Response to the comments on the manuscript (**HESS-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 color Times New Roman 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 combined with the response file has clearly indicated all changes to the original manuscript, tables and figures. Also, in the marked PDF file, marked in ~~a blue 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 #1 Dr. Joseph Kasprzyk's Comments

I am serving as a requested referee for this manuscript. The paper presents a new optimization algorithm, linked to hydrological models for the purpose of informing water management in China. Overall, the paper does provide an interesting case study. However, the authors could do a better job of contextualizing their work relative to the state-of-the-art literature in this field, summarized in my general comments below. I also provide specific comments referencing lines in the manuscript itself.

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

General comments:

I. The need for a new MOEA should be justified. Moreover, since MOEAs are typically designed for general case studies outside of water management, the authors should indicate whether the new algorithm is available for use.

[Response] Indeed, the several state-of-the-art MOEAs (*e.g.*, ε-NSGAII (Kollat et al., 2006), MOEA/D (Zhang and Li, 2007), NSGAIII (Deb and Jain, 2014), Borg (Hadka and Reed, 2013)) have been tested on the standard test problems even on the real-world problems and achieved the promising results in solving many-objective problems. However, due to the diversity and complexity of real-word decision-making problems, efforts should be made to develop the advanced MOEAs (**Lines 126-133**). Moreover, the aim of our research is to construct an effective many-objective optimization framework for water resources management in arid inland basin rather than implement comparative study of the state-of-the art MOEAs to justify the optimality of the algorithm.

On the other hand, we acknowledge that the performance of ε-MOMA has to be tested to prove the availability for general case studies. Considering the reviewer's concerns, we have investigated the performance of ε-MOMA by the benchmark test problems in **Section 2.2.2** (*i.e.*, 3 to 6-objective DTLZ1 and DTLZ3 problems) (Deb et al., 2002). The results show that ε-MOMA can provide reliable and diverse Pareto-optimal solutions to many-objective optimization problems (**Table S1** in the Supplementary Materials). Meanwhile, the basin-scale case study of this paper further shows the potential of ε-MOMA for the real-world water resources management.

Deb, K., Jain, H.: An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part I: solving problems with box constraints, IEEE Trans., 18(4), 577-601, https://doi.org/10.1109/TEVC.2013.2281535, 2014.

Deb, K., Thiele, L., Laumanns, M., Zitzler, E.: Scalable multi-objective optimization test problems, in: proceeding of the congress on evolutionary computation (CEC-2002), 825-830, 2002.

Hadka, D., and Reed, P.M.: Borg: an auto-adaptive many-objective framework, Evol. Comput, 21(2), 213-259, https://doi.org/10.1162/EVCO_a_00075, 2013.

Kollat, J. B., Reed, P. M.: Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design, Adv. Water Resour., 29(6), 792-807, https://doi.org/10.1016/j.advwatres.2005.07.010, 2006.

Zhang, Q., Li, H.: MOEA/D: A multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput., 11(6), 712-731, https://doi.org/10.1109/TEVC.2007.892759, 2007.

II. I would like to see more description of the optimization in general, since the calibration of hydrological models is not really the focus of the analysis.

[Response] Comment accepted. We have made detailed explanations to present the algorithmic process step by step in **Section 2.2.1**. The hydrological model, as a prerequisite for the simulation-optimization method, has to be calibrated to reflect the responses of water resources system under the management schemes. Considering the referee's concern, we have briefly stated the calibrated results of key state variables in **Section 3.2** and put the results in the Supplementary Materials as shown in **Fig. S2**. Moreover, the analysis of water balance in Bosten Lake paves the way for the construction of management model.

III. The results should be generalizable to a broader context. What are the take-home messages for the HESS audience? This is hinted at in the Conclusion, but could be better motivated in the Introduction.

[Response] The point is well taken. The study results show that Pareto-optimal solutions considering environmental and socioeconomic factors can be achieved for the basin-scale water resources management involving complicated groundwater-river-lake interactions. Meanwhile, due to the water scarcity and climate change, the conservative water management options may be implemented to sustain the fragile ecosystem in the arid inland basin. Considering reviewer's concerns, we have added necessary explanations in the section "Introduction" to present the motivation (**Lines 53-65**) and the general results (**Lines 196-202**).

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

1. The authors should consider editing lines 25-29 to clarify the novelty of the paper. A study of one basin in China may not be compelling to an international audience, so if there is something new about the coupling of optimization to model, that should be highlighted. The same comment is relevant for the introduction; the scientific contribution of the paper is not sufficiently stated.

[Response] Comment accepted. We appreciate the reviewer's insight and have modified the statement in Abstract (**Lines 24-33**) and the section "Introduction" (**Lines 176-181**) in the revised manuscript to clearly present the contribution of the study.

2. Line 48: There are several grammatical errors in the beginning of the paper ("In arid and semi-arid basin,") as well as a disconnect between talking about water management in general and moving quickly to the specifics of China. A native English speaker should proofread the manuscript throughout.

[Response] Comment accepted. We have modified the statements (**Line 53**). To avoid the disconnect raised by the referee, we have reorganized the statements in the Introduction. First, we have clarified the need for water management in the arid inland basin (**Lines 53-63**). Second, we explained the meaning of many-objective optimization framework in the water resources management and planning (**Lines 81-109**) and the optimization techniques (**Lines 110-137**). After that, we introduced the specifics of water resources development in Yanqi Basin (**Lines 144-160)** to explain the suitability of the case study. As for the language problem, a native English speaker is difficult for us to find. However, in the revised manuscript, one of the co-authors who ever worked as a visiting scholar in the USA for several years has made extra efforts in current revision to correct the grammatical and wording errors.

3. Line 73-74: "to tackle intricate SW and GW management model": Is this a typo? I think the intended word might be "SW and GW management problems". Also "tackle" is probably not an appropriate word to use.

[Response] Comment accepted. We have modified the statement as “in solving the complex SW and GW management problems” in the revision **(Lines 90-92**).

4. Line 77: Before the first mention of "bi-objectives", the authors should provide a very brief introduction to optimization. Otherwise, readers may be confused by what is meant by "objective" throughout this paragraph.

[Response] The point is well taken. We have added necessary explanations to briefly introduce the process of simulation-optimization approach (**Lines 82-86**).

5. When introducing MOEAs, it would be good to cite Maier et al (2019), which is an introductory overview appropriate for readers to be introduced to the topic.

[Response] Comment accepted and change made as suggested (**Lines 110-113**).

6. Lines 102-113: I am glad the authors have brought up some recent and relevant topics in many-objective optimization. However, the paragraph was confusing and will be difficult for readers to follow. For example, the Borg algorithm is briefly mentioned, but there is no clear transition to the next algorithm ("In order to enhance the local optimality..."). Did Sindya et al. add to Borg or create a new algorithm? Moreover, it is unclear whether the authors made a new algorithm, and whether it builds on the work of Hadka and Reed and Sindhya. Moreover, given that these new algorithms have been extensively tested (e.g., Reed et al 2013), it is worth justifying why a new algorithm is needed.

[Response] In the revised manuscript, we have firstly stated the difficulty in the many-objective optimization (*i.e.*, the domination-resistance phenomenon) (**Lines 113-116**). Then we presented two kinds of state-of-art MOEAs by which an attempt to alleviate the difficulty is feasible (**Lines 116-126**). Finally, we proposed a new MOEA, named epsilon multi-objective memetic algorithm (ε-MOMA), which utilized several advanced techniques from Borg MOEA and a local search operator to enhance the capacity of evolutionary search.

Sindya et al. (2013) proposed a hybrid framework for evolutionary multi-objective optimization and overcame some shortcomings of MOEAs (*e.g.*, slow convergence, inefficient termination criterion). In this study, we cited the work of Sindya et al. (2013) to show the efficiency of the hybrid framework (*i.e.*, memetic algorithm) for multi-objective optimization (**Lines 122-126**).

As stated in **Lines 127-133**, the state-of-the-art MOEAs have been extensively used in the optimization problems, however, the complex real-world problems still show the deficiency of some advanced MOEAs. For example, Zheng et al. (2016) implemented the comparison of three MOEAs (NSGAII, SAMODE, Borg) in the water distribution system design. Results show NSGAII exhibits a more robust performance than other MOEAs. Borg converges quickly to the Pareto-optimal front whereas decreases the diversity of Pareto solutions.

As stated in the response to Dr. Kasprzyk's **General Comment I** above, this study has supplementarily exploited classical DTLZ problems to test the performance of ε-MOMA in **Section 2.2.2**. The optimization results show the potential of our algorithm (**Table S1** in the Supplementary Materials) and it would be further applied to solve basin-scale water resources management. Certainty, the performance of the algorithm needs to be validated on the challenging real-world problems, that's our focus in the future.

Sindhya, K., Miettinen, K., Deb, K.: A hybrid framework for evolutionary multi-objective optimization, IEEE Trans., 17(4), 485-511, https://doi.org/10.1109/TEVC.2012.2204403, 2013.

Zheng, F., Zecchin, A.C., Maier, H.R., Simpson, A.R.: Comparison of the searching behavior of NSGA-II, SAMODE, and Borg MOEAs applied to water distribution system design problems, J. Water Resour. Plann. Manage., 142(7), 04016017, https://doi.org/10.1061/(ASCE)WR.1943-5452.0000650, 2016.

7. Line 114: The section would benefit from a better transition between the MOEA material and the GW modeling material. Also, since the GW modeling is being done in the context of decision making, I would like to see a clearer discussion of the decision variables and objectives of the optimization as the problem is being introduced.

[Response] Comment accepted. We have made revisions in the paragraph to highlight the details of optimization model (**Lines 170-176**) and deleted the redundant statements of simulation model **(Lines 160-170)**.

8. Line 125: Ideally, a paragraph would express one idea at a time. Here, the authors have transitioned from discussing their method to providing details about their case study. This material should be separated.

[Response] Comment accepted and change made as suggested **(Lines 181-182)**.

9. Line 168-169: What is meant by "decision makers" here? In many systems, different people make decisions about the irrigation diversions, lake storage, and groundwater pumping. Without a clear context for decision making, this section is too vague.

[Response] In **Section 2.1**, our purpose is to state the general problem formulation for conjunctive management of surface water and groundwater in the arid inland basin. The decision makers in this study refer to the local water resources authority in the local government. Considering Referee Dr. Kasprzyk's concerns, we have made necessary revisions for the context of decision making in the revised manuscript (**Lines 228-231**).

10. Line 179-186: There is some repetition here compared to the introduction. Although I agree with the points about nonlinearity, nonconvexity, etc., it is more useful at this point in the paper to explain the details of the proposed new algorithm.

[Response] Comment accepted. To clearly state the algorithmic process and investigate the performance of the algorithm, we split the section into **Section 2.2.1** "Main algorithmic structure" and **Section 2.2.2** "Benchmark test". In **Section 2.2.1**, we have deleted the repetition (**Lines 243-248**) and presented process of the proposed algorithm step by step (**Lines 250-288**).

11. Is this the first introduction of the e-MOMA (ε-MOMA) algorithm? If not, it would be very helpful to have a citation to the original reference, since there is not enough detail given here. At the least, the authors should justify how their algorithm differs from Hadka and Reed, and others.

[Response] The ε-MOMA is a new MOEA and firstly applied to solve many-objective optimization problems. As stated in the response to specific **Comment #10** above, we have added the process of the algorithm step by step (**Lines 250-288**). The basic framework of ε-MOMA is similar to the traditional NSGAII with significant change in recombination operators and ε-dominance archive from Borg and a local search operator. Borg includes an adaptive population sizing operator that is not used in the proposed algorithm. The strategy adapts the population size in terms of archive size which is considered as a metric of complexity of problems. However, population size will be dramatically increased along with augmentation of archive size, which probably results in a large number of function evaluations. In simulation-optimization method, for CPU-intensive simulation model, this strategy may lead to unaffordable computational burden.

12. Line 253: The discussion of the Ecological Water Conveyance Project is interesting. I'd like to see it integrated better within the text. Is this study supporting that analysis?

[Response] The point is well taken. In northwest China, Tarim River, the longest inland river in China, is a typical meandering river that sustains the fragile ecosystem in the basin. However, in the past decades, many tributaries of Tarim River have lost the surface hydraulic interaction with the main stream due to sharply increased water demands. Therefore, Tarim River basin has undergone serious ecological degradation (*e.g.*, land desertification) especially in the lower reaches of Tarim River. In order to restore "Green Corridor" in the lower reaches of Tarim River, Chinese government has implemented the water-conveyance project since 2000 to increase the recharge of groundwater system and raise the local groundwater levels. The project transferred water from Bosten Lake to the Daxihaizi Reservoir and then to the lower reaches of the Tarim River, and finally to the terminal lake (Chen et al., 2010; Yao et al., 2018). Considering the reviewer's concerns, we have added some necessary explanations in the revised text (**Lines 351-356**) and illustrated the details of the water-conveyance project in the **Fig. S1** of Supplementary Materials.

Chen, Y., Chen, Y., Xu, C., Ye, Z., Li, Z., Zhu, C., Ma, X.: Effects of ecological water conveyance on groundwater dynamics and riparian vegetation in the lower reaches of Tarim River, China, Hydrol. Process., 24, 170-177, https://doi.org/10.1002/hyp.7429, 2010.

Yao, J., Chen, Y., Zhao, Y., and Yu, X.: Hydro climatic changes of Lake Bosten in Northwest China during the last decades, Sci. Rep., 8, 9118, https://doi.org/10.1038/s41598-018-27466-2, 2018.

13. Equations 3-5: Why were different metrics used for different variables?

[Response] The Nash-Sutcliffe Efficiency (NSE) criterion is a popular method to evaluate model efficiency when the state variables change over time as showed in **Fig. S2a-S2c**. Root mean square error (RMSE) and correlation coefficient (R) are generally used to show goodness-of-fit of calculated and observed variables over the entire stress period as shown in **Fig. S2d**.

14. Line 322-323: This statement should be justified. It speaks to the wider question of how the hydrological modeling is serving the ultimate goal of the management problem, as well as the general contribution of the paper itself. If the focus of the paper is too diffused, it becomes hard to follow its details.

[Response] In this study, we firstly built simulation model to evaluate the effect of water management practices on the water resources system. As stated in the revised manuscript (**Lines 433-439**), the water balance of Bosten Lake was calculated by the well-calibrated model and then we found the significance of surface runoff inflow to lake. Therefore, the surface runoff can be considered as the management objective. The analysis paves the way for construction of the management model. Meanwhile, the contribution of the inflow from Kaidu River to Bosten Lake is very close to the result from the previous work of Guo et al. (2015) and Yao et al. (2018).

Guo, M., Wu, W., Zhou, X., Chen, Y., and Li, J.: Investigate of the dramatic changes in lake level of the Bosten Lake in northwestern China, Theor Appl Climatol, 119, 341-351, https://doi.org/10.1007/s00704-014-1126-y, 2015.

Yao, J., Chen, Y., Zhao, Y., and Yu, X.: Hydro climatic changes of Lake Bosten in Northwest China during the last decades, Sci. Rep., 8, 9118, https://doi.org/10.1038/s41598-018-27466-2, 2018.

15. Line 348: To what extent can the groundwater extraction rate be controlled? In some systems, farmers have juristiction on how much to pump. If there is an implicit assumption about a set of water managers who can dictate water usage, this should be stated.

[Response] The purpose of the study is to provide suggestions for water managers in local water resources authority. Indeed, some schemes in the Pareto-optimal solutions may be unfeasible for the stakeholders due to the greater extent of regulation of the existing water management scheme. However, a significant advantage of multi-objective optimization is to provide diverse and alternative schemes. The water managers can select the suitable scheme among the Pareto-optimal solutions in terms of specific demands for water management practices. In the optimization, the range of decision variables is specified according to the potential of water use in the irrigation districts or diversion point recorded in the reports of local water resources authority.

16. Lines, 353, 357, etc.: Is there a citation to the water price data? Or was this just an assumption?

[Response] The cost coefficients refer to the regulations of the local government. (http://www.xjyq.gov.cn/page.do?danwei=1&fenlei=4000&nian=2017&liushui=19&type=2)

17. Line 406: Guidance on interpreting parallel plots should be provided.

[Response] Comment accepted and change made (**Lines 524-526**).

18. Line 534: When the authors say "This study implemented...", were they implying that this occurred across the entire study? Or only in one part of the study? This should be clarified.

[Response] Comment accepted. The optimization in three runoff scenarios is the last part of the study to explore the effect of runoff change related to climate change on the water management practices in the basin. We have made some necessary revisions as Dr. Kasprzyk suggested (**Line 651**).

19. Line 541-542: My impression is that hypervolume analyses are usually done to compare optimization runs with the true Pareto set. Is this known? In general, since the optimization

seems to be the focus of this paper, items such as Hypervolume Analysis should be covered in the Methodology (which means that some hydrological modeling detail can be removed)

[Response] Comment accepted. For real-world optimization problems, it is computationally expensive to implement many trial runs for the reference Pareto set. In this study, we only calculate the volume of the objective space dominated by a Pareto approximate set (*i.e.*, HV_{as} defined in **Section 2.2.2**). The hypervolume indicator in the section is used to evaluate the optimality of Pareto solutions under different runoff scenarios rather than the convergence and diversity of our proposed algorithm. We have included the hypervolume analysis (**Lines 300-311**) based benchmark test and deleted the statements in the section (**Lines 663-666**).

20. Line 546: "obvious" is usually not appropriate in technical writing.

[Response] Comment accepted. We have modified "obviously" as "clearly" (**Line 668)**.

21. Conclusion section: The quality of writing here is much better than in the introduction. Some of this material should inform the Introduction, since this more clearly articulates the purpose of the study than the beginning of the paper did.

[Response] Comment accepted. We appreciate the reviewer's positive comment. We have added necessary statements in the Introduction (**Lines 55-57, Lines 176-178,** and **Lines 196-202**).

22. In spite of comment #21, I would like to see slightly more discussion about the management implications of this study - in the local case study as well as how the results can be transferred to other basins (especially given different legal and regulatory structures).

[Response] Comment accepted. We have added more discussion in the section "Conclusion" to present more implications (**Lines 724-729**). And the findings are also applicable to regional water resources management in other typical arid inland basins with complex groundwater-river-lake interactions and intensive agricultural development (**Lines 735-737**). As for different legal and regulatory structures for the other basin-scale water management, we need to reconstruct the management model and develop the interactive optimization framework.

23. Table 1: Was random seed analysis performed? If so, the parameters of this analysis should also be provided here. The epsilon values seem quite small - were larger epsilons attempted?

[Response] In this study, we didn't perform random seed trials and used the default setting in MATLAB for the rand number generation in which random seed is zero. We performed some optimization trials to select the epsilon value and results show the value in **Table 1** is a good choice. Also, increasing the epsilon value probably reduces the diversity of Pareto solutions.

24. Figure 4: If the paper is too long, I could imagine this figure could go into supplemental material. Also, I noticed that the NSE values appear in the figure but were not referenced in the text.

[Response] Comment accepted. We have presented **Fig. 4** of the original manuscript in the supplemental file (**Fig. S2**). The NSE values have been added in the manuscript (**Line 416**; **Line 432**).

25. Figure 9: If possible, the other solutions that are Pareto optimal in 4 dimensions but not in two, should be shown on this plot. Otherwise, the idea that the highlighted solutions fall "outside the front" will be confusing to readers. The Kollat and Reed (2007) paper referenced in this manuscript shows how to do this.

[Response] Comment accepted and change made (see **Fig. 8** in the revision).

26. Figure 12: The figure would be easier to understand if the authors reminded reader what these scenarios represent (see also comment #18 - the scenario analysis could be better explained overall).

[Response] Comment accepted and change made (**Caption of Fig. 11**).

References

Maier, H.R., Razavi, S., Kapelan, Z., Matott, L.S., Kasprzyk, J., Tolson, B.A., 2019. Introductory overview: Optimization using evolutionary algorithms and other metaheuristics. Environmental Modelling & Software 114, 195-213. https://doi.org/10.1016/j.envsoft.2018.11.018.

Reed, P.M., Hadka, D., Herman, J.D., Kasprzyk, J.R., Kollat, J.B., 2013. Evolutionary Multiobjective Optimization in Water Resources: The Past, Present and Future. Advances in Water Resources 51, 438-456. https://doi.org/10.1016/j.advwatres.2012.01.005.

[Response] These references mentioned above have been cited in the revision (**Lines 112-113**).

Response to Anonymous Referee #2's Comments

This paper developed a multi-objective simulation-optimization framework for sustainably conjunctive use of surface water and groundwater and applied it to water allocation in Yanqi Basin, an arid region in northwest China. The framework employed the epsilon multi-objective memetic algorithm with the MODFLOW-NWT based simulation model and used four management objectives in their optimization. The final results are very useful for sustainable water management in the study area and provided useful support to decision makers for water allocation. This paper can be suggested for possible publication in HESS after taking carefully into account the comments listed below.

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

Specific comments:

1. This study developed a multi-objective simulation-optimization framework for sustainably conjunctive use of surface water and groundwater. I didn't really see the new insights the readers can get, if only from the introduction part of this manuscript. Can the authors clarify the differences between their work and others? Partially solving the domination resistance phenomenon seems not new. Adding an epsilon to MOMA seems not new as well.

[Response] The proposed new MOEA (epsilon multi-objective memetic algorithm, ε-MOMA) is similar with the algorithmic structure of NSGAII with significant change in the auto-adaptive recombination operator, ε-dominance archive process (Laumanns et al., 2002; Hadka and Reed, 2013) and a local search operator. Comparing with Borg MOEA, ε-MOMA has no change in population size in terms of archive size that is considered as a metric of complexity of problems. The adaptive population sizing probably dramatically increases the number of function evaluations in the optimization, which means the unaffordable computational burden with CPU-intensive model running. Moreover, ε-MOMA revives a local search operator in every several generations of evolutionary search to enhance the local optimality of archived Pareto solutions, which conforms the hybrid framework of MOEA, *i.e.*, multi-objective memetic algorithm (Sindhya et al. 2013).

In the many-objective optimization, the convergence and diversity of Pareto-optimal front are the critical metrics to evaluate the availability of MOEA. The novelty of ε-MOMA is to utilize the ε-dominance concept to archive elite individuals for the maintenance of diversity and the auto-adaptive recombination operator with local search for the enhancement of convergence on the framework of NSGAII. In addition, we linked the proposed MOEA with the numerical model to implement the basin-scale SW-GW management considering complex groundwater-river-lake interactions. To our knowledge, there are no other MOEAs including aforementioned techniques in solving the integrated SW-GW management problems. The detailed algorithmic structure can be found in **Section 2.2.1**.

As stated in the Introduction Section of revised manuscript (**Lines 113-116**), we have firstly stated the difficulty in the many-objective optimization (*i.e.*, the domination-resistance phenomenon). Then we presented two kinds of state-of-art MOEAs by which an attempt to alleviate the difficulty is feasible (**Lines 116-126**). After that, we stated that the developed ε-MOMA attempts to guarantee the diversity and convergence of Pareto-optimal solutions simultaneously in the many-objective optimization. Moreover, this study implemented the benchmark test using the classical DTLZ problems (3-6 objectives) to prove the availability of ε-MOMA (**Table S1** in the Supplementary Materials). Based on above all, we believe that the novelty of the simulation-optimization framework for the conjunctive management of SW and GW developed in this paper deserves consideration for publication in this journal (see the response to the referee's Comment 3 below).

Hadka, D., and Reed, P.M.: Borg: an auto-adaptive many-objective framework, Evol. Comput, 21(2), 213-259, https://doi.org/10.1162/EVCO_a_00075, 2013.

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

Sindhya, K., Miettinen, K., Deb, K.: A hybrid framework for evolutionary multi-objective optimization, IEEE Trans., 17(4), 485-511, https://doi.org/10.1109/TEVC.2012.2204403, 2013.

2. You mentioned SFR2, LAK3 and MODFLOW-NWT. Since this is an important part of the framework, can you add more details about these simulation models in the revised manuscript? For example, SFR2 is a streamflow-routing package. Does this model include hydrological simulation, or just a hydraulic model since it is only named as a routing model? How was MODLOW-NWT developed in the study area?

[Response] Comment accepted. MODFLOW-NWT is a Newton-Raphson formulation for MODFLOW-2005, which has an obvious advantage in solving drying and rewetting nonlinearities of the unconfined groundwater flow equation (Harbaugh, 2005; Niswonger, et al., 2011). Therefore, MODFLOW-NWT is a newer version of MODFLOW-2005. Most modular packages supported by MODFLOW-2005 can be used with MODFLOW-NWT, including SFR2 and LAK3 packages.

Streamflow-Routing Package (SFR2), as a modular package in MODLFOW-NWT, can be used to model the interactions between streams and underlying aquifers while consider unsaturated flow beneath streams for the disconnected river (Richard and David, 2010). SFR2 is just a modular package to model streamflow in the river channel based on the continuity equation assuming steady and uniform flow rather than an independent hydrological simulation model. The Manning's Equation is used to represent the relation between river stage and discharge and Darcy's Law is used to calculate the infiltration/exfiltration rate between streams and aquifers.

Considering the referee's concerns, we have added more details of the modular packages to elucidate the model (**Lines 372-375, Lines 382-386, Lines 388-394**).

The model used SFR2 package to simulate the streamflow routing in Kaidu River and surface water diversion to the 11 aqueducts from the mainstream of Kaidu River. The LAK3 package was used to model the variation of lake level of Bosten Lake in response to lake atmospheric recharge evaporation, surface runoff inflow from Kaidu River and withdrawal of ecological water conveyance. The runoff in gaging stations and observed lake levels were used to calibrate the parameters of SFR2 and LAK3. The observed groundwater levels were employed to calibrate the regional groundwater flow process.

Richard, G.N. and David, E.P.: Documentation of the Streamflow-Routing (SFR2) Package to Include Unsaturated Flow Beneath Streams-A Modification to SFR1, U.S. Geological Survey Techniques and Methods, pp. 6-A13, 2010.

Michael, L.M. and Leonard, F.K.: Documentation of a Computer Program to Simulate Lake-aquifer Interaction Using the Modflow Ground-water Flow Model and the Moc3d Solute-transport Model, U.S. Geological Water-Resources Investigations Report, 2000.

Harbaugh, A.W.: MODFLOW-2005, the U.S. Geological Survey modular ground-water model - the Ground-Water Flow Process: U.S. Geological Survey Techniques and Methods 6-A16, 2005.

Niswonger, R.G., Panday, S., and Ibaraki, M.: MODFLOW-NWT, A Newton formulation for MODFLOW-2005: U.S. Geological Survey Techniques and Methods 6-A37, 44 p, 2011.

3. Was the epsilon MOMA algorithm developed by yourself? The references attached are not enough to understand the algorithm. Please add more details about the logic line of the algorithm.

[Response] Yes. As stated in **Comment #1**, we developed ε-MOMA algorithm based the previous work of the state-of-the-art MOEAs. **In Section 2.2.1**, we have presented the logic line of the proposed algorithm step by step (**Lines 250-288**).

4. Figure 2: the figure didn't show clearly the river names in the basin. For example, I cannot find Kongqi River and lower Tarim River in the figure. This figure should help us understand the rivers, aqueducts etc. Please add a more detailed map.

[Response] Comment accepted. In the revised manuscript, **Fig. 2** has been modified to present all the rivers (*i.e.*, Kaidu River, Huangshuigou River, Qingshui River, Kongqi River) and 11 main aqueducts in the study area. To state the artificial outflow of Bosten Lake, we have also briefly introduced the Ecological Water Conveyance Project in the revised manuscript (**Lines 351-356**), although the project is not focus of our study. Considering the referee's concerns, we have illustrated the project in the **Fig. S1** of Supplementary Materials to present all the rivers stated in the manuscript.

5. When setting up the simulation model, what kind of data and also the details of data should be explained. What data were used for model calibration and validation?

[Response] Considering the referee's concerns, we have clearly listed the data for model set-up in the **Table S2** of Supplementary Materials (**Lines 400-401**). **Table S2** provides the data details used to build up the model in this study which can be grouped into three categories. The first category is the data depicting hydrological features and stratigraphic characteristics, including the spatial structure of regional aquifer and Bosten Lake, the network of Kaidu River and aqueducts. The second category is to input dynamic source and sink terms including boundary groundwater flux and groundwater level, weather observations, boundary river inflow, artificial pumping from Bosten Lake and conjunctive use of surface water and groundwater for agricultural irrigation. The third category is the hydrological observation data for model calibration. Due to the data scarcity, all available observation data is used to calibrate the numerical model.

6. What is "stress period"?

[Response] The simulation period is divided into a series of "stress period" within which specified stress data are constant. The stress data include the finite-difference cell dimension, time information, boundary conditions, initial heads, aquifer hydraulic properties, and control information required by the numerical solution scheme. The concept of stress period is the fundamental components in solving groundwater flow process using MODFLOW program (Harbaugh, 2005), which is similar to "time step" in hydrologic model.

Harbaugh, A.W., 2005, MODFLOW-2005, the U.S. Geological Survey modular ground-water model -- the Ground-Water Flow Process: U.S. Geological Survey Techniques and Methods 6-A16.

7. What is the time resolution in your simulation model? From Fig.4, you can see that the resolution is very coarse, semiannually? This model fails to show even the seasonality of runoff, lake level and water allocation.

[Response] As stated in the manuscript (**Lines 394-397**), the length of stress period in the non-irrigation and irrigation period is 5 and 7 months, respectively. We acknowledge that the time resolution is relatively coarse in the hydrological modeling subject to the availability of the data of groundwater abstraction and surface water diversion in the monthly scale, and lack of long-term monitoring of groundwater level during simulation period. However, Yanqi Basin is an arid inland basin with intensive agricultural development. Therefore, agricultural irrigation dominates the dynamic of groundwater level due to groundwater abstraction, and the variation of streamflow in Kaidu River due to surface water diversion in the basin. From the perspective of water managers, the model reflects the key relations between water resources exploitation and agricultural development, that's the critical components of multi-objective simulation-optimization modeling. Therefore, the model can be used to implement the integrated management of surface water and groundwater in Yanqi Basin.

8. How did the simulation consider all human activities in the model? For example, how SFR2 take into account the diversion or abstract of water from the river?

[Response] In Yanqi Basin, human activities on water resources include groundwater abstraction and surface water diversion. Firstly, we have the spatial location and yearly pumping rate of all pumping wells only in 2009 from national water resources census. The groundwater abstraction is mainly used for the crop water demand in the basin. Since we only have yearly total pumping rates from 2003 to 2013 in the basin, we reallocate the total pumping rates into each well in the other years according to the percentage of each pumping rate calculated in 2009. Then we disaggregated the yearly pumping data in each well into non-irrigation and irrigation period based on the investigation of local farmers' irrigation behaviors. Finally, the pumping data are rescaled to temporal and spatial scales required by the numerical model. The Well Package, as a modular package in MODFLOW-NWT, is used to model groundwater abstraction.

In SFR2 package, we can specify the water volume of surface water diversion in the diversion point of each aqueduct, which are recorded in the reports from the local water resources authority. Moreover, the aqueduct can be considered a "river" to model the water exchange with the underlying aquifer using SFR2 package. In the optimization, the amount of surface water diversion in seven diversion points can be considered as the decision variables to implement optimal surface water allocation in the basin.

9. Page 17: How did you obtain the scheme before optimization?

[Response] As stated in the manuscript (**Lines 499-501**), the management period is the last two stress periods (from November 2012 to October 2013) of the simulation period (from November 2003 to October 2013). Therefore, the scheme before optimization is known.

10. Climate change has substantial impacts on river runoffs in arid rivers in Xinjiang Province. The authors used only three simple scenarios (Current runoff; reduce 10% runoff and reduce 20% runoff) to investigate the impacts of climate change. These scenarios are just toys and don't provide useful information for climate change adaptation for the study area. Why didn't the authors use more practical climate change scenarios like RCPs?

[Response] The point is well taken. The climate-driven changes have a significant effect on the streamflow in snow-fed and glacier-fed basins, *e.g.*, Kaidu River Basin (KRB). The KRB drains an area of 18649 km^2 above Dashankou (DSK) gauge station and is considered as the upper mountainous headwater regions of Yanqi Basin (Shen, et al., 2018). The streamflow in DSK station, dominated by the hydrological regimes in KRB, is of critical importance for the integrated management of surface water and groundwater in Yanqi Basin. Ba et al. (2018) employed the SWAT model with three RCMs (regional climate models) to analyze the influences of climate change on the streamflow in DSK station. The study results show that the annual streamflow will decreases during 2020-2049 and reaches to the largest reduction percentage of 20.1% and 22.3% during 2040-2049 under RCP4.5 and RCP8.5 scenarios, respectively. Therefore, in this study, we defined the three runoff scenarios (*i.e.*, current runoff, reduce 10% runoff and reduce 20% runoff) based the work of Ba et al., (2018) to elucidate the impacts of climate change. However, the much heterogeneity in the climate change models and assumptions results in the uncertainty of runoff prediction in the future climate scenarios, that's not the focus of our study. Considering the referee's concerns, we have added the Reference and modified the statement in the manuscript (**Lines 653-660**).

Ba, W., Du, P., Liu, T., Bao, A., Luo, M., Mujtaba, H., and Qin, C.: Simulating hydrological responses to climate change using dynamic and statistical downscaling methods: a case study in the Kaidu River Basin, Xinjiang, China. J. Arid Land, 10(6): 905-920, https://doi.org/10.1007/s40333-018-0068-0, 2018.

Shen, Y.J., Shen, Y., Fink, M., Kralisch, S., and Brenning, A.: Unraveling the hydrology of the glacierized Kaidu Basin by integrating multisource data in the Tianshan Mountains, Northwestern China, Water Resour. Res., 54: 557-580. https://doi.org/10.1002/2017WR021806, 2018.

11. Possible uncertainty in the simulation-optimization model and decision making should be discussed in the manuscript.

[Response] Indeed, we acknowledge that the parameter uncertainty with limited data availability in the basin-scale full-coupled model and the limitations of model structure are inevitable. However, in this study, the numerical model can reflect the responses of water resources system to the conjunctive use of surface water and groundwater for agricultural irrigation. The simulation-optimization model also provides insights into basin-scale water resources management in the Yanqi Basin or other arid land basins with intensive agricultural development. The parameter uncertainty can be addressed with the construction of adequate and sustainable observing system in the future work. Considering the referee's concerns, we have modified the statements in the revised manuscript (**Lines 735-741**). In addition, the study focuses on the many-objective optimization of water allocation in the basin under the certain environment. The possible uncertainty (*e.g.*, deep uncertainty) also can be considered to implement many-objective robust optimization under the noisy environment (Watson and Kasprzyk, 2017), that's the focus of our future work (**Lines 744-746**).

Watson, A.A., and Kasprzyk, J.R.: Incorporating deeply uncertain factors into the many objective search process, Environ. Model. Softw., 89: 159-171. http://dx.doi.org/10.1016/j.envsoft.2016.12.001, 2017.

Technical corrections: Only minor typo is found.

[Response] Comment accepted. We have thoroughly checked the manuscript and revised the original manuscript to improve its quality and readability.

Response to Dr. Qiankun Luo's Short 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 Dr Luo'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 53-63**). Secondly, we explained the meaning of many-objective optimization framework in the water resources management and planning (**Lines 81-109**) and the optimization techniques (**Lines 110-137**). After that, we introduced the details of water resources exploitation in Yanqi Basin (YB) (**Lines 144-160**) to present the suitability of the case study. Then, we stated that it is necessary for YB water management to consider the deep uncertainty derived from climate change which probably results in the runoff reduction in Kaidu River (**Lines 182-190**). Finally, we showed the general results of the study for the HESS readers (**Lines 196-202**).

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 250-288**) and **Section 2.2.2** "Benchmark test" to investigate the performance of the algorithm (**Lines 296-313**). 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 tests also show the availability of our algorithm (**Table S1** in the 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:

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

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

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

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 the surface water (SW) in an aqueduct system and the 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 735-737**) 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 (**Line 231**). 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 258-267**), 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 408**).

4. Line 417: where the increment of f_{TPR} and f_{TDR} 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 536-537**).

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 678-681**).

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

[Response] Comment accepted (**Line 701**).

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 agriculture 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. ~~for sustainably conjunctive use of SW and GW in Yanqi Basin (YB), a typical arid region with intensive agricultural irrigation in northwest China. The S-O model integrates~~ 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.~~based simulation model for examining the hydraulic interactions between SW and GW~~ 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. ~~Four conjunctive management objectives,~~The management model, involving maximizations of total water supply rate, groundwater storage and surface runoff inflow to ~~Bosten Lake~~ the terminal lake, and minimization of water delivery cost, was proposed to explore the tradeoffs between socioeconomic and environmental ~~demands~~ 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~~, so as to~~. The Pareto-optimal solutions avoid the prevalence of decision bias caused by the low-dimensional optimization formulation. Decision-makers are then able to identify their desired water ~~use~~ management schemes with preferred objectives and achieve maximal socioeconomic and ecological benefits simultaneously. Moreover, three representative runoff scenarios ~~under changing climatic conditions~~ in relation to ~~the~~ climate change were

specified to quantify the effect of decreasing river runoff ~~in the river~~ on the ~~YB~~ water ~~resources~~ management in YB. Results show that runoff ~~reduction~~ depletion would be of great negative impact on the management objectives.~~the total water supply, surface runoff inflow to the lake and regional groundwater storage in the aquifer.~~ Therefore, the integrated SW and GW management is of critical importance for the fragile ecosystem in YB 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 irrigation water is diverted from groundwater (GW) abstraction and surface water (SW) diversion in the densely populated oasis regions in northwest China.~~ 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, it is essential for the conjunctive management of GW and SW to~~is essential for~~ deal~~ing~~ with the contradiction between demand and supply of water resources in the arid regions with water shortage ~~the requirement of local economic development and eco-environmental conservation~~ (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) methods 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 complex SW and GW management problems Evolutionary algorithms have been integrated with simulation model to tackle intricate SW and GW management model due to the effectiveness of solving non-linear and multimodal

~~optimization problems~~ (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 decision-maker 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 evolutionary search ability, ε-box technique ~~for the Pareto sorting and~~

~~injection strategy~~ to ensure the diversity and adaptive population sizing scheme to avoid search stagnation. ~~of evolutionary search and archived optimal solutions in handing many-objective optimization. In order to enhance the local optimality of solutions, a memetic algorithm composed of~~ 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 ~~ensure the convergence of the MOEA~~ overcome some shortcomings of the traditional MOEA (*e.g.*, slow convergence, inefficient termination criterion) (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 simultaneously. 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 archive process, the auto-adaptive recombination operator and a local search operator into the basic framework of NSGAII (Deb et al., 2002b). Then, the proposed multi-objective optimization framework is applied to solve the integrated management of SW and GW in Yanqi Bain (YB). ~~This study attempts to utilize the ε-dominance concept, the modified auto-adaptive recombination operators to alleviate domination resistance problem, and a local search operator to enhance the local optimality of archived solutions with the framework of NSGA-II (Deb et al., 2002). The improved algorithm, named epsilon multi-objective memetic algorithm (ε-MOMA), is applied to the many-objective optimization of conjunctive management of SW and GW for agricultural irrigation in 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 resources 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.~~In this study, a regional numerical model using MODFLOW-NWT (Niswonger, 2011) is developed for quantitatively evaluating water budget and interaction of river-lake-groundwater in YB. The model is calibrated according to long-term series of observation data during simulation period from 2003 to 2013. Kaidu River and Bosten Lake are simulated with Streamflow-Routing package (SFR2) (Richard and David, 2010) and Lake package (LAK3) (Michael and Leonard, 2000). The lake and river simulation is calibrated based on observed lake level and runoff data at the gaging stations, respectively. Then, a well-calibrated model is linked with the ε-MOMA to explore optimal water supply schemes which consider multi-stakeholders' benefits simultaneously. Moreover, in order to encourage decision-makers to use the optimized~~

schemes, an interactive tool is employed to visualize and analyze all the Pareto-optimal solutions and provide suggestions on the practical operation of water allocation. 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 environmental flow for hydro-ecosystem conservation (*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 with 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 in relation 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. ~~is implemented using the novel multi-objective evolutionary algorithm (ε-MOMA).~~ The optimization results demonstrate that ~~water managers~~ decision-makers 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 multi-objective optimization under the runoff reduction scenarios ~~optimization~~ shows that the conservative water management options may be desired in the face of deep uncertainty associated with climate changes. The study results can also provide valuable insights for water allocation in other arid inland basins. ~~under the runoff reduction scenarios also provide valuable insights for water use practices in the face of climate changes in the arid inland basin.~~

2. Methodology

As shown in Fig. 1, this study aims to develop a multi-objective decision-making framework to optimize the 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 agricultural 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 process

2.2.1 Main algorithmic structure

Module II in the optimization framework (Fig. 1) illustrates the algorithmic process of ε-MOMA. The metaheuristic algorithms are superior to the classical optimization methods and have been successfully applied to water resources management and planning (Maier et al., 2014) due to the ability to solve complex problems with nonlinear, nonconvex and high-dimensionality features. To address domination resistance phenomenon in the many-objective optimization, the proposed algorithm integrates a ε-box technique, adaptive multi-operators recombination and a local search operator into the framework of NSGA-II. 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 the 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., 2002a), 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: *ε*-domination archive process:

The *ε*-box technique proposed by Laumanns et al. (2002) attempts to ensure convergence and diversity of the approximate Pareto-optimal 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.

In the many-objective optimization, *ε*-MOMA utilizes the *ε*-dominance concept to archive elite individuals for the maintenance of diversity and the auto-adaptive recombination operator with local search for the enhancement of convergence on the basis of the framework of NSGAII. Hence, the algorithm possesses the ability of highly effective global search with auto-adaptive recombination operator and ε-dominance archive 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., 2002c). 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 these 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 the global optimal Pareto front (Table S1 in the Supplementary Materials). In higher-dimensional objective space, the performance of ε-MOMA can be maintained by augmenting the number of function evaluations. Therefore, the proposed ε-MOMA is effective in addressing many-objective optimization from 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 ~~sub-optimal~~ 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~~with 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 °C, 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 ~~3.41×10^{9}~~ 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 ~~8.8×10^9~~ 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). As illustrated in Fig. S1, the project firstly transfers water through Kongqi River from Bosten Lake to Daxihaizi Reservoir and then to the lower reaches of Tarim River, and finally to the terminal 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, the 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 regional 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~~ in the aquifer system.

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. The program applies the Newton-Raphson formulation and unstructured, asymmetric matrix solvers to solving drying and rewetting nonlinearities of the complex unconfined groundwater flow problem (Niswonger, 2011) while supports most modular packages in MODFLOW-2005 (Harbaugh, 2005). 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. LAK3 package models the lake and aquifer interactions by calculating the exchange rate, which is determined by the difference between lake level and groundwater, the hydraulic conductivity of adjacent aquifer and the material of lakebed. The lake level responses to the hydraulic stresses including lake atmospheric recharge and evaporation, overland runoff, and any direct withdrawal or recharge of the lake volume. 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). SFR2 package, as a modular package in MODLFOW-NWT, can be used to model the interactions between streams and underlying aquifer while consider unsaturated flow beneath streams for the disconnected river. The streamflow is routed based on the continuity equation assuming steady and uniform flow. The Manning's Equation and Darcy's Law are used to represent the relation between river stage and discharge and calculate the infiltration/exfiltration rate between streams and aquifers, respectively. 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 numerical model. The more data details can be found in Table S2.

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 precision of groundwater head was assessed based on root mean square error (RMSE) and correlation coefficient (R). The performance criteria can be stated as:

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

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

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

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; $\bar{y}_m$ and $\bar{y}_o$ are the average value of simulated and observed data. Fig. S2a and S2b compare the simulated and observed runoff at Yanqi and Baolangsumu Stations for the stress periods between 2004 and 2012 (lack of observed runoff in 2013) and suggest that the long-term fluctuation of runoff in Kaidu River can be well reproduced with NSE of 0.89 and 0.90, respectively. Fig. S2d 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. S2e 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. S2c 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 (m^3/d); $\mathbf{X}$ 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 ~~1×10^6 m^3/yr~~ 1.0 million m^3/yr (Mm^3/yr) and $Q_{g,max}$ is ~~1×10^8 m^3/yr~~ 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 ~~1×10^7 m^3/yr~~ 10.0 Mm^3/yr at diversion points DP1 and DP2 and ~~5×10^6 m^3/yr~~ 5.0 Mm^3/yr at DP3-DP7, $Q_{s,max}$ is ~~4×10^8 m^3/yr~~ 400.0 Mm^3/yr at DP1 and ~~2×10^8 m^3/yr~~ 200.0 Mm^3/yr at DP2 and ~~1×10^8 m^3/yr~~ 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 ~~3.0×10^8 m^3/yr~~ 300.0 Mm^3/yr and ~~5.5×10^8 m^3/yr~~ 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 ith 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 ~~4.16×10^8 m^3/yr~~ 416.0 Mm^3/yr whereas the growth of f_{TDR} only is ~~1.14×10^8 m^3/yr~~ 114.0 Mm^3/yr across all the Pareto solutions. Therefore, groundwater abstraction can be adjusted largely to satisfy management objectives based 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~~ four 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 ~~3.82×10^7 m^3/yr~~ 38.2 Mm^3/yr and the depletion in groundwater storage obtains the reduction of ~~1.99×10^7 m^3/yr~~ 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 ~~1.43×10^{8} m^3/yr~~ 143.0 Mm^3/yr of f_{TWS} in the scheme before optimization can achieve the increment of groundwater storage with ~~2.19×10^{7} m^3/yr~~ 21.9 Mm^3/yr and augment ~~6.30×10^{7} m^3/yr~~ 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 (~~8.39×10^{7} m^3/yr~~83.9 Mm^3/yr) is more rapid than the reduction of surface runoff inflow to the lake (~~1.85×10^{7} m^3/yr~~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 ~~8×10^{7} m^3/yr~~ 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, in Solution 6, 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 (~~1.31×10^8 m^3/yr~~131.0 Mm^3/yr) at the cost of river leakage (~~0.30×10^8 m^3/yr~~30.0 Mm^3/yr) can lower surface water diversion (~~0.67×10^8 m^3/yr~~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. Ba et al. (2018) employed the SWAT model with three RCMs (regional climate models) to analyze the influences of climate change on the streamflow in Dashankou station. The study results show that the annual streamflow will decreases during 2020-2049 and reaches to the largest reduction percentage of 20.1% and 22.3% during 2040-2049 under RCP4.5 and RCP8.5 scenarios, respectively. We defined three runoff scenarios in relation to climate change in terms of the work of Ba et al. (2018), 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. ~~The hypervolume metric (HV) is used to evaluate the convergence of Pareto-optimal solutions under the three scenarios. The advantage of HV is the monotonically increasing relationship between the metric value and Pareto dominance, which shows the optimal tradeoff surface can achieve maximum hypervolume (Bader and Zitzler, 2011).~~ Fig. 11 shows all Pareto-optimal solutions in the four-dimensional objective space under the ~~different~~ runoff ~~change~~ scenarios. It is clearly ~~obviously~~ 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 in relation to climate change. In Fig. 11, the approximate Pareto solutions in Scenarios A0, A1 and A2 does not exists when f_{SRI} is greater than 1801.33 Mm^3/yr in Scenario A0, 1596.33 Mm^3/yr in Scenario A1 and 1374.58 Mm^3/yr in Scenario A2,~~a certain value~~ 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~~ l~~L~~ake 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~~ The~~based~~ solutions in Scenario A0 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 complex interactions 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~~ stricter water resources 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. Due to the data-scarcity in the basin-scale full-coupled~~water cycle~~ modeling and limitations of simulation model, the predictive uncertainty is inevitable. However, the simulation model can reflect the responses of water resources system to the conjunctive use of SW and GW for agricultural irrigation. The parameter uncertainty can be addressed with the construction of adequate monitoring system for modeling in the future work. Meanwhile, future research should focus on exploiting fully coupled simulation model to accurately model basin-scale water resources system~~water cycle~~ and avoid decision bias derived from the limitations of model. Moreover, the deep uncertainty showing the lack of consensus on their underlying probability distribution and consequences (*e.g.*, land use change, climate change~~, etc.~~) is a key factor to affect the robustness and reliability of the optimal solutions under~~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.

Code and data availability

The data used in this study are provided on request by the Xinjiang Tarim River Basin Authority in China and are not publicly accessible. The detailed data information can be found in Table S2 in the supplementary material. The codes can be provided through direct request to the corresponding author.

Supplement

The supplement related to this article is available on the uploaded file (Supplement_to_HESS-2019-278.pdf).

Author contribution

JS, YY, JFW and JCW conceptualized the paper and its scope. XMS, JL and MW collected the data. JS implemented the simulation model with some contributions from MW. JS developed the code, performed the study, and wrote the initial manuscript. JS, YY and JFW revised the paper. All authors contributed to the manuscript preparation.

Competing interests

The authors declare that they have no conflict of interest.

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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

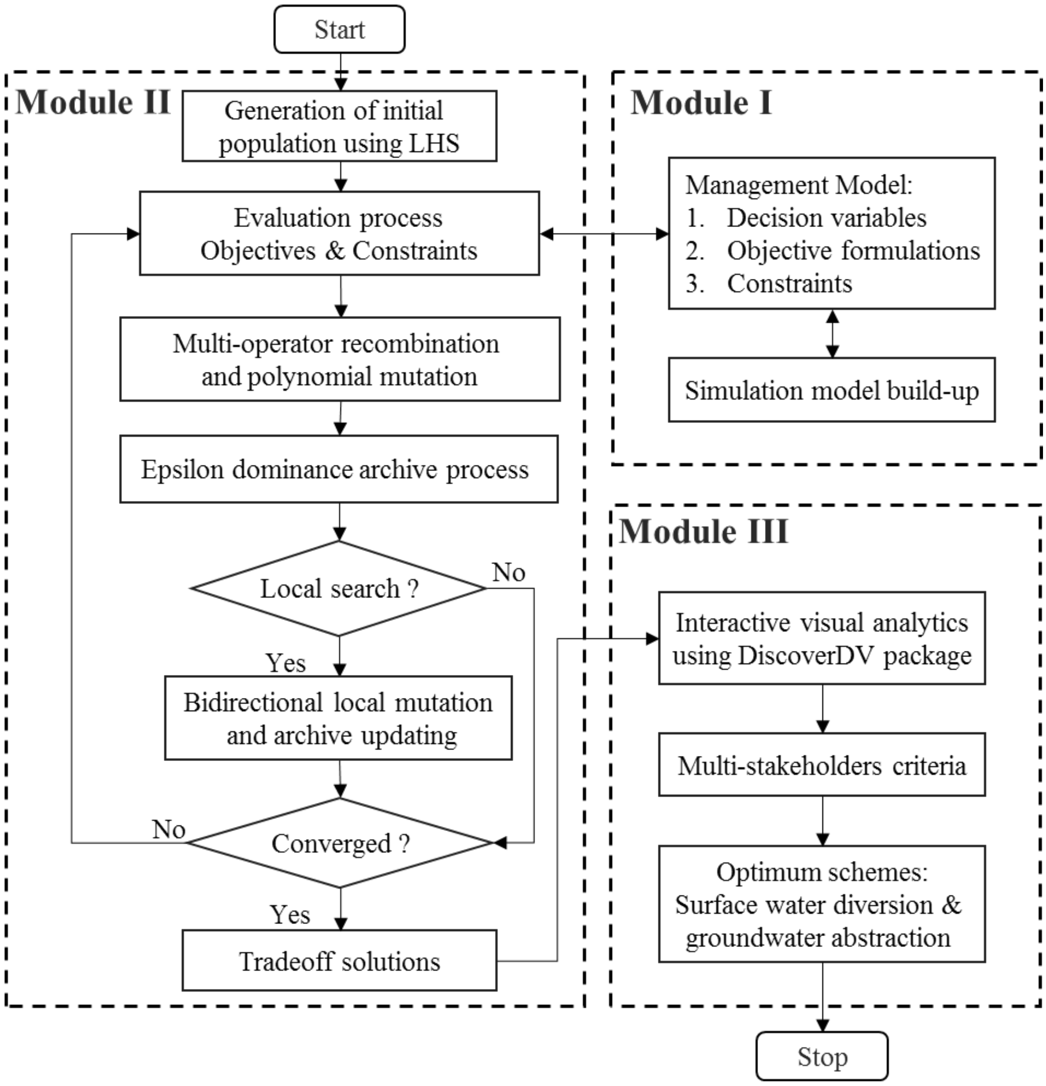

Fig. 1. Framework of multi-objective optimization for integrated SW-GW management.

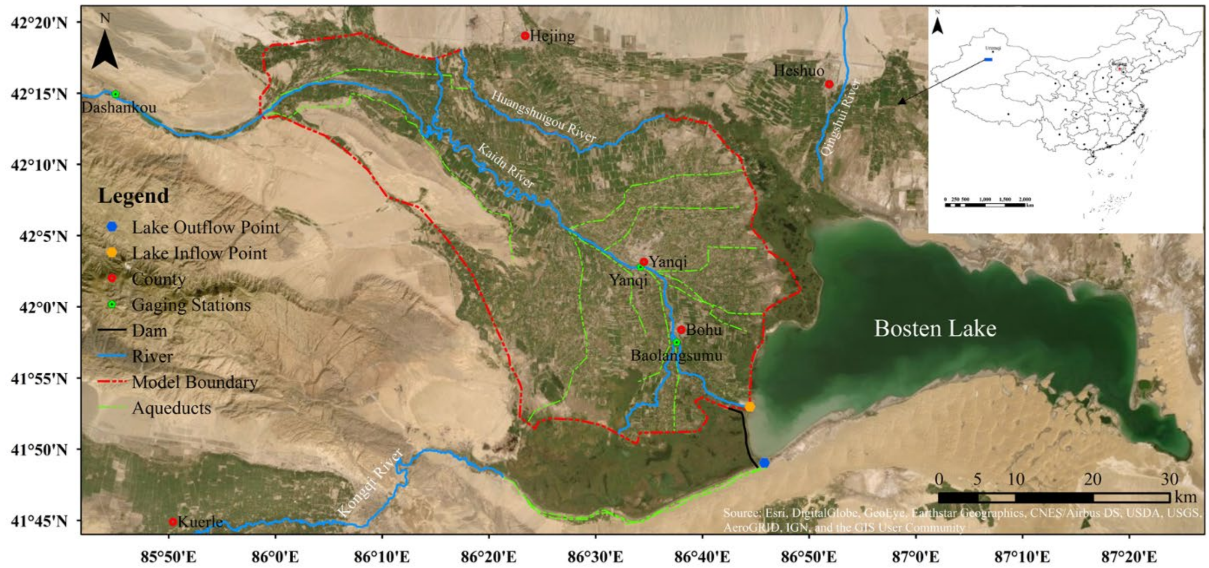

Fig. 2. The location of Yanqi Basin and the model domain of interest for this study. Source: DigitalGlobal, Inc. (imagery).

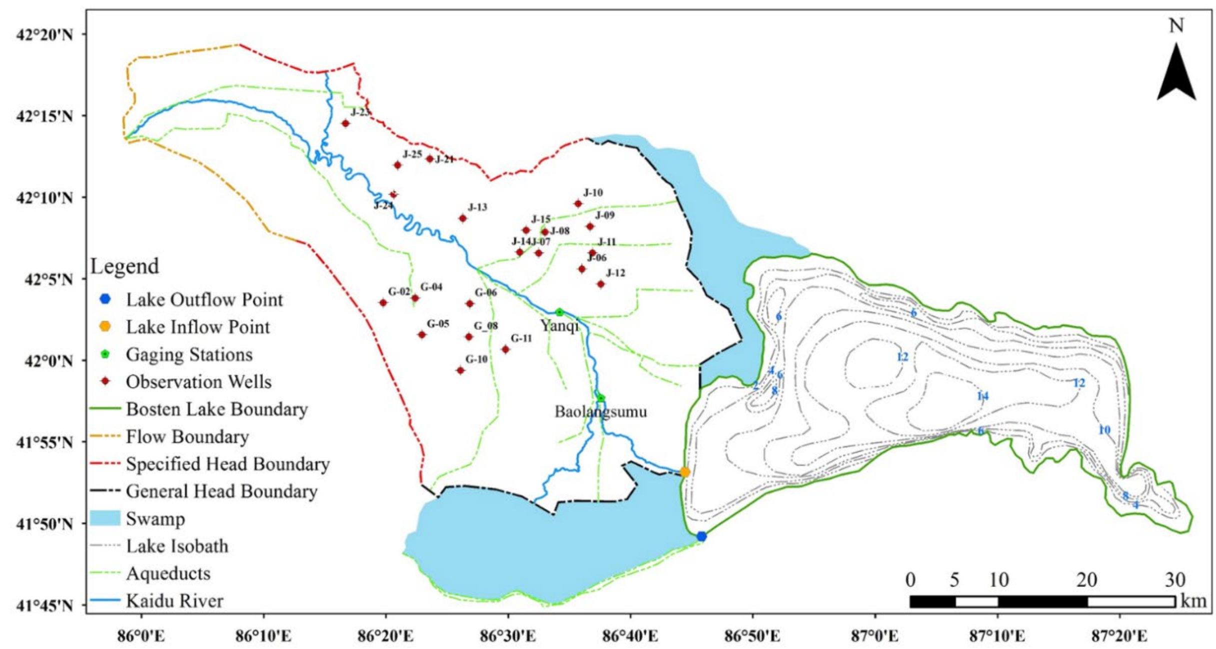

Fig. 3. The boundary conditions of model domain, monitoring locations of groundwater level and surface runoff, aqueduct system and bathymetric contours in meters for Bosten Lake.

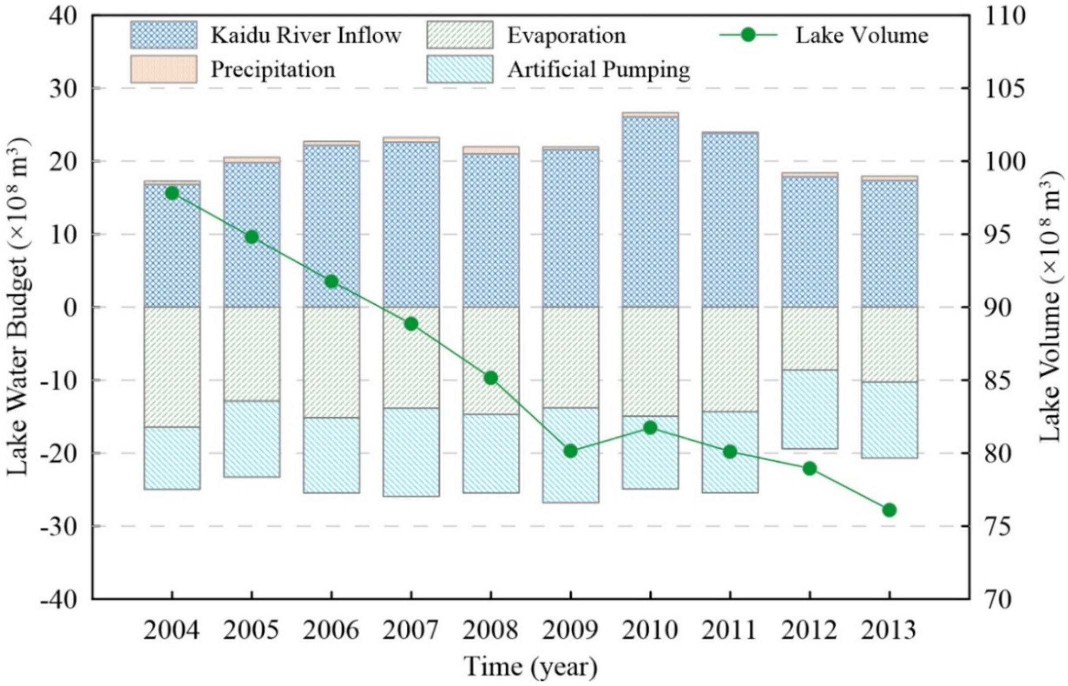

Fig. 4. The water balance terms of Bosten Lake and resulting lake volume in the simulation period.

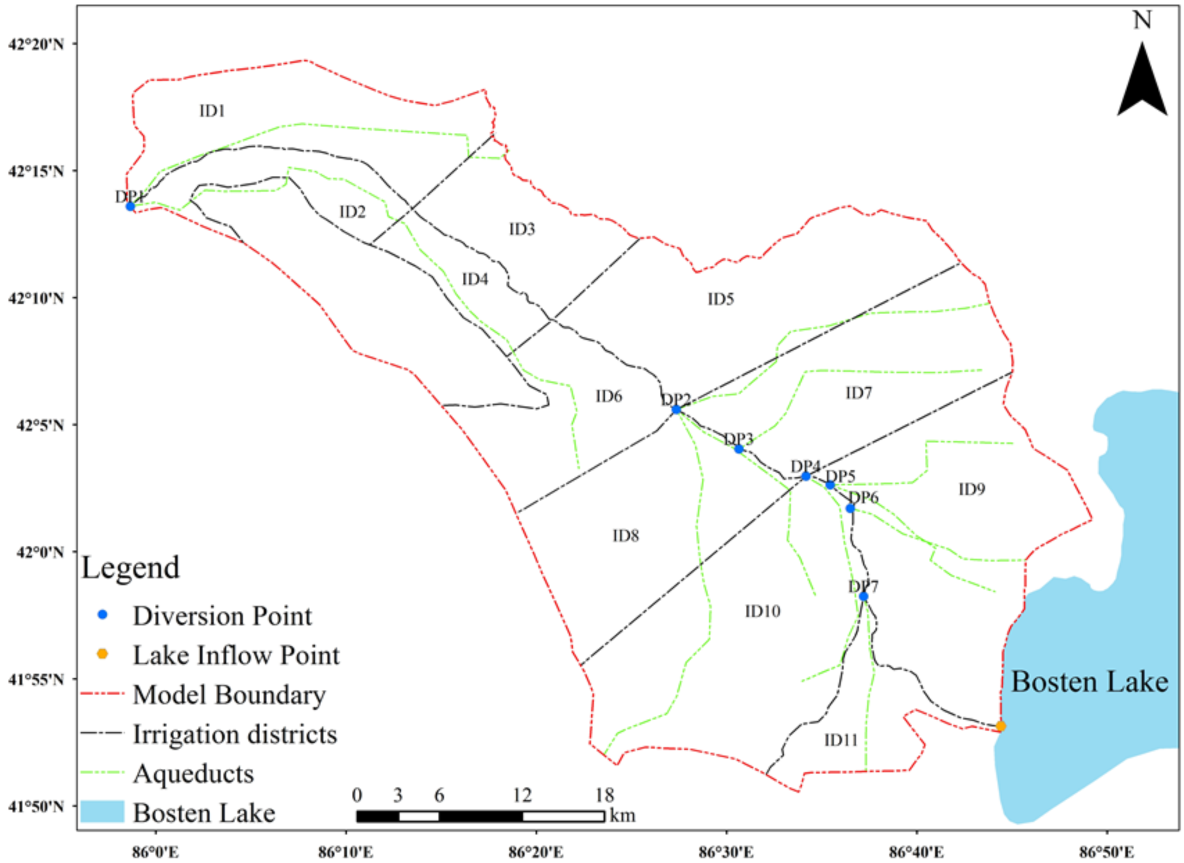

Fig. 5. The locations of surface water diversion points and subdomains of irrigation districts for groundwater abstraction.

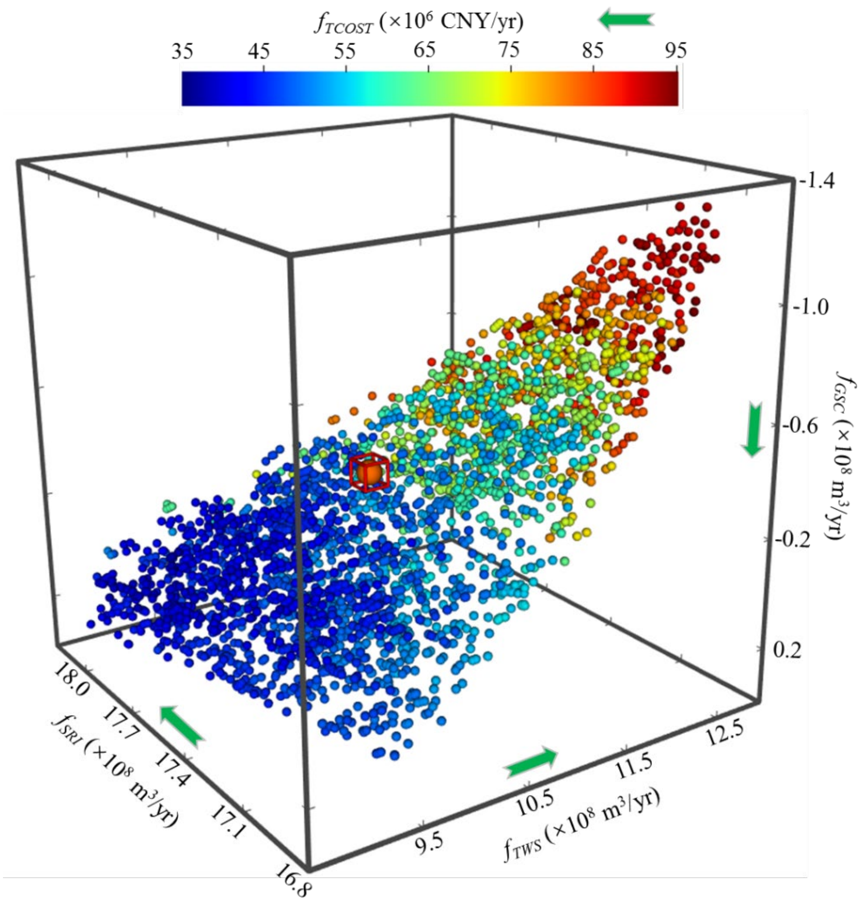

Fig. 6. The tradeoff surface to the integrated SW-GW management in Yanqi Basin. Each spheric symbol represents a water use scheme corresponding to specific objective values of the total water supply rate (f_{TWS}), total cost of water delivery (f_{TCOST}), surface runoff inflow to lake (f_{SRI}) and 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.

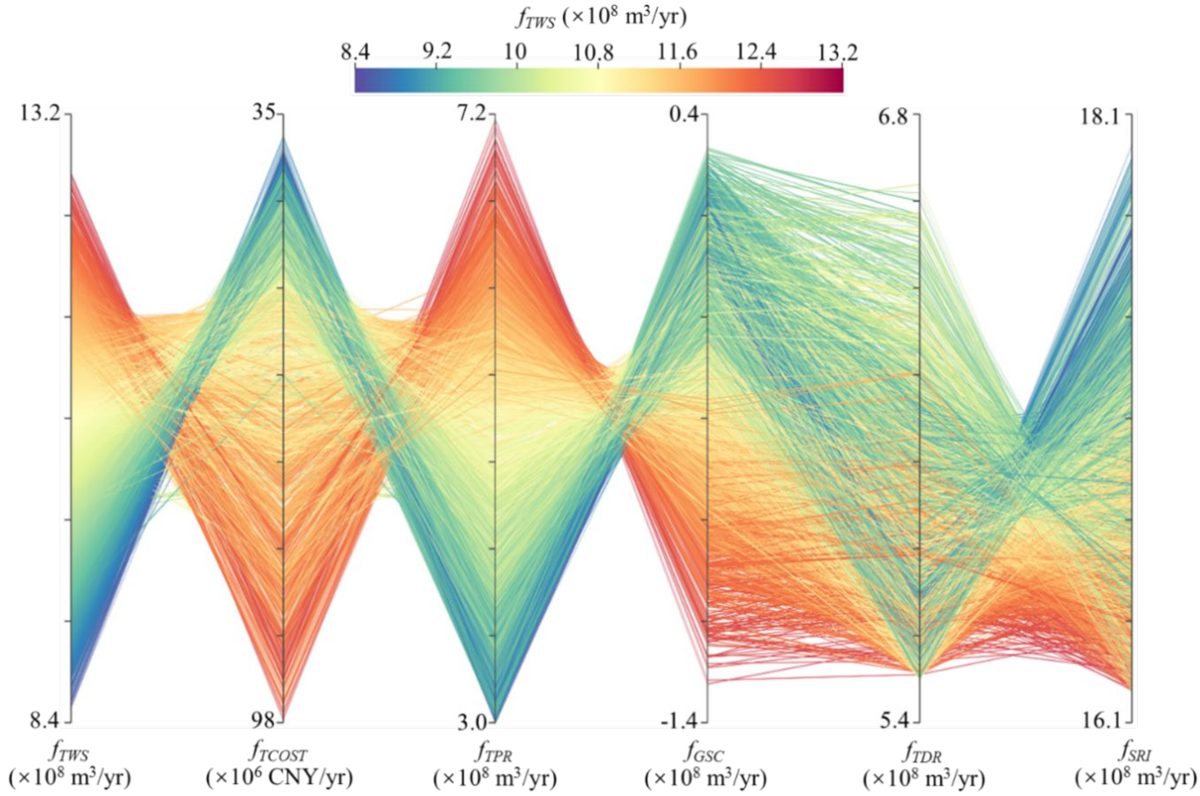

Fig. 7. The objective values (*y*-axis) are plotted over management objectives f_{TWS}, f_{TCOST}, f_{GSC}, f_{SRI}, total pumping rate f_{TPR} and total surface water diversion rate f_{TDR} (*x*-axis), f_{TWS} is represented in color. The preferred direction for each index is upward.

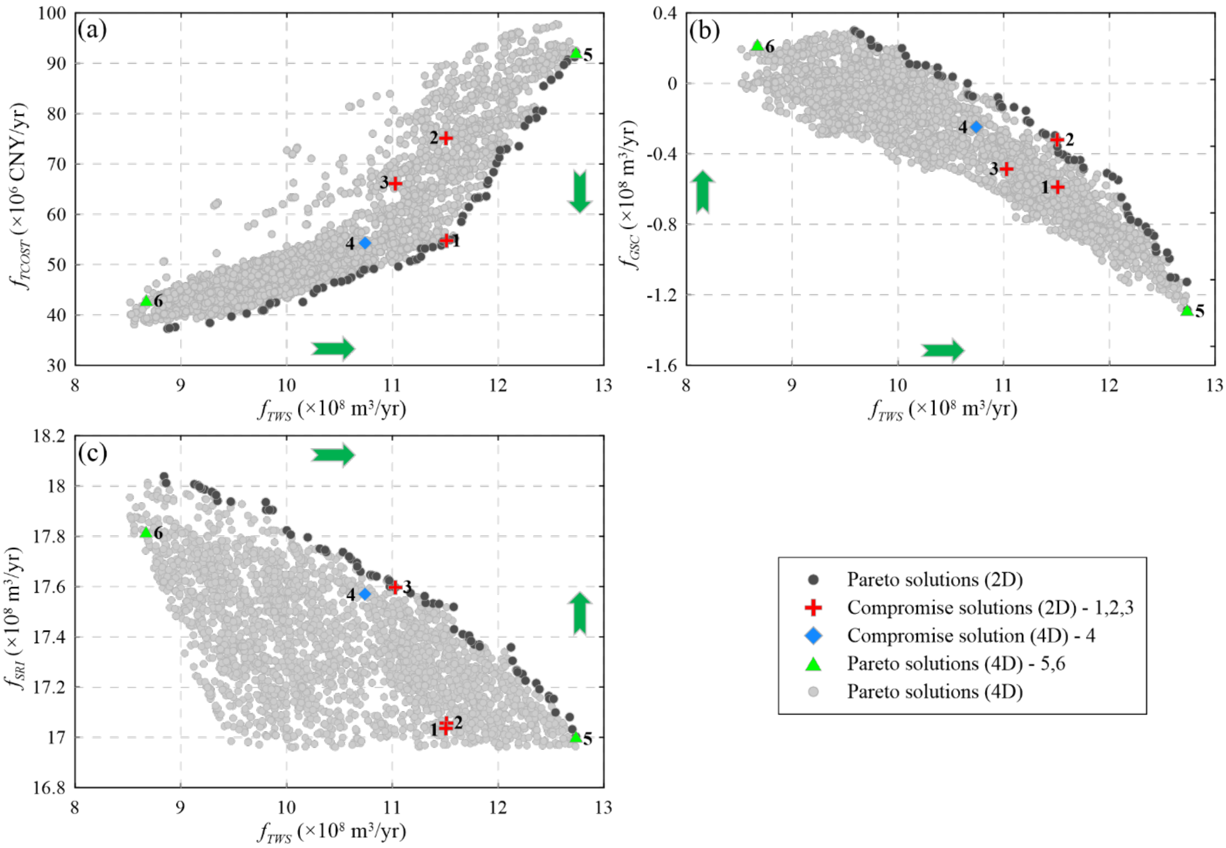

Fig. 8. Identification of six interesting solutions (Solutions 1-6) from the four-dimensional approximate Pareto set and the green arrow is the preferred direction for each objective.

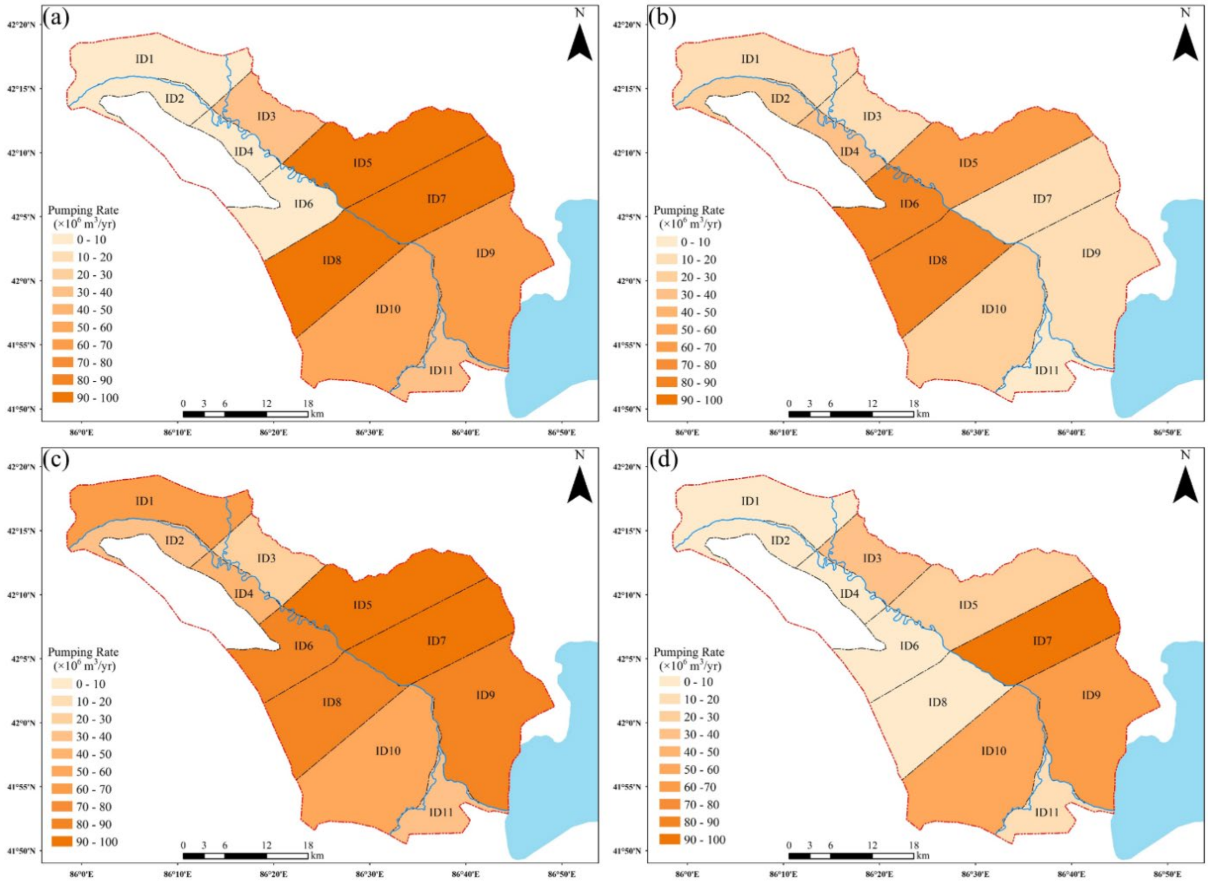

Fig. 9. The spatial distribution of the pumping rates in the 11 irrigation districts for the four selected schemes of (a) Solution 4, (b) Solution 7, (c) Solution 5, and (d) Solution 6, respectively.

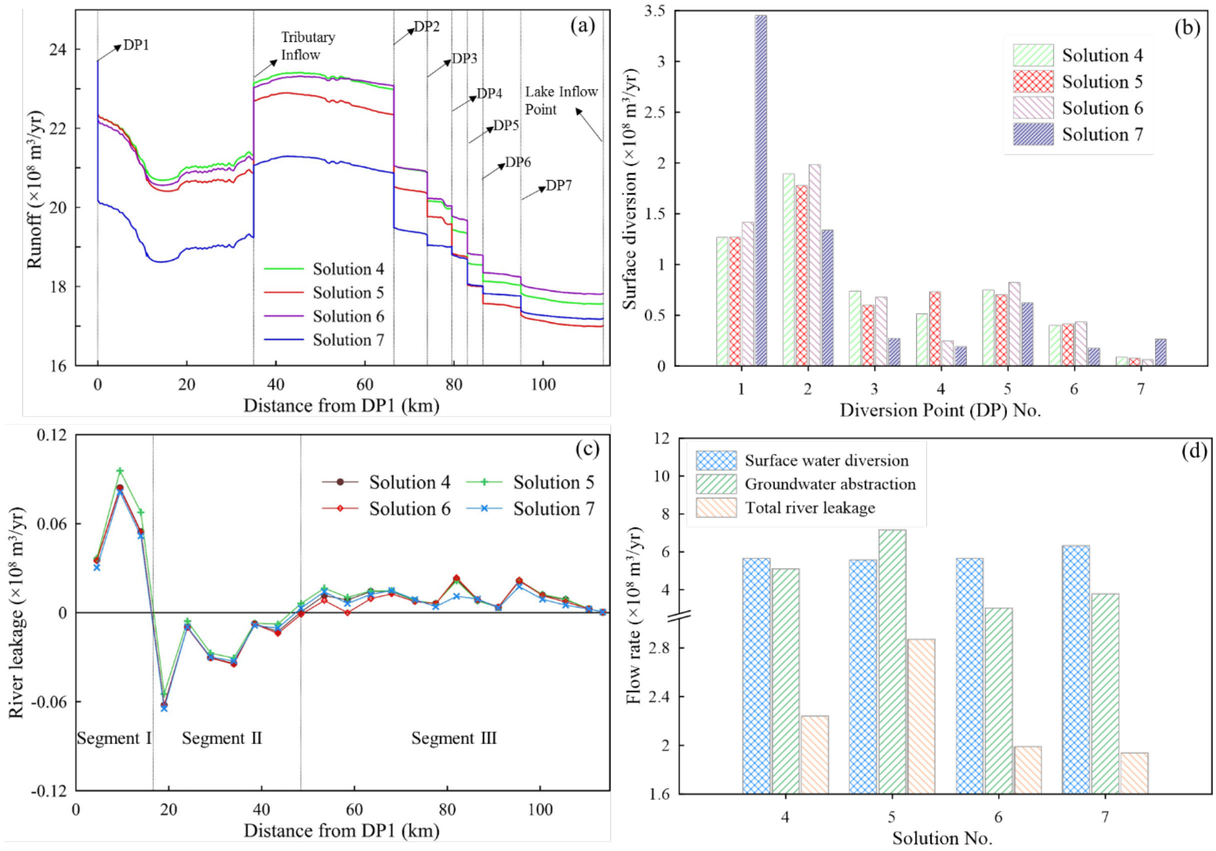

Fig. 10. Variation of surface runoff and river leakage along the stem stream of Kaidu River: (a) the profile of river runoff; (b) the distribution of surface water diversion at the different diversion points; (c) the profile of river leakage; (d) the components of total river leakage, groundwater abstraction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

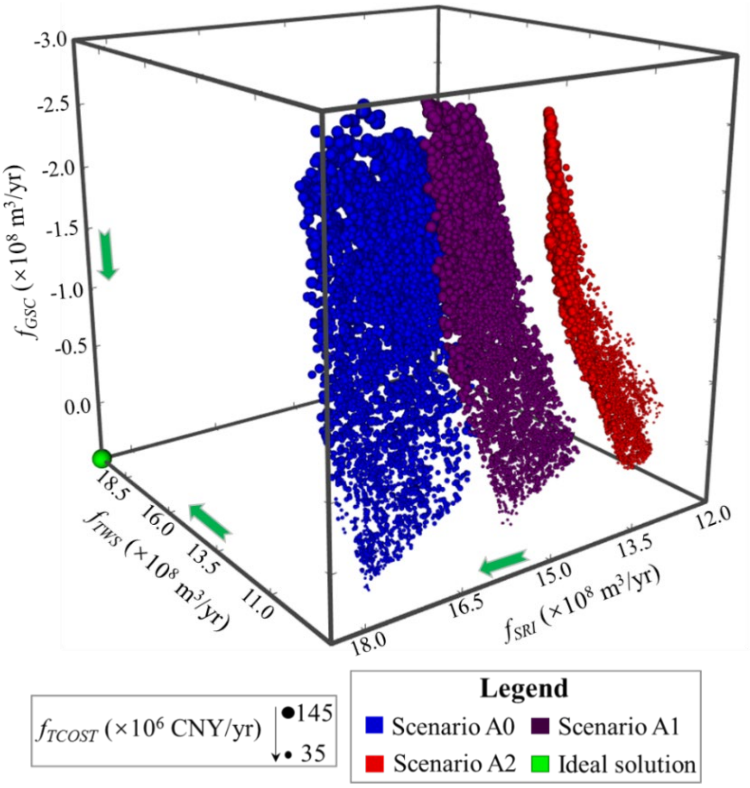

Fig. 11. The tradeoff solutions under Scenarios A0 (maintain current runoff), A1 (reduce the runoff by 10%) and A2 (reduce the runoff by 20%), and the sphere size indicates the value of f_{TCOST}. The green arrow is the direction of better performance for each objective.

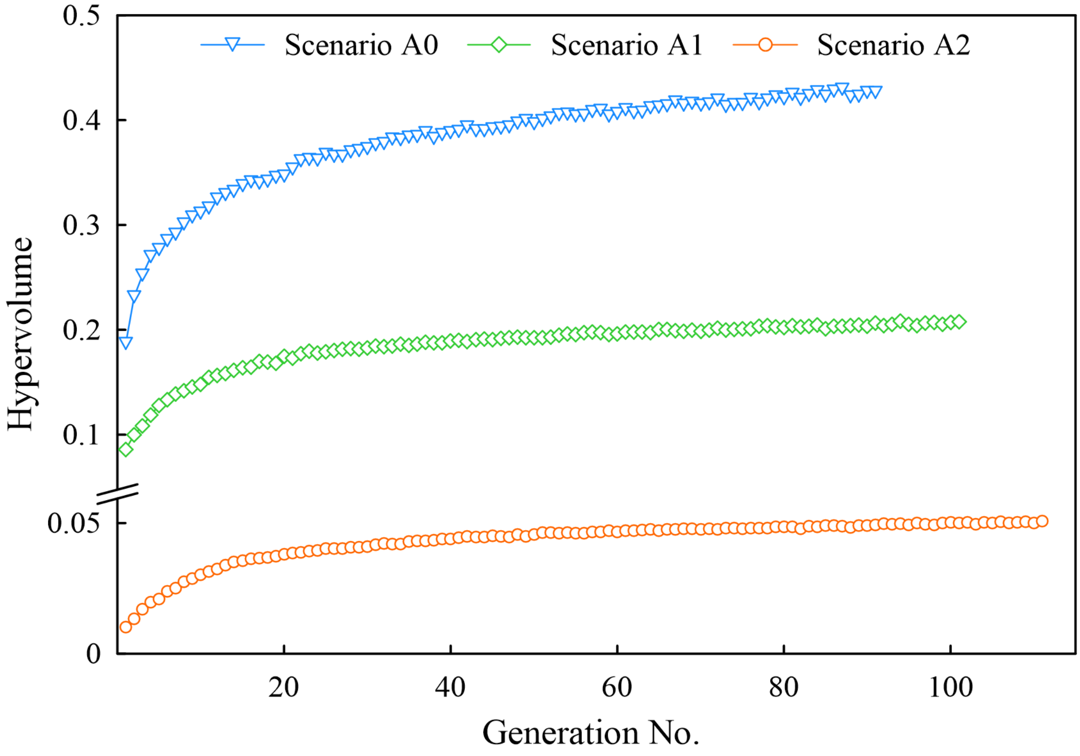

Fig. 12. Evolution of the hypervolume metric over the generation number for Scenarios A0, A1 and A2.

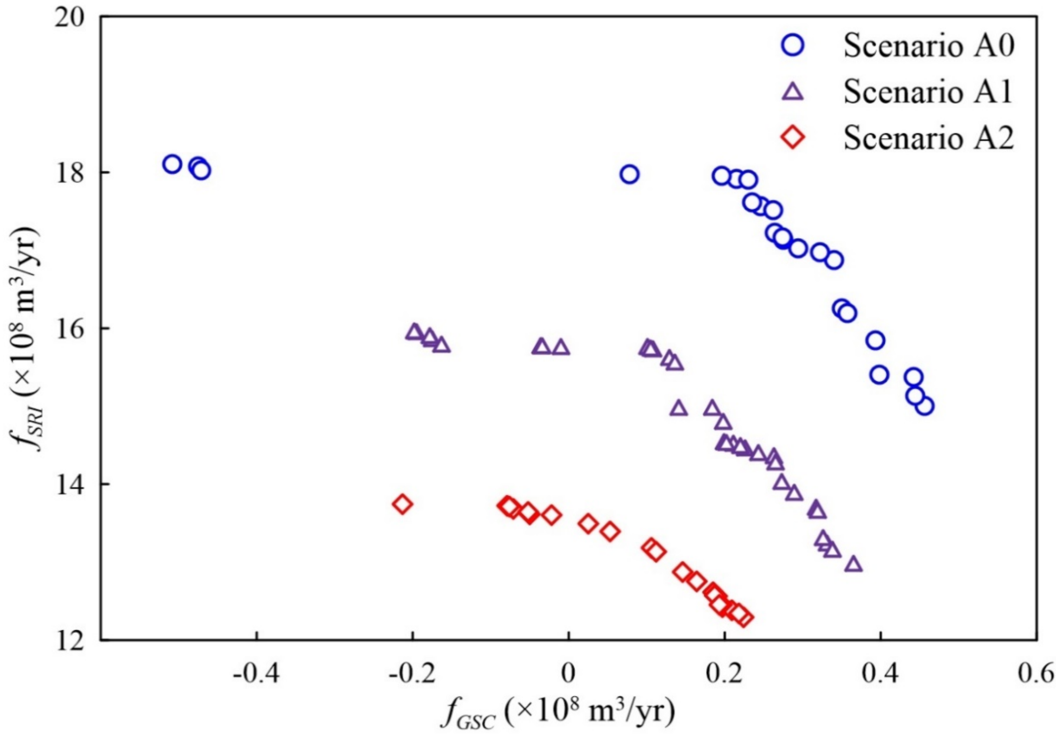

Fig. 13. Non-dominated fronts of Scenarios A0, A1 and A2 between objectives of f_{GSC} vs. f_{SRI}.

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.

Table S2 Multisource data for the model build-up

Category	Data	Data Time	Spatial Resolution
Initial parameterization and resolution	DEM	2008	90×90 m
	River network	2009	(Google Map)
	Aqueducts	2009	(Reports)
	Hydrogeology Map	1977	1:200000
	Lake topography	1977	1:200000
	Bottom of aquifer	1977	1:200000
Dynamic data and resolution	Boundary river inflow	2003-2012 (monthly)	1 station
	Boundary groundwater inflow	2009 (yearly)	(Reports)
	Boundary groundwater level	2003-2013 (non-irrigation and irrigation periods)	5 monitoring wells
	Meteorological observations	2003-2013 (monthly)	3 stations
	Surface water diversion	2003-2013 (non-irrigation and irrigation periods)	11 aqueducts
	Groundwater pumping	2003-2013 (yearly)	11 irrigation districts
	Lake artificial pumping	2003-2013 (monthly)	1 station
Calibrated data and resolution	Streamflow	2003-2012 (monthly)	2 stations
	Groundwater level	2003-2013 (non-irrigation and irrigation periods)	7 wells (2003-2013) 14 wells (2012-2013)
	Lake level	2003-2013 (monthly)	1 station

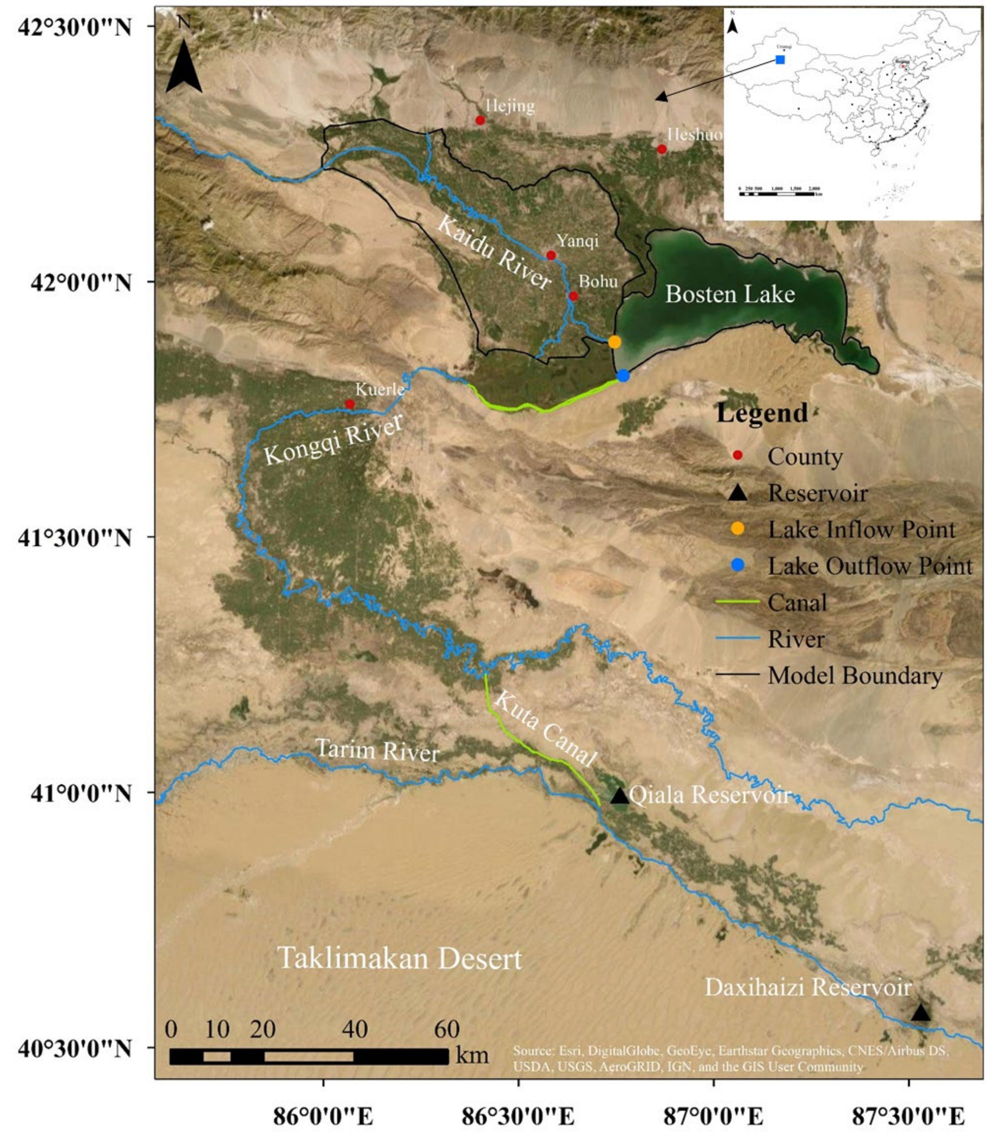

Fig. S1 The Ecological Water Conveyance Project

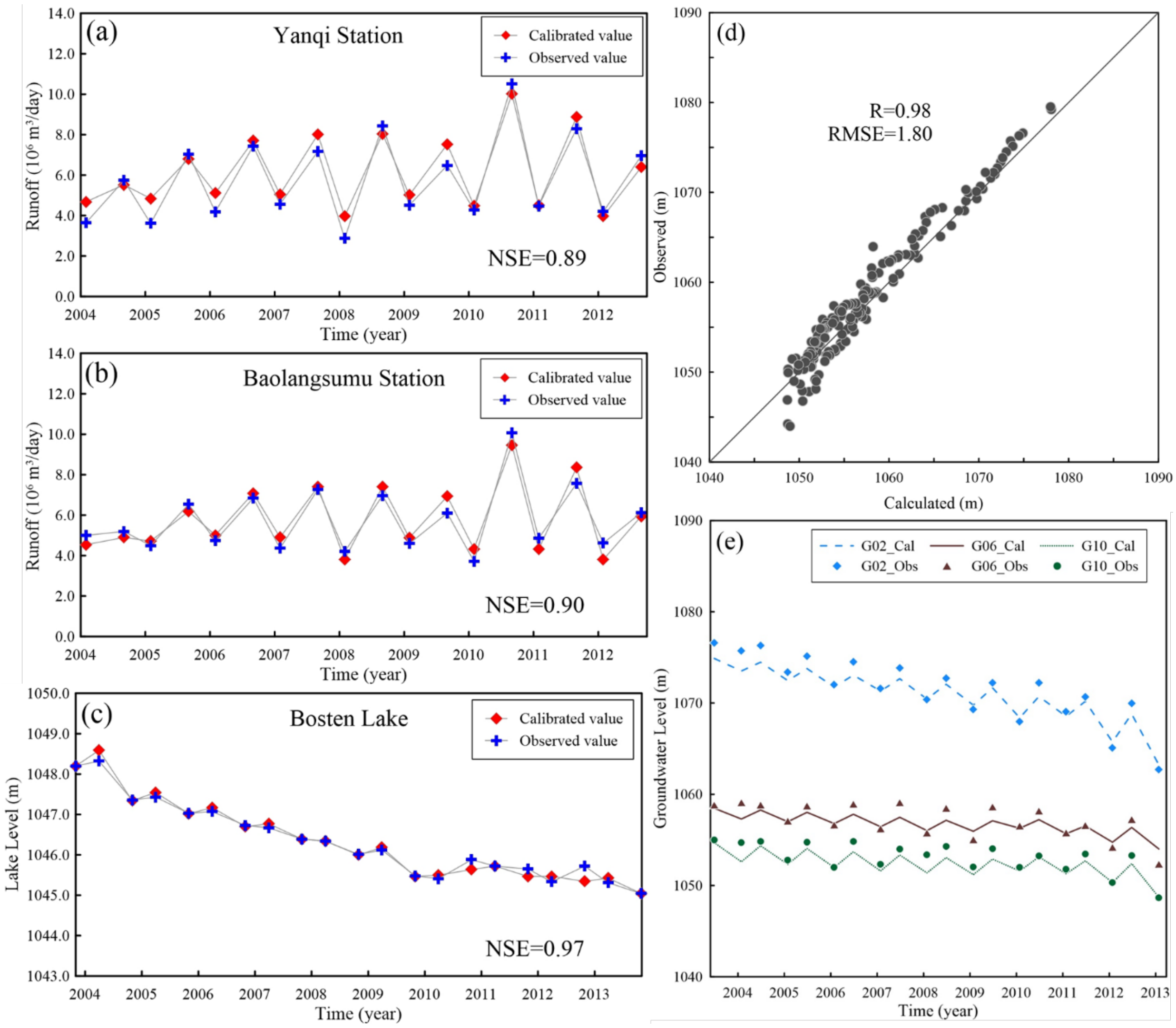

Fig. S2 The calibrated results of the transient model showing (a) observed vs. calibrated runoff at Yanqi station over time, (b) observed vs. calibrated runoff at Baolangsumu station over time; (c) observed vs. calibrated lake level over time; (d) comparison of observed and calibrated groundwater heads at all observation wells, and (e) observed vs. calibrated groundwater heads over time at three typical observation locations as labeled in Fig. 3.