Response to the comments on the manuscript (**HESSD-2019-278**)
"**Basin-scale multi-objective simulation-optimization modeling for conjunctive use of surface water and groundwater in northwest China**"
by Jian Song, Yun Yang, Xiaomin Sun, Jin Lin, Ming Wu, Jianfeng Wu, and Jichun Wu

Note that the following text in Arial Narrow font denotes Referee's comments and in Times New Roman font denotes our response to the comments in the discussion. In our resubmission, the marked PDF file as follows has clearly indicated all changes to the original manuscript, tables and figures. Also, in the PDF file, marked in ~~a green strikethrough font~~ is the text that should be removed from the original manuscript and marked in a red font is the text that has been added to the revision. In addition, Line number(s) mentioned below can be referred to as that line numbering in the marked revised manuscript.

Response to Referee Dr. Qiankun Luo's Comments

This manuscript focus on the topic of conjunctive using of surface water and groundwater based on the multi-objective simulation and optimization method. In the manuscript, a novel multi-objective optimization model with four objective functions is developed to balance the water demand for agriculture, socioeconomic development and environmental demands. In order to find the Pareto optimal solutions for the special model, a new multi-objective evolutionary algorithm, named ε-MOMA, is presented. The optimization results of Yanqi Basin (YB) in northwest China certified the applicability of the new model and optimization algorithm. Generally, the manuscript does make an important contribution on water resources management research. However, there are some general and specific comments referencing lines in the manuscript which will be helpful for the improvement of the manuscript.

[Response] We appreciate Dr. Qiankun Luo's insightful comments and constructive suggestions. We have fully addressed the concerns into the revised manuscript and given a point-by-point response as below.

General comments:

1. The introduction usually includes the research background, the research problems, a review of the advantages and disadvantages of the previous and latest research results, and the new solving method of the present research. Thus, the description of the detailed condition of the study area should be move into section 3.1.

[Response] Considering the referee's concerns, we have reorganized the statements in the Introduction. Firstly, we clarified the necessity of water resources management in the arid inland basin to present the motivation of our study (**Lines 47-56**). Second, we explained the meaning of many-objective optimization framework in the water resources management and planning (**Lines 73-100**) and the optimization techniques (**Lines 101-126**). After that, we introduced the details of water resources exploitation in Yanqi Basin (YB) (**Lines 127-143**) to present the suitability of the case study. Then, we stated that it is necessary for YB water management to consider the deep uncertainty from climate change which probably results in the reduction of runoff in Kaidu River (**Lines 155-163**). Finally, we showed the general results of the study for the HESS readers (**Lines 164-174**).

2. The advantage of the newly developed optimization algorithm should be given in detail. For example, why the ε-MOMA is better than the other MOEA in solving groundwater management problems? What is the main difference between ε-box and the elite individual preservation strategy?

[Response] The point is well taken. We have split **Section 2.2** into **Section 2.2.1** "Main algorithmic structure" to present the process of the new algorithm step by step (**Lines 215-252**) and **Section 2.2.2** "Benchmark test" to investigate the performance of the algorithm (**Lines 259-277**). The new algorithm ε-MOMA which used several promising techniques from Borg MOEA and a local search operator to improve the optimality of Pareto solutions, has been validated to present the effectiveness in solving the many-objective optimization. In this study, it is not the focus to implement comparative study of the state-of-the-art MOEAs in solving water resources management problems. The benchmark test also show the potential of our algorithm (**Table S1 in Supplementary Materials**). After all, our study aims to propose a promising multi-objective optimization framework for the integrated surface water and groundwater management in the typical arid inland basin.

The concepts of Pareto dominance and ε-dominance can be defined as follows and we assume that all objectives are to be minimized. The vectors $\boldsymbol{f}=(f_1, f_2, f_3,\ldots, f_m)$ and $\boldsymbol{g}=(g_1, g_2, g_3,\ldots, g_m)$ can be denoted as objective values where m is the number of objectives and $\boldsymbol{\varepsilon}=(\varepsilon_1, \varepsilon_2, \varepsilon_3,\ldots,\varepsilon_m)$ is the allowable tolerance vector specified by the users.

The objective vector $\boldsymbol{f}$ is said to Pareto dominate $\boldsymbol{g}$, if:

$$\begin{aligned} f_i \le g_i \qquad & \forall i \in \{1,\ldots,m\} \\ f_i < g_i \qquad & \exists i \in \{1,\ldots,m\} \end{aligned} \tag{1}$$

The objective vector $\boldsymbol{f}$ is said to ε-dominate $\boldsymbol{g}$, if:

$$\left(1-\varepsilon_i\right) f_i \le g_i \qquad \forall i \in \{1,\ldots,m\} \tag{2}$$

The ε-dominance allows the decision-makers to specify the resolution of the Pareto set approximation by selecting an appropriate ε value while guarantees the diversity of Pareto solutions over the optimal Pareto front (Laumanns et al., 2002; Deb et al., 2005).

Laumanns, M., Thiele, L., Deb, K., and Zitzler, E. (2002). Combining convergence and diversity in evolutionary multi-objective optimization. Evolutionary Computation, 10(3): 263-282. https://doi.org/10.1162/106365602760234108.

Deb, K., Mohan, M., and Mishra, S. (2005). Evaluating the ε-domination based multi-objective evolutionary algorithm for a quick computation of Pareto-optimal solutions. Evolutionary Computation, 13(4): 501-525. https://doi.org/10.1162/106365605774666895.

3. In the numerical simulation process, the irrigation backflow should be considered. How to deal with the irrigation backflow in the groundwater flow numerical simulation model of the YB?

[Response] The point is well taken. The irrigation water including surface water (SW) in an aqueduct system and groundwater (GW) in the regional aquifer. We allocate SW diverted from Kaidu River to an irrigation district according to the source of irrigation water derived from which aqueduct. The GW can be allocated in terms of the locations of pumping wells distributed in the irrigation district. The return flow from agriculture irrigation can be calculated by multiplying the irrigation water demands by the irrigation infiltration coefficient based on reports from the local water resources authority.

4. YB is a typical arid inland basin in China. The optimization results of YB are seemed reliably, can this optimization model be used directly in other basin or field?

[Response] The proposed many-objective optimization framework can be extended to solve the integrated SW-GW management problems (**Lines 681-683**) once the simulation model can be built in the other basins or fields. The simulation model can be developed with the fully-coupled hydrological model to reduce the prediction error derived from numerical model that is our focus in the future study.

Specific comments, where line numbers refer to the PDF version of the HESSD paper:

1. Line 168: I suggest to changing the “decision-maker” to “water manager” in the manuscript. The author sometimes uses “decision-maker” and sometimes uses “water manager”, which will confuse the readers.

[Response] Comment accepted and change made (**Lines 201-202**). We have modified the “decision-maker” to “water manager” in the context of elucidating water resource management throughout the manuscript.

2. Line 199-201: Did all of the referred recombination operators (SBX, DE, SPX, PCX, LX, UM) used in the new optimization method? Or only one of them was adopted? The author should clear it.

[Response] As stated in the manuscript (**Lines 223-232**), the crossover probability of each recombination operator is updated periodically based on the proportion of the solutions generated by the operator in the ε-dominance archive. In the optimization, we firstly assign same probability for all of the operators which can be used in the preliminary stage. The optimal operator can be chosen with the highest probability at the later stage of evolutionary search.

3. Line 291: There is a mistake in Equation 4, the "2" was lost.

[Response] Comment accepted and change made (**Line 359**).

4. Line 417: where the increment of fTPR and fTDR from, the explanation should be given.

[Response] The increments indicate the range of f_{TPR} and f_{TDR} across all the Pareto solutions to show the extent of regulation of groundwater abstraction and surface water diversion in the post-optimization (**Lines 488-489**).

5. Line 539-541: Why the lake level is changed to a smaller value? And why the maximum groundwater drawdown is reset to 10m?

[Response] The reduction of runoff in Kaidu River directly lowers the runoff inflow to the terminal lake which results in the decline of lake level. Meanwhile, the groundwater exploitation must be augmented to offset the reduction of available runoff for irrigation water demands, which increases the groundwater drawdown in the regional aquifer. In the optimization, the constraints of minimum lake level and maximum groundwater drawdown need to be altered to avoid much more infeasible solutions in the population which inhibits convergence of the MOEA. The optimization under Scenarios A0, A1 and A2 is to implement comparative analysis for quantifying the effect of runoff reduction on the YB water management.

6. Line 557: "a certain value" should be given explicitly for the case study.

[Response] The point is well taken. We have modified the statement in the revised manuscript (**Lines 624-626**).

7. Line 578: Change "Yanqi Basin" to "YB".

[Response] Comment accepted and change made (**Line 647**).

Basin-scale multi-objective simulation-optimization modeling for conjunctive use of surface water and groundwater in northwest China

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ABSTRACT

In the arid inland basins of China, the long-term unregulated agricultural irrigation from surface water diversion and groundwater abstraction has caused unsustainability of water resources and degradation of ecosystems. This requires integrated management of surface water (SW) and groundwater (GW) at basin scale to achieve scientific decision supports for sustainable water resources allocation in China. This study developed a novel multi-objective simulation-optimization (S-O) modeling framework. The optimization framework integrated a new epsilon multi-objective memetic algorithm (ε-MOMA) with MODFLOW-NWT model to implement the real-world decision-making for water resources management while pondering the complicated groundwater-lake-river interaction in the arid inland basin. Then the optimization technique was validated through the SW-GW management in Yanqi Basin (YB), a typical arid region with intensive agricultural irrigation in northwest China. The management model, involving maximizations of total water supply rate, groundwater storage and surface runoff inflow to the terminal lake, and minimization of water delivery cost, was proposed to explore the tradeoffs between socioeconomic and environmental factors. It is shown that the tradeoff surface can be achieved in the 4-dimensional objective space by optimizing spatial groundwater abstraction in the irrigation districts and surface water diversion in the river. The Pareto-optimal solutions avoid the prevalence of decision bias caused by the low-dimensional problem formulation. Water managers are then able to identify their desired water management schemes with preferred objectives and achieve maximal socioeconomic and ecological benefits simultaneously. Moreover, three representative runoff scenarios related to the climate change were specified to quantify the influence of decreasing runoff in the river on the YB water management. Results show that runoff depletion would be of great negative impact on the management objectives. Therefore, the integrated SW and GW management is of critical importance for the fragile ecosystem under changing climatic conditions.

Keywords: Multi-objective optimization; Water resources management; Conjunctive use; Yanqi Basin; Bosten Lake

1. Introduction

In arid and semi-arid inland basins, the intensive irrigation for agricultural development caused the deterioration of natural ecosystem sustained with scarce water resources (Wichelns and Oster, 2006; Wu et al., 2016). In such cases, water managers are faced with choosing the optimal water supply scheme for the local economic development and eco-environmental conservation. In general, the pattern of water allocation in such regions incorporates groundwater (GW) abstraction from aquifer systems and surface water (SW) diversion from surface rivers (Liu et al., 2010; Wu et al., 2014). Hence, the conjunctive management of GW and SW is essential for dealing with the contradiction between demand and supply of water resources in the arid regions with water shortage (Khare et al., 2006; Safavi and Esmikhani, 2013; Singh, 2014; Hassanzadeh, et al., 2014; Wu et al., 2016).~~ Yanqi Basin (YB) is a typical oasis in an arid inland basin located to the southern Tianshan Mountains in Xinjiang Province, northwest China. The surface water resource in YB is mainly composed of a river and a lake, namely Kaidu River and Bosten Lake, the biggest freshwater inland lake in China (Wang et al., 2014; Zhou et al., 2015). Kaidu River supplies approximately 95% of total inflow to Bosten Lake (Gao and Yao, 2005; Liu et al., 2013; Yao et al., 2018) which is the major water source of the Kongqi River recharged by an artificial pumping station built in 1983. Therefore, the water supply scheme in YB dominates the water balance in Bosten Lake and has a significant influence on the Kongqi River and the lower reaches of Tarim River where the serious water crisis has taken place. With the intensive agricultural development, surface water diverted from Kaidu River can no longer meet crop water requirements. Thus, groundwater became the alternative water source for crop production whereas the excessive groundwater exploitation has caused the deterioration of local ecosystem associated with the decline of groundwater~~

~~level and altered the hydraulic interaction between GW and SW (Hu et al., 2007; Zhang et al., 2014; Tian, et al., 2015, Yao et al., 2015). For this reason, the integrated SW and GW management is essential for rational utilization of water resources in the arid inland basin due to the physical water scarcity.~~

In the water resources planning and management, the simulation-optimization (S-O) approaches can provide optimal schemes to guide and inform stakeholders (Maier et al., 2014). In the S-O framework, the simulation model explains the physical behaviors of water resources system and the management model explains the evaluation criteria of the water supply options (Singh, 2014). The management model includes objective functions as the performance metric of candidate schemes and constraint conditions defining the feasible decision space. However, the real-world water management problems are often complex, and associated with nonlinear and multimodal objectives and constraints. This complexity probably leads to the unavailability of the classical optimization algorithms such as mathematical programming and dynamic programming (Woodruff et al., 2013). For this reason, evolutionary algorithms have been extensively proved to be effective and reliable in solving the limitations of complex water resources management (McPhee and Yeh, 2004; Yang, et al., 2009; Safavi and Esmikhani, 2013; Singh and Panda, 2013; Rothman and Mays, 2013; Wu et al., 2014; Parsapour-Moghaddam et al., 2015; Wu et al., 2016). Yang et al. (2009) considered conflicting bi-objectives with the conjunctive use of GW and SW to achieve optimal pumping and recharge schemes. Rothman and Mays (2013) developed an optimization model including cost control, aquifer protection and growth objectives using multi-objective genetic algorithm. Wu et al. (2016) performed the temporal optimization of monthly volume of surface water diverted from Heihe River by linking a physical-based integrated modeling with a simple single-objective management model. However, these studies rarely consider multi-objective optimization in the basin-scale water management with conjunctive use of SW and GW. The management model including the typical single objective or bi-objective formulation probably results in the decision bias (*i.e.*, cognitive myopia or short-sightedness) due to the sub-optimal solution only considering the fewer preference criteria (Kasprzyk et al., 2012, 2015; Woodruff et al., 2013; Matteo et al., 2019). Therefore, the water resources management with the strong and complex interactions between SW and GW calls for water manager to consider many-objective optimization that refers to the system design with four or more objectives (Fleming et al., 2005).

Multi-objective evolutionary algorithms (MOEAs) can obtain the tradeoff solutions that cater to multiple competing objectives and reflect comprehensive decision information for practitioners in real-world applications (Reed et al., 2013; Beh et al., 2017; Eker and Kwakkel, 2018; Maier et al., 2019). However, many-objective optimization often suffers from the domination resistance phenomenon (Purshouse and Fleming, 2007; Hadka and Reed, 2013), which shows that the diminishing Pareto-sorting capacity triggers many non-dominated solutions in the population and then results in stagnation of evolutionary search. In order to alleviate the difficulty, Borg MOEA (Hadka and Reed, 2013) employed auto-adaptive recombination operators to enhance the ability of evolutionary search, ε-box technique to ensure the diversity and adaptive population sizing scheme to avoid search stagnation. The hybrid MOEA framework, namely multi-objective memetic algorithm, composed of the biological process of natural selection and cultural evolution capable of local refinement, was applied to overcome some shortcomings of the traditional MOEA (*e.g.*, slow convergence, inefficient termination criterion, etc.) (Sindhya et al., 2011; 2013). These state-of-the-art MOEAs have been extensively validated and evaluated in addressing multi-objective optimization problems. However, due to the diversity and complexity of real-word decision-making problems, the algorithms may be inefficient in maintaining the diversity and convergence of Pareto front. For example, Zheng et al. (2016) implemented the comparison of

NSGAII, SAMODE and Borg in designing water distribution systems. The result indicated that Borg can converge quickly to the Pareto-optimal front whereas decrease the diversity of solutions. Hence, further efforts should be focused on advancing the MOEAs. This study aims at developing a new MOEA, named epsilon multi-objective memetic algorithm (ε-MOMA), which integrates the ε-dominance concept, the auto-adaptive recombination operator and a local search operator into the basic framework of NSGAII (Deb et al., 2002). Then, the proposed multi-objective optimization framework is applied to solve the integrated management of SW and GW in Yanqi Bain (YB).

YB is a typical oasis in an arid inland basin located to the southern Tianshan Mountains in Xinjiang Province, northwest China. The surface water resource in YB is composed of Kaidu River and Bosten Lake, the largest freshwater inland lake in China (Wang et al., 2014; Zhou et al., 2015). Kaidu River, as the largest river in the basin, supplies the vast majority of surface water for agricultural irrigation and recharge for Bosten Lake (Gao and Yao, 2005; Liu et al., 2013; Yao et al., 2018). Therefore, surface water diversion in the river dominates the water balance in Bosten Lake, which is the main water source for the lower reaches of Tarim River where the serious water crisis has taken place. With the intensive agricultural development in the past decades, surface water diverted from Kaidu River can no longer meet crop water requirements. Hence, groundwater became the alternative water source for crop production whereas the excessive groundwater abstraction has caused the deterioration of local ecosystem associated with the decline of groundwater level and altered the hydraulic interaction between GW and SW (Hu et al., 2007; Zhang et al., 2014; Tian, et al., 2015, Yao et al., 2015). Current water resources regulations in YB have shown the low performance in maintaining regional water balance, *e.g.*, decline of lake level in Bosten Lake. Therefore, the spatial pattern of water utilization (*i.e.*, decision variables) should be regulated to satisfy the preferred management objectives. The pattern is composed of groundwater abstraction in irrigation districts and surface water diversion through the aqueduct system connected with the river. The management objectives comprise minimizing the capital and operation costs of water delivery, maximizing water use demands for agricultural development (*i.e.,* total volume of surface water and groundwater use) and the environmental flow for conservation of the ecosystem (*i.e.*, the regional groundwater storage and surface runoff inflow to the terminal lake). This study implements the integrated management of SW and GW by investigating the performance of tradeoffs including environmental, economic, social factors in designing optimal water allocation schemes by the new optimization framework. To our knowledge, there are very few researches about the many-objective optimization for the conjunctive management of SW-GW involving complex groundwater-river-lake interactions in arid inland basins within S-O framework.

In the changing world, the optimized schemes probably exhibit low performance even unfeasible under the future conditions (Maier et al., 2016). In YB, Kaidu River mainly gains water from seasonal precipitation that runs off the mountainous landscape and snow and glacier that melts in the upper Tianshan Mountains region known as a main water tower in the Central Asia. Therefore, the runoff variation in Kaidu River, which is highly sensitive to the changes of precipitation and glacier mass loss dominated by the climate change, greatly affects the water resources and water cycle in the basin. Three representative runoff scenarios related to climate change are specified to explore the effects of runoff reduction in Kaidu River on the integrated SW and GW management practices.

This study firstly constructed the multi-objective SW-GW management model to consider water demands and environmental benefits including regional groundwater storage and surface runoff inflow to the terminal lake. Then the spatial conjunctive optimization of surface water diversion and groundwater abstraction was implemented based on the proposed optimization framework. The optimization results demonstrate that water managers can achieve the

Pareto-optimal schemes constrained by satisfying the water demands and sustaining the fragile ecosystem in the arid inland basin with strong and complex SW-GW interactions. The implication from the runoff reduction scenarios based optimization shows that the conservative water management options may be desired in the face of the deep uncertainty from the climate changes. The study results can also provide valuable insights for water allocation in other arid inland basins.

2. Methodology

As shown in Fig. 1, this study aims to develop a multi-objective decision-making framework to optimize irrigation schemes of surface water diversion and groundwater abstraction for the integrated SW and GW management. The optimal schemes can assist water managers~~decision-makers~~ to achieve water demands and ensure water balance of ecosystem in the arid inland basin. The optimization framework includes three main modules and their details are stated in the following sections.

Figure 1.

2.1 Problem formulation

Module I in the optimization framework is to formulate an integrated SW and GW management model to implement water resources management in the basin. The water utilization patterns for irrigation are composed of diverting surface water from the inland reach of river basin and pumping groundwater from the regional aquifer. Therefore, the decision variables comprise the volume of surface water diversion in the aqueduct system and groundwater abstraction in the irrigation districts. In general, the optimal water supply strategies are maximizing the total volume of water supply and minimizing the capital and operation costs of water delivery. However, in the arid inland basin with water scarcity, the intensive agricultural development requires enough irrigation water to ensure local economic development while the sustainability of ecosystem also needs to follow specific requirements for maintaining environmental flows. For example, the excessive surface water diversion can significantly reduce the runoff inflow to the terminal lake, which causes obvious decline of lake level and results in the degradation of local ecosystem associated with the lake. Meanwhile, immoderate exploitation of groundwater stored in the aquifer to offset the surface water shortage triggers a series of environment problems (*e.g.*, dramatic decrease of groundwater storage). Therefore, the conflict between agricultural development and environmental conservation constrained by water scarcity stimulates the local water resources authority to implement scientific water management practices. The water managers~~decision-makers~~ should consider the total water supply rate and the cost of water delivery from multiple sources as socioeconomic metrics, and describe the runoff inflow to the lake and groundwater storage as environmental metrics. Then, water managers can assess water use practices by weighing these preference criteria. The performances of all schemes are evaluated based on the well-calibrated numerical model. The detailed formulation of management model can be seen in Section 3.3. Finally, the optimization model formulates water use practices as decision variables, socioeconomic and environmental metrics as management objectives, practical limitation of water exploitation and water demands for ecosystem as constrained conditions for the basin-scale SW and GW management.

2.2 Optimization approach

2.2.1 Main algorithmic structure

Module II in the optimization framework illustrates the algorithmic process of ε-MOMA. The main steps can be recapitulated as follows:

Step 1: Generation of initial population: N_{pop} individuals are firstly sampled over the decision space using Latin Hypercube Sampling (LHS) that is an effective sample scheme to ensure the uniform distribution of initial population.

Step 2: Evaluation process of objectives and constraints: The original simulation model is run with the calibrated parameters. Then objectives and constraints are calculated from the model output variables (*i.e.*, state variables).

Step 3: Evolutionary operators for the creation of offspring population: The auto-adaptive multi-operator recombination proposed by Hadka and Reed (2013) is a promising technique to select optimal operator for real-world optimization problems. The crossover probability of each operator is updated periodically based on the proportion of the solutions generated by each operator in the ε-dominance archive. The recombination strategy is essential for the intricate multi-objective optimization in the real-world problems due to the inability to know a prior the optimal recombination operator. This study integrated the six real-valued recombination operators (*i.e.*, simulated binary crossover (SBX) (Deb and Agrawal, 1994), differential evolution (DE) (Storn and Price, 1997), simplex crossover (SPX) (Tsutsui et al., 1999), parent-centric crossover (PCX) (Deb et al., 2002), Laplace crossover (LX) (Deep and Thakur, 2007), uniform mutation (UM)) into the ε-MOMA to enhance the potential of evolutionary search in higher order objective spaces. Additionally, the polynomial mutation is applied to the recombination population.

Step 4: The ε-dominance archive process: The ε-box technique proposed by Laumanns et al. (2002) attempts to ensure convergence and diversity of the approximate Pareto solutions. Moreover, decision-makers can define the minimum resolution of objective vector with epsilon vector to satisfy their acceptable precision target and restrict the archive size. This study implemented the ε-dominance archive process after the fast non-dominated sorting of offspring individuals and alleviated the difficulties derived from the domination resistance in the many-objective optimization.

Step 5: Bidirectional local mutation: The archived solutions are operated based on Gaussian perturbation in the neighborhood of decision variables. Given an archived individual $\mathbf{v}=(v_1,v_2,v_3,\ldots,v_n)$, the mutated individuals can be stated as:

$$\mathbf{v}^{+}=\left(v_1,v_2,\ldots,v_i+p\times\left(m_i-w_i\right),\ldots,v_n\right) \quad (1)$$

$$\mathbf{v}^{-}=\left(v_1,v_2,\ldots,v_i-p\times\left(m_i-w_i\right),\ldots,v_n\right) \quad (2)$$

where $\mathbf{v}=(v_1,v_2,\ldots,v_n)$ is an n-dimensional decision variable vector; $\boldsymbol{m}=(m_1,m_2,\ldots,m_n)$ and $\boldsymbol{w}=(w_1,w_2,\ldots,w_n)$ are two individuals randomly selected from the archive; c follows standard Gaussian distribution. The process is effective with the probability of $1/n$ (Chen et al., 2015). The algorithm revives the local search operator in every several generations and then updates the archive again.

Step 6: Return to Step 2 if the termination criterion is not satisfied. This study specified the number of function evaluations as termination condition.

The basic framework of ε-MOMA is similar to the traditional NSGA-II with significant change in recombination operators and ε-dominance archive with a local search operator. The algorithm possesses the ability of highly effective global search with adaptive recombination operator and epsilon domination to find higher quality and diverse solutions with local search operator.

2.2.2 Benchmark test

To investigate the performance of ε-MOMA in the many-objective optimization, we implement benchmark test with the 3 to 6 objectives DTLZ1 and DTLZ3 problems (Deb et al., 2002). The test instances are deceptive and probably converge to the sub-optimal Pareto front, which provides a severe challenge for the algorithm to get close to the global Pareto-optimal front. The hypervolume metric (HV) is applied to evaluate the convergence and diversity of approximate Pareto front (Zitzler et al., 2003). The global Pareto-optimal front for DTLZ problems is known and can be considered as the reference set. The HV metric indicates the dominated region of the non-dominated solutions relative to the reference point that is the extent of the reference set. The HV of the reference set (HV_{rs}) and the approximate set (HV_{as}) can be calculated using a fast search algorithm proposed by Bader and Zitzler (2011) in the high-dimensional objective space. This study uses the normalized HV (*i.e.*, $HV_n = HV_{as}/HV_{rs}$) to evaluate the performance of ε-MOMA for the test problems. The approximate Pareto front completely converges to the reference set when HV_n is equal to one. The test results show that ε-MOMA is capable of achieving a larger value of HV_n metric (over 95%), indicating that the approximate Pareto front is very close to global optimal Pareto front (Table S1 in the Supplementary Materials). In higher-dimensional objective space, the performance of ε-MOMA can be maintained by increasing the number of function evaluations. Therefore, the proposed ε-MOMA is effective in addressing many-objective optimization based on the benchmark test.

2.3 Visual analytics of Pareto-front

In the many-objective optimization, it is difficult for water managers to distinguish the performance of single solution and discover desired schemes without the interactive visual analytics. Module III used a visual analytics package, DiscoveryDV (Hadka et al., 2015; Kollat and Reed, 2007), to explore and analyze water management practices in the high-order objective spaces. The package employed multi-dimensional coordinate plot and parallel coordinate plot (Inselberg, 2009) to visualize Pareto solutions. Visualizing performance objectives can assist stakeholders to compare with the scheme before the optimization and select key tradeoff schemes with a clearer perspective (Matteo et al., 2019; Maier et al., 2014). Moreover, decision-makers can eliminate redundant schemes based on the preferred objectives or concerns and filter the optimal subsets those probably adopted by the experienced practitioners.

3 Case study

3.1 Study area

YB is a typical oasis in an arid inland desert basin in the southern Tianshan Mountains, Xinjiang Province, northwest China and includes Yanqi County, Hejing County, Bohu County and Heshuo County, with a total area of about 7600 km^2 (Fig. 2). In the model domain, the northwest is mountainous and the south is a low-lying desert, and the terrain slopes from northwest to lower southeast. YB is located in the temperate zone of continental desert climate with an annual mean temperature of 14.6 ºC, an annual precipitation of 50.7-79.9 mm, and a potential evaporation of 2000.5-2449.7 mm (Mamat et al., 2014). The basin is mainly composed of the Kaidu River, Huangshuigou River and Qingshui River. Kaidu River originates from the Hargat Valley and the Jacsta Valley in the middle part of the Tianshan Mountain with a maximum altitude of 5000 m and ends in Bosten Lake (Xu et al., 2016). Kaidu River is the largest river in YB which provides annual mean runoff of 3.41 billion m^3 (Wang et al., 2013) and plays an utmost role in protecting the lake and its surrounding ecology and environment. The Dashankou station is the dividing point that divides the mainstream of the river into middle and lower reaches. In YB, the runoff in Kaidu River is mainly diverted for agricultural irrigation and finally flows into Bosten Lake, which contributes to about 95% of the water recharge for the lake (Yao et al., 2018). Bosten Lake is a largest freshwater inland lake in China covering the area of about 1005 km^2 with a length of 55 km and a width of 25 km. The lake water volume is approximately 8.80 billion m^3, with an average depth of 7 m and a maximum depth of 17 m (Xiao et al., 2010). The evaporation and an artificial discharge by a pumping station built in 1983 control the outflow of the lake. As shown in Fig. 2, the pumping channel starting from the outflow point is used to divert the lake water to recharge Kongqi River and supply water to the lower Tarim River. The dam is built to sustain higher lake level for the water diversion. Therefore, Bosten Lake is a main water source to the lower reaches of Tarim River, which has suffered from severe degradation of ecological environment resulted from unregulated water exploitation in the past decades. In order to regenerate "Green Corridor" in the lower reaches of Tarim River, Chinese government has implemented the Ecological Water Conveyance Project since 2000 to increase the recharge of groundwater system that is crucial for the growth of natural vegetation (Xu et al., 2007; Hao and Li, 2014). The project firstly transfers water from Bosten Lake to Daxihaizi Reservoir and then to the lower reaches of Qiwenkur River, a large tributary of Tarim River, and finally to Taitema Lake (Chen et al., 2010). However, YB is an intensive agricultural area where is mostly made up of farmland growing crops of tomato and pepper. The irrigation water demands accounted for 90% of the total water consumption in the basin due to the rapid increase of farmland area in the recent years (Yao, et al., 2018). Consequently, scientific water management strategies should strike for balancing the demands of existing irrigation and eco-environmental water use to sustain enough water inflowing from Kaidu River to the lake and the aquifer.

This study selects the core part of YB comprising the majority of irrigation districts and Kaidu River. The river plays a vital role in regulating and maintaining regional water balance in the basin. The model domain (Fig. 2) is bounded by the mountains on the northwest, Huangshuigou River on the northeast, swamp areas and Bosten Lake on the south. As shown in Fig. 2, an aqueduct system conveys and redistributes the surface runoff from the mainstream of Kaidu River and the wells are used to pump groundwater from the aquifer.

Figure 2.

3.2 Numerical model

The numerical model in this study is modified from the previous work of Wu et al. (2018) using MODFLOW-NWT (Niswonger, 2011). Then we perform a multi-objective optimization with the corrected model. The specified boundary conditions in the model are illustrated in Fig. 3. The northwest border was defined as the flow boundary to simulate recharge of groundwater runoff in the interface between mountains and plain. Huangshuigou River and southwest border were considered as the specified head boundary based on observed groundwater level. The swamps and Bosten Lake were modelled using the General Head Boundary (GHB) package and Lake package (LAK3) (Michael and Leonard, 2000), respectively. The bathymetric contours of Bosten Lake were used to confirm the lake bottom topography. Kaidu River and aqueducts were simulated using the Streamflow-Routing package (SFR2) (Richard and David, 2010). The simulation period in the transient model was defined from November in 2003 to October in 2013. Totally 20 stress periods were discretized, two periods for each year including non-irrigation period (from November to next March) and irrigation period (from April to October of each year), over the entire simulation period. The key parameters for both SW and GW were adjusted to reproduce the fluctuation of groundwater levels at the observation wells and streamflow in the gaging stations (*i.e.*, Yanqi and Baolangsumu stations). The observed lake levels in the simulation period were employed to calibrate the model.

Figure 3.

The model calibration was manually implemented by the trial-and-error method. The Nash-Sutcliffe Efficiency (NSE) was applied to evaluate the simulated precision of runoff and lake level. The predicted accuracy of groundwater head was assessed based on root mean square error (RMSE) and correlation coefficient (R). The performance criteria can be stated as:

$$\mathrm{NSE} = 1\text{-}\frac{\sum_{t=1}^{T}\left(y_{m,t}-y_{o,t}\right)^2}{\sum_{t=1}^{T}\left(y_{o,t}-\overline{y}_o\right)^2} \tag{3}$$

$$\mathrm{RMSE}=\sqrt{\sum_{i=1}^{N}\left(y_{m,i}-y_{o,i}\right)^2 / N} \tag{4}$$

$$R = \frac{\sum_{i=1}^{N}\left(y_{m,i}-\overline{y}_m\right)\left(y_{o,i}-\overline{y}_o\right)}{\sqrt{\sum_{i=1}^{N}\left(y_{m,i}-\overline{y}_m\right)^2 \times \sum_{i=1}^{N}\left(y_{o,i}-\overline{y}_o\right)^2}} \tag{5}$$

where $y_{m,t}$ and $y_{o,t}$ are the simulated and observed runoff or lake level for tth stress period, respectively; T is the number of stress periods; $y_{m,i}$ and $y_{o,i}$ are the simulated and observed groundwater head at the ith observation well, respectively; N is the number of observation wells; $\overline{y}_m$ and $\overline{y}_o$ are the average value of simulated and observed data. In the Supplementary Materials, Fig. S1a and S1b compare the simulated and observed runoff at Yanqi and Baolangsumu Stations for the periods between 2004 and 2012 and suggest that the long-term fluctuation of runoff in Kaidu River can be well reproduced with NSE of 0.89 and 0.9, respectively. Fig. S1d shows the simulated groundwater heads have a good-fit with observed heads at the all observation wells with RMSE of 1.8 m and R of 0.98. Fig. S1e compares the observed and calibrated groundwater level over time in the three observation wells and the groundwater variation trend in the irrigation and non-irrigation period can be achieved.

The interaction between Bosten Lake and the aquifer is dominated by the hydraulic conductivity of the lakebed, of which value is very small owing to the existence of the thick low-permeability sediment in the region. The main inflow term of the lake is the surface runoff from Kaidu River which has been calibrated with the runoff data in the gauging stations. The recharge for the lake from precipitation is not significant in the arid inland basin. The outflow terms are mainly composed of the evaporation and artificial pumping to divert water from the lake to Kongqi River. The local water resources authority in YB provided the data of artificial pumping in the simulation period. However, the average evaporation in Bosten Lake calculated using potential evaporation data or Penman's equation is not accurate because the temperature and relative humility exhibit the significant difference over the approximately 945.0 km^2

evaporation surface. Therefore, the observed lake stages were applied to calibrate evaporation rate in the lake. Fig. S1c illustrates the calibration results of lake level (NSE=0.97) and indicates that the decline trend of lake level can be adequately captured. Then, the water balance of Bosten Lake can be achieved as shown in Fig. 4. In the simulation period from 2004 to 2013, surface runoff inflow in Kaidu River represents 97.4% of the total annual inflow to the Bosten Lake. The total annual outflow of the lake consists of 54.9% of lake evaporation and 44.2% of artificial pumping. Therefore, the surface runoff in Kaidu River is a crucial factor to maintain the water balance of Bosten Lake. The surface runoff inflow can be considered as a significant performance metric to evaluate the water use practices in the basin. Finally, the well-calibrated model can be employed to integrated SW and GW management.

Figure 4.

3.3 Management model

The integrated SW and GW management focuses on not only the water resources exploitation subject to social and economic benefits but also the effect of water exploitation on environment benefits. The study formulated an integrated SW and GW optimization problem including four management objectives: (1) to maximize total water supply rate (f_{TWS}); (2) to minimize total cost of water delivery from water intake points to water use destinations (f_{TCOST}); (3) to maximize the groundwater storage change of saturated zone between the beginning and end of management period (f_{GSC}) which is negative when the storage decreases and vice versa; and (4) to maximize surface runoff inflow from Kaidu River to Bosten Lake (f_{SRI}). f_{TWS} and f_{TCOST} are defined as the metrics to satisfy the local irrigation water demands while maintain the lower costs of water use. f_{GSC} is formulated as the metric indicating the extent of groundwater abstraction and a greater value shows a preferred situation. f_{SRI} is defined to evaluate the influence of surface runoff from Kaidu River on the water balance in Bosten Lake, which contributes about 97.4% of the total inflow (Fig. 4). As shown in Fig. 5, the decision variables are the total volume of surface water diverted in the mainstream of Kaidu River in the diversion point (DP1-DP7) and groundwater abstraction in the irrigation districts (ID1-ID11). The formulations of management model are given as follows:

$$\text{Max} \quad f_{TWS} = \sum_{i=1}^{N_\mathrm{p}} Q_{g,i} + \sum_{i=1}^{N_\mathrm{d}} Q_{s,i} \tag{6}$$

$$\text{Min} \quad f_{TCOST} = \sum_{k=1}^{N_t} \sum_{i=1}^{N_w} q_{g,i,k} C_g \left(H_i - h_{i,k} \right) T_k + \sum_{k=1}^{N_t} \sum_{i=1}^{N_d} q_{s,i,k} C_s T_k \tag{7}$$

$$\text{Max} \quad f_{GSC} = \sum_{j=1}^{N_g} \left(h_{end,j} - h_{ini,j} \right) Sy_j A_j \tag{8}$$

$$\text{Max} \quad f_{SRI} = f_{gaging}(\mathbf{X}) \tag{9}$$

$$\mathbf{X} = \left(Q_{g,1}, Q_{g,2}, \ldots, Q_{g,N_\mathrm{p}}; Q_{s,1}, Q_{s,2}, \ldots, Q_{s,N_d} \right) \tag{10}$$

where $Q_{g,i}$ is total groundwater abstraction rate at ith irrigation district (m^3/yr); $Q_{s,i}$ is total volume of surface water diverted from ith diversion point (m^3/yr); N_p is the number of irrigation districts; N_d is the number of diversion point based on the locations of aqueducts; N_t is the number of stress period including irrigation and non-irrigation period; N_w is total number of pumping wells; $q_{g,i,k}$ is the pumping rate at the ith well in kth stress period (m^3/d); C_g is the cost per unit pumping rate per length of hydraulic lift in case of wells (0.015 CNY/m^3/m), and CNY stands for Chinese Yuan; H_i is the surface elevation at the ith pumping well (m); $h_{i,k}$ is the groundwater level at the ith well in kth stress period (m); T_k is the length of the kth stress period (d); $q_{s,i,k}$ is the surface water diversion rate at the ith diversion point in kth stress period (m^3/d); C_s is the cost per unit diversion volume (0.055 CNY/m^3); N_g is the total number of active cell in the model domain; $h_{end,j}$, $h_{ini,j}$ is the groundwater level at the end and beginning of management period (m); Sy_j is the specific yield at jth active cell; A_j is the area of jth grid cell (m^2); f_gaging outputs the surface runoff in Kaidu River at the inflow point of Bosten Lake; **X** is a water use scheme.

Figure 5.

The management model consists of a set of constraints given by:

$$Q_{g,min} \le Q_{g,i} \le Q_{g,max} \quad Q_{s,min} \le Q_{s,i} \le Q_{s,max} \tag{11}$$

$$d_{max} \le d_c \quad h_{lake} \ge h_c \tag{12}$$

$$\sum_{i=1}^{N_p} Q_{g,i} \ge TP_{min} \quad \sum_{i=1}^{N_d} Q_{s,i} \ge TD_{min} \tag{13}$$

$$Q_{out,i} > 0.0 \tag{14}$$

where $Q_{g,min}$ and $Q_{g,max}$ are the capacity of total groundwater abstraction at specified irrigation district and $Q_{g,min}$ is uniformly assumed to 1.0 million m^3/yr (Mm^3/yr) and $Q_{g,max}$ is 100.0 Mm^3/yr; $Q_{s,min}$ and $Q_{s,max}$ are the constraints of surface water diversion at diversion point, $Q_{s,min}$ is 10.0 Mm^3/yr at diversion points DP1 and DP2 and 5.0 Mm^3/yr at DP3-DP7, $Q_{s,max}$ is 400.0 Mm^3/yr at DP1 and 200.0 Mm^3/yr at DP2 and 100.0 Mm^3/yr at DP3-DP7; d_{max} is the maximum drawdown and must less than the permission value d_c which is set to 5 m based on the existing management schemes; h_{lake} is lake level and must greater than minimum level h_c (1045 m in this study) to divert lake water to recharge Kongqi River; TP_{min} and TD_{min} is the prescribed minimum water demands of total groundwater abstraction and total surface diversion to satisfy the agricultural development and are set to 300.0 Mm^3/yr and 550.0 Mm^3/yr based on the reports from the local water resources authority; $Q_{out,i}$ represents outflow of the end reach of *i*th stream segment and must greater than zeros which means the potential diversion at each diversion point does not exceed the available streamflow in the current segment to avoid significant error of water budgets in the optimization (Wu et al., 2015). This study aims at optimizing spatial distribution of groundwater abstraction at different irrigation district and surface water diversion at each diversion point. The management period was set to one year with duplicated model inputs and parameters from November 2012 to October 2013 including the non-irrigation and irrigation periods. Then the conjunctive management of SW and GW is implemented based on the multi-objective optimization framework carried out in MATLAB software (http://www.mathworks.com/products/matlab).

4 Results and discussion

4.1 Pareto-optimal solutions

This study applied ε-MOMA to solve the integrated SW and GW management model with four objectives (f_{TWS}, f_{TCOST}, f_{GSC} and f_{SRI}) to search for optimal water use schemes. The algorithm parameters and objective epsilon values are summarized in Table 1. Fig. 6 shows a global view of tradeoff surface in a 4-dimensional coordinate plot. The management model consists of maximizing the f_{TWS}, f_{GSC} and f_{SRI} objectives and minimizing the f_{TCOST} objective. The f_{TWS}, f_{SRI} and f_{GSC} are plotted on the x, y and z axes and f_{TCOST} is represented with color in Fig. 6. The green arrow indicates the direction of optimality in each objective. It can be observed that the trade-off relationship exists between f_{TWS} and other objectives (f_{TCOST}, f_{GSC} and f_{SRI}). Augmenting the total amount of water supply increases the cost of transporting water with the solutions marked in red color and reduces surface runoff inflow to the lake and groundwater storage at the end of management period. Therefore, the regional water resources exploitation conflicts with the socioeconomic and environmental benefits in YB. The scheme before optimization is marked in red square box in Fig. 6. We can see that the scheme is located above the tradeoff surface and exhibits larger cost value. Thus, the current management scheme is sub-optimal and can be regulated to obtain optimal performances.

Table 1.

Figure 6.

To explain the discrepancy of the Pareto-optimal solutions, the parallel coordinates (PC) is used to explore the tradeoff surface. PC is composed of *N* equal-spaced parallel axes representing *N*-dimensional objective vector. Each polyline intersecting its axis in terms of objective value represents the decision scheme in the Pareto-optimal solutions. Meanwhile, the total pumping rate (f_{TPR}) and total surface water diversion rate (f_{TDR}) are added to elucidate the effect of conjunctive use of SW and GW. In Fig. 7, the segments with higher f_{TWS} exist for higher f_{TCOST} and lower f_{GSC} and f_{SRI}, showing that increasing water demands requires more financial investment and depletes more surface runoff inflow to the lake and groundwater storage. The findings are consistent with the previous inferences in Fig. 6. Moreover, the many slope segments exist between f_{TPR} and f_{GSC}, f_{TDR} and f_{SRI}, which indicates that enlarging groundwater abstraction and surface water diversion are the dominated factors for the depletion of groundwater storage and surface runoff recharge for the lake, respectively. It is noteworthy that the variation trend of f_{TPR} is very close to the change of f_{TWS} while the change in f_{TDR} exists obvious difference. The increment of f_{TPR} can be reached to 416.0 Mm^3/yr whereas the growth of f_{TDR} only is 114.0 Mm^3/yr across all the Pareto solutions. Therefore, groundwater abstraction can be adjusted largely to satisfy management objectives based water managers'~~decision-makers'~~ preference whereas surface water diversion should be restricted. The reasons behind this bias are that surface water diversion is highly sensitive to the lake level and the intensive groundwater abstraction augments the river leakage that indirectly causes the decrease of the available runoff.

Figure 7.

4.2 Optimized management schedule

The superiority in many-objective optimization is the full exploration of optimal solutions to avoid the decision bias derived from the lower dimensional objective formulation. The decision-makers can firstly analyze the performance of the Pareto solutions in the sub-problem (*e.g.*, single or two-objective optimization) and then explore the tradeoff solutions using the previous analysis in the higher order objective space to satisfy the multi-stakeholders' benefits. Figs. 8a-8c illustrate the projection of four-objective Pareto solutions onto two-objective space with non-dominated front of the sub-problem constructed by the f_{TWS} and other objectives (f_{TCOST}, f_{GSC} and f_{SRI}), respectively. As shown in Figs. 8a-8c, Solutions 1-3 are the compromise solutions in the Pareto front in the two-objective sub-problem which may be selected by the decision-makers with no preference in the certain objectives. However, these high-performance solutions in the two-objective optimization exhibit worse performance in the other objective spaces. As illustrated in the plots (Fig. 8), Solutions 2 and 3 have higher f_{TCOST} than Solution 1 in Fig. 8a, Solutions 1 and 3 have lower f_{GSC} than Solution 2 in Fig. 8b and Solutions 1 and 2 show lower f_{SRI} than Solution 3 in Fig. 8c. Therefore, the decision-makers need identify the true compromise solution that performs well in the multiple objectives simultaneously. In this study, Solution 4 is closest to the corresponding objective values of the compromise solutions (Solutions 1-3) simultaneously and can be the true compromise solution in the 4-dimensional tradeoff surface. Additionally, Solution 5 has the largest objective value of total water supply rate in the approximate Pareto front satisfying the constraints of maximum groundwater drawdown and minimum lake level. Solution 6 corresponds to the compromise solution in the non-dominated front of f_{GSC} and f_{SRI}, which indicates the perfect performance in the protection of regional groundwater storage and water balance of the lake.

Figure 8.

In this study, Solutions 4, 5 and 6 are selected to elucidate the variation of groundwater abstraction and surface water diversion compared with the scheme before optimization (Solution 7). The objective values of selected solutions are listed in Table 2. It can be observed that Solution 4 can achieve similar total water supply rate while the cost of water delivery can reduce 34.4% compared with Solution 7. The result shows that Solution 7 is sub-optimal from the aspect of expenditure of water supply. Moreover, the surface runoff inflow to lake in Solution 4 achieves the increment of 38.2 Mm^3/yr and the depletion in groundwater storage obtains the reduction of 19.9 Mm^3/yr. However, f_{GSC} of Solution 4 is still less than zero, which demonstrates the loss of groundwater storage compared with initial state. Therefore, Solution 6 is a preferred water use scheme from the aspects of the maximization of groundwater storage and surface runoff inflow to lake simultaneously. The objectives of Solution 6 in Table 2 show reducing 143.0 Mm^3/yr of f_{TWS} in the scheme before optimization can achieve the increment of groundwater storage with 21.9 Mm^3/yr and augment 63.0 Mm^3/yr of surface runoff inflow to lake. Solution 5 represents the potential of water resources exploitation in YB and can augment 26% of total water supply rate compared with Solution 7. Interestingly, it can be found that, in Solutions 5 and 7, groundwater storage depletion (83.9 Mm^3/yr) is more rapid than the reduction of surface runoff inflow to the lake (18.5 Mm^3/yr). Hence, groundwater abstraction is probably preferred option to provide the resiliency of water supply in the face of the increased water demands.

Table 2.

Fig. 9 illustrated the spatial distribution of the pumping rates of the selected solutions at 11 irrigation districts. As shown in Figs. 9a and 9b, Solution 4 shows groundwater abstraction in the ID3, ID5 and ID7-ID11 can be increased in comparison to Solution 7. It can be noted that the pumping rates in ID7 and ID9 can be largely elevated due to lower exploitation in the past and shallow groundwater depth. The groundwater abstraction in ID1, ID2, ID4 and ID6 should be reduced especially for the pumping rate in ID6 which exhibits abrupt decline. As shown in Fig. 9c, Solution 5 with the maximization of f_{TWS} demonstrates that a large amount of groundwater can be abstracted in the ID5-ID9 (greater than 80.0 Mm^3/yr) which implies water managers can implement groundwater abstraction in those districts to satisfy the augmentation of water supply. In Fig. 9d, Solution 6 is a desired scheme with the maximization of environment benefits in groundwater storage and runoff recharge to the lake. The spatial differentiation of groundwater abstraction in Solution 6 is similar with those in the 4-dimensional compromise solution (Solution 4). However, Solution 6 based the pumping rates in the ID5 and ID8 show obvious decline, which implies that water managers can lower the groundwater abstraction in these regions to achieve more environment benefit in groundwater storage.

Figure 9.

Fig. 10 illustrates the spatial patterns of surface water diversion along the main stream of Kaidu River. As show in Fig. 10a, seven diversion points (DP1-DP7) with the reduction of runoff are clearly identified. The runoff at the 35 km from DP1 exhibits obvious rise due to the inflow in the tributary. The river runoff at the lake inflow point is the surface runoff inflow to the lake that is f_{SRI} objective. It can be observed that the surface runoff in the scheme before optimization (Solution 7) in DP1 shows the abrupt decline than Pareto-optimal solutions (Solutions 4, 5 and 6) which responds to the distribution of surface diversion in Fig. 10b. Moreover, Solution 7 has the lowest runoff between DP1 and DP4 even though exists slight increase in the lake inflow point. Therefore, a significant increase of surface water diversion in DP1 controls the available runoff in the downstream segments. The water managers should reduce the surface water diversion in DP1 to ensure sufficient runoff in the lower reaches of Kaidu River for the adjustment of multi-stakeholders' benefits. Solution 4 is a compromise scheme that exhibits lower runoff compared with Solution 6 from DP4 to the end of river, due to the larger water diversion in DP4, which triggers the reduction of surface runoff inflow to lake. Solution 5 is a potential of regional water resources exploitation in YB and has smaller available runoff than Solutions 4 and 6, approximating to more water diversion in Kaidu River. Fig. 10c further demonstrates the interaction of surface water and groundwater along the mainstream of the river. The upper segment (Segment I) is a losing segment that means surface water exchange from stream to aquifer and the middle segment (Segment II) is a gaining segment that indicates groundwater exchange from aquifer to stream. Then the lower segment (Segment III) turns into a losing segment. It can be noted that Segment I and Segment II have strong interaction between SW and GW whereas Segment III exhibits exchange with a lower leakage rate. As illustrated in Fig. 10d, the distribution of total river leakage shows that Solution 5 with the potential of water supply corresponds to the maximum river leakage caused by the maximum groundwater abstraction. The river leakage in Solutions 6 and 7 corresponds to lower groundwater abstraction. Consequently, groundwater abstraction is a dominated factor for the interaction of SW and GW in the basin. The river leakage in Solution 4 is clearly larger than Solution 7, which is seemingly undesired for water managers. However, augmenting groundwater abstraction (131.0 Mm^3/yr) at the cost of river leakage (30.0 Mm^3/yr) can lower surface water diversion (67.0 Mm^3/yr) that is highly sensitive to the runoff inflow to Bosten Lake. Therefore, groundwater abstraction is probably a desired water use pattern in YB.

Figure 10.

4.3 Impacts of runoff change

Kaidu River plays a crucial role to sustain regional water balance in YB and flows through Dashankou station (Fig. 2) into the basin. The river supplies the majorities of surface water diversion by an aqueduct system for agricultural irrigation and constitutes about 97% of total annual inflow to the Bosten Lake. The runoff in Kaidu River is mainly originated from mountainous precipitation and melting glacier water in the Tianshan Mountains region. However, the remarkable climate changes have caused a significant increase in both temperature and precipitation over the past 50 years in Xinjiang (Li et al., 2013). The changing climate probably increased the glacier melt and snowmelt in the upper part of Kaidu River and then caused the growth of the river runoff between 1999 and 2002, with the highest runoff in

2002 of 5.7 billion m^3/year (Zhou et al., 2015). However, the long-term climate change may reduce runoff in Kaidu River attributing to the depletion of small or mid-size glaciers and snow line receding in the middle Tianshan Mountains region. Li et al., (2012) observed that surface area of snow in Kaidu River Basin reduced largely between 2000 and 2010. Therefore, it is essential to explore the impact of runoff reduction in Kaidu River on the regional water resources management for the local socioeconomic and environmental development.

The last part of our study implemented multi-objective optimization by resetting the runoff inflow at the first diversion point (DP1) in Kaidu River with the duplicated model parameters and the inputs of source and sink terms. We defined three scenarios which are to maintain the current runoff (Scenario A0), reduce 10% of the runoff (Scenario A1) and reduce 20% of the runoff (Scenario A2), respectively. In the management model, the constraint of lake level is altered to the smaller value (1044.5m) and maximum groundwater drawdown is reset to 10m to avoid much more infeasible solutions in the population, which probably inhibits the convergence of the optimization. Fig. 11 shows all Pareto-optimal solutions in the 4-dimensional objective space under different runoff change scenarios. It is clearly observed that the tradeoff surface with current runoff (Scenario A0) is closest to the ideal solution and those with runoff reduction are farther from the solution. Scenario A2 based solutions exhibit worst performance owing to the greatest extent of runoff reduction. Moreover, we rescaled the objective range to the interval [0, 1] and set the reference point to the objective vector [1, 1, 1, 1] to calculate the HV metric of approximate Pareto solutions under the runoff scenarios. Fig. 12 shows the evolution of HV and the number of generation. Judged from the performance evolution, tradeoff solutions under Scenario A0 achieve the largest HV and those in Scenario A2 have the lowest HV, which shows the solutions are far away from the ideal Pareto solution. Therefore, the exploitation extent of surface diversion and groundwater abstraction should be diminished in the face of runoff reduction related to climate change. In Fig. 11, the approximate Pareto solutions in Scenarios A0-A2 does not exist when f_{SRI} is greater than 1801.33 Mm^3/yr in Scenario A0,~~ a certain value~~ 1596.33 Mm^3/yr in Scenario A1 and 1374.58 Mm^3/yr in Scenario A2, which means the loss of diversity of Pareto solutions. The reason is that augmenting f_{TWS} causes more decline of f_{SRI} and the lake level compared with no reduction in runoff in Scenario A0, which probably generates a large amount of unfeasible solutions violating the constraint of minimum lake level. The finding also shows that runoff in Kaidu River through YB is a dominant factor controlling the variation of Bosten Lake level. To investigate the effect of runoff reduction on the environmental benefits, Fig. 13 shows the non-dominated fronts in the f_{GSC} and f_{SRI} objectives space across Scenarios A0, A1 and A2. The solutions in Scenario A2 are completely dominated by the solutions in Scenarios A0 and A1. Scenario A0 based solutions show the best Pareto optimality. Therefore, the runoff reduction results in obvious loss of environmental benefits. It is noteworthy that f_{SRI} with Scenarios A1 and A2 will be reduced under the similar f_{GSC}. In the optimization, in order to maximize irrigation water supply, sustaining similar groundwater storage in Scenarios A1 and A2 has to be at the cost of river runoff decline to increase surface water diversion. Hence, it is essential for water managers to realize the conflict of conjunctive use of SW and GW for the water resources management in arid inland basin.

Figure 11.

Figure 12.

Figure 13.

5. Conclusions

The study proposed a multi-objective optimization framework for the integrated surface water and groundwater management and demonstrated its effectiveness through a spatial optimization of water use practices for the agricultural irrigation in YB~~Yanqi Basin~~, a typical arid inland basin in northwest China. The well-calibrated simulation model with MODFLOW-NWT was developed to model the interaction of surface water (*i.e.*, Kaidu River and Bosten Lake) and groundwater. Then this study presented a new MOEA (the epsilon multi-objective memetic algorithm, ε-MOMA) and linked it with the numerical model to solve the multi-objective management model. The optimization model is composed of the four conflicting objectives: maximizing total water supply rate, minimizing total cost of transporting water from water intake points to water use destinations, maximizing the groundwater storage in the aquifer and maximizing the surface runoff inflow from Kaidu River to Bosten Lake. An interactive visualization tool was applied to explore 4-dimensional tradeoff surface in a global view. Results showed augmenting water supply caused the larger cost of water delivery, reduced the runoff inflow to lake and aggravated the loss of groundwater storage. The 2-dimensional compromise schemes selected from the non-dominated fronts between f_{TWS} and other objectives exhibited significant decision bias in the higher order objective spaces. Therefore, it is crucial for water managers~~decision-makers~~ to explore water management schemes in the multi-objective tradeoff surface.

The 4-dimensional compromise solution is obtained to investigate performance of existing scheme. Result shows that the water use practices before optimization have to be regulated to avoid unnecessary capital expenditure of transporting water. However, the compromised solution indicates groundwater storage is still decreasing. Thus, the water managers may be inclined to adopt the Pareto-optimal scheme satisfying minimum water demands to prevent the loss of groundwater storage and runoff inflow to the lake. In the practical application, the water managers~~decision-makers~~ should identify specific irrigation water demands and environmental constraints to discover preferred water use schemes. Moreover, the regulation of groundwater abstraction is more flexible than surface water diversion in the Pareto-optimal solutions, which is an important implication for the resiliency of water resources management. The water use schemes are subject to the spatial complexity of strong SW-GW interaction. That is to say, the integrated management of SW-GW is highly desired to reflect the interaction of water resources system in the optimization. The scenarios of runoff change were then generated to investigate the effect of runoff depletion in Kaidu River on the regional water resources management. The findings showed that reducing runoff inflow to the basin could lead to the degradation of Pareto solutions compared with those based on the current runoff scenario. In this light, it is crucial to implement stringent water management and explore potential water-saving strategies under the future conditions.

The findings are applicable to regional water resources management in other typical arid inland basins with complex groundwater-river-lake interactions and intensive agricultural development. However, due to the data-scarcity in the basin-scale water cycle and limitations of simulation model, the current model may be not enough to reflect the true response of water resources systems. Future research should focus on exploiting fully coupled numerical model to accurately simulate basin-scale water cycle and avoid decision bias derived from the numerical model. Meanwhile, deep uncertainty (*e.g.*, land use change, climate change, etc.) is a key factor to affect the robustness and reliability of the optimal solutions in the changing world. In the simulation-optimization framework, integrating these factors into the management model to explore optimal schemes is a research focus in the future.

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Tables

Table 1 The control parameters of ε-MOMA and epsilon value of objectives

Parameter	Value
Population size (N_{pop})	200
Maximum function evaluation (N_{eval})	6×10^4
Crossover probability (P_c)	0.90
Mutation probability (P_m)	0.05
f_{TWS} epsilon (m^3/yr)	1×10^4
f_{TCOST} epsilon (CNY/yr)	1×10^2
f_{GSC} epsilon (m^3/yr)	1×10^4
f_{SRI} epsilon (m^3/yr)	1×10^4

Table 2 The objective values corresponding to several solutions

Objective	Solution 4	Solution 5	Solution 6	Solution 7
f_{TWS} (×10^8 m^3/yr)	10.7406	12.7355	8.6712	10.1032
f_{TCOST} (×10^6 CNY/yr)	54.3013	92.1498	42.9522	82.7827
f_{GSC} (×10^8 m^3/yr)	-0.2471	-1.2856	0.2192	-0.4462
f_{SRI} (×10^8 m^3/yr)	17.5698	17.0030	17.8180	17.1880

Figures

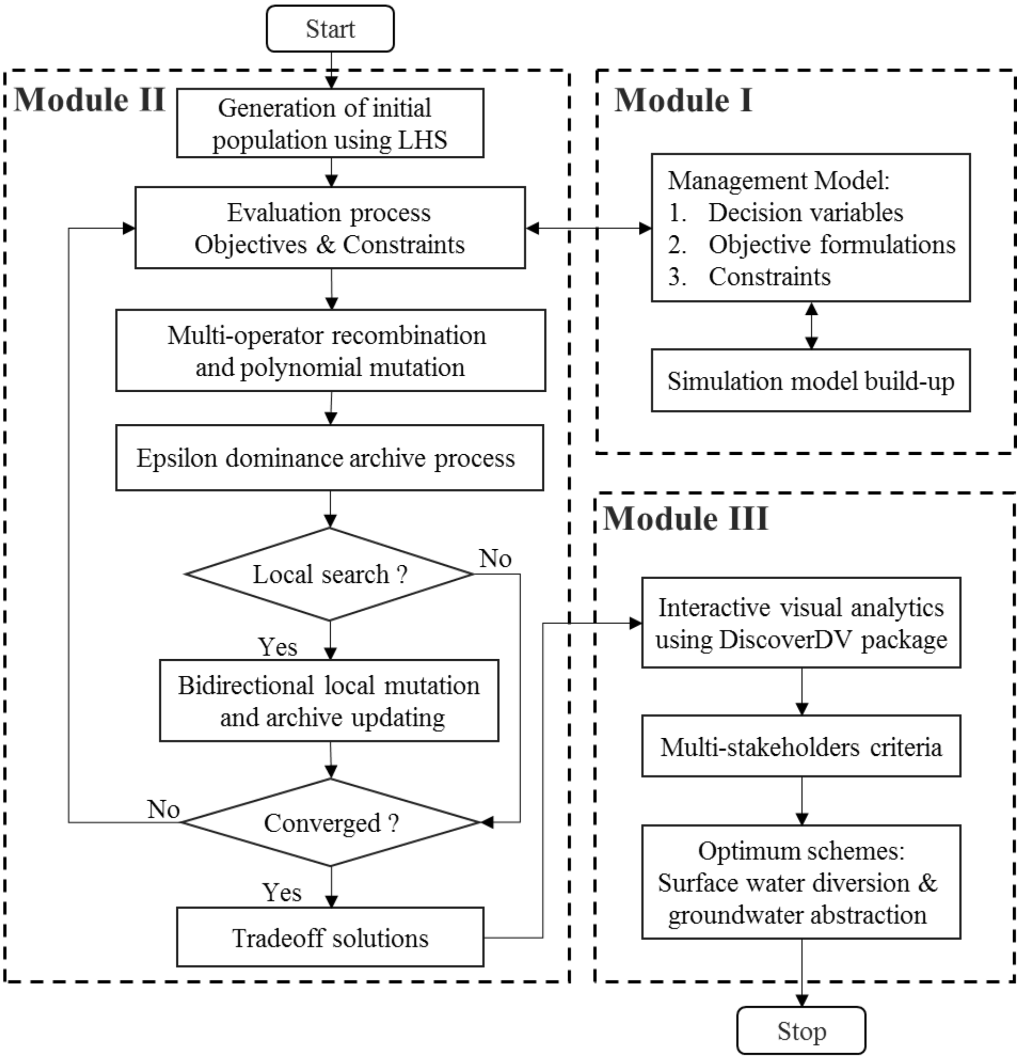

Fig. 1. Framework of multi-objective optimization for integrated SW-GW management.

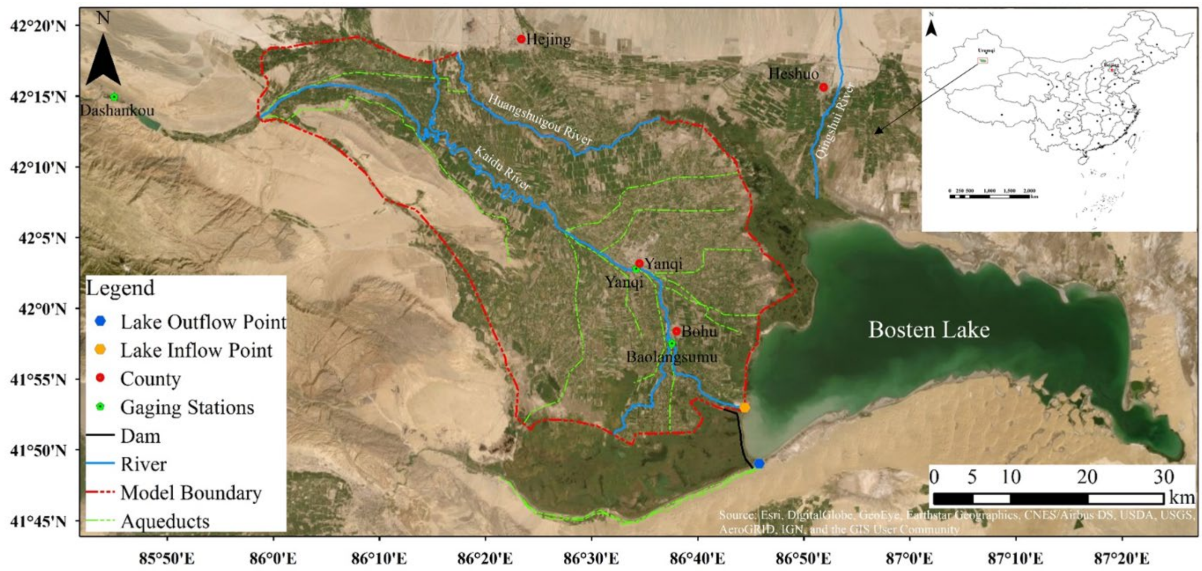

Fig. 2. The location of Yanqi Basin and the model domain of interest for this study. Source: DigitalGlobal, Inc. (imagery).

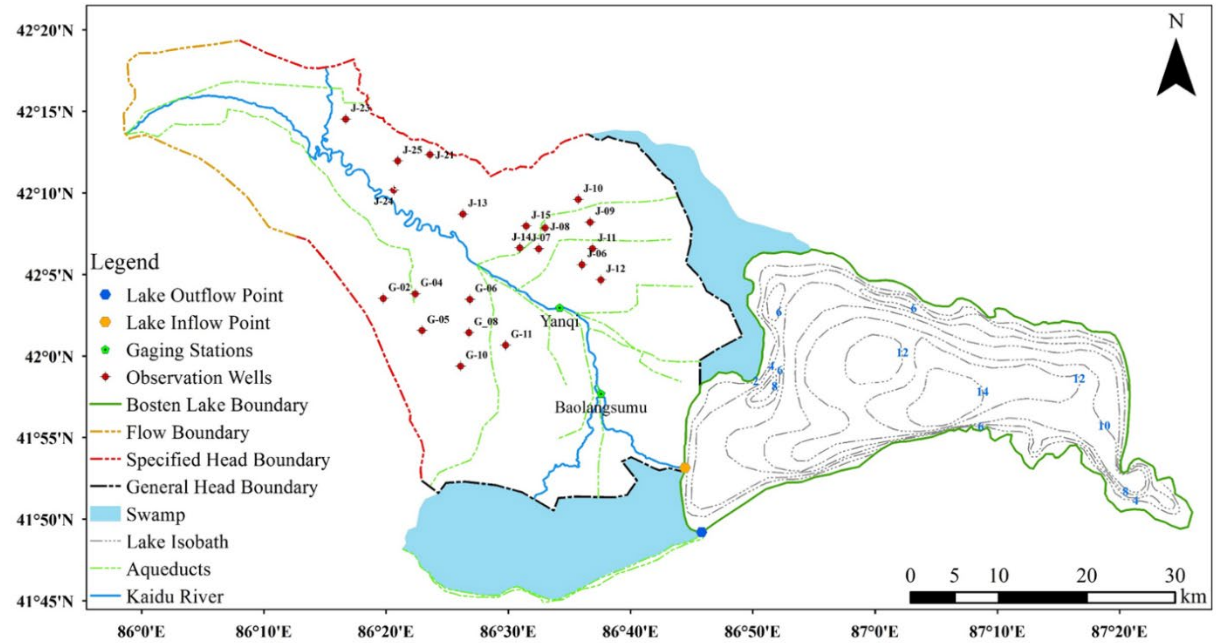

Fig. 3. The boundary conditions of model domain, monitoring locations of groundwater level and surface runoff, aqueduct system and bathymetric contours in meters for Bosten Lake.

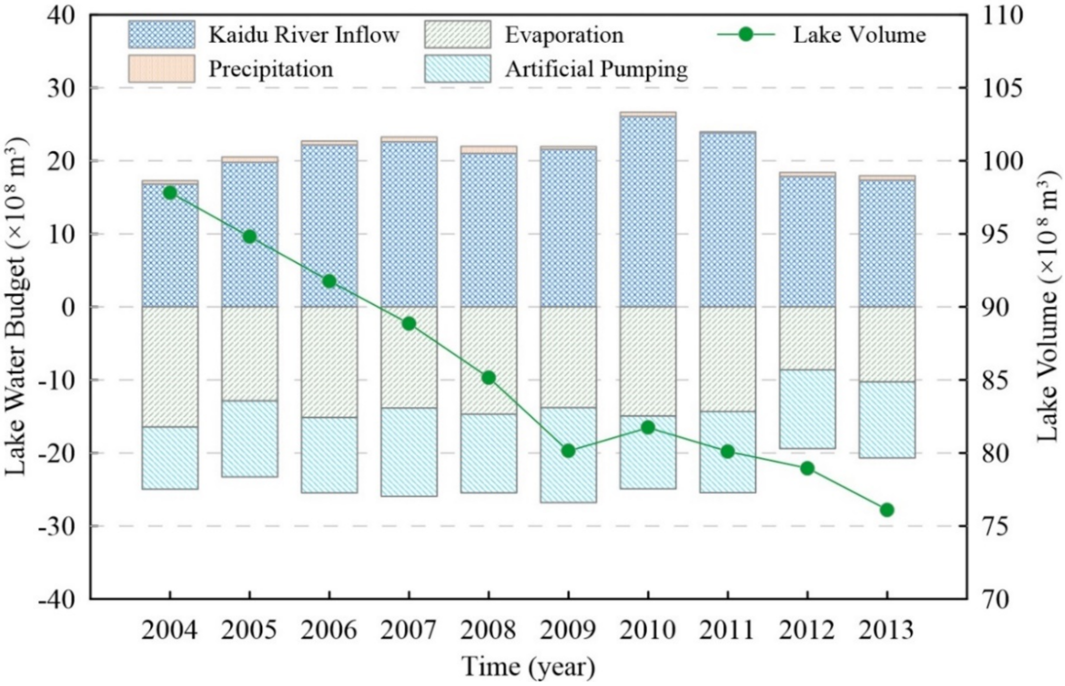

Fig. 4. The water balance terms of Bosten Lake and resulting lake volume in the simulation period.

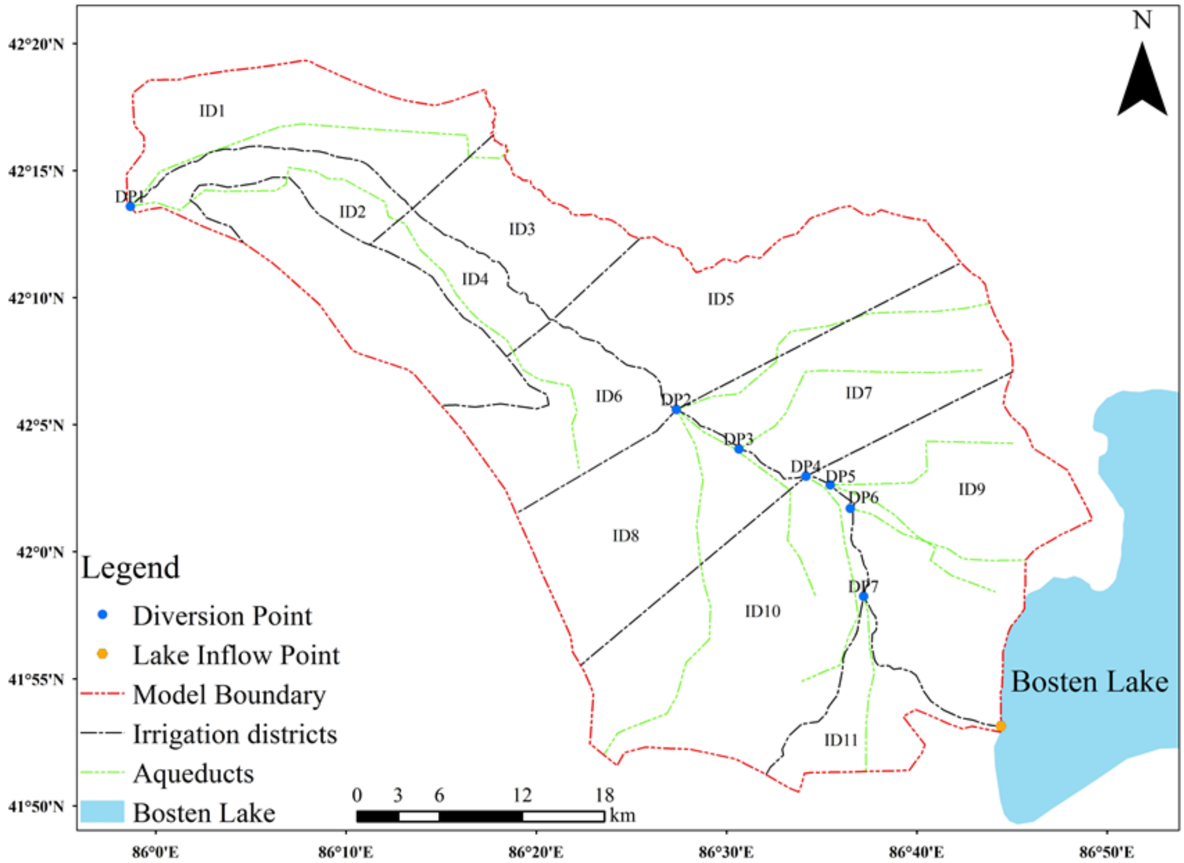

Fig. 5. The locations of surface water diversion points and subdomains of irrigation districts for groundwater abstraction.

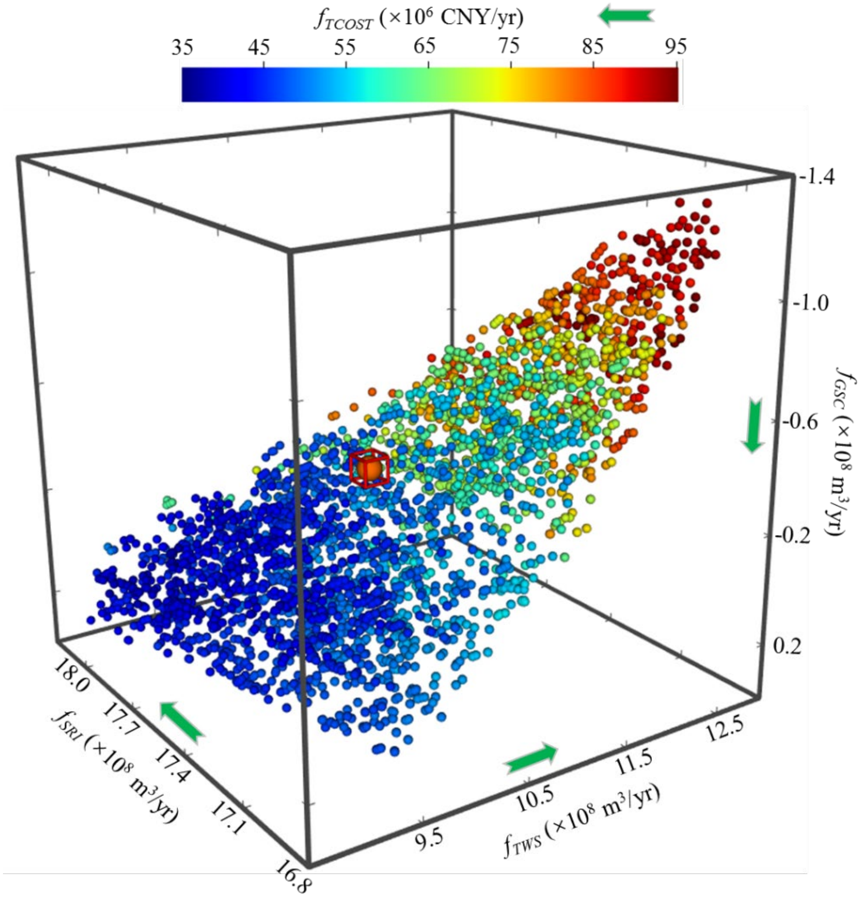

Fig. 6. The tradeoff surface to the integrated SW-GW management in Yanqi Basin. Each spheric symbol represents a water use scheme corresponding to specific objective values of the total water supply rate (f_{TWS}), total cost of water delivery (f_{TCOST}), surface runoff inflow to lake (f_{SRI}) and groundwater storage change (f_{GSC}). f_{TCOST} is symbolized in color to identify the objective value against others. The green arrow is the direction of better performance for each objective. The scheme before optimization is marked in a red square box.

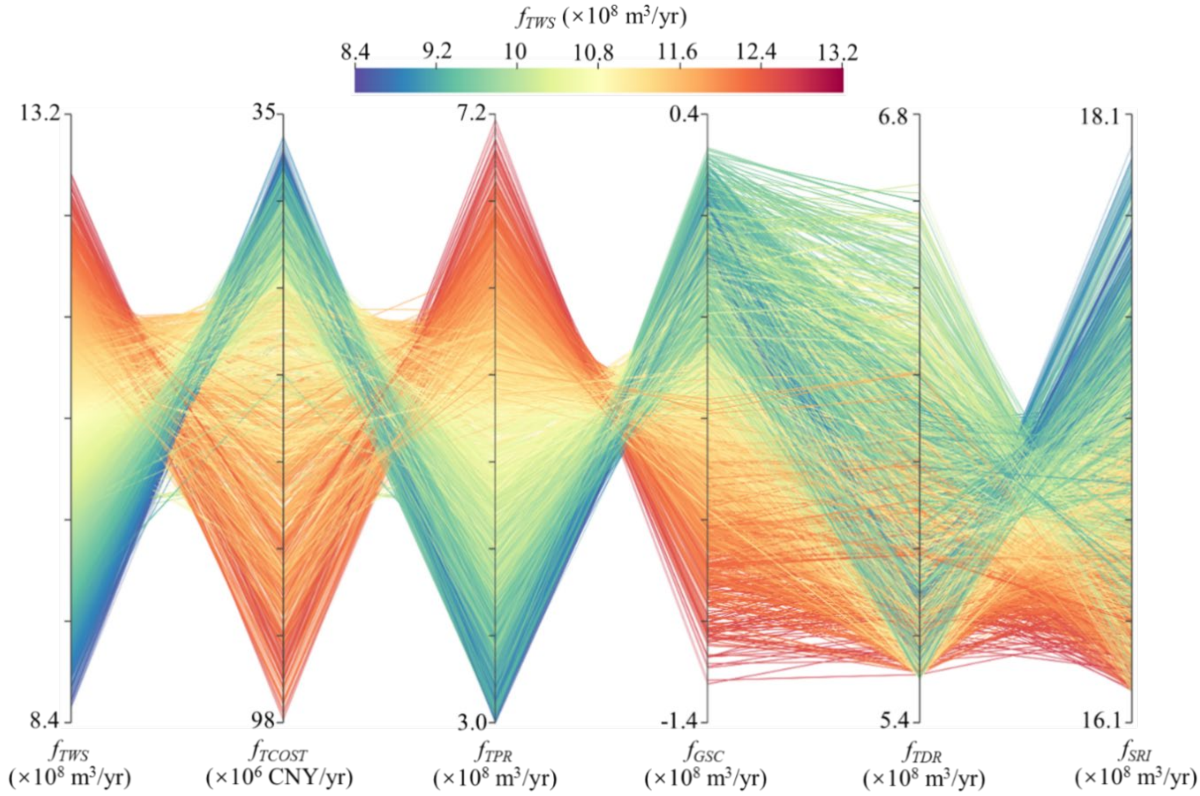

Fig. 7. The objective values (y-axis) are plotted over management objectives f_{TWS}, f_{TCOST}, f_{GSC}, f_{SRI}, total pumping rate f_{TPR} and total surface water diversion rate f_{TDR} (x-axis), f_{TWS} is represented in color. The preferred direction for each index is upward.

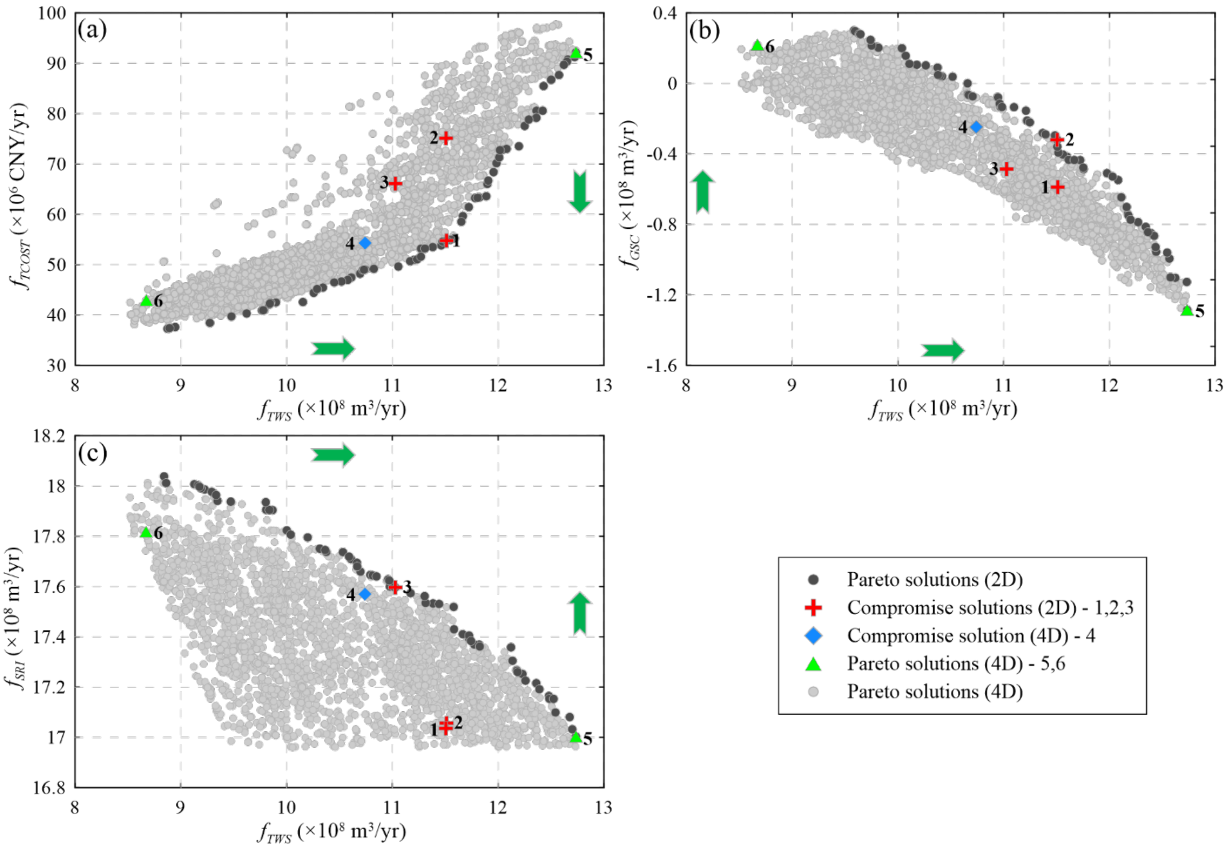

Fig. 8. Identification of six interesting solutions (Solutions 1-6) from the four-dimensional approximate Pareto set and the green arrow is the preferred direction for each objective.

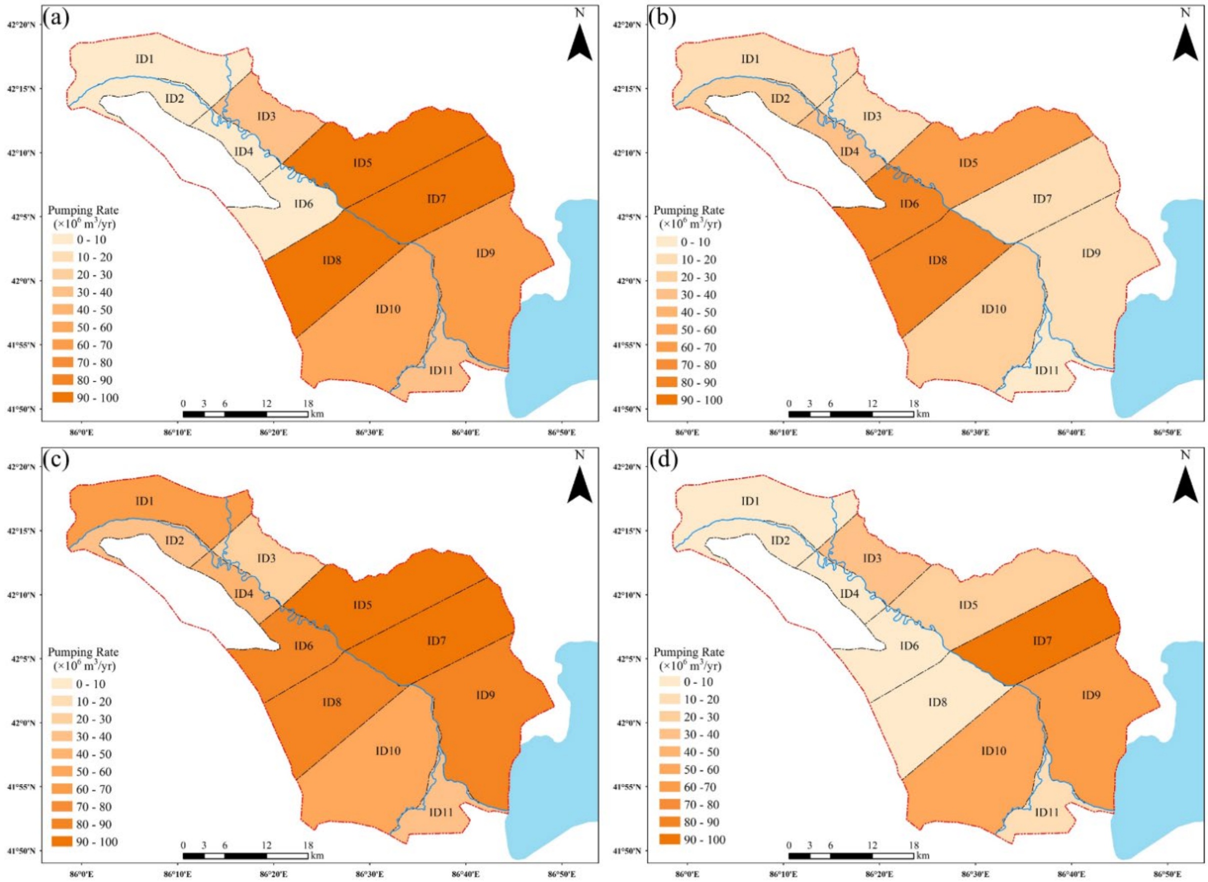

Fig. 9. The spatial distribution of the pumping rates in the 11 irrigation districts for the four selected schemes of (a) Solution 4, (b) Solution 7, (c) Solution 5, and (d) Solution 6, respectively.

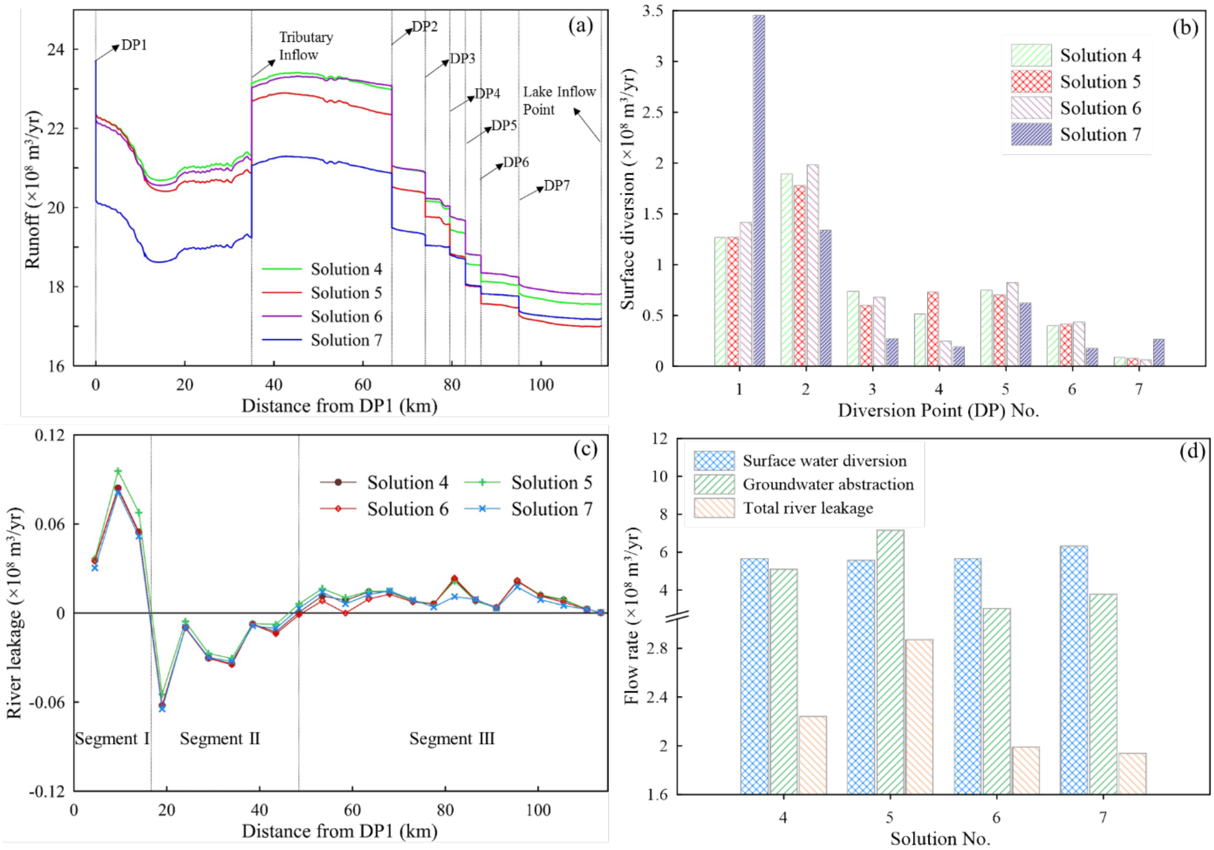

Fig. 10. Variation of surface runoff and river leakage along the stem stream of Kaidu River: (a) the profile of river runoff; (b) the distribution of surface water diversion at the different diversion points; (c) the profile of river leakage; (d) the components of total river leakage, groundwater abstraction and surface water diversion for several typical Solutions 4-7.

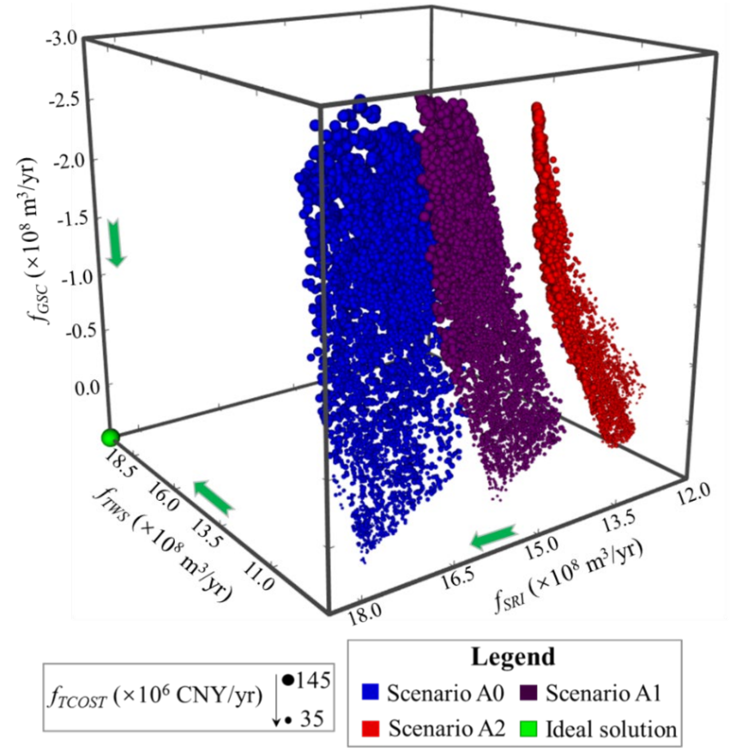

Fig. 11. The tradeoff solutions under Scenarios A0 (maintain current runoff), A1 (reduce the runoff by 10%) and A2 (reduce the runoff by 20%), and the sphere size indicates the value of f_{TCOST}. The green arrow is the direction of better performance for each objective.

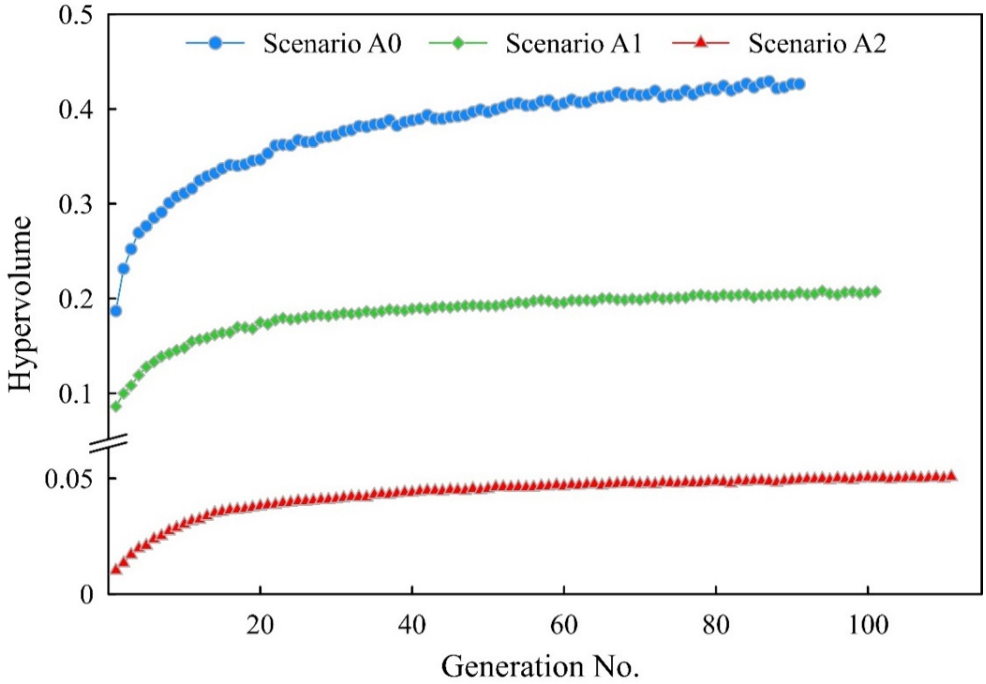

Fig. 12. Evolution of the hypervolume metric over the generation number for Scenarios A0, A1 and A2.

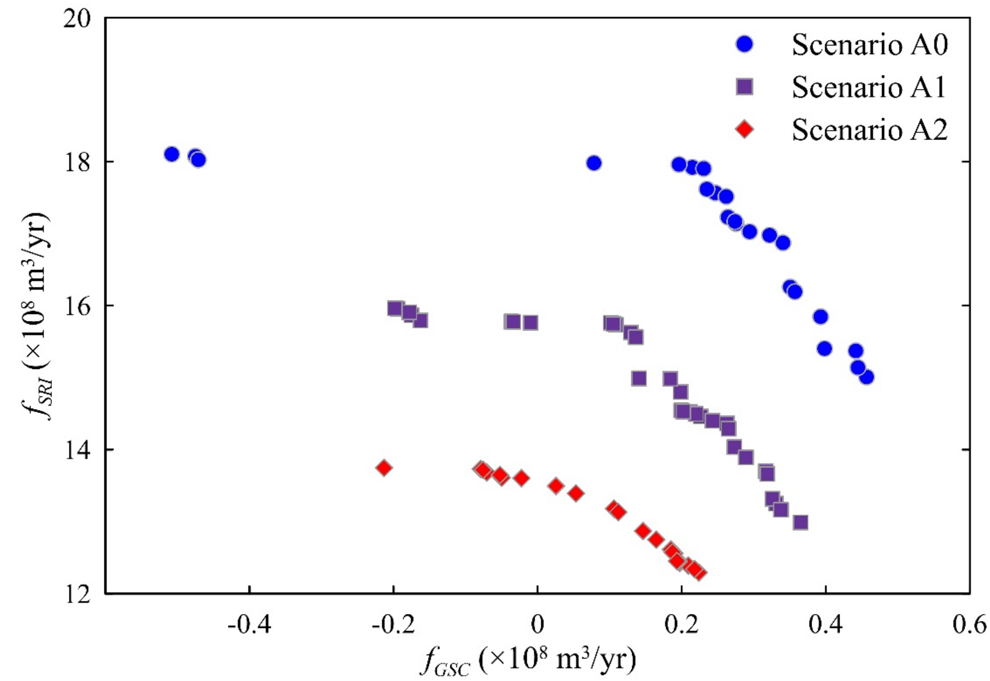

Fig. 13. Non-dominated fronts of Scenarios A0, A1 and A2 between objectives of f_{GSC} vs. f_{SRI}.

Supplementary Materials for

Basin-scale multi-objective simulation-optimization modeling for conjunctive use of surface water and groundwater in northwest China

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Table S1 The control parameters and hypervolume metric obtained for ε-MOMA on M-objective DTLZ1 and DTLZ3 problems

Problem	M	N_{dv}	N_{pop}	N_{eval}	ε_{obj}	rp	HV_{rs}	HV_{as}	HV_n
DTLZ1	3	M+9	200	100,000	0.01	0.55	0.14575	0.14480	0.9935
	4			150,000			0.08883	0.08828	0.9939
	5			200,000			0.05000	0.04982	0.9964
	6			400,000			0.02763	0.02759	0.9985
DTLZ3	3	M+9	200	100,000	0.01	1.05	0.63507	0.61857	0.9740
	4			150,000			0.89568	0.85577	0.9554
	5			200,000			1.08860	1.03550	0.9512
	6			400,000			1.23140	1.19210	0.9681

Note: M = number of objectives; N_{dv} = number of decision variables; N_{pop} = population size; N_{eval} = number of function evaluations; ε_{obj} = epsilon value for each objective; rp=the value of reference point for each objective; HV_{rs} = hypervolume of Pareto reference set; HV_{as} = hypervolume of Pareto approximate set; HV_n = the normalized hypervolume.

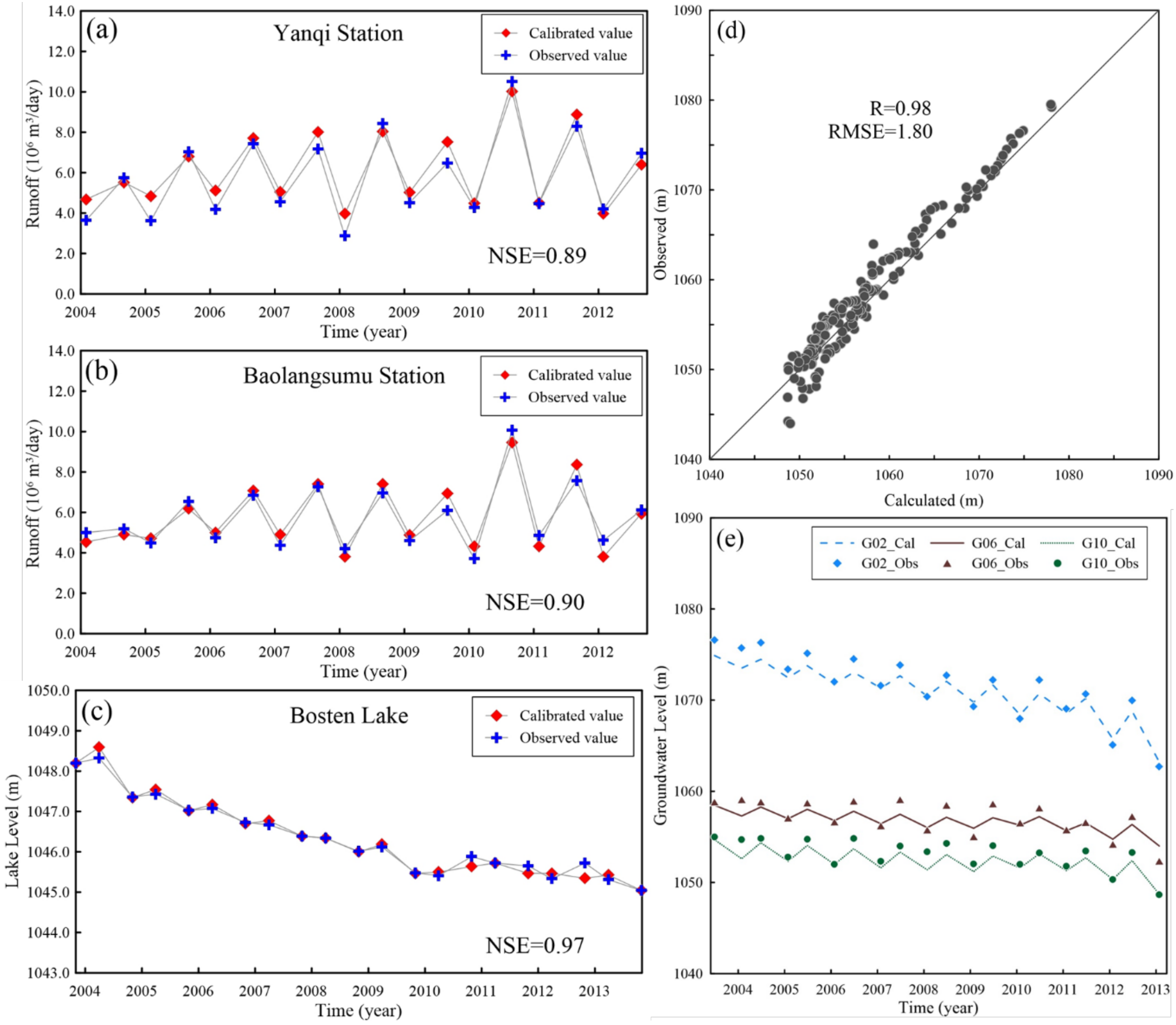

Fig. S1 The calibrated results of the transient model showing (a) observed vs. calibrated runoff at Yanqi station over time, (b) observed vs. calibrated runoff at Baolangsumu station over time; (c) observed vs. calibrated lake level over time; (d) comparison of observed and calibrated groundwater heads at all observation wells, and (e) observed vs. calibrated groundwater heads over time at three typical observation locations as labeled in Fig. 3.