Response to CC1

We sincerely thank the reviewer for the positive evaluation of our manuscript and for providing the opportunity to revise it. We have carefully considered all the comments raised by the reviewer. We hope that the revised version now meets the quality standards for publication. Detailed responses to each comment are provided below (blue text indicates our responses and black text indicates the original comments).

Comment 1: Several figures (e.g., Figures 4-7) contain dense scatter plots and parallel coordinate lines that are difficult to interpret at first glance. Adding brief quantitative annotations (e.g., correlation coefficients or key threshold markers) would improve readability and interpretability.

Response: Thank you for this helpful suggestion. We have revised the relevant figures as follows to improve their readability.

In the revised Figure 4, black solid lines are used to highlight the optimal solutions for the four single-objective optimizations, corresponding to maximum economic benefit (f_{AB}), maximum groundwater level rise (f_{GL}), maximum lake area (f_{LA}), and minimum nitrogen load (f_{TN}). The compromise solution is indicated by a red solid line, and this has been clearly explained in the legend.

In the revised Figures 5-7, text annotations identifying the single-objective optimal solutions and the compromise solutions (S5, S10, and S15) have been added to each subplot.

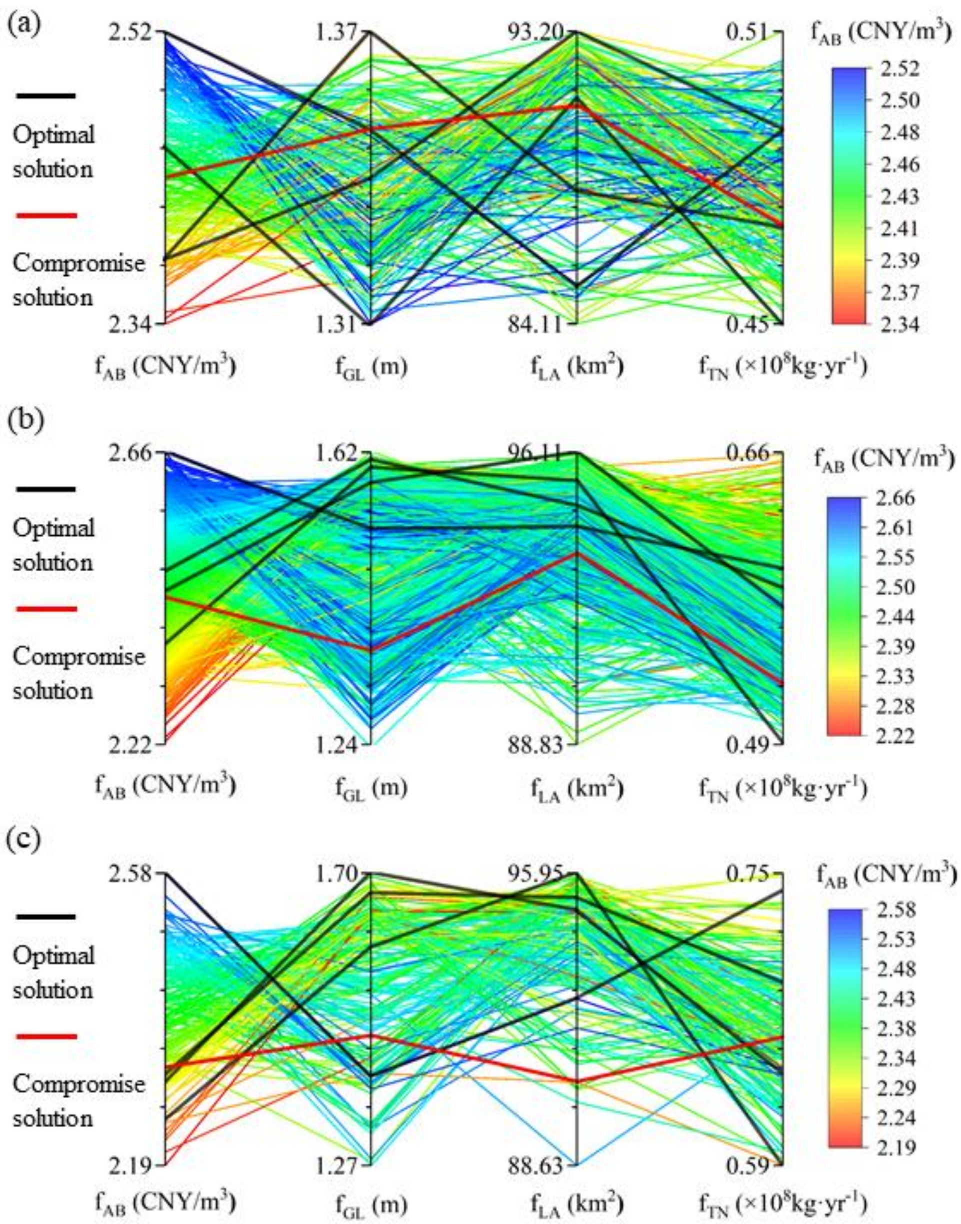

Figure 4. Objective values (y axis) plotted against management objectives f_{AB}, f_{GL}, f_{LA} and f_{TN}, with panels (a, b, c) representing dry, normal, and wet years, respectively.

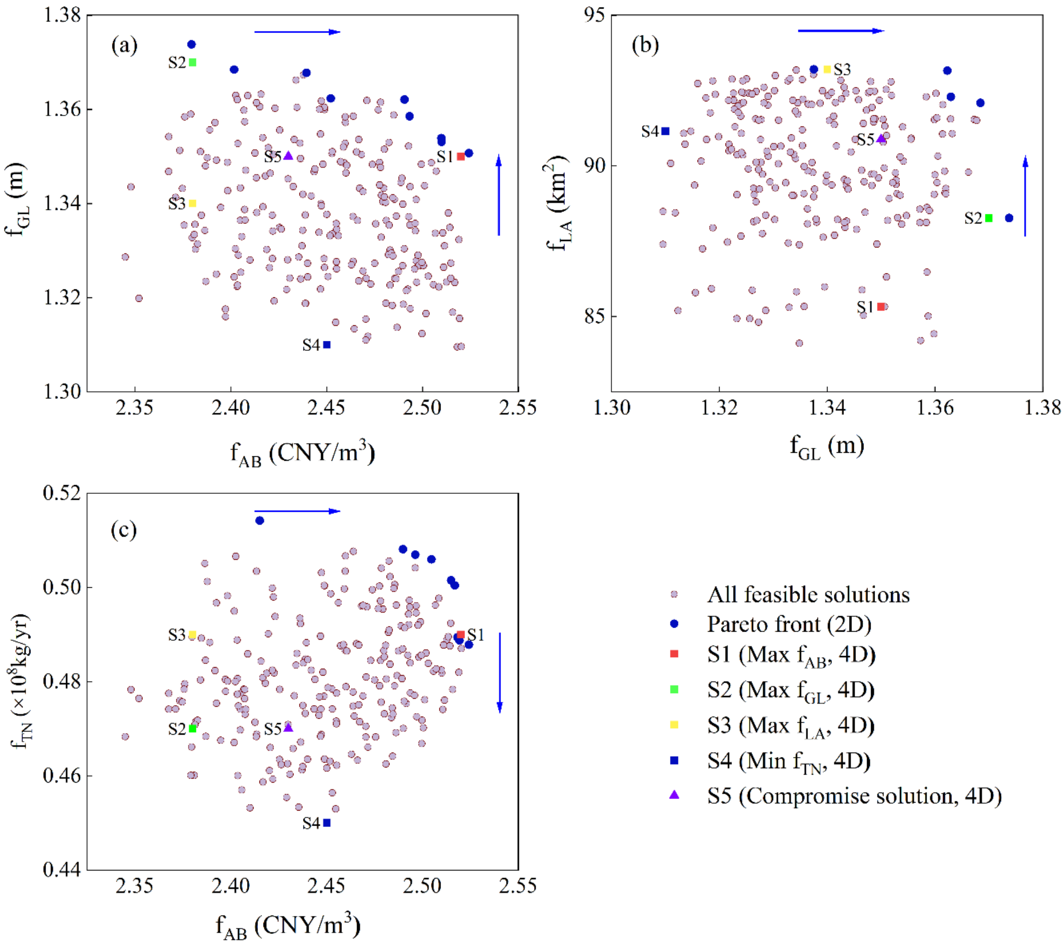

Figure 5. Scatter plots for optimization in a dry year exhibiting the correlation between each pair of objectives, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Each dot represents a feasible solution. The representative solutions for dry scenario (S1-S5) can be identified by rectangles with different color. The navy-blue arrow indicates the direction of Pareto optimality.

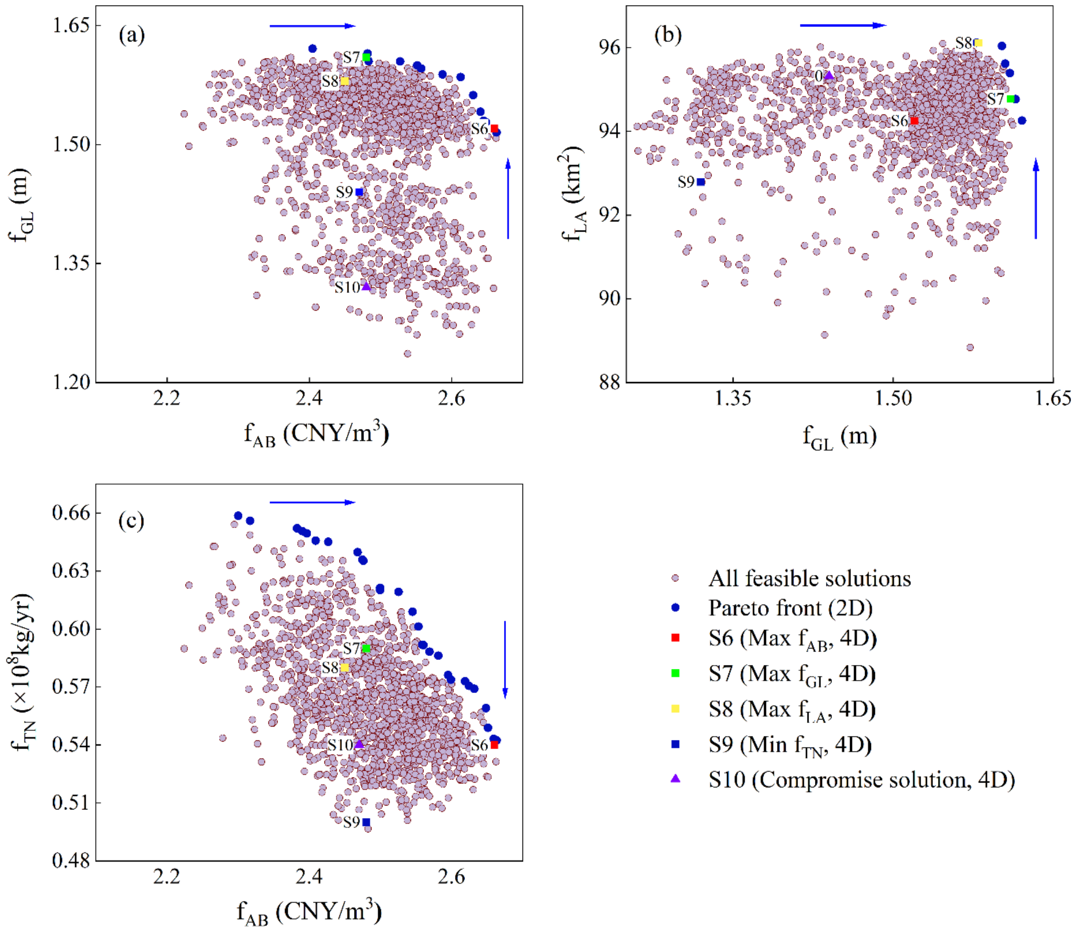

Figure 6. Scatter diagrams depicting correlations among objective pairs in a normal year, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Representative normal-year solutions (S6-S10) are marked using colored rectangles.

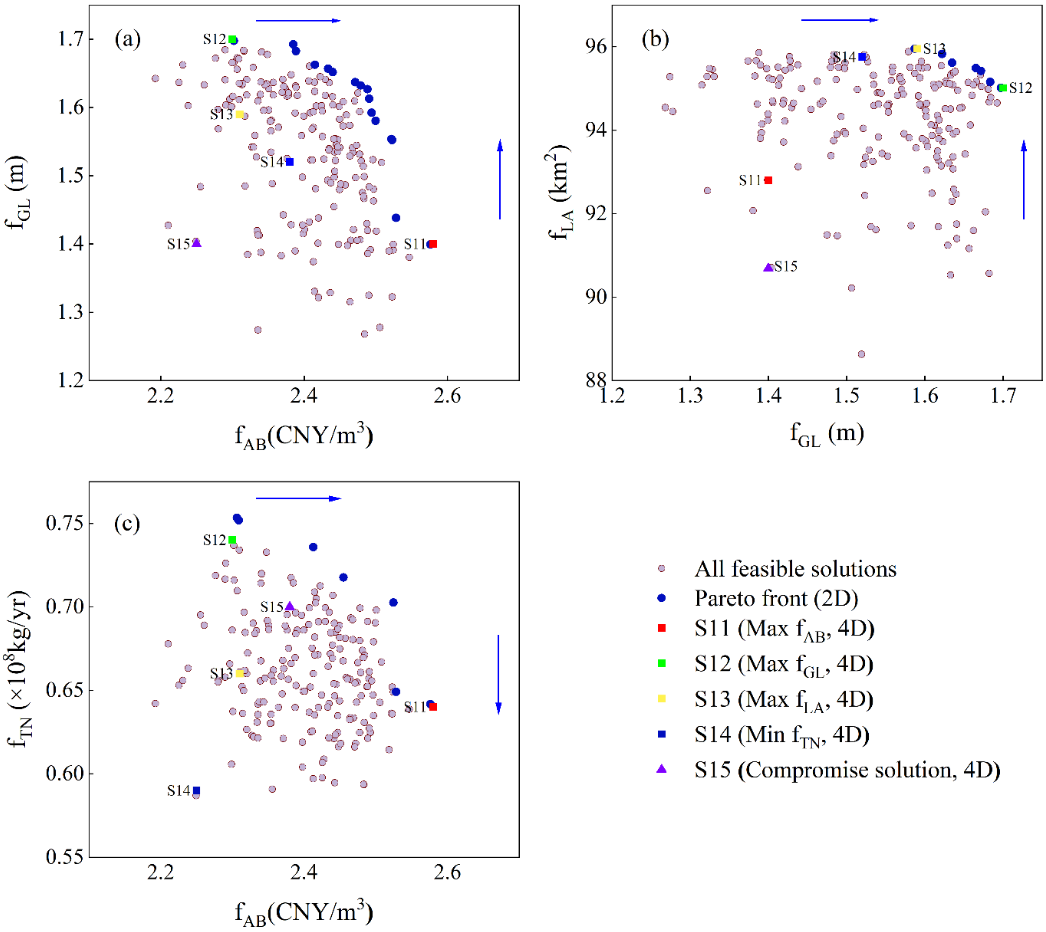

Figure 7. Scatter diagrams depicting correlations among objective pairs under a wet year, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Representative wet-year solutions (S11-S15) are marked using colored rectangles.

Comment 2: The manuscript alternates between the terms WEA and WAE when referring to the water-ecosystem-agriculture system. Please standardize terminology throughout the text for consistency.

Response: Thank you for pointing out this issue. We have carefully checked the entire manuscript and standardized the terminology by consistently using "WEA" as the abbreviation for Water-Ecosystem-Agriculture. All occurrences of "WAE" have been corrected to "WEA."

Comment 3: Although the surrogate model performance is strong (R^2 =0.98), the paper would benefit from explicitly stating how surrogate prediction errors may influence decision-making, especially near Pareto front extremes where trade-offs are most sensitive.

Response: Thank you for this important suggestion. In the extreme trade-off regions of the Pareto front, the objective functions may be more sensitive to inputs, including potential errors in the surrogate model. As an approximation of the complex physical process model, uncertainty in the surrogate model predictions is inevitably present.

To evaluate how this uncertainty affects the performance of the optimized solutions, we validated all Pareto-optimal solutions obtained using the surrogate model. Specifically, each optimal solution was re-evaluated using the original GSFLOW model to compute the corresponding objective values, and the results were compared with the surrogate model predictions. The Relative Deviation (RD) was used to quantify the difference between the original model results and the surrogate model predictions:

$$RD_j = \frac{|f_{pre,j} - f_{post,j}|}{f_{post,j}}$$

where RD_j represents the relative deviation for the j-th management objective, $f_{pre,j}$ is the predicted value from the surrogate model, and $f_{post,j}$ is the simulated value from the original GSFLOW model.

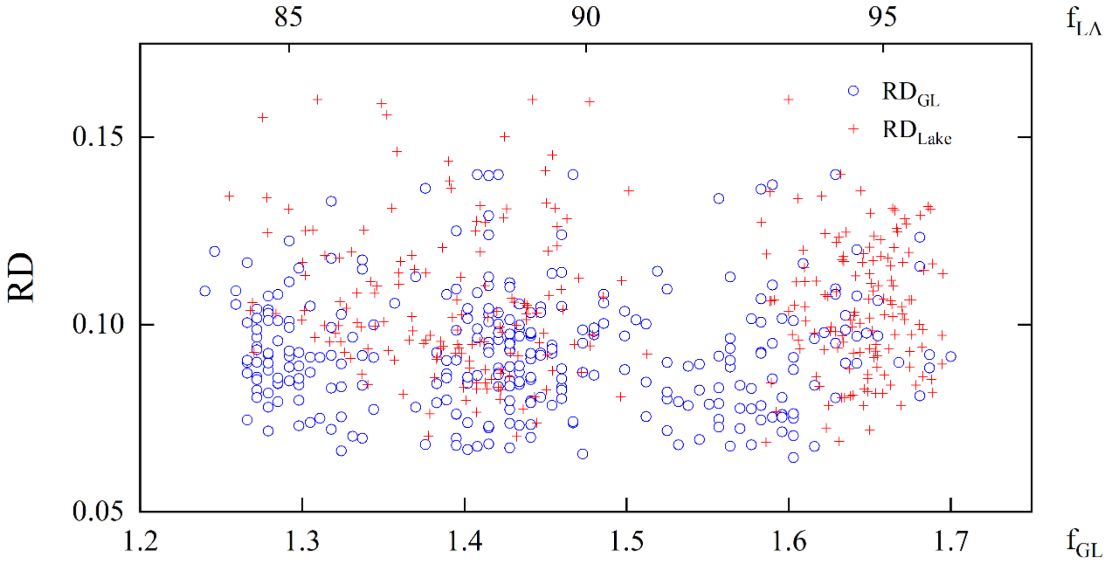

Figure R1. RD values of the surrogate model for Pareto optimal solutions across different management objectives.

The RD for each management objective among the Pareto-optimal solutions is shown in Figure R1. The results indicate that the RD values are slightly higher at the two ends of the Pareto front than in other regions of the front, but they generally remain below 0.15. This suggests that although prediction errors of the surrogate model are somewhat amplified in these sensitive regions, their impact on the final solution performance remains within a controllable range. In contrast, in the remaining regions of the Pareto front, more than 90% of the solutions exhibit RD values below 0.1, indicating strong predictive robustness.

Overall, these results suggest that the prediction errors of the surrogate model have an acceptable influence on the actual performance of decision solutions. The Pareto solution set identified through surrogate-based optimization and subsequently verified using the original model can provide decision-makers with a series of management strategies that are both reliable in practical performance and feasible for implementation.

Comment 4: While the study carefully calibrates the coupled SRM-GSFLOW model and validates the surrogate RBF-NN, uncertainty is not explicitly propagated through the optimization results. Key sources of uncertainty, such as climate forcing, groundwater parameters, crop water requirements, and fertilizer coefficients, may significantly affect Pareto fronts and identified "compromise solutions." I recommend to add this limitation in the conclusion part.

Response: We fully agree with the reviewer that systematically addressing uncertainty is essential for improving the reliability of management decisions. To address this issue, we have added a paragraph in Section 5.2 "Limitations of the study" (line 571- 583).

"*Multiple sources of uncertainty have not yet been systematically quantified or propagated through the optimization process. Key inputs, including climate forcing data, hydrogeological parameters, crop water requirement coefficients, and fertilizer-related parameters, all contain uncertainties that may accumulate and propagate step by step, affecting the shape and range of the Pareto front as well as the stability of compromise solutions. In addition, scale transformation during model construction - coupling basin-scale hydrological simulations with grid-based land use and crop distribution data - introduces errors from spatial scaling and parameter aggregation that are difficult to fully quantify. The influence of future climate change on runoff patterns and crop water requirements has also not been explicitly addressed. Future research may introduce a Hierarchical Bayesian Model (Wu et al., 2010) to quantify and control the impacts of different uncertainty sources on optimization solutions, providing more robust management strategies for decision makers. Including climate change scenarios constitutes another key avenue for future studies.*"

Reference

Wu, W., Clark, J. S., and Vose, J. M.: Assimilating multi-source uncertainties of a parsimonious conceptual hydrological model using hierarchical Bayesian modeling, J. Hydrol., 394, 436-446, https://doi.org/10.1016/j.jhydrol.2010.09.017, 2010.

Comment 5: I do strongly suggest that the authors consider relevant studies that have explored the "assimilation of Sentinel-derived leaf area index to improve the representation of surface-groundwater interactions in irrigation districts". Citing and briefly discussing such work would strengthen the linkage between the proposed framework and existing literature.

Response: Thank you for this valuable suggestion. We fully agree that assimilating remotely sensed vegetation indices into hydrological models is an effective way to improve the representation of surface water-groundwater interactions and is also an important direction for future improvement in this study. Following your suggestion, we have added the following discussion at the end of Section 5.2 (Limitations of the Study) and cited the relevant literature (line 591-603).

"Although the GSFLOW model can simulate coupled surface water-groundwater processes, its representation of vegetation mainly relies on predefined crop coefficients and canopy parameters, which makes it difficult to fully capture the spatiotemporal dynamics of vegetation growth and their influence on the hydrological cycle. Recent studies have shown that assimilating satellite-derived vegetation indices (e.g., Leaf Area Index, LAI) into hydrological models can significantly improve simulations of evapotranspiration, soil moisture, and groundwater recharge. For example, studies by Paul et al. (2021), Bian et al. (2019), and Li et al. (2009) demonstrated that assimilating MODIS-LAI data can effectively improve watershed-scale runoff and evapotranspiration simulations. At the irrigation district scale, Zafarmomen et al. (2024) further showed that assimilating high-resolution Sentinel-2 LAI into hydrological models can more accurately represent the effects of vegetation dynamics on evapotranspiration, irrigation return flows, and groundwater recharge, thereby improving the simulation of surface water-groundwater interactions. Future research could build upon these approaches by assimilating multi-source remote sensing LAI data into the coupled modeling framework used in this study, thereby improving the representation of hydrological processes, particularly the effects of ecological water replenishment, and providing more reliable distributed hydrological state information for multi-objective optimization."

References

Bian, Z., Gu, Y., Zhao, J., Pan, Y. E., Li, Y., Zeng, C. and Wang, L.: Simulation of evapotranspiration based on leaf area index, precipitation and pan evaporation: A case study of Poyang lake watershed, China, Ecohydrol. Hydrobiol., 19(1), 83-92, https://doi.org/10.1016/j.ecohyd.2018.03.005, 2019.

Li, H., Zhang, Y., Chiew, F. H. and Xu, S.: Predicting runoff in ungauged catchments by using Xinanjiang model with MODIS leaf area index, J. Hydrol., 370(1-4), 155-162, https://doi.org/10.1016/j.jhydrol.2009.03.003, 2009.

Paul, M., Rajib, A., Negahban-Azar, M., Shirmohammadi, A. and Srivastava, P.: Improved agricultural water management in data-scarce semi-arid watersheds: Value of integrating remotely sensed leaf area index in hydrological modeling, Sci. Total Environ., 791, 148177, https://doi.org/10.1016/j.scitotenv.2021.148177, 2021.

Zafarmomen, N., Alizadeh, H., Bayat, M., Ehtiat, M., and Moradkhani, H.: Assimilation of Sentinel-based leaf area index for modeling surface-ground water interactions in irrigation districts, Water Resour. Res., 60, e2023WR036080, https://doi.org/10.1029/2023WR036080, 2024.

Response to RC1

We sincerely thank the reviewer for the positive evaluation of our manuscript and for providing the opportunity to revise it. We have carefully considered the comments raised by the reviewer. We hope that the revised manuscript now meets the quality standards for publication. Detailed responses to the review comments are provided below (blue text indicates our responses and black text indicates the original comments).

Specific Comments

Comment 1: Regarding the construction of the surrogate model, the current description of its input variables (e.g., which key GSFLOW parameters or optimization decision variables are included), the size and dimensionality of the training sample set generated via Latin Hypercube Sampling, as well as the method and specific proportion for dividing the training and test sets, remains insufficient. Additional explanation is needed.

Response: Thank you for pointing out this deficiency. We have supplemented the description of the surrogate model construction process in Section 3.3 of the revised manuscript (line 321-330).

"To elaborate further, the input variables of the surrogate model are the decision variables to be optimized. Specifically, they include the planting areas of six major crops (cotton, maize, oil crops, vegetables, melons, and fruits) across seven irrigation zones, as well as the allocation coefficients of ecological water use during key months (May-September), resulting in a total of 47 decision variables. The output variables of the surrogate model consist of two hydrological variables simulated by the coupled hydrological model (GSFLOW), namely the change in the average groundwater depth in the study area and the area of the terminal lake. For surrogate construction, Latin hypercube sampling was first applied to generate samples within the input variable space. Each sample set was then used as input to the GSFLOW model to obtain the corresponding outputs, thereby forming an input-output dataset. The dataset was subsequently randomly divided into a training set (70%) and a test set (30%). The training set was used to train the radial basis function neural network (RBF-NN), while the testing set was used to evaluate the predictive accuracy and generalization

capability of the surrogate model."

Comment 2: Although the paper mentions that model results still require validation with field data, the discussion of potential real-world constraints during the implementation of the proposed solutions is not yet sufficient. It is recommended to supplement the analysis by discussing the potential impacts of the Pareto-optimal solutions-such as the suggested dynamic adjustments to cropland scale and planting structure-on local livelihoods (e.g., residents and the economy), regional agricultural production stability, and food security. This would strengthen the linkage between the research findings and actual management decision-making.

Response: We thank the reviewer for this important suggestion. We fully recognize that the implementation of the optimized solutions in practice needs to consider socio-economic constraints such as local livelihoods, agricultural stability, and food security. However, the primary objective of this study is to develop a coupled optimization framework centered on the water–ecology–agriculture physical system, with a focus on revealing the trade-offs among multiple objectives in the natural system and their regulation pathways, rather than providing a comprehensive assessment of socio-economic feasibility. Section 5.2 of the manuscript has also pointed out that the practical feasibility of the optimized solutions still requires further validation with field data, and acknowledges that the current model has not systematically incorporated socio-economic factors. Specifically, analyses of impacts on local livelihoods, agricultural production stability, and food security can be regarded as an important extension for translating natural optimization results into practical management decisions. In the future, these aspects can be further studied by incorporating regional economic models or farmer behavior models, so as to enhance the feasibility and social adaptability of the optimized solutions in real-world applications.

Comment 3: The paper notes that the estimation of agricultural non-point source pollution relies on a simplified model, but the explanation of the method's applicability assumptions and limitations could be further deepened. It is suggested to elaborate on the context in which the simplified method is applied in this study (e.g., its computational efficiency advantages in strategic, large-scale multi-objective optimization analyses) and to specify its main limitations more clearly, such as the inability to depict the transport and transformation processes of nitrogen in the "soil-groundwater-surface water" system. Building on this, a more targeted discussion could be provided regarding potential future improvements, such as coupling the hydrological model with a biogeochemical process model (e.g., MODFLOW-MT3DMS) to enhance the precision and reliability of pollutant simulation.

Response: Thank you for the reviewer's insightful comment. We have provided a more detailed description in the discussion section regarding pollution estimation in Section 5.2 (line 584-590).

"*This study employs the Export Coefficient Model to estimate agricultural nitrogen loads. This method offers high computational efficiency for strategic, long-term analyses at the watershed scale, making it suitable for the rapid assessment of pollution risks under multiple scenarios. However, as a static, spatially lumped empirical model, it is inherently limited in its ability to accurately describe the transport and transformation processes of nitrogen within the soil-groundwater system and their spatial heterogeneity under different irrigation or fertilization regimes. Therefore, the model is better suited for comparative analysis and relative risk assessment among different management schemes, rather than for the precise, process-based quantification and prediction of pollution.*"

Comment 4: The justification for selecting the compromise solutions (S5, S10, S15) in Section 4.2.2 is currently quite brief. It is recommended to supplement the explanation with the specific criteria and rationale used for choosing these compromise solutions, thereby increasing the feasibility and transparency of the proposed method.

Response: Thank you for pointing out this issue. We have supplemented the method for selecting compromise solutions in Section 4.2.2 (line 404-407).

"*The compromise solutions were identified using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), where normalized objective values were compared against ideal and negative-ideal solutions, and the solution closest to the ideal and farthest from the negative-ideal was selected.*"

Comment 5: It is suggested to add a technical workflow diagram in the Methods section to clearly illustrate the overall process and data flow among the key steps (e.g., SRM, GSFLOW, surrogate model, NSGA-III optimization). This would enhance the intuitive understanding of the framework's logic.

Response: We thank the reviewer for the suggestion. In response, we have added a schematic workflow in Section 3 “Methods” of the revised manuscript. The figure illustrates the complete processes, including input of basic data, coupled surface-groundwater model simulation, surrogate model training, NSGA-III multi-objective optimization, and decision support. It shows the logical relationships among the different modules.

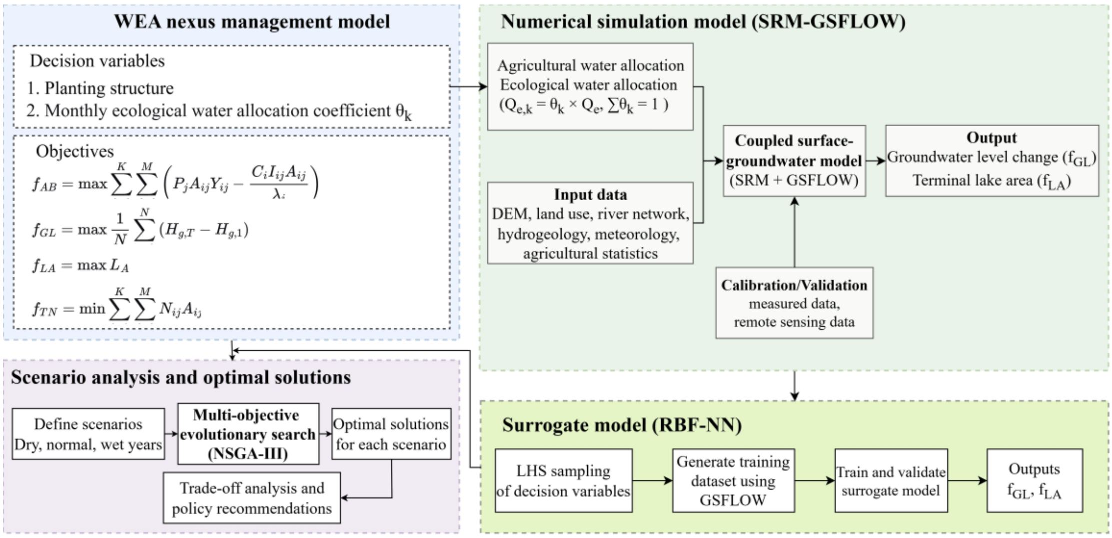

Figure R1. Framework of the multi-objective simulation-optimization for the WEA nexus management.

Minor Comments

1. It is recommended to unify the formatting for numerical ranges throughout the text, for example, consistently using the format "11.3×10^4 - 14.3×10^4 hm^2."

Response: Line 22. We have standardized the formatting of all numerical ranges throughout the manuscript according to the recommendation.

2. The thresholds used in Table 4 for classifying hydrological year types based on the runoff anomaly percentage (P) are not rigorously defined. It is recommended to use symbols such as "⩽" to clearly specify the interval boundaries.

Response: Line 371. We have revised Table 4, using the symbols “≤” and “<” to clearly define the interval boundaries for each hydrological year type.

3. The terminology for describing hydrological year types is inconsistent in the text. It is suggested to standardize the terms, for example, consistently using "wet/normal/dry year" throughout the main text, avoiding mixed usage with terms like "High/Low Flow Year."

Response: Line 371 and Line 510. In the revised manuscript, we have consistently used the terms “wet year,” “normal year,” and “dry year” to ensure terminological consistency.

4. There are errors in the sub-figure labels in Figure 9. The letters (f)-(l) overlap with (i)-(q), and the number of labeled sub-figures does not match the number of representative schemes described in the text. Please correct the labels according to the actual content.

Response: Line 514. We have checked and corrected Figure 9, ensuring that each sub-figure accurately corresponds to the 15 representative solutions (S1-S15) described in the text.

Response to RC2

We sincerely thank the reviewer for the positive evaluation of our manuscript and for providing the opportunity to revise it. We have carefully considered the comments raised by the reviewer. We hope that the revised manuscript now meets the quality standards for publication. Detailed responses to the review comments are provided below (blue text indicates our responses and black text indicates the original comments).

Specific Comments

Comment 1: This study adopts multiple methods, but the methodology appears somewhat overloaded and fragmented. It is recommended to briefly introduce the Data in this section and present the detailed information in the form of supplementary materials or appendices. Also, a flowchart is suggested here to clearly illustrate the integration of the adopted methods. Furthermore, the descriptions of the design of the GSFLOW model and the surrogate model are insufficient, and detailed information (e.g. parameters and variables for the surrogate model) is needed.

Response: Thank you for this important suggestion. We have revised and supplemented the methodology section as follows.

(1) We have added a schematic workflow in Section 3 "Methods" of the revised manuscript (line 180). The figure illustrates the complete processes, including input of basic data, coupled surface-groundwater model simulation, surrogate model training, NSGA-III multi-objective optimization, and decision support. It shows the logical relationships among the different modules.

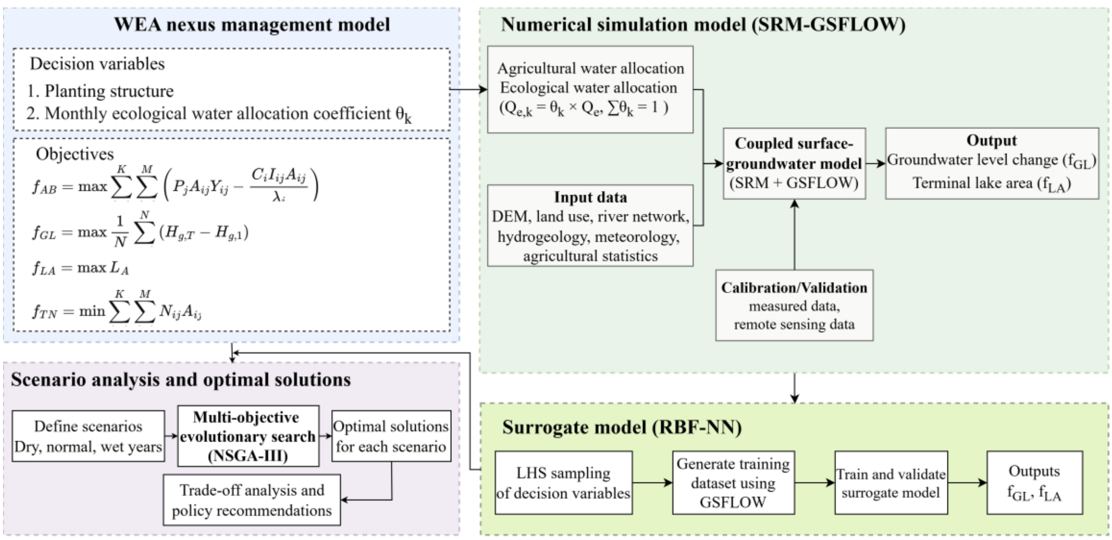

Figure R1. Framework of the multi-objective simulation - optimization for the WEA nexus management.

(2) Line 137- 169. The data section has been streamlined and structurally optimized. In the revised manuscript, the main text provides only a brief overview of the types of data used, their primary sources, and their roles in the study. The detailed information on the datasets, including sources, spatial and temporal resolutions, and specific applications and data processing procedures, as well as Table 1 from the original manuscript, have all been moved to the Supplementary Materials. The revised Section 2.2 (Data) and the dataset descriptions in the Supplementary Materials are provided below.

Revised text

2.2 Data

The datasets used in this research encompass topography, land use, climate, hydrogeology, and socio-economic information, with a primary temporal coverage from 2002 to 2021. Snow cover information was obtained from the High Asia MODIS daily snow cover fraction product developed by Qiu and Wang (2020). This dataset, derived using the MODIS Normalized Difference Snow Index (NDSI), offers daily data at a spatial resolution of 500 m and serves as a critical input for the snowmelt runoff model (SRM). Terrain-related information was sourced from the Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model (ASTER GDEM), which has a spatial resolution of 30 m (NASA/METI, 2019). These elevation data were used to extract terrain attributes, including slope, aspect, and river networks.

Land use, vegetation, and soil property data were obtained from multiple sources. Land cover information was obtained from the FROM-GLC dataset (Gong et al., 2013), soil properties were derived from the Harmonized World Soil Database (Wieder et al., 2014), and vegetation attributes were derived from the Vegetation Map of China (Li et al., 2017). Collectively, these datasets provided key inputs for simulating land surface processes and parameterizing soil-related processes in the coupled model.

Hydrogeological conditions were primarily derived from borehole data and regional hydrogeological maps reported by Li et al. (2003). Key parameters, including hydraulic conductivity and specific yield, were assigned based on dominant lithological units.

Meteorological forcing for the coupled surface water-groundwater model consisted of precipitation and temperature (maximum and minimum), which were obtained from the ERA5 reanalysis dataset (Hersbach et al., 2020). Model calibration *and validation for the groundwater component relied on monthly groundwater level measurements from 139 monitoring wells distributed throughout the study area (Xue et al., 2024).*

Daily streamflow records from five representative hydrological stations within the Tarim River Basin (2002-2021) were used to calibrate surface runoff simulations and model parameters.

To further evaluate the groundwater simulations of the GSFLOW model, terrestrial water storage anomaly (TWSA) data from the GRACE and GRACE-FO satellite missions (Save et al., 2016; Save, 2020) were used for model validation. In addition, the coupled model was cross-validated using evapotranspiration (GLEAM) (Martens et al., 2017) and soil moisture(Chinese Soil Moisture Dataset) (Mao, 2021; Meng et al., 2021). A comprehensive summary of all datasets employed in this study is provided in Supplementary Table S1.

Socio-economic data were primarily collected from the China Statistical Yearbook (National Bureau of Statistics, 2002-2021), Xinjiang Water Resources Bulletin (Xinjiang Water Resources Department, 2002-2021), and the National Agricultural Product Cost-Benefit Compilation together with annual crop price statistics (Ministry of Agriculture and Rural Affairs of Xinjiang, 2002-2024). These datasets provide information on crop planting areas, yields, and fertilizer and pesticide application rates.

Supplementary Materials

S1 Data sources and preprocessing

This section provides detailed information on the datasets used in this study, including their sources, spatial and temporal resolutions, and specific applications, supplementing the brief description in Section 2.2 (Data).

The datasets employed in this study primarily include meteorological forcing data, remote sensing products, hydrological observations, and model validation data. Surface runoff and snowmelt runoff data were obtained from the GLDAS-2.1 Noah model product, spatially downscaled to a 2 km × 2 km resolution, and further aggregated to daily values to drive the GSFLOW model. Meteorological variables, including precipitation, daily maximum temperature, and daily minimum temperature, were derived from the ERA5 reanalysis dataset and similarly downscaled for use as model inputs.

GRACE data were obtained from the RL06 Mascon Level-3 product released by *the Center for Space Research (CSR) at the University of Texas at Austin, covering the period from April 2002 to December 2021. Missing monthly values were filled using cubic spline interpolation. For the gap between the GRACE and GRACE-FO missions (July 2017 to May 2018), terrestrial water storage reconstruction data developed by Zhong et al. (2019, 2020) were used to ensure a continuous time series. Monthly terrestrial water storage change (TWSC) was calculated from the TWSA series as follows:*

$$TWSC(t) = TWSA(t) - TWSA(t-1)$$

where TWSC(t) represents the change in terrestrial water storage (mm) during month t, and TWSA(t) represents the corresponding storage anomaly.

Detailed information on the spatial and temporal resolutions of these datasets and their specific applications is provided in Supplementary Table S1.

***Table S1.** Data for the coupled hydrology-agriculture optimization framework.*

Data	**Dataset / Source**	**Spatial & Temporal Resolution**	**Usage**
Snow cover	High Asia MODIS daily snow cover fraction dataset	500 m| Daily	Model input
Climate forcing	ERA5 reanalysis	0.25°×0.25°| hourly	Model input
Topography	ASTER GDEM	30 m	Model input
Hydrogeology	hydrogeological maps, borehole data	Site-specific	Model input
Land surface	FROM-GLC, HWSD, Vegetation Map of China,	Dataset-specific	Model input
Socio-economic data	XSB, XWRB, NAPCBC & ARAX	Annual	Model input
Groundwater level	Monitoring wells	Monthly	Model validation
Terrestrial water storage changes	GRACE/GRACE-FO (CSR RL06 Mascon)	0.25°×0.25°| month	Model validation
Evapotranspiration	GLEAM	0.25°×0.25°|monthly	Model validation
Soil moisture	Soil Moisture in China dataset	0.05°×0.05°|monthly	Model validation

(3) Line 192-196. In Section 3.1.1, a brief introduction to the GSFLOW model has been added.

"*GSFLOW is a physically based distributed coupled hydrological modeling system that integrates the PRMS (Precipitation-Runoff Modeling System) surface hydrological process module with the MODFLOW groundwater flow module to simulate surface water-groundwater interactions at the watershed scale (Markstrom et al., 2008). The* *model is capable of simulating key hydrological processes such as precipitation, evapotranspiration, infiltration, surface runoff, groundwater recharge, and stream-aquifer exchange.*"

(4)Line 321-330. In Section 3.3 "Surrogate Model Construction and Validation," additional details regarding the construction of the surrogate model have been provided.

"*To elaborate further, the input variables of the surrogate model are the decision variables to be optimized. Specifically, they include the planting areas of six major crops (cotton, maize, oil crops, vegetables, melons, and fruits) across seven irrigation zones, as well as the allocation coefficients of ecological water use during key months (May-September), resulting in a total of 47 decision variables. The output variables of the surrogate model consist of two hydrological variables simulated by the coupled hydrological model (GSFLOW), namely the change in the average groundwater depth in the study area and the area of the terminal lake. For surrogate construction, Latin hypercube sampling was first applied to generate samples within the input variable space. Each sample set was then used as input to the GSFLOW model to obtain the corresponding outputs, thereby forming an input-output dataset. The dataset was subsequently randomly divided into a training set (70%) and a test set (30%). The training set was used to train the radial basis function neural network (RBF-NN), while the testing set was used to evaluate the predictive accuracy and generalization capability of the surrogate model*."

Comment 2: The findings of this study need to be further discussed to enhance the value of the manuscript. It is recommended to discuss the advantages and limitations of the multi-objective optimization framework used in this study compared with previous research (e.g. for single methods or combinations of two methods). It would greatly increase the significance of the study, if quantitative comparison can be presented. The discussion could also be strengthened by addressing how the findings of this study could be applied to other regions. This may involve identifying which of the datasets used has the greatest impact on the results, as well as considering how errors from different datasets could limit the applicability of the methodology in other areas.

Response: Thank you for the reviewer's comment. We have added the following discussion in Section 5.1 "Implications for WEA Synergistic Management and Adaptation in Arid Basin Regions" (line 549-564).

"*Compared to previous studies in the Tarim River Basin that primarily focused on single or dual objectives, the multi-objective optimization framework developed in this study provides a more comprehensive analytical approach for coordinating WEA conflicts. By integrating a coupled surface water-groundwater model with multi-objective decision-making methods, this framework transforms ecological responses from static constraints into optimization objectives that can be dynamically adjusted with management strategies. This approach enhances the ability to characterize the relationship between agricultural water use and ecological feedback. Although simplifications in the coupled hydrological model are inevitable, it still provides a more structured cognitive perspective for analyzing trade-offs within the WEA system.*

When this method is to be extended to other basins, its applicability does not depend on the simple transplantation of models or data, but on the ability to implement spatially differentiated management according to local conditions. For example, in regions lacking hydrogeological data, a more generalized hydrological model could be used to represent water cycle processes. When the accuracy of crop spatial distribution data is limited, statistical data can be used to impose total area constraints at the regional scale. Furthermore, attention should be paid to uncertainty factors that significantly influence the optimization results (such as key hydrogeological parameters and agricultural management parameters), and their impact on decision-making outputs should be quantified through sensitivity analysis to provide necessary risk warnings for practical applications. The research framework presented in this study may provide useful insights for other basins facing similar water resource challenges, although it should be further adapted and validated according to local conditions."

Minor Comments

1. Line 23 Please unify the units used in the manuscript, such as hm, km, etc., throughout the text.

Response: We have standardized and unified the units throughout the manuscript. The area unit has been consistently expressed as hm^2, and the volume unit has been consistently expressed as 10^4 m^3.

2. Line 51 References should be added here. Also, references are lacked in some parts of the remain Introduction.

Response: Line 52-58. We have added the requested references at Line 51 and throughout the relevant parts of the Introduction.

"The mainstream reach of the Tarim River Basin represents a representative arid inland river system in China (Wang et al., 2020). Agricultural production in this region is highly dependent on hydraulic infrastructure and is characterized by intensive irrigated agriculture (Hartmann et al., 2016). Long-term and large-scale abstraction of groundwater and diversion of surface water for irrigation have supported regional agricultural development and food security. However, these practices have also resulted in pronounced ecosystem degradation, manifested by declining groundwater levels, intensified desertification, and the shrinkage of terminal lakes (Lu et al., 2026; Zhang et al., 2013; Pang et al., 2010). Consequently, the need to balance agricultural water use with ecosystem stability has become a critical concern for the oversight of water resources in the Tarim River Basin."

References

Hartmann, H., Snow, J. A., Su, B., and Jiang, T.: Seasonal predictions of precipitation in the Aksu-Tarim River basin for improved water resources management, Glob. Planet. Change, 147, 86-96, https://doi.org/10.1016/j.gloplacha.2016.10.018, 2016.

Lu, C., Feng, Q., Gao, X., Liu, W., and Ning, T.: Human-water adaptation in drylands: Reconciling water use and ecological security in arid inland river basins of China, J. Clean. Prod., 542, 147561, https://doi.org/10.1016/j.jclepro.2026.147561, 2026.

Pang, Z., Huang, T., and Chen, Y.: Diminished groundwater recharge and circulation relative to degrading riparian vegetation in the middle Tarim River, Xinjiang Uygur, Western China, Hydrol. Process., 24, 147-159, https://doi.org/10.1002/hyp.7438, 2010.

Wang, W., Chen, Y., and Wang, W.: Groundwater recharge in the oasis-desert areas of northern Tarim Basin, Northwest China, Hydrol. Res., 51, 1506-1520, https://doi.org/10.2166/nh.2020.071, 2020.

Zhang, X., Chen, Y., Li, W., Yu, Y., and Sun, Z.: Restoration of the lower reaches of the Tarim River in China, Reg. Environ. Change, 13, 1021-1029, https://doi.org/10.1007/s10113-013-0403-0, 2013.

3. Line 83-87 This paragraph is unnecessary.

Response: According to your suggestion, we have removed the content in Lines 83-87 to improve the conciseness and logical coherence of the manuscript.

4. Line 158 This is the first time GSFLOW appears, and it is recommended to provide a brief introduction. However, since this section is actually about the Data, please briefly introduce GSFLOW in the appropriate place.

Response: Line 192-196**.** Thank you for this suggestion. We have added a brief introduction to the GSFLOW model in Section 3.1.1 of the Methods section.

"*GSFLOW is a physically based distributed coupled hydrological modeling system that integrates the PRMS (Precipitation-Runoff Modeling System) surface hydrological process module with the MODFLOW groundwater flow module to simulate surface water-groundwater interactions at the watershed scale (Markstrom et al., 2008). The model is capable of simulating key hydrological processes such as precipitation, evapotranspiration, infiltration, surface runoff, groundwater recharge, and stream-aquifer exchange.*"

5. Line 261 Please unify the use of these symbols.

Response: Line 256 - 298. We have comprehensively checked and unified the formulas and symbols in Section 3.2 and throughout the manuscript to ensure consistency in variable definitions and symbol usage.

(1) Groundwater depth is expressed as D, and groundwater level is expressed as H;

(2) The subscript for groundwater grid cells is uniformly expressed as g, thus $H_{g,T}$ and $H_{g,1}$ replace the previous H_{iT} and H_{i1}; the symbol i is used only to represent agricultural zones;

(3) A new subscript j is introduced to represent crop types (j = 1,…, M, where M = 6, representing maize, cotton, vegetables, melons, fruit trees, and oil crops);

(4) Agricultural economic benefit (Equation 10): the double-subscript variables A_{ij}, Y_{ij}, and I_{ij} are introduced to replace the previous single-subscript variables, indicating that these variables are determined by both agricultural zone and crop type;

(5) Total nitrogen load (Equation 13): N_{ij} replaces the previous N_i, indicating that this variable is determined by both agricultural zone and crop type;

(6) The water surface area of Taitema Lake is consistently represented as L_A in both the constraints and the objective functions.

6. Line 503 The order of the subfigures in the figure captions does not match their actual order.

Response: Line 513. Thank you for pointing out this issue in the figure. We have checked and redrawn Figure 9, ensuring that the subfigure labels from (a) to (o) correspond sequentially to the 15 representative solutions (S1-S15) discussed in the text.

Response to RC3

We sincerely thank the reviewer for the insightful evaluation of our manuscript and for the opportunity to revise it. The reviewer's comments are of great significance for improving the academic rigor, transparency, and reproducibility of the paper. We have carefully considered the comments raised by the reviewer. We hope that the revised manuscript now meets the quality standards for publication. Detailed responses to the review comments are provided below (blue text indicates our responses and black text indicates the original comments).

Specific Comments

1.There are multiple citations within the manuscript that are not added to the reference list. This prevented me from assessing the quality of the data the authors used and from corroborating some of their assumptions and interpretations. This is something the authors need to correct to maintain the overall integrity of their work. I strongly encourage the authors to review the manuscript and verify that all their references are included. Here are some of the ones I found missing.

1. Line 59, "Chen (2018)".
2. Line 125, "Liao et al. (2020)."
3. Line 148 "Li et al. (2003)."
4. Line 156 "Xue et al. (2024)"
5. Line 160 "(Save et al., 2016; Save, 2024)"
6. Line 162 "Zhong et al. (2019)."
7. Line 198 "Chen et al. (2025)."
8. Line 306 "Deb and Jain (2014)."
9. Line 534 "Taon et al. (2012)."
10. Line 593 "Miralles et al. (2011)"

Response: We sincerely thank the reviewer for carefully pointing out the missing references in the reference list. We deeply apologize for this oversight and appreciate your help in improving the academic rigor and completeness of the manuscript.

Following your suggestion, we have conducted a systematic check of all references throughout the manuscript, comparing the in-text citations with the reference list one by one to ensure that all cited literature is correctly included. The missing references identified by the reviewer have now been added to the reference list, and the corresponding citations in the manuscript have been verified and updated.

The newly added references mainly include the following (listed according to their order of appearance in the manuscript):

Chen, S.: Optimal allocation of water resources in the Tarim River mainstream based on "three red lines", Master thesis, Huazhong University of Science and Technology, https://doi.org/10.27157/d.cnki.ghzku.2019.003542, 2019.

Liao, S., Xue, L., Dong, Z., Zhu, B., Zhang, K., Wei, Q., Fu, F., and Wei, G.: Cumulative ecohydrological response to hydrological processes in arid basins, Ecol. Indic., 111, 106005, https://doi.org/10.1016/j.ecolind.2019.106005, 2020.

Li, W., Hao, A., Liu, Z., and Wan, L. Research on Prospective Areas for Groundwater Exploration in the Tarim Basin[M]. Beijing: Geological Publishing House, 2003. 149p. ISBN 7-116-03169-3. (In Chinese)

Xue, D., Gui, D., Ci, M., Liu, Q., Wei, G., and Liu, Y.: Spatial and temporal downscaling schemes to reconstruct high-resolution GRACE data: A case study in the Tarim River Basin, Northwest China, Sci. Total Environ., 907, 167908, https://doi.org/10.1016/j.scitotenv.2023.167908, 2024.

Save, H., Bettadpur, S., and Tapley, B. D.: High resolution CSR GRACE RL05 mascons, J. Geophys. Res.-Sol. Ea., 121, 7547-7569, https://doi.org/10.1002/2016JB013007, 2016.

Save, H.: CSR GRACE and GRACE-FO RL06 mascon solutions v02, [data set], https://doi.org/10.15781/cgq9-nh24, 2020.

Zhong, Y., Feng, W., Zhong, M., and Ming, Z.: Dataset of reconstructed terrestrial water storage in Mainland China based on precipitation (2002-2019), National Tibetan Plateau/Third Pole Environment Data Center, [data set], https://doi.org/10.11888/Hydro.tpdc.270990, 2020.

Chen, D., Zeng, X., Gui, D., Wang, D., and Wu, J.: Quantifying the hydrological processes in the Tarim River Basin, China, using a coupled groundwater/surface water model, Hydrogeol. J., 33, 1637-1661, https://doi.org/10.1007/s10040-025-02947-7, 2025.

Deb, K. and Jain, H.: An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints, IEEE T. Evolut. Comput., 18, 577-601, https://doi.org/10.1109/TEVC.2013.2281535, 2014.

Tao, J., Zuo, Q., Xue, H., Wang, Y., and Zhang, L.: Control indicators and determination method of the "three red lines" in the strictest water resources management system, Water Sav. Irrig., (4), 64-67, https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD&filename=JSGU201204019, 2012.

Miralles, D. G., De Jeu, R. A. M., Gash, J. H., Holmes, T. R. H., and Dolman, A. J.: Magnitude and variability of land evaporation and its components at the global scale, Hydrol. Earth Syst. Sci., 15, 967-981, https://doi.org/10.5194/hess-15-967-2011, 2011.

2. The paragraphs starting in lines 95, 99, 107, 111, 115, and 120 contain information related to the study area. Is this information calculated by the authors, or does it come from other studies? I encourage the authors to include references to the source of this information for transparency. This includes the reports related to the Ecological Water Conveyance Project (EWCP) that are mentioned but not referenced in the manuscript.

Response: Thank you for this important suggestion. The information on natural geographic conditions, climatic characteristics, land use, and ecological restoration background of the study area mainly comes from published literature and official statistical reports, rather than being calculated by this study. Following the reviewer's suggestion, we have added the corresponding references at the relevant locations.

Line 95: "The region exhibits a temperate continental arid climate, characterized by an annual mean temperature of 10.6 °C and total precipitation below 80 mm, mainly occurring from May to August, while the annual potential evapotranspiration is over 2500 mm (Tuoliewubieke et al., 2025; Cui et al., 2024; Ling et al., 2014)."

Line 99: "The Tarim River mainstream stretches approximately 1321 km in a west-east direction and is typically categorized into upstream, midstream, and downstream sections (Cui et al., 2024; Chen et al., 2006)."

Line 107: "By 2015, approximately 1307 km^2 of land were under irrigation, of which about 1073 km^2 is cultivated land (Xinjiang Bureau of Statistics, 2016)."

Line 111: "The area contains several large irrigation districts, where water for irrigation is primarily drawn from the Tarim River mainstream, supplemented by groundwater (Hao et al., 2015)."

Line 115: "The downstream ecosystem is extremely fragile. Ecological degradation has intensified since the 1950s with the area of Populus euphratica forests decreasing by approximately 86% compared to historical conditions (Jiang et al., 2005)."

Line 120: "To mitigate ecological degradation in downstream reaches, China launched the Ecological Water Conveyance Project (EWCP) along the Tarim River mainstream in 2000, aiming to restore river connectivity, groundwater levels, and riparian vegetation in downstream areas (Gao et al., 2026; Wang et al., 2025; Jiao et al., 2022; Dou et al., 2022; Xu et al., 2007)."

References

Chen, Y., Takeuchi, K., Xu, C., Chen, Y., and Xu, Z.: Regional climate change and its effects on river runoff in the Tarim Basin, China, Hydrol. Process., 20(10), 2207-2216, https://doi.org/10.1002/hyp.6200, 2006.

Bureau of Statistics of Xinjiang Uygur Autonomous Region: Xinjiang Statistical Yearbook 2015, [data set], Xinjiang Bureau of Statistics Official Website, available at: https://tjj.xinjiang.gov.cn/, 2016.

Cui, B., Wang, G., Wei, G., Gui, D., Abd-Elmabod, S. K., Goethals, P., and Ahmed, Z.: Proactive policies are the key to reversing desertification in the main stream of the Tarim River in the past 30 years, J. Environ. Manage., 370, 122919, https://doi.org/10.1016/j.jenvman.2024.122919, 2024.

Dou, X., Ma, X., Huo, T., Zhu, J., and Zhao, C.: Assessment of the environmental effects of ecological water conveyance over 31 years for a terminal lake in Central Asia, CATENA, 208, 105725, https://doi.org/10.1016/j.catena.2021.105725, 2022.

Gao, B., Xu, J., Deng, M., and Ling, H.: Study on the synergistic effects of ecological water conveyance and climate change on ecological restoration in arid areas: a case study of the Tarim River Basin, Ecol. Eng., 222, 107793, https://doi.org/10.1016/j.ecoleng.2025.107793, 2026.

Hao, Z., Chen, S., Li, Z., Yu, Z., Shao, Q., Yuan, F., and Shi, F.: Quantitative assessment of the impacts of irrigation on surface water fluxes in the Tarim River, China, Hydrol. Res., 46(6), 996-1007, https://doi.org/10.2166/nh.2015.215, 2015.

Ling, H., Guo, B., Xu, H., and Fu, J.: Configuration of water resources for a typical river basin in an arid region of China based on the ecological water requirements (EWRs) of desert riparian vegetation, Global Planet. Change, 122, 292-304, https://doi.org/10.1016/j.gloplacha.2014.09.008, 2014.

Jiang, L., Chen, X., and Bao, A.: Analysis on the changing dynamics of groundwater level in the lower reaches of the Tarim River, Xinjiang, Arid Land Geogr., 28(1), 33-37, https://doi.org/10.13826/j.cnki.cn65-1103/x.2005.01.007, 2005. (In Chinese)

Jiao, A., Wang, W., Ling, H., Deng, X., Yan, J., and Chen, F.: Effect evaluation of ecological water conveyance in Tarim River Basin, China, Front. Environ. Sci., 10, 1019695, https://doi.org/10.3389/fenvs.2022.1019695, 2022.

Tuoliewubieke, D., Yao, J., Mao, W., Chen, P., Ma, L., Chen, J., and Li, S.: Dominant spring precipitation anomaly modes and circulation characteristics in the Tarim Basin, Central Asia, Atmos. Res., 313, 107767, https://doi.org/10.1016/j.atmosres.2024.107767, 2025.

Wang, X., Xu, H., Liu, K., Zhao, X., Wei, G., Aili, A., and Zheng, G.: Ecological water conveyance-driven wetland hydrological connectivity and morphological changes in arid regions: an analysis of the Taitema Lake wetland, J. Environ. Manage., 385, 125615, https://doi.org/10.1016/j.jenvman.2025.125615, 2025.

Xu, H., Ye, M., Song, Y., and Chen, Y.: The natural vegetation responses to the groundwater change resulting from ecological water conveyances to the lower Tarim River, Environ. Monit. Assess., 131, 37-48, https://doi.org/10.1007/s10661-006-9455-7, 2007.

3. Clarifications are needed regarding the data and model construction.

3.1. The authors mentioned that the surface water and groundwater systems within the region are closely connected (lines 102-103). Is this a result of this study or of other studies? Please clarify and add proper references.

Response: Thank you for the correction. This statement is based on the consensus from previous research, not first proposed in our study. The interaction between surface water and groundwater in the Tarim River Basin has been systematically analyzed in multiple studies. We have added the relevant references in the revised manuscript and cited them at the appropriate locations to clarify the reliability of this statement.

References

Chen, D., Zeng, X., Gui, D., Wang, D., and Wu, J.: Quantifying the hydrological processes in the Tarim River Basin, China, using a coupled groundwater/surface water model, Hydrogeol. J., 33, 1637-1661, https://doi.org/10.1007/s10040-025-02947-7, 2025.

Li, Z., Wang, Y., Chang, J., Guo, A., Wang, L., Niu, C., Hu, R., and He, B.: Multi-objective double layer water optimal allocation and scheduling framework combing the integrated surface water - groundwater model, Water Res., 262, 122141, https://doi.org/10.1016/j.watres.2024.122141, 2024.

Liu, Q., Hanati, G., Danierhan, S., Zhang, Y., and Zhang, Z.: Modeling of multiyear water-table fluctuations in response to intermittent artificial recharge, Hydrogeol. J., 29, 2397-2410, https://doi.org/10.1007/s10040-021-02388-y, 2021.

Schilling, O. S., Doherty, J., Kinzelbach, W., Wang, H., Yang, P. N., and Brunner, P.: Using tree ring data as a proxy for transpiration to reduce predictive uncertainty of a model simulating groundwater-surface water vegetation interactions, J. Hydrol., 519 (Part B), 2258-2271, https://doi.org/10.1016/j.jhydrol.2014.08.063, 2014.

3.2. The authors derived their hydrogeologic conditions from borehole and regional hydrogeologic maps reported by Li et al. (2003) (citation not presented in the reference list). I have a few questions regarding this data,

3.2.1. Are the authors looking at confined and unconfined aquifers? Have these aquifers been reported in the area? Is there any groundwater pumping that might alter their model assumptions or the water allocation parameter? I encourage the authors to provide this additional information and add potential limitations.

3.2.2. According to the authors, the hydrogeologic parameters were constrained based on the primary lithology and parameter ranges reported in previous studies (lines 149-150). However, there is no citation for this statement. I encourage them to provide the necessary references and a table or map containing geologic units and the hydraulic conductivity values selected, as this will enhance the reproducibility of their work.

Response: We sincerely thank the reviewer for the careful review and for pointing out the omission in the reference list. We apologize for this oversight and have added the following references to the revised manuscript.

References

Chen, D., Zeng, X., Gui, D., Wang, D., and Wu, J.: Quantifying the hydrological processes in the Tarim River Basin, China, using a coupled groundwater/surface water model, Hydrogeol. J., 33, 1637-1661, https://doi.org/10.1007/s10040-025-02947-7, 2025.

Li, W., Hao, A., Liu, Z., and Wan, L. Research on Prospective Areas for Groundwater Exploration in the Tarim Basin[M]. Beijing: Geological Publishing House, 2003. 149p. ISBN 7-116-03169-3. (In Chinese)

Regarding the specific questions raised by the reviewer, our responses are as follows.

Response to Comment 3.2.1

In the groundwater model developed in this study, the aquifer system is explicitly represented as a multi-layer structure, consisting of one unconfined aquifer (Layer 1) and five underlying confined aquifers (Layers 2-6). This hydrogeological structure and the hydraulic connections between these aquifer layers were defined based on regional hydrogeological cross-sections and borehole data (Li et al., 2003). Existing hydrogeological surveys indicate that the study area is widely underlain by Quaternary unconsolidated sediments forming a multi-layer aquifer system, with an upper unconfined aquifer and several confined aquifers beneath it.

In addition, human activities, especially groundwater pumping caused by agricultural irrigation, are important factors affecting the regional water cycle. In this study, groundwater extraction has been explicitly incorporated into the model as an external stress. The relevant data were obtained from the Xinjiang Water Resources Bulletin published annually by the Xinjiang water resources management department (XJDWR, 2002–2021), and were input as a pumping time series to reflect the impact of agricultural abstraction on the groundwater system.

To reasonably represent the influence of agricultural activities under changing conditions, we used historical pumping data as a baseline in our scenario simulations. When simulating different cropping patterns or planting areas, the pumping amount was proportionally adjusted according to changes in planting area. This approach is intended to maintain a logical correspondence between agricultural water demand and groundwater withdrawal, enabling the model to better capture the potential impacts of land-use changes. Following the reviewer's suggestion, we have added a discussion of limitations in Section 5.2 of the revised manuscript(line 577-580).

"Additionally, the proportional adjustment method used for groundwater abstraction represents a simplified treatment. When the intensity or spatial distribution of groundwater abstraction changes significantly, the model should be updated and recalibrated using the latest statistical data to ensure the reliability of simulation and prediction results."

Response to Comment 3.2.2

The values of key hydrogeological parameters in the model (such as horizontal and vertical hydraulic conductivity, specific yield, and specific storage) are based on our previous study (Chen et al., 2025), where these parameters were systematically described. Based on the regional lithological information provided by Li et al. (2003), the study area was divided into hydrogeological zones, and corresponding initial parameter ranges were assigned to different lithological units. We have added a geological cross-section map of the model area in the Supplementary Materials. This figure was constructed based on regional borehole data and clearly shows the spatial distribution of aquifers and lithological variations in the study area, providing direct geological evidence for the conceptualization of the aquifer structure in the model. The complete input files of the coupled groundwater–surface water model used in this study (including parameter settings) have been uploaded to a public data repository: https://doi.org/10.5281/zenodo.18924068

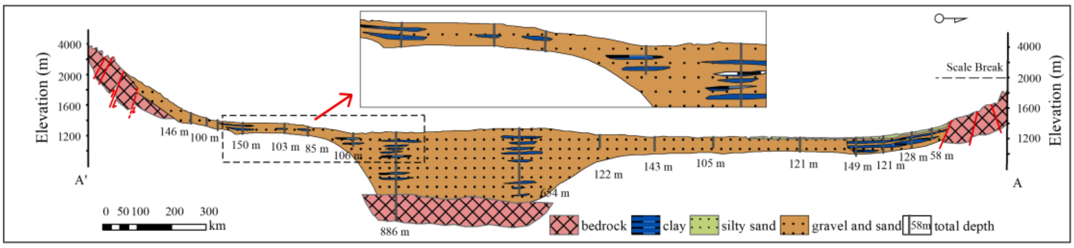

Figure R1. Geological section map of model area

3.3. They mentioned that their coupled surface water-groundwater model was developed based on the GSFLOW framework proposed by Chen et al. (2025), which is not in the reference list. The authors should add this reference and provide additional clarifications to their modeling approach. Mainly,

3.3.1. The current groundwater model is discretized into 6 layers. Is the depth between the layers coming from the geologic data? What is the hydraulic conductivity of these layers? How was the depth of the aquifer (i.e., depth to a confining unit) determined for this area?

3.3.2. I also encourage the authors to provide a figure that shows the boundary conditions they used for their model.

3.3.3. The authors calibrated their model using 139 monitoring wells from Xue et al. (2024), which is another work not in the reference list. Is this information looking at unconfined aquifers in the area, or is it also looking at confined aquifers? This can have important implications for the model's calibration that depends on the conceptualization of the subsurface structure.

3.3.4. They also mention that other key parameters, such as infiltration coefficients and aquifer hydraulic conductivity, were calibrated using a Bayesian uncertainty framework (lines 209-210). However, they do not provide the specifics of their calibration scheme or the distribution of values used for calibration. I encourage the authors to provide this additional information.

3.3.5. They used evapotranspiration data from the GLEAM dataset. However, different crop compositions will increase or decrease evapotranspiration. Did the authors consider this in their optimization process?

3.3.6. This reviewer understands the limitations behind their complex modeling approach. However, there is not much information in the modeling section about nitrogen loads. Are the authors also including a transport model to move nitrogen through the system? Or do they assume this is a point-source contamination that stays in crop areas? The authors should to clarify how they are handling nitrogen loads in their optimization scheme.

Response: Thank you for the reviewer's valuable suggestions. We have added the relevant reference to Chen et al. (2025) in the revised manuscript. That study systematically introduced the basic structure, parameter zoning method, and coupling mechanism of the GSFLOW model in the Tarim River Basin. Based on that modeling framework, this study recalibrated the model using new observational data from the Tarim River mainstream region.

The responses to the reviewer's specific questions are provided below.

Response to Comment 3.3.1

The six-layer structure of the groundwater model and the thickness of each aquifer layer were mainly determined based on regional hydrogeological maps and borehole data, which were obtained from Li et al. (2003) and related reports from the Xinjiang Geological Survey. The elevations of the top and bottom of each layer were obtained through interpolation of borehole data, based on which a three-dimensional aquifer structure was constructed. Hydraulic conductivity values for each layer were assigned according to the dominant lithology (e.g., clay, silt, fine sand, medium-coarse sand, and gravel). The prior parameter ranges were determined based on regional hydrogeological data and previous studies, and the posterior distributions of these parameters were identified using the Markov Chain Monte Carlo method during model calibration. In addition, according to the collected borehole data, the thickness of Quaternary unconsolidated sediments in the study area is approximately 200-400 m, underlain by a relatively stable basement confining layer. This depth range was used as the bottom boundary of the model.

Response to Comment 3.3.2

Thank you for the reviewer’s suggestion. To more clearly present the model structure, we have added a schematic diagram of the model boundary conditions in the Supplementary Materials.

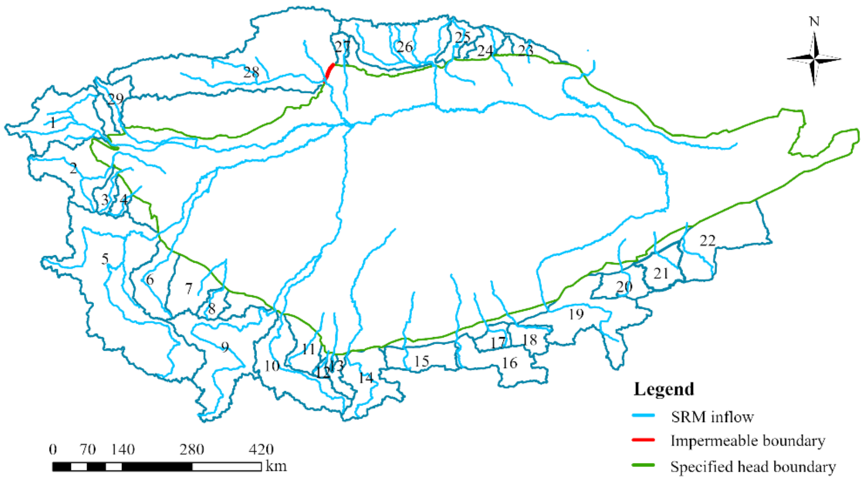

Figure R2. Schematic diagram of model boundaries.

Response to Comment 3.3.3

We thank the reviewer for pointing out the missing reference, and we have added the following reference in the revised manuscript:

Xue, D., Gui, D., Ci, M., Liu, Q., Wei, G., and Liu, Y.: Spatial and temporal downscaling schemes to reconstruct high-resolution GRACE data: a case study in the Tarim River Basin, Northwest China, Sci. Total Environ., 907, 167908, https://doi.org/10.1016/j.scitotenv.2023.167908, 2024.

The 139 monitoring wells used for model parameter identification include both shallow monitoring wells and deep monitoring wells. Water level data from both shallow and deep wells were used in the parameter identification process to ensure that the model can reasonably represent groundwater dynamics in the multilayer aquifer system.

Response to Comment 3.3.4

Thank you for the reviewer’s suggestion. In this study, the DREAM$_{ZS}$ (Differential Evolution Adaptive Metropolis with sampling from past states) algorithm was used to perform Bayesian parameter uncertainty analysis. This algorithm can effectively explore high-dimensional parameter spaces and estimate the posterior distributions of parameters. We set up three parallel Markov chains, each running 20,000 iterations, including a burn-in period of 5,000 iterations. The likelihood function was defined using a Gaussian distribution. The parameters to be identified and their prior ranges are listed in Table S1 of the Supplementary Materials. The prior ranges of these parameters were mainly determined based on regional hydrogeological survey reports (e.g., data from the Xinjiang Geological Survey) and related literature (e.g., Li et al., 2003), ensuring that the parameters remain physically reasonable.

Table S1 The unknown model parameters in GSFLOW

Parameters	Unit	Prior Range
Soil maximum available capillary water-holding capacity	cm	12.0 - 42.0
Linear coefficient of gravity drainage	cm/d	0.00015 - 2.5
Hydraulic conductivity	m/d	0.01 - 65
Specific yield	-	0.02 - 0.30
Specific storage	10^{-6} m^{-1}	1 - 36
Maximum evapotranspiration depth	m/d	0.5 - 8
Streambed hydraulic conductivity	m/d	0.02 - 60

Response to Comment 3.3.5

In this study, GLEAM evapotranspiration dataset was used only for the validate of the hydrological model results, not as model input or driving data. The GSFLOW model dynamically calculates actual evapotranspiration based on energy balance and water balance processes, taking into account vegetation type and soil moisture conditions. For agricultural areas, GSFLOW sets parameters such as crop coefficients according to crop type. Therefore, when the optimization model changes the crop planting area A_{ij}, the evapotranspiration simulated by GSFLOW will automatically respond to the new crop structure, thereby reflecting the impact of agricultural structure changes on the water consumption process.

Response to Comment 3.3.6

This study mainly focuses on the water quantity processes within the coupled system and does not construct a complete nitrogen transport and transformation model. The total agricultural nitrogen load (f_{TN}) is estimated using an empirical approach based on crop fertilization intensity:

$$f_{TN} = \Sigma (N_{ij} \times A_{ij})$$

where N_{ij} is the annual nitrogen load per unit area for crop j in irrigation district i, and A_{ij} is the corresponding planting area. This method has been widely used in multi-objective agricultural water management studies to characterize the potential environmental pressure caused by agricultural intensification, rather than to simulate the actual transport and transformation of nitrogen in the soil-groundwater system (e.g., Tang et al., 2024; Song et al., 2022). This simplified approach is suitable for strategic analyses of large-scale watershed water resource management and ecological security assessment. It enables rapid characterization of regional agricultural non-point source pollution risk while maintaining computational efficiency, making it suitable for multi-objective coupled optimization decision-making at large watershed scales. Following the reviewer's suggestion, we have further clarified this simplifying assumption in Section 5.2 (Limitations) of the revised manuscript and noted that future studies will consider incorporating a complete solute transport model.

References

Song, J., Yang, Y., Yin, Z., Wu, J., Sun, X., Lin, J., and Wu, J.: Satellite data-driven multi-objective simulation-optimization modeling for water-environment-agriculture nexus in an arid endorheic lake basin, J. Hydrol., 612, 128207, https://doi.org/10.1016/j.jhydrol.2022.128207, 2022.

Tang, X., Huang, Y., Pan, X., Liu, T., Ling, Y., and Peng, J.: Managing the water-agriculture-environment-energy nexus: trade-offs and synergies in an arid area of Northwest China, Agr. Water Manage., 295, 108776, https://doi.org/10.1016/j.agwat.2024.108776, 2024.

3.4. In the multi-objective optimization model section, the authors provide decision variables, their constraints, and the objective functions. Although there are equations for all of them, I don't seem to find where the monthly ecological water allocation coefficient is presented within the modeling scheme. Is this an extraction within the hydrological model? Where is it drawn from? It would be helpful to have a schematic of the optimization process.

Response: Thank you for the reviewer's careful review and valuable suggestion. We agree that the explanation of the relationship between the monthly ecological water allocation coefficient θ_k and the hydrological model was not sufficiently clear in the original manuscript, which may affect readers' understanding of the model coupling process. Following your suggestion, we have systematically supplemented and clarified this part in the revised manuscript.

In the multi-objective optimization model constructed in this study, the monthly ecological water allocation coefficient $\theta_k (k = 5, 6, \ldots, 9)$ is defined as a key decision variable used to control the distribution of the annual ecological water volume among the key ecological water conveyance months (May-September). The optimization model first determines the annual ecological water conveyance amount Q_e and then θ_k determines the ecological water volume for each month:

$$Q_{e,k} = \theta_k \cdot Q_{e,}, \quad \sum_{k=5}^{9} \theta_k = 1$$

where $Q_{e,k}$ represents the ecological water conveyance amount in month k.

In the coupled hydrological model, these monthly ecological water volumes are not directly converted into surface infiltration recharge but are instead introduced as additional stream diversion inputs into the river system. Within the GSFLOW framework, this process is simulated through the MODFLOW SFR (Streamflow Routing) module. After ecological water enters the river channel, it first alters streamflow and river stage, and then influences groundwater recharge through stream-aquifer exchange processes. Specifically, increased streamflow raises the river stage, which enhances riverbed leakage and consequently increases groundwater recharge to the riparian aquifer. This ultimately affects the simulated groundwater level changes (objective function f_{GL}) and the terminal lake area (objective function f_{LA}).

To further improve the readability and reproducibility of the model description, we have made the following additions in the revised manuscript(line 249-255):

"During the hydrological model coupling process, the monthly ecological water conveyance is introduced into the GSFLOW model as an additional river diversion boundary condition and simulated through the SFR module in MODFLOW. After entering the river system, the ecological water first changes river discharge and river stage, and then affects groundwater recharge through riverbed leakage mechanisms. When the river stage is higher than the groundwater level, the river recharges the aquifer; otherwise, groundwater may discharge to the river. Therefore, the monthly ecological allocation coefficient θ_k becomes an important variable linking the multi-objective optimization decisions with hydrological process simulations."

In addition, to clearly illustrate the theoretical framework of this study, we have added a schematic diagram of the multi-objective optimization-hydrological simulation coupling framework in the main text.

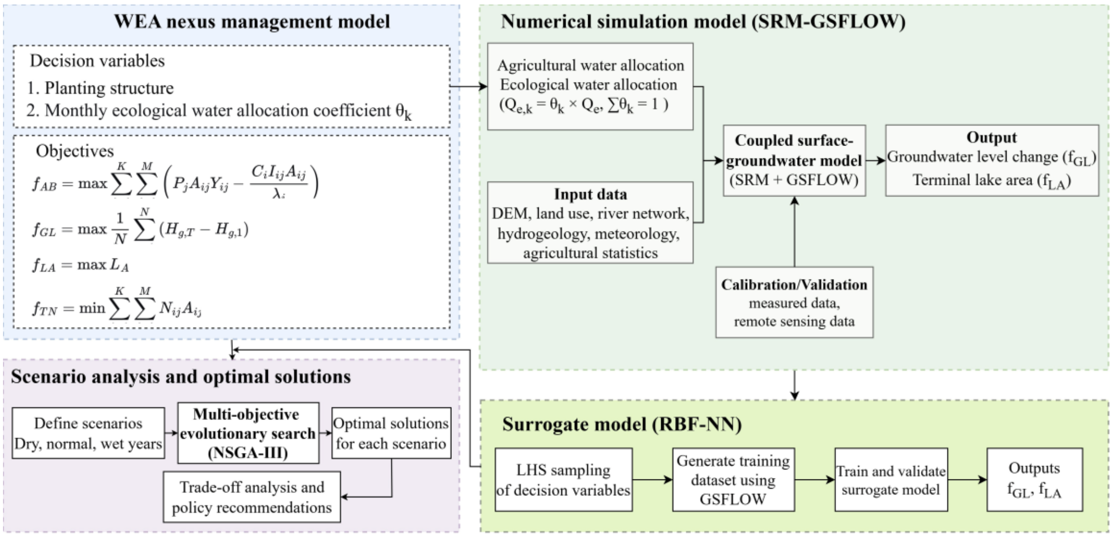

Figure R3. Framework of the multi-objective simulation–optimization for the WEA nexus management.

3.5. Due to the complexity of their hydrological model, the authors opted to train an RBF-NN as a surrogate model. However, it is unclear what the model's input and output variables are, as well as its structure. I encourage the authors to include this information to improve reproducibility.

Response: Thank you very much for your valuable suggestion. In Section 3.3 "Surrogate Model Construction and Validation"(line 321-330), we have supplemented a detailed description of the surrogate model construction.

"To elaborate further, the input variables of the surrogate model are the decision variables to be optimized. Specifically, they include the planting areas of six major crops (cotton, maize, oil crops, vegetables, melons, and fruits) across seven irrigation zones, as well as the allocation coefficients of ecological water use during key months (May-September), resulting in a total of 47 decision variables. The output variables of the surrogate model consist of two hydrological variables simulated by the coupled hydrological model (GSFLOW), namely the change in the average groundwater depth in the study area and the area of the terminal lake. For surrogate construction, Latin hypercube sampling was first applied to generate samples within the input variable space. Each sample set was then used as input to the GSFLOW model to obtain the corresponding outputs, thereby forming an input-output dataset. The dataset was subsequently randomly divided into a training set (70%) and a test set (30%). The

training set was used to train the radial basis function neural network (RBF-NN), while the testing set was used to evaluate the predictive accuracy and generalization capability of the surrogate model."

3.6. Also, the authors show that the model performs better by giving additional training points, which is expected. However, doing this might also lead the model to overfit. I encourage them to consider using a cross-validation scheme for their surrogate model.

Response: Thank you for this important suggestion. To further evaluate the generalization capability of the surrogate model and reduce the risk of overfitting, we adopted a five-fold cross-validation approach to systematically assess the predictive performance of the surrogate model. The training dataset was generated using the Latin Hypercube Sampling method. During model validation, the training dataset was randomly divided into five non-overlapping subsets. In each iteration, four subsets were used as training data and the remaining subset was used as validation data. This process was repeated so that each subset served once as an independent validation dataset. The cross-validation results show that the surrogate model maintains relatively stable prediction errors under different data partition conditions, with small RMSE variations among the folds, and no obvious overfitting phenomenon was observed.

Table S2. Results of the 5-fold cross-validation for the surrogate models

Target	Fold 1 RMSE	Fold 2 RMSE	Fold 3 RMSE	Fold 4 RMSE	Fold 5 RMSE	Mean RMSE	Std RMSE
Groundwater level	0.031	0.035	0.032	0.036	0.033	0.033	0.002
Lake area	1.012	1.124	1.036	1.146	1.058	1.075	0.057

Technical Corrections

1. The text within Figure 1 is difficult to read; consider increasing the font size.

Response: The font size has been increased. The revised Figure 1 is shown below.

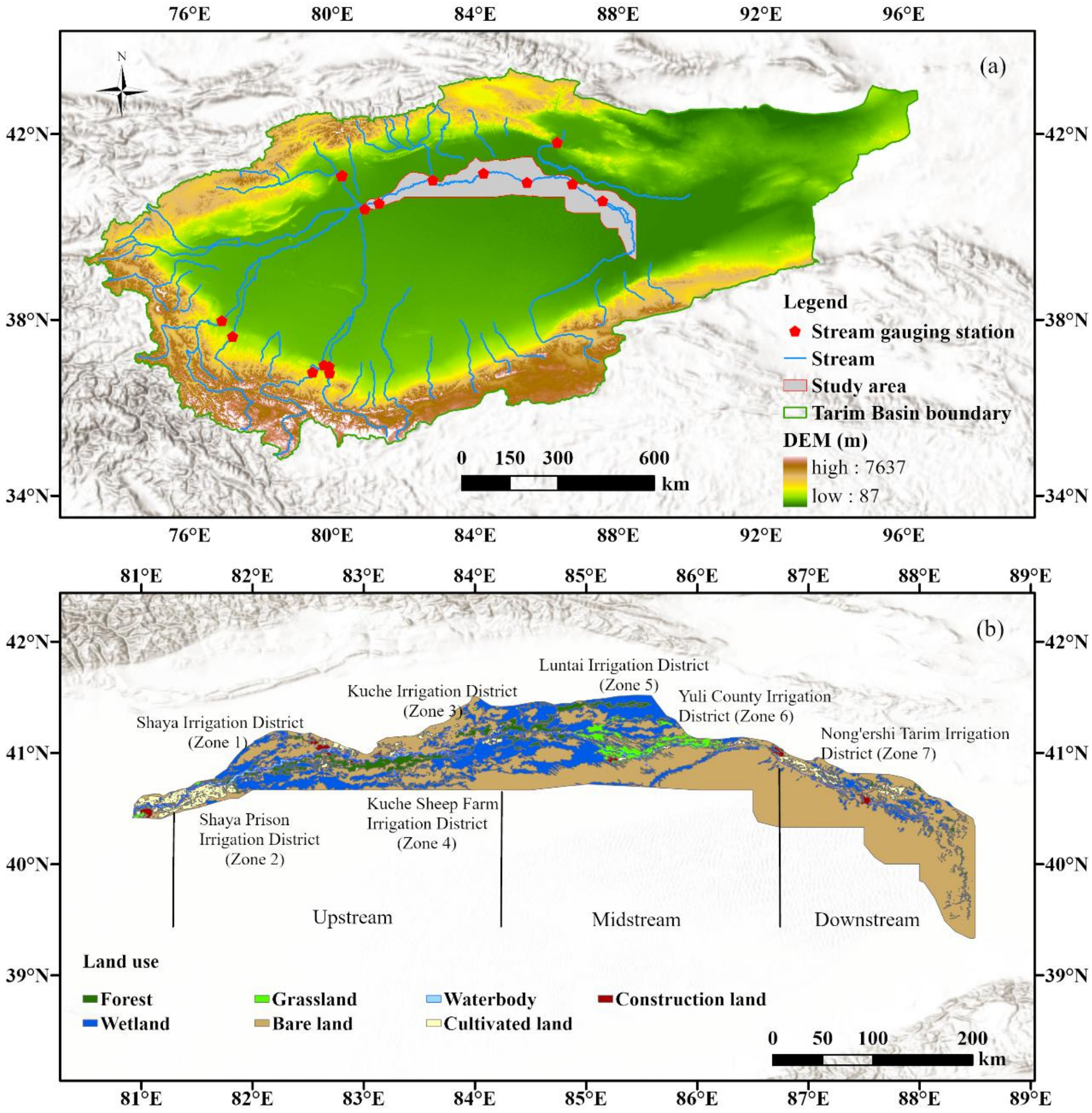

Figure 1. (a) The location of the Tarim River mainstream region. (b) Land use types across the Tarim River mainstream region. Sources: Esri; Powered by Esri; Basemap: Esri World 286 Hillshade (Esri).

2. In line 96, the authors state "and a total precipitation below 80 mm." Is this total "annual" precipitation? Please clarify.

Response: Thank you for the question. The annual precipitation in the Tarim River mainstream region is indeed below 80 mm, and the original statement was correct. To avoid ambiguity, we will explicitly revise it to "annual total precipitation below 80 mm."

3. Correct comma placement in "This dataset" (line 137).

Response: The punctuation error has been corrected.

4. Labels in Figure 2 are difficult to read. I recommend increasing the font size and

removing the x-labels from figures (a) through (d), as they are the same; this can give you more space in the figure.

Response: The font size has been increased and the repeated x-axis labels have been removed. The revised Figure 2 is shown below.

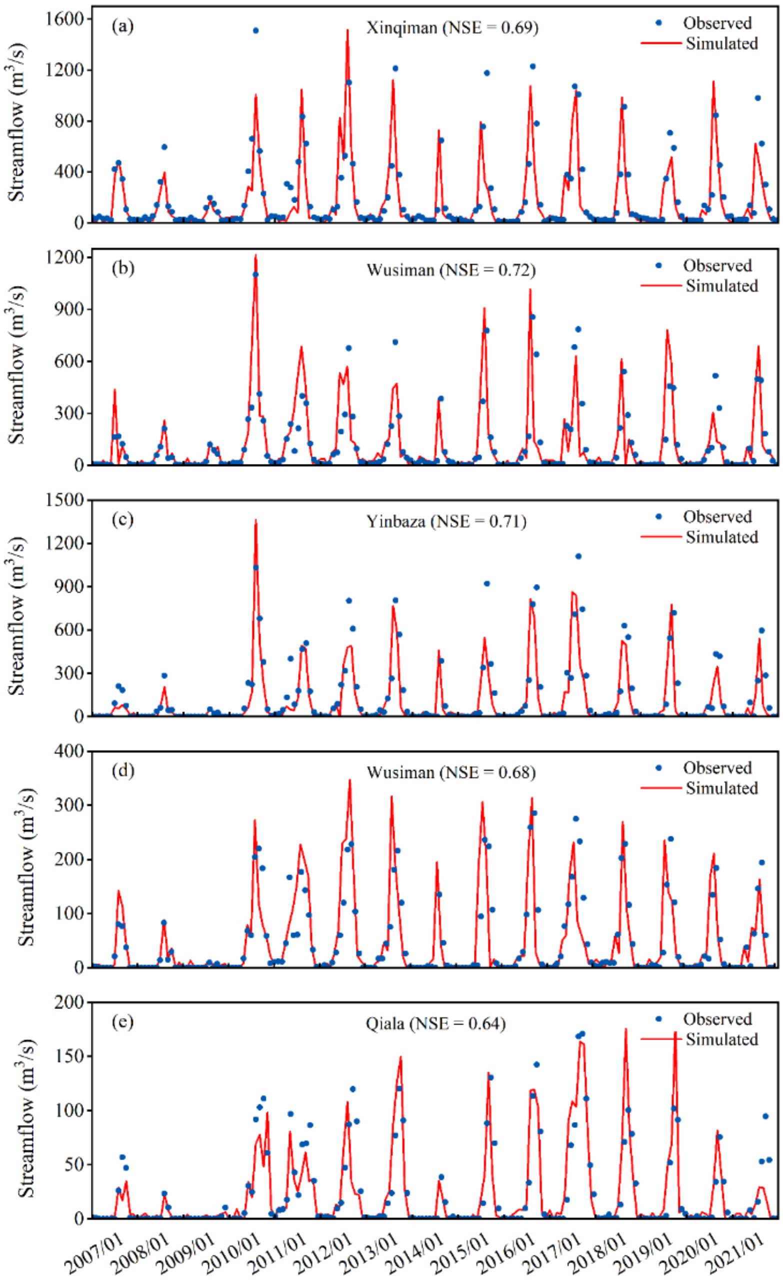

Figure 2. (a) - (e) present the evaluation of monthly streamflow simulations against observations at Alar and Xinqiman, Yingbaza, Wusiman, and Qiala gauging stations, respectively.

5. Table 5 is referenced before Figures 5-7. I recommend changing the order of their presentation in the manuscript.

Response: Line 432.The order of figures and tables has been adjusted in the revised manuscript so that they appear in logical sequence