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.
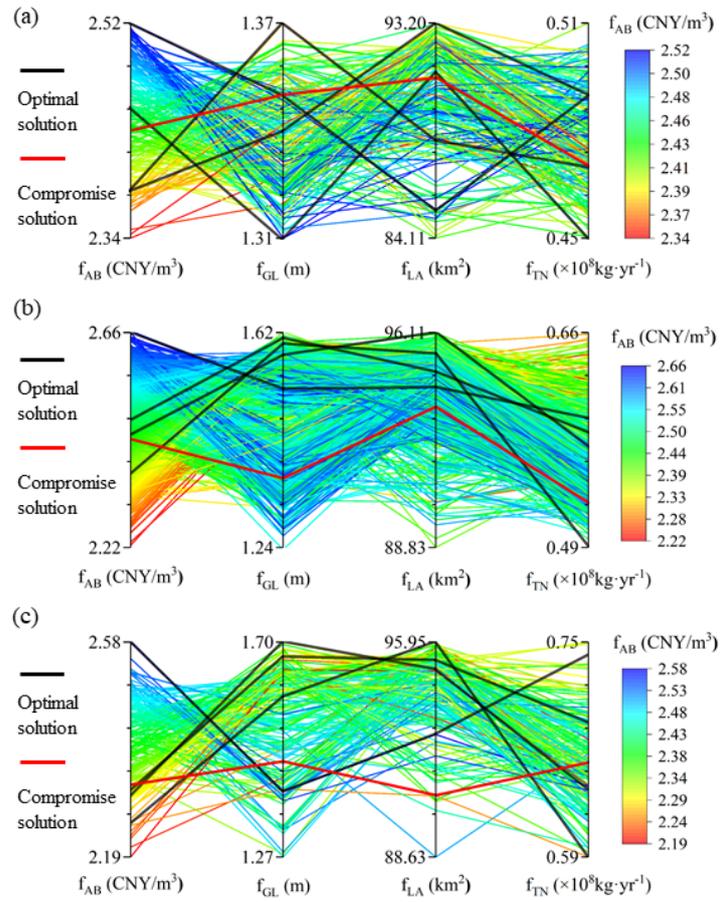
Figure 4. Objective values (y axis) plotted against management objectives f_{AB}, f_{GL}, f_{LA} and f_{TN}, with panels (a, b, c) representing dry, normal, and wet years, respectively.
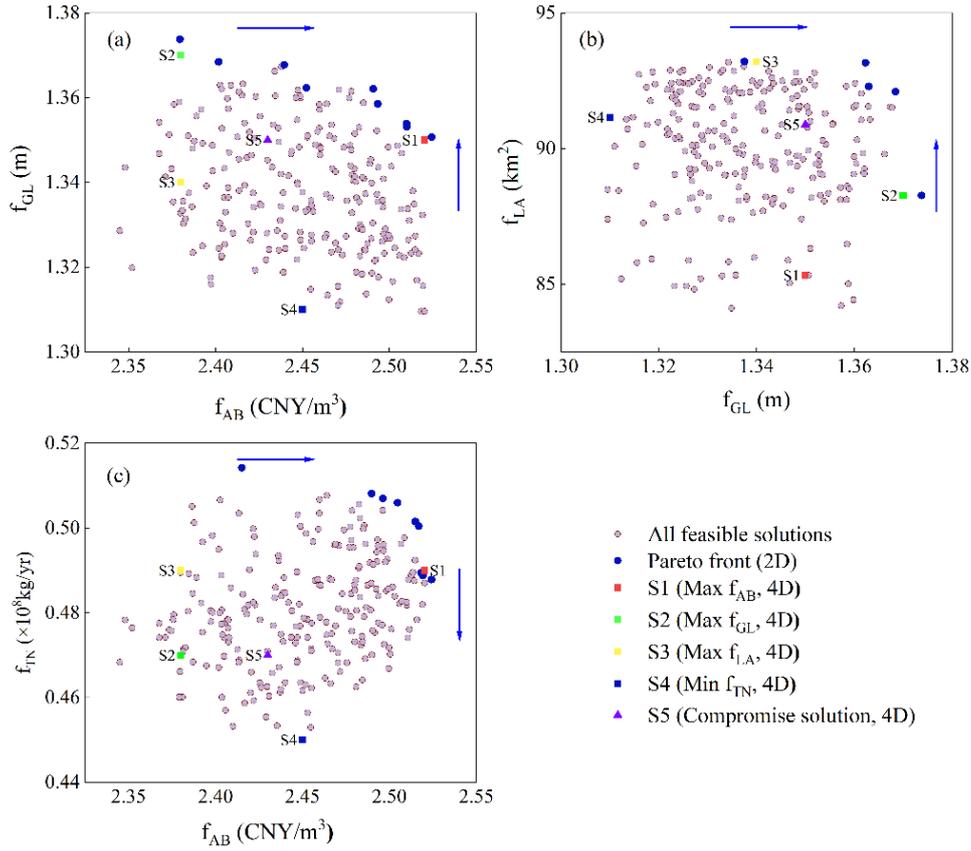
Figure 5. Scatter plots for optimization in a dry year exhibiting the correlation between each pair of objectives, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Each dot represents a feasible solution. The representative solutions for dry scenario (S1-S5) can be identified by rectangles with different color. The navy-blue arrow indicates the direction of Pareto optimality.
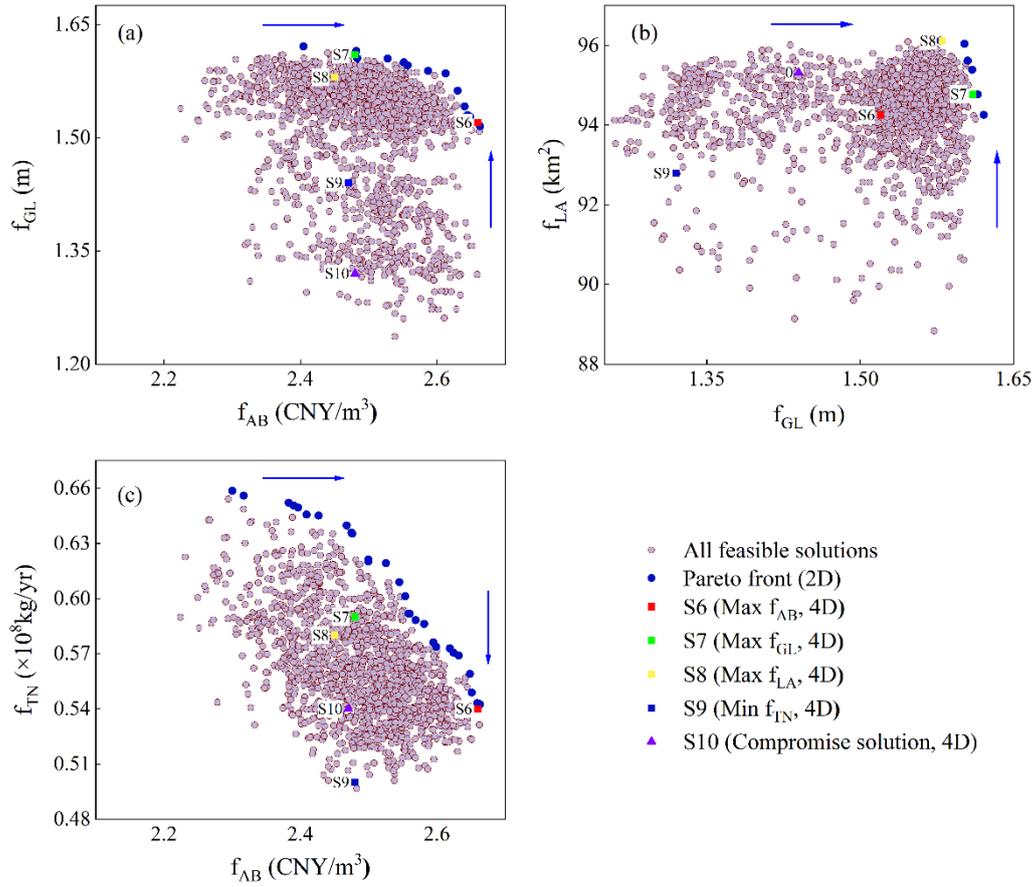
Figure 6. Scatter diagrams depicting correlations among objective pairs in a normal year, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Representative normal-year solutions (S6-S10) are marked using colored rectangles.
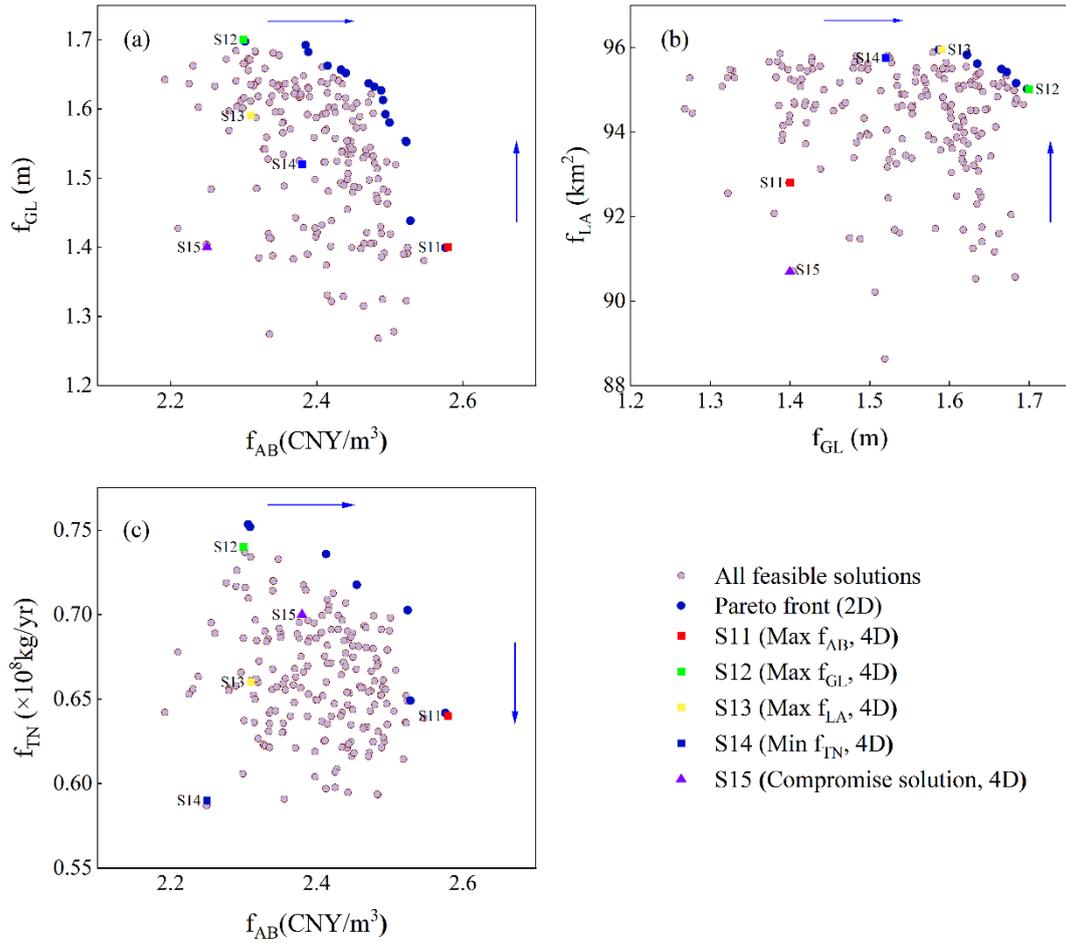
Figure 7. Scatter diagrams depicting correlations among objective pairs under a wet year, (a) f_{AB} and f_{GL}; (b) f_{GL} and f_{LA}; and (c) f_{AB} and f_{TN}. Representative wet-year solutions (S11-S15) are marked using colored rectangles.

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.
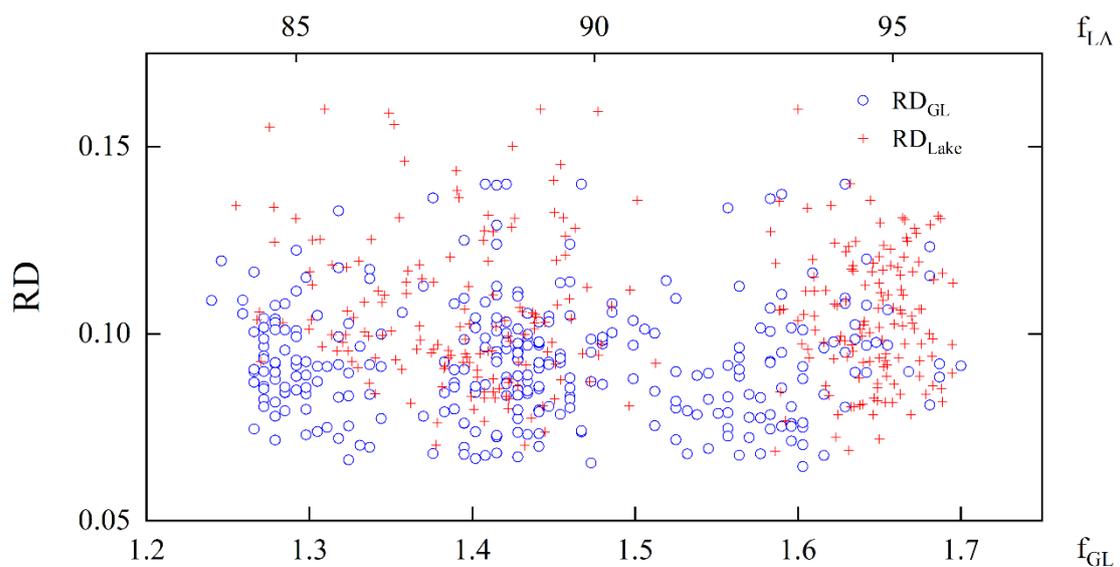

Figure R1. RD values of the surrogate model for Pareto optimal solutions across different management objectives.

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".

"Second, this study has not yet conducted a systematic quantification and propagation analysis of multiple sources of uncertainty. Key inputs, including climate forcing data, hydrogeological parameters, crop water requirement coefficients, and fertilizer-related parameters, all contain uncertainties. These uncertainties may accumulate and propagate step by step during the model simulations and the subsequent optimization process, thereby affecting the shape and range of the Pareto front as well as the stability of compromise solutions, and thus increasing potential risks in the decision-making process. 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."

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.

"Accurately representing vegetation dynamics in large-scale hydrological models remains a challenge, and this study adopted a simplified treatment. 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. In recent years, studies have shown that assimilating satellite-derived vegetation indices (such as Leaf Area Index, LAI) into hydrological models can significantly improve simulations of evapotranspiration, soil moisture, and groundwater recharge. For example, the 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. This direction has important application potential in

arid regions where in situ observations are relatively scarce."

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.