solving the multi-objective optimization model in GAMS, a series of Pareto sets [47] were obtained, each of which represented an allocation scheme. Comprehensive benefits were further calculated as follows:

$$F'_s = \frac{F_{s,max} - F_s}{F_{s,max} - F_{s,min}}, \forall s \quad (14)$$

$$F = \sum_{s=1}^S F'_s \eta_s \quad (15)$$

$$\sum_{s=1}^S \eta_s = 1 \quad (16)$$

Here, $F_{s,max}$ and $F_{s,min}$ are the maximum and minimum values of objective F_s ($s = 1, 2, 3$); F'_s is the dimensionless value. F is the comprehensive benefit, and η_s is the weight of benefit objective F_s .

3. Case study

In order to demonstrate the work of the SD-MOO framework, Jiaying City was used as a case study. Due to data limitations and practical simplifications, this case study is not intended to be a realistic characterization of future conditions or to recommend policy solutions.

3.1. Study Area

Located in the central-eastern area of the Yangtze River Delta, Jiaying City has a flat terrain with a land area of 3915 km^2 and a population of 4.72 million. The mean annual rainfall reaches 1193.5 mm , and the multiyear average water resources reach $20.07 \text{ billion m}^3$. However, Jiaying has been facing intense conflicts between water supply and demand, as well as a deteriorating water quality due to pollution from rapid social and economic development. In 2017, the per capita occupancy of water resources of Jiaying was 546 m^3 , which is considerably lower than that of the current national average ($2074.5 \text{ m}^3/\text{person}$) [48]. Limited water resources have become the main bottleneck restricting the sustainable development of the city.

Surface water in Jiaxing City consists of two parts. This consist of local water generated by precipitation, and secondly transit water exchanged with that of Huzhou and Hangzhou in the west, Jiangsu Province in the north, and Shanghai in the east. The average transit volume in 2011–2018 was 3.74 times that of local water. During the same period, the utilization rate of surface water (including transit water) fluctuated around 20% [49]. According to the historical data, the local water resources in typical hydrological years at 50, 75, and 90% frequencies in Jiaxing City are 2.154, 1.206, and 0.9 billion m³, respectively, whereas the transit water resources are 6.221, 4.12, and 3.49 billion m³, respectively. Groundwater extraction was prohibited in 2016. To expand water sources, reclaimed water of 1.05×10^5 m³/d has been adopted as an unconventional water source in recent years. Eight reclaimed water facilities are to be constructed by 2025, supplying an additional 3.25×10^5 m³/d of reclaimed water. In 2035, the amount of reclaimed water will increase by 1.25×10^5 m³/d, reaching 5.5×10^5 m³/d. Considering the local shortage of high-quality water sources, Jiaxing plans to divert water from Qiandao Lake and Taihu Lake outside the city, with diversion amounts of 2.3×10^8 and 5.5×10^8 m³ in 2020 and 2.3×10^8 and 6.5×10^8 m³ in 2030, respectively.

3.2. Data Sources

The input data of the SD model included the initial values of stock variables and the dynamic change value of the table function. The initial stock values were taken from local statistics, including the Jiaxing Statistical Yearbook for social and economic data (Table S2), Jiaxing Water Resources Bulletin for water supply and demand, Zhejiang Natural Resources and Environment Statistical Yearbook for land use. The agricultural production data (e.g., farmland irrigation area, amount of livestock, and fishpond area) were obtained from the Jiaxing Agriculture and Rural Affairs Bureau. Water quotas of all users (Table S3) refer to the Water Quota Standard of Zhejiang Province and were estimated according to the medium and long term water saving plans of Jiaxing City. Surface water and transit water resources under 50, 75 and 90% guarantee rates were provided by the Zhejiang Hydrology Management Center. The amount of unconventional water supply, sewage treatment, and state of socioeconomic development in 2020, 2025, and 2035 refers to Jiaxing Water Resource Protection Planning, Municipal Sewage Planning and Jiaxing Urban Master Planning. Further, the water cost coefficient y_{ij} in the MOO model adopted the water prices of Jiaxing. The wastewater discharge coefficient and COD concentration (Table S4) were estimated according to the statistical data of the Jiaxing Bureau of Ecology and Environment.

3.3. Parameter Selection and Scenarios in Model Application

3.3.1. SD Model for Water Supply and Demand Prediction

According to the system flow diagram of the water–economic–society–environment composite system (Figure 2(a)), three supply sources including surface water (WS₁), diversion water (WS₂) and reclaimed water (WS₃) were considered in the study. Groundwater supply was not considered because groundwater exploitation was forbidden [31]. In order to take into account the impact of hydrological uncertainty, three hydrological conditions were set according to the long-term rainfall observations, namely high-, mid-, and low-inflow levels corresponding to the hydrological guarantee rates of 50, 75 and 90%.

There were four water users involved in the study. Agricultural users (WD₁), industrial users (WD₂), domestic users (WD₃), and environmental users (WD₄), whose water demands were calculated according to the equations in Table S1.

3.3.2. Parameters for Dynamic Adjustment

In the proposed SD model (Figure 2), WSR was the only state variable which meant $m = 1$ in Equations (5)–(7). As the ideal situation is that the total water demand is satisfied, the expected value μ of WSR was 0. The water supply is normally no more than twice the

water demand, thus, σ was set to 100%. Eleven parameters (p_1 – p_{11}) were selected as the policy adjustable variables according to the cause tree of the WSR and classified into three groups based on their properties (Table 1). Group 1 contains water quotas, Group 2 includes variables concerning economic and population growth, and Group 3 includes the utilization rates of water resources. The variables in Group 1 and Group 2 followed the negative feedback rule, whereas the variables in Group 3 followed the positive feedback rule. Different groups were combined to establish different dynamic adjustment scenarios. Variables in each scenario were adjusted with the same f to simplify operation, and the feedback intensity f was increased from 0 to 1 at an interval of 0.1.

Table 1. Three groups of policy adjustable variables.

Group	Adjustable Variable (p_n)
Group1	water quota for paddy field (p_1), water quota for dry land (p_2), water use efficiency of industry (p_3), water use efficiency of the tertiary industry (p_4), rural domestic water demand per capita (p_5), urban domestic water demand per capita (p_6)
Group2	change rate of added value of industry (p_7), change rate of added value of the tertiary industry (p_8), population growth rate (p_9)
Group3	utilization rate of surface water (p_{10}), utilization rate of reclaimed water (p_{11})

3.3.3. MOO Model for Water Allocation

Parameter values in Equations (8)–(10) are shown in Table S4. WS_i and WD_j were adopted according to the output results of the SD module or the results after dynamic adjustment; $WD_{j,min}$ and $WD_{j,max}$ were obtained based on WD_j and its corresponding satisfaction range. The domestic water demand, industrial water demand, agricultural water demand and environmental water demand were met at 100, 90–100, 60–100 and 95–100%, respectively. In addition to the basic constraints, there were some further hypotheses:

- (1) No less than 40% and no more than 60% of the domestic water would be supplied by diversion water ($0.4WD_3 \leq x_{23} \leq 0.6WD_3$);
- (2) Diversion water was only for industrial and domestic users ($x_{21} = x_{24} = 0$);
- (3) Reclaimed water was only for industrial users ($x_{31} = x_{33} = x_{34} = 0$).

The weights for the scheme should take into account the multi-stakeholder benefits in the water resource allocation. In this case, we assume that the social, economic, and environmental benefits were equally important, i.e., $\eta_1 = \eta_2 = \eta_3 = 1/3$.

3.4. Results

3.4.1. SD Model Validation

State variables and auxiliary variables affected by long feedback loop are key to an accurate simulation. Such variables that are closely related to the total water supply and demand are summarized in Table 2. Parameter values were estimated a priori from direct observations from 2011–2014, and then revised during iterations to optimize fitting to historical data. Observed data from 2015–2017 were used to evaluate the performance of SD model according to Equations (2)–(4). The MREs of the variables were close to 0, varying from -0.025 to 0.117 , which indicates that the simulation results were acceptable. The R^2 and NSE values of most of the variables were in the intervals of $[0.688, 1]$ and $[0.653, 1]$, respectively. However, the NSE of the agricultural water demand was 0.367 , which was closer to 0 rather than 1, indicating that its process error was large but the overall result was reliable. The results showed that the SD model was suitable for water supply and demand prediction.

Table 2. Performance of the SD model.

Variables	MRE (%)	R ²	NSE
total population	−0.004	0.985	0.703
added value of industry	−0.010	0.944	0.938
added value of tertiary industry	−0.025	0.975	0.933
agriculture water demand	0.036	0.934	0.367
industrial water demand	−0.004	0.688	0.665
domestic water demand	−0.017	0.860	0.653
environmental water demand	0.000	1.000	1.000
reclaimed water supply	0.117	0.973	0.946

3.4.2. Water Supply and Demand Prediction

According to the predicted results (Figure 3), surface water remains the main supply contributor. With surface water utilization rates of 20, 25, and 30% at high-, mid-, and low-inflow levels, the available amounts of surface water (WS₁) will reach 1.655, 1.332, and 1.317 billion m³, respectively. The current water project plan can offer 0.78 billion m³ (WS₂) of diversion water regardless of the inflow level and time. Affected by the improvement in sewage treatment capacity and the utilization rate of the reclaimed water, the available amount of reclaimed water (WS₃) will increase to 42.4, 63.8, and 139.8 million m³ in 2020, 2025, and 2035, respectively.

The agricultural water demand (WD₁), which accounts for the largest proportion of the total water requirement, is expected to decline slightly in the predicted years due to improvements in water use efficiency. Moreover, WD₁ showed a negative correlation with precipitation as agriculture does not require much additional water when rainfall is relatively abundant at a high-inflow level. Industry (WD₂) is the second largest water user, accounting for 23.39–27.95% of the total water demand in 2020. Although WD₂ continues to increase annually, its proportion of water demand is decreasing and will drop to 21.84–24.88% in 2035. The domestic water demand (WD₃) will soar and surpass industry to be the second largest water sector in 2024, and the proportion of water demand was predicted to reach 32.60–37.13% in 2035. According to the urban land planning, urban green space is expected to continuously expand, leading to a growth in the environmental water demand (WD₄), although the proportion remained below 6%.

There is no risk of water scarcity during the simulated times at the high inflow level when comparing the total water supply and demand (Figure 3a). The first water shortage points of mid- and low-inflow levels occurred in 2025 and 2022, respectively (Figure 3b,c), after which the WSR gradually increased reaching maximum values of 16.80% (mid) and 20.07% (low) in 2035.

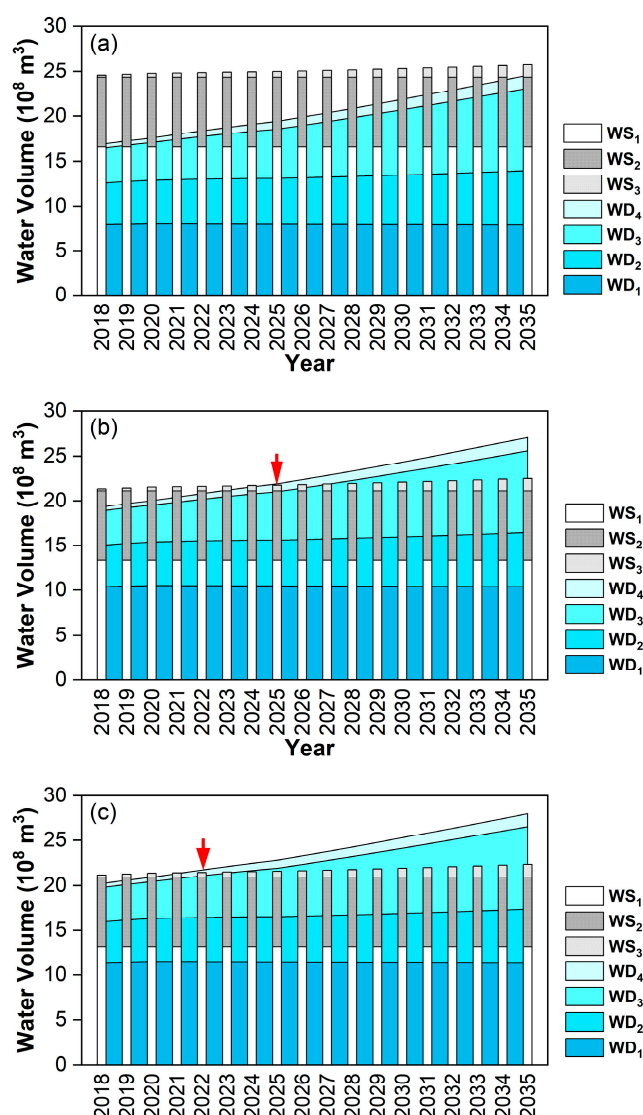


Figure 3. Predicted results of water supply and demand at (a) high-, (b) mid-, and (c) low-inflow levels from 2018 to 2035. The grey series of stacked bar charts namely WS_1 , WS_2 , WS_3 represent surface, diversion and reclaimed water supply, while the blue series of stacked area charts namely WD_1 , WD_2 , WD_3 , WD_4 represent agricultural, industrial, domestic and environmental water demand. Red arrows indicate the predicted first water shortage points.

3.4.3. Dynamic Adjustment

To mitigate the water scarcity risk at mid- and low-inflow levels, seven dynamic adjustment scenarios were established by different combinations of the three groups of variables (Table 3). Although the dynamic adjusted *WSR* continued to climb over time, the rising trend has slowed down comparing to *S0* that does not have any policy regulation. The policy control variables, such as improving the utilization rate of water resources, or reducing the population growth rate, output growth rate and water quotas, were all conducive to cutting down *WSR*. Each scenario achieved the largest reduction in *WSR* at a feedback intensity of 1 (Figure S1 and S2). The adjusted *WSR* in 2025 and 2035 at the mid- and low-inflow levels are summarized in Table 3.

The dynamic adjustment scenario analysis based on the SD model considers the interactions among social, economic, environmental, and water resource subsystems. According to Table 3, all the scenarios effectively reduced the *WSR* compared to *S0*. Among the single-group-controlled scenarios (*S1*–*S3*), the improvement in the water use efficiency

in S1 produced the best effect, reducing the WSR by more than 50%. S2 limited the population and output value growth rates, resulting in a negligible effect on WSR in the near term. These impacts can also be seen in S4 and S6, which coupled Group2 and another group, and had less WSR reduction than S5. Overall, the dynamic adjustment effect of the WSR ranks as $S7 > S5 > S4 > S1 > S6 > S3 > S2$, indicating that the integrated strategies are superior to individual controls. By employing scenario S7 ($f = 1$) in which 11 policy variables were adjusted simultaneously, the agricultural water demand will be reduced by up to $1.05 \times 10^8 \text{ m}^3$. Although the adjusted reclaimed water utilization rate keeps rising, reclaimed water supply will fall off slightly because of the reduction in domestic and industrial water demands. In contrast, surface water supply will increase significantly, with maximum increments of 1.12×10^8 and $1.3 \times 10^8 \text{ m}^3$ at the mid- and low- inflow levels, respectively (Table 4). Values of policy variables before (p_n) and after adjustment (with $f = 1$ in scenario S7, p'_n) were supplemented in Figure S3 and S4.

Table 3. Water shortage rates after adjustment at the mid and low inflow levels.

Scenario	Dynamic Adjustment	Water Shortage Rate (%)			
		Mid-2025	Mid-2035	Low-2025	Low-2035
S0	/	0.67	16.80	5.33	20.07
S1	Group1	0.28	7.79	2.28	9.36
S2	Group2	0.66	14.25	5.02	16.39
S3	Group3	0.33	9.06	2.73	11.05
S4	Group1 + Group2	0.28	7.19	2.22	8.47
S5	Group1 + Group3	0.20	5.54	1.62	6.71
S6	Group2 + Group3	0.33	8.26	2.65	9.81
S7	Group1 + Group2 + Group3	0.20	5.41	1.59	6.28

Table 4. Directly predicted and dynamically adjusted values of water supply and demand. Units: 10^8 m^3 .

Subdivision	Directly Predicted Values				Dynamic Adjusted Values (S7, $f = 1$)			
	Mid-2025	Mid-2035	Low-2025	Low-2035	Mid-2025	Mid-2035	Low-2025	Low-2035
WS ₁	13.32	13.32	13.17	13.17	13.39	14.44	13.51	14.47
WS ₂	7.80	7.80	7.80	7.80	7.80	7.80	7.80	7.80
WS ₃	0.64	1.40	0.64	1.40	0.64	1.38	0.64	1.36
WD ₁	10.44	10.36	11.36	11.29	10.38	9.54	11.09	10.24
WD ₂	5.16	6.11	5.16	6.11	5.15	5.57	5.04	5.42
WD ₃	5.42	9.12	5.42	9.12	5.41	8.42	5.31	8.09
WD ₄	0.88	1.46	0.88	1.46	0.88	1.46	0.88	1.46

3.4.4. Optimal Allocation of Water Resources

The Pareto set obtained by solving the MOO model represented all feasible allocation schemes. Generally, as the social benefit (F_1) reduced, the economic (F_2) and environmental benefits (F_3) were rapidly optimized, regardless of the time and inflow levels (Figure S5). Given equal weights, these three individual benefits were combined into a comprehensive benefit F . The nine schemes with the greatest F were selected as the optimal allocation schemes for the years of 2020, 2025, and 2035, and with high-, mid-, and low- inflow levels. The detailed allocation of the water from sources to different users is depicted by the Sankey diagrams for these nine scenarios with the optimal F values (Figure 4).

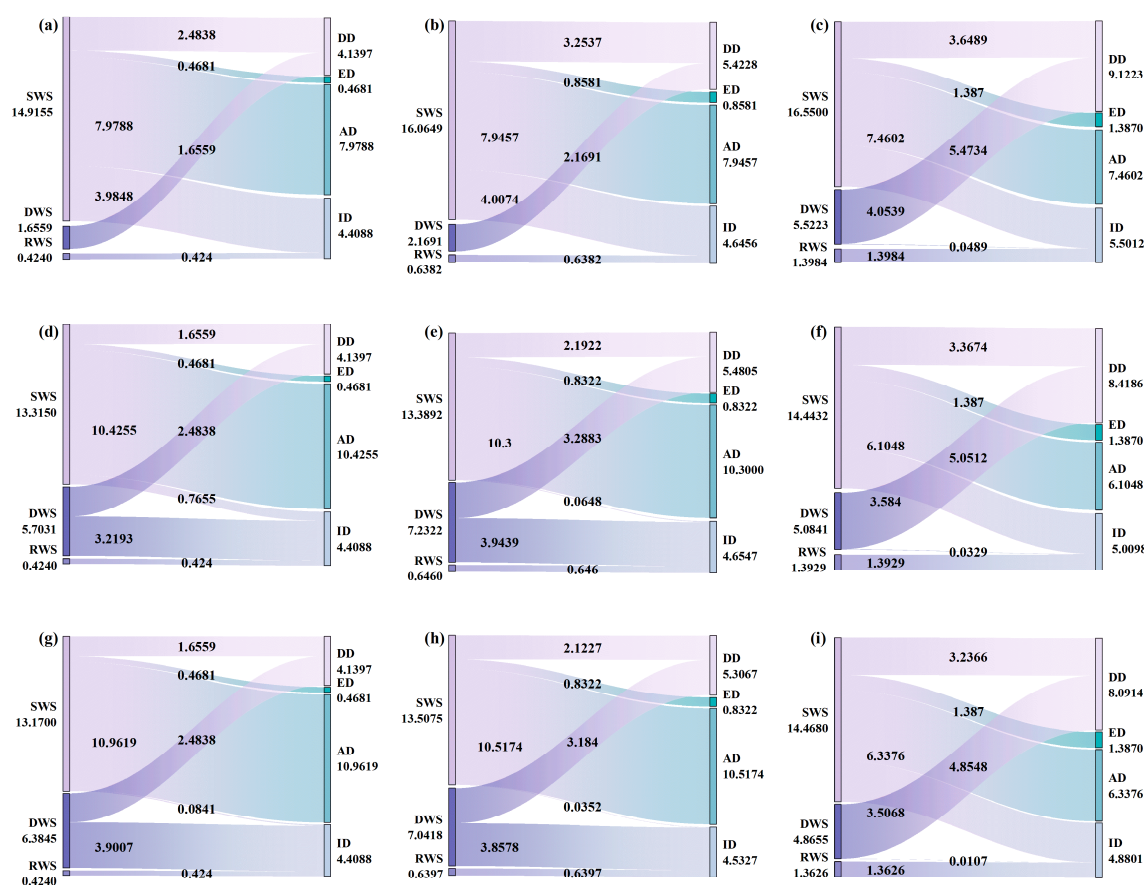


Figure 4. Sankey diagrams of optimal water resource allocation schemes under the scenarios of (a) High-2020, (b) High-2025, (c) High-2035, (d) Mid-2020, (e) Mid-2025, (f) Mid-2035, (g) Low-2020, (h) Low-2025, and (i) Low-2035. SWS, DWS, and RWS represent the optimized surface water, diversion water, and reclaimed water supply in the allocation schemes; DD, ED, AD, and ID represent the optimized domestic, environmental, agricultural, and industrial water demand in the allocation schemes. (Unit: 10^8 m^3).

From the perspective of water supply, surface water was the absolute main source that accounted for 70.51–87.76% at the high-inflow level and 62.96–79.91% at the mid- and low-inflow levels for the years of 2020, 2025, and 2035. Reclaimed water supply accounted for a small portion; however, its contribution improved notably with time, regardless of the inflow levels. The supply proportion of diversion water varied greatly, ranging from 9.74 to 23.54% at the high-inflow level, and 23.51–34.01% at the mid- and low-inflow levels for the years 2020, 2025, and 2035. This is because the diversion water is only a regional supplementary water source, and its priority is lower than that of surface water. The increase in surface water supply generally lowers the amount of diversion water, while the decrease in surface water supply usually increases the amount of diversion water, as long as it does not exceed the limit of the current project of $7.8 \times 10^8 \text{ m}^3$.

The results of the above optimal allocation demonstrated that domestic water demand had the highest allocation priority, and the demand was met under all allocation schemes. The environmental water demand ranked the second, met at approximately 95%. Although the industrial water demand showed a marked increasing trend with time, it was met at approximately 90% by the optimal allocation scheme. The agricultural water demand showed great flexibility, being met at 95–100% when water resources were abundant but only 64% (Mid-2035) or 62% (Low-2035) when water resources were scarce.

According to the water allocation path shown in Figure 4, the agricultural and environmental water demands rely on surface water supply only, whereas domestic and industrial users have more choices, which leads to competition for high-quality and cheap water resources. The allocation schemes of different inflow levels and planning years could be divided into four categories:

- (i). High supply and low demand (High-2020, High-2025): the ratio of surface water and diversion water allocated to domestic was 3:2; most industrial water was provided by surface water and the remainder was supplied by reclaimed water; no diversion water was used.
- (ii). Low supply and low demand (Mid-2020, Mid-2025, Low-2020, Low-2035): agriculture and environment accounted for 82–87% of surface water, forcing domestic and industrial users to use diversion water as a supplement. To maximize economic benefits, industry was allocated a large amount of diversion water due to its high economic density [50], accounting for approximately 73–89% of the total industrial water allocation; the domestic sector uses surface water and diversion water at a ratio of 2:3.
- (iii). High supply and high demand (High-2035): sufficient water supply guaranteed harmonious allocation. The percentages of surface water supplied to agriculture, environment, domestic, and industry were 45.07, 0.08, 23.31, and 24.81%, respectively, meeting 40% of domestic and 70% of industrial water demands. The reclaimed water supply has risen sharply with technological advances and can satisfy a quarter of the industrial water demand.
- (iv). Low supply and high demand (Mid-2035, Low-2035): the high WSR led to all users tolerating a certain degree of water scarcity; however, it also intensified competition for surface water resources. Domestic water had the highest priority in water allocation; with a satisfaction degree of 100%, it was supplied by surface water and diversion water at a ratio of 2:3. Compared with other users, agriculture was in a relatively disadvantaged position, resulting in a low satisfaction degree (60%). This prevented agriculture from consuming a large portion of surface water and created an opportunity for industry to use surface water. Similar to High-2035, the share of diversion water for industry remained lower than those of inexpensive surface water and reclaimed water.

4. Discussion

Most water resource management projects focus either on water policy simulation or on ensuring water use equity, economic vitality and excellent environmental quality through rational water allocation [28,51,52]. In fact, various social, economic, and environmental impacts caused by water shortage could alert authorities to take efficient actions to maximize the comprehensive benefits [53]. Based on the SD-MOO model, the closed-loop management of water resources was realized, which emphasized both the allocation results and the driving forces of water resources.

The traditional water resource allocation mode is “prediction + multi-objective optimization”, in which the predicted water supply and demand are taken to constraint multi-objective optimization [54]. Water scarcity indicates that the estimated population and economic development may overload water resources, and some necessary actions are needed [55]. The “prediction + dynamic adjustment + multi-objective optimization” model fully considers the compensatory actions by dynamic adjustment. In our case, water resources in Mid-2025, Low-2025, Mid-2035, Low-2035 were allocated by both the traditional “prediction + MOO” mode (Mode I) and the newly developed “prediction + dynamic control + multi-objective optimization” mode (Mode II). Comparing the individual benefits of optimal allocation schemes in the two modes, water shortage rate, water fee, and COD emission for schemes in Mode I are all higher than those in Model II (Figure 5).

This proves that dynamic adjustment alleviates the pressure of water resources and expands the benefits of the allocation scheme.

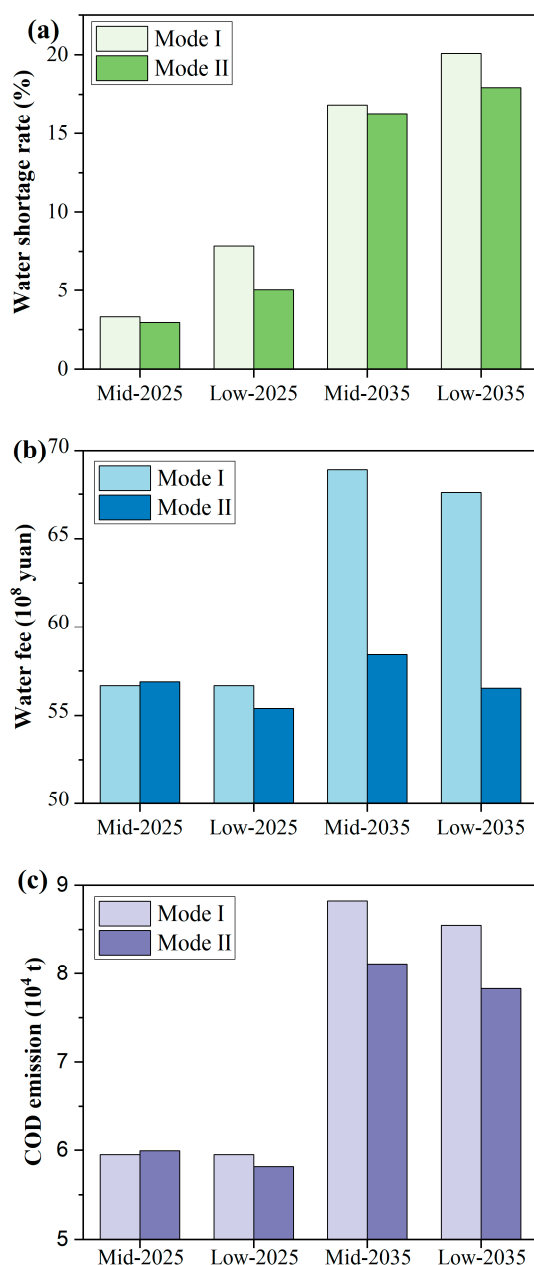


Figure 5. Benefit comparison of (a) water shortage rates, (b) water fee and (c) COD emission between two modes: “prediction + multi-objective optimization” (Mode I) and “prediction + dynamic adjustment + multi-objective optimization” (Mode II).

The dynamic adjustment with feedback mechanisms was not based on intuition or a trial-and-error simulation experiment [56], but was related to the system state and was dynamically adjusted by the internal driving force of the system [57]. To ensure monotonicity of the sinusoidal feedback function, the feedback intensity f was conservatively limited to $[0, 1]$ to simulate relatively moderate policy control. The lowest WSR was obtained with $f = 1$ in all scenarios (Figures S1 and S2); however, it does not mean that relevant variables have reached their regulatory limits. In theory, if a model is convergent,

increasing f can always achieve a lower WSR. For example, within the limited feedback intensity range, WSR was as low as 9.93 % in S6 at the low inflow level. If f is continuously raised, WSR can be further reduced to 3.93 % with a feedback intensity of four; however, the model fails to converge after f exceeds eight. Selecting a feedback intensity should consider whether the simulated dynamic adjustment is technically and financially feasible. In addition, it was observed that the exponential function and modified logistic function were used to describe the feedback relationship between state variables and regulatory variables [44,58]. Gain function, correlation function, and least square function were also used to dynamically modify the preset schemes [59]. However, it has not been reported how different feedback functions affect the effectiveness of adjustment, and the design of a differentiated and adaptive feedback function system warrants further study.

In addition, the policy adjustment is limited to some extent. Controlling population growth to deal with water crisis is a global consensus [60–62], but the effectiveness of this policy varies regionally [63]. In Jiaxing, the strategy of slowing down population growth was not as powerful as improving water efficiency, which may be attributed to the impact of population scale. The simulation results showed that increasing water supply is a quick and effective measure for dealing with water shortage but yet implementation is difficult. The plain topography and coastal location make it difficult to store the abundant transit water in Jiaxing. The upstream water in the flood season has to be discharged to ensure a safe water level. In addition, supplying reclaimed water is a complex decision-making process involving various economic, technical and environmental standards [40]. Improving the water reuse capacity may help to reduce fresh water withdrawal, but if the reclaimed water utilization rate exceeds a certain threshold then this requires more external financial assistance [64].

The major goal of this case study was to demonstrate how to apply the SD-MOO model framework. Because of the difficulty in obtaining data, the parameters were simplified and estimated according to local plans in the case study. This may have resulted in some data being inconsistent with realistic development. For example, the “universal two-child policy” has led to a rebound in the fertility rate since 2015 but will not fundamentally reverse the decline and aging trend of the population in the long term in China [65,66]. Thus, the natural population growth rate of Jiaxing may be overestimated. However, by analyzing population statistics data in recent years, we found that population mobility contributes more to the population growth of Jiaxing than natural growth, which may justify the selected natural growth rate. As another example, it is unrealistic to ignore the randomness of precipitation change and keep the surface water constant during the simulation time. To make up the hydrological uncertainty, three hydrological scenarios with high, mid and low inflow levels were set in the models to cover the randomness of precipitation.

Flexibility of water resource allocation can be achieved by setting the weights of benefit targets [28]. The current case study adhered to sustainable development and gave equal weights to the three optimization goals. However, when extreme water shortage occurs, the poor satisfaction of agricultural water demand (Mid-2035, Low-2035) may exacerbate water stress and lead to declines in crop yield and agricultural productivity [53,67]. At this point, if basic water demand and food security are prioritized, the weight of social benefit should be higher than the weights of environmental and economic benefits (Figure 5).

Regarding the economic benefits, water users always prefer cheaper water sources [68]. In the allocation schemes of the above mentioned categories (i), (iii), and (iv), industry always uses up the remaining available surface water first, rather than diversion water, which is more expensive than surface water. However, when social equity and basic livelihoods are prioritized, some economic interests must be abandoned. In category (ii) of the allocation schemes, domestic users, as low economic output users, won the competition for surface water, while industrial users were allocated a large amount of high-priced diversion water. The industrial users will resist the implementation of allocation schemes

because of high costs. Economic policies such as water price subsidies, water-saving incentives, and segmented tax rates [69–71] may be prudently introduced to improve user acceptance of certain allocation schemes. In addition, the cost coefficients of different types of water were fixed during the simulation period, and the water price was limitedly adjusted to alleviate the water shortage. However, the water price will fluctuate due to water shortages. The lack of a link between water price and water scarcity and the absence of incentives for water-saving behavior may weaken users' perception of water scarcity [72,73]. Therefore, a market-based water price response to water shortage should be involved in the model in the future study.

5. Conclusions

Based on the system dynamics and multi-objective optimization method, this study established an SD-MOO modeling framework that integrated water supply and demand simulations, dynamic adjustment, and optimal allocation, exploring a comprehensive optimal water resource management method. A case study in Jiaxing City showed that water shortage risk would be alleviated by simultaneously improving water use efficiency, controlling growth rates of the population and gross production value, and increasing the utilization rates of surface water and reclaimed water. In water resource allocation schemes that have the best comprehensive benefit, both domestic and industrial users tended to use cheaper surface water. However, industry was required to make compromises (more diversion water was allocated) because of its higher economic density. When extreme water scarcity occurred, agricultural demand would be greatly suppressed. The proposed framework is dynamic, flexible in water allocation, and can be helpful in supporting local water resource management.

Compared with static control and simple allocation optimization in previous SD studies, the integrated water management framework based on the SD-MOO model has been improved as follows: (1) Feedback intensity was introduced to help decision makers devise abundant policy packages and quickly determine their effectiveness in curbing water scarcity; (2) policies and actions were adjusted based on the current water scarcity, emphasizing the dynamic management of water resources; and (3) flexible, reasonable, and multi-beneficial water resource allocation schemes were obtained through implementing dynamic adjustment and MOO. However, some issues, such as the impact of different feedback mechanisms on dynamic adjustment, dynamic changes of parameters and the weights selection in the multi-objective model of water resource allocation, need to be further explored.

Supplementary Materials: The following are available online at www.mdpi.com/xxx/s1, Figure S1: Effect of feedback intensity f (from 0 to 1) on water shortage rates (WSR) for various scenarios at mid inflow level (2025–2035), Figure S2: Effect of feedback intensity f (from 0 to 1) on WSR for various scenarios at low inflow level (2022–2035), Figure S3: Values of policy adjusted variables in scenario (p_n) and S7 (with $f = 1$, p'_n) at mid-inflow level, Figure S4: Values of policy adjusted variables in scenario (p_n) and S7 (with $f = 1$, p'_n) at low-inflow level, Figure S5. Individual and combined benefits of Pareto sets. (a) High-2020, (b) High-2025, (c) High-2035, (d) Mid-2020, (e) Mid-2025, (f) Mid-2035, (g) Low-2020, (h) Low-2025, (i) Low-2035. Table S1: SD equations in Vensim (High inflow level), Table S2: Observed and predicted values of social-economic parameters of Jiaxing, Table S3: Water quota of each sector in Jiaxing, Table S4: Water resource cost coefficient of each water user.

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