Reviewer #3 Comment on essd-2022-422 (Anonymous Referee #3)

Dear Anonymous Referee #3,

Thank you for your time and efforts in reviewing our manuscript. Please find attached point-to-point responses regarding your comments (marked in purple) and made corresponding changes in the main manuscript (in red). We hope that the improved manuscript can help the readers to better understand our study.

Kind regards.

General comments

Dams and reservoirs play an important role in water resource management and regulation. The authors provided new and comprehensive reservoir datasets over China (the Reservoir dataset in China, Res-CN), which featured reservoir-catchment characteristics for 3254 reservoirs. I have the following concerns for authors in ongoing revision and improvements.

R3C0: Thank you for your recognition of the strengths of our study. We appreciate your constructive feedback and have carefully considered all of your suggestions and comments. We hope that these revisions have improved the overall quality of the manuscript. We are grateful for your time and expertise in reviewing our work, and we believe that your feedback has made a valuable contribution to the study's scientific value. Thank you again for your comments, and we hope that the revised manuscript will meet your expectations.

Authors may need to provide more details on why they only focus on reservoirs in China, and why they chose to use GeoDAR while a more recent study published more comprehensive reservoir dataset for China.

R3C1: Thank for your constructive comments. We have re-organized the introduction, adding more details on the reason why we only focus on Chinese reservoirs, and thanks for altering us about the new data, we have explained it in the Summary, applications and outlook. We acknowledge all great efforts made by our scientific members. We argue the new added reservoir shapefiles are mainly very small reservoirs. Our study aims to provide a comprehensive and extensive dataset of reservoir-catchment characteristics in China for a better understanding of reservoir impacts on hydrological and biochemical cycles, these thousands of very small reservoirs are not included in our study. Thus, Res-CN still shows significant improvements and unique contribution in its comprehensive and complete information. We hope that our datasets will contribute to the development of more effective water quality management strategies for Chinese reservoirs and serve as a valuable resource for researchers and policymakers in this field. Please find the revised texts below. Hope it addressed your concerns.

Introduction:

The role of reservoirs in the hydrological and biogeochemical cycles is closely tied to their characteristics of water surface area, water level, evaporation, and storage variation. In addition, the amount and rate of water and materials flowing into and out of reservoirs depends on their location in the river network, reservoir upstream catchment attributes (e.g., catchment size, topography, geology, soil, and land cover) as well as meteorological variables (e.g., precipitation, and temperature). An explicit spatial knowledge of all these characteristics (see in Fig. A1) is crucial for determining surface water availability and modulating water flux interactions among various Earth system components, including terrestrial water storage dynamics (Busker et al., 2019; Chaudhari et al., 2018); terrestrial carbon cycle (Marx et al., 2017); geochemical cycle (Maavara et al., 2020); surface energy budget (Buccola et al., 2016); climate-related effects (Boulange et al., 2021); and alterations in the hydrological and ecological processes such as sediment reduction (Li et al., 2020), degradation of water quality (Barbarossa et al., 2020), land use changing pattern (Carpenter et al., 2011), and fish biodiversity decline (Ngor et al., 2018). Therefore, to fully uncover the functioning of reservoirs for better scientific studies and water resources managements, it is essential to develop a comprehensive publicly available reservoir data set in the context of growing interest of reservoir studies and water managements.

China is the world's most populous country that has undergone an impressive average GDP growth rate of 10% over the past two decades (Gleick, 2009). Meanwhile, it has simultaneously experienced notable expansion of irrigation and encountered challenges arising from limited water resources, frequent floods, and droughts (Wang et al., 2020). To ensure water security, reservoir construction is proliferating across the country. As of 2015, China had constructed approximately 98,000 reservoirs and dams, including almost 40% of the world's largest dams (Song et al., 2022). The world's largest clean energy corridor, comprised of six mega hydropower dams, is newly formed in China. Despite these developments, there remains a data gap regarding the surface water dynamics and upstream attributes of these reservoirs at the catchment level.

In recent years, multiple efforts have been made to produce reservoir inventories, including those of China. For the inventories of water surface area, water level, evaporation, and storage anomaly, there are different research projects and studies producing satellite datasets for reservoirs at regional and global scales (Crétaux et al., 2011; Birkett et al., 2011; Schwatke et al., 2015; Markert et al., 2019; Tourian et al., 2022; Tortini et al., 2020; Zhao & Gao, 2018; Liu et al., 2021; Donchyts et al., 2022; Vu et al., 2022; Tian et al., 2022). However, information of reservoir characteristics is still insufficient and scarce across different regions.

5 Summary, applications and outlook

Although Res-CN presents significant improvements over existing datasets and holds potential for various applications identified above, a few limitations should be acknowledged. Res-CN is generated using GeoDAR v1 shapefiles (Wang et al., 2022) instead of the newly produced datasets by Song et al. (2022), which added an additional near sixty thousand very small reservoir shapefiles (< 1 km²). As this study aims to provide a comprehensive and extensive dataset of reservoir-catchment characteristics in China for a better understanding of reservoir impacts on hydrological and biochemical cycles, these thousands of very small reservoirs are not included in our study. Meanwhile, it is currently not feasible to generate satellite-based datasets for these small reservoirs due to the limitations of current satellite altimetry missions, which are unable to detect such reservoirs because of the sparsity of their altimetric ground tracks. These additional small reservoirs only account for 8% of total water capacity in China. Nonetheless, users can freely access our codes to calculate any reservoir attributes for individual applications, other areas, and can enrich the inventory if new data available.

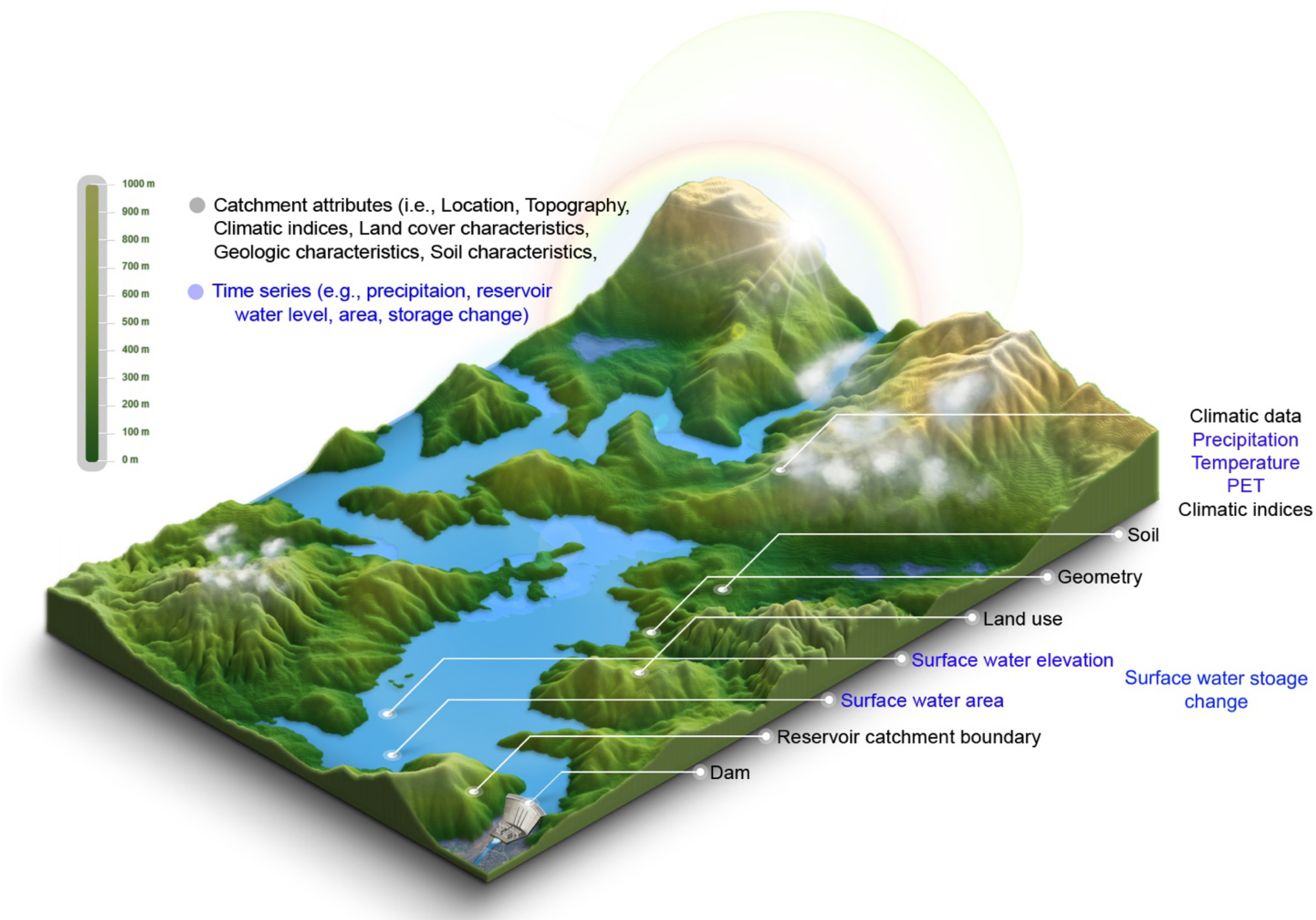

Figure A1. Illustration of the datasets provided in our Res-CN.

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Song, C., Fan, C., Zhu, J., Wang, J., Sheng, Y., Liu, K., Chen, T., Zhan, P., Luo, S., Yuan, C., and Ke, L.: A comprehensive geospatial database of nearly 100 000 reservoirs in China, Earth Syst. Sci. Data, 14, 4017–4034, https://doi.org/10.5194/essd-14-4017-2022, 2022.

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Huziy, O., and Sushama, L.: Impact of lake–river connectivity and interflow on the Canadian RCM simulated regional climate and hydrology for Northeast Canada, Climate Dynamics, 48, 709-725, https://doi.org/10.1007/s00382-016-3104-9, 2017.

Stieglitz, M., Shaman, J., McNamara, J., Engel, V., Shanley, J., and Kling, G. W.: An approach to understanding hydrologic connectivity on the hillslope and the implications for nutrient transport, Global Biogeochemical Cycles, 17(4), 1105, https://doi.org/10.1029/2003GB002041, 2003.

Soranno, P. A., Cheruvelil, K. S., Webster, K. E., Bremigan, M. T., Wagner, T., and Stow, C. A.: Using landscape limnology to classify freshwater ecosystems for multi-ecosystem management and conservation, Bioscience, 60(6), 440–454, https://doi.org/10.1525/bio.2010.60.6.8, 2010.

Authors have provided comprehensive climatic characteristics (L450~L451) and human activity characteristics of reservoirs but did not explicitly state why these characteristics should be provided. Therefore, I suggest that the authors to offer a more compelling motivation to start their Introduction, and also discuss why these much informaiton is needed for understanding reservoir changes. Otherwise it may look like too much information to digest for certain users.

R3C2: Our study involved the integration of multiple attributes, offering a good dataset to comprehending the features of reservoir-catchments in China systematically. The Res-CN dataset holds considerable potential in advancing the comprehension of the processes involved in Chinese reservoirs. We have further elaborated on this dataset in the introduction, summary, and applications sections. Hope this addressed your concerns.

Introduction:

The role of reservoirs in the hydrological and biogeochemical cycles is closely tied to their characteristics of water surface area, water level, evaporation, and storage variation. In addition, the amount and rate of water and materials flowing into and out of reservoirs depends on their location in the river network, reservoir upstream catchment attributes (e.g., catchment size, topography, geology, soil, and land cover) as well as meteorological variables (e.g., precipitation, and temperature). An explicit spatial knowledge of all these characteristics (see in Fig. A1) is crucial for determining surface water availability and modulating water flux interactions among various Earth system components, including terrestrial water storage dynamics (Busker et al., 2019; Chaudhari et al., 2018); terrestrial carbon cycle (Marx et al., 2017); geochemical cycle (Maavara et al., 2020); surface energy budget (Buccola et al., 2016); climate-related effects (Boulange et al., 2021); and alterations in the hydrological and ecological processes such as sediment reduction (Li et al., 2020), degradation of water quality (Barbarossa et al., 2020), land use changing pattern (Carpenter et al., 2011), and fish biodiversity decline (Ngor et al., 2018). Therefore, to fully uncover the functioning of reservoirs for better scientific studies and water resources managements, it is essential to develop a comprehensive publicly available reservoir data set in the context of growing interest of reservoir studies and water managements.

In addition to the time series of reservoir datasets described above, reservoir upstream catchment attributes (e.g., climate, geology & soil, topography, land cover, and anthropogenic activity characteristics) are also important as reservoirs collect materials from upstream catchments. These attributes affect the water balance and water quality of a reservoir, such as temperature, dissolved oxygen, and turbidity (Yang et al., 2022). Moreover, the limnological properties of one reservoir have the potential to impact other reservoirs through the transfer of water mass, nutrients, energy, and sediments via connecting rivers, as previously demonstrated in studies by Huziy and Sushama (2017) and Stieglitz et al. (2003). Thus, researchers can better understand catchment-level landscape limnology by incorporating these attributes (Soranno et al., 2010). The values of these catchment-level attributes are also proved in the Catchment Attributes and MEteorology for Large-sample Studies (CAMELS) introduced by Addor et al. (2017) and follow-up studies such as CAMLES-CL, CMALES-BR, CAMLES-GB, (Alvarez-Garreton et al., 2018; Chagas et al., 2020; Coxon et al., 2020), LamaH-CE (Klingler et al., 2021), CCAM (Hao et al., 2021), LakeALTAS (Lehner et al., 2022), as well as the works by Chen et al. (2022) and Liu et al. (2022). However, there is a data gap of reservoir-catchment characteristics in China, and even the geometric boundaries of reservoir upstream catchment, which hindered the spatially explicit applications of such catchment information. Furthermore, allocating reservoirs on river network is also valuable for river models incorporating reservoirs as reservoir datasets and river network datasets are usually developed independently, and they are not well corresponding and could cause some issues when integrating reservoirs in river model.

Summary, applications and outlook:

We envision that Res-CN with its comprehensive and extensive attributes can provide strong supports to a wide range of applications and disciplines. Firstly, our two types of catchments along with their catchment-level attributes allow investigations within individual catchments and interconnected river networks. For example, as illustrated in Figure 2, users may quantify the relative contributions of upstream reservoirs and local drainage catchment on water quality (e.g., algae contributions and water color) of downstream reservoir by tracking temperature and nutrient flows from upstream reservoirs and intermediate catchments (e.g., Hou et al., 2022; Yang et al., 2022). Besides, water and sediment transfer can be also more accurately simulated in such a spatially explicit context if appropriate approaches are used. Machine-learning methods make it possible to predict reservoir storage change at 1- to 3-month lead from reservoir upstream attributes and time-series of reservoir states (Tiwari et al., 2019). Secondly, Res-CN provide thus far the most comprehensive reservoir states in China for assessing impacts of reservoir regulation and dynamics. Tracking the spatiotemporal balance of reservoir evaporative and water storage can provide a basis for local water management in a warming climate (Di Baldassarre et al., 2019). The reservoir operational rules or impacts of reservoir regulation on flow regimes are possibly to be inferred from reservoir water dynamics in Res-CN (Vu et al., 2022). This is particularly true if the reservoir inflow is also utilized. Recently, the gridded natural runoff provided by Gou et al. (2021) provides exciting opportunities for quantifying the human water regulation in combination with Res-CN (Dang et al., 2022; Shin et al., 2020). Thirdly, our extracted catchment-level attributes can contribute to a better understanding of reservoir water amount and water quality changes by spatially incorporating geophysical and anthropogenic characteristics of their upstream catchments and their respective contributions. For example, cropland in reservoir upstream catchments controls the nutrient-driven primary production, while wetland coverage affects dissolved organic material transport downstream, ultimately impacting primary production and CO2 emissions in lakes (Balmer and Downing, 2011; Borges et al., 2022; Maberly et al., 2013). Gradient and altitude in the reservoir geological attributes may affect greenhouse gas emissions and biogeochemistry of a reservoir (Casas-Ruiz et al., 2020). Furthermore, these catchment-level attributes can be used to explore water fluxes and sediment transportation even in reservoirs that have not been sampled. Studies on cascading patterns in reservoir attributes found that each attribute may display linear function of catchment area, concluding that cascading patterns of each attribute have different implications for dam management (Faucheux et al., 2022). For instance, one study combined knowledge of catchment attributes with economic, climate, and landscape data to inform reservoir removal decisions in California's Central Valley basin (Null et al., 2014). Lastly, carbon dioxide emissions from reservoirs show significant spatial and seasonal variation, highlighting the importance of hydrology in terrestrial–reservoir carbon transfers and the need to consider this effect when plumbing terrestrial carbon budgets. Res-CN also offers exciting opportunities to address changes in reservoir storage that may be linked to carbon dioxide changes.

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Although authors argued the need for intermediate catchments, however, I still failed to understand how data for these intermediate ones can be used to understand changes in reservoirs as I thought it may be missing essential water balance components? Can authors add more discussions and also clarify?

R3C3: We have added explanations in the Summary, applications, and outlook. Hope the above comments addressed your concern. Taking the first application as an example, we can use the modeled outflow or sediment of upstream reservoirs, and modeled sediment or water mass in the local drainage catchment of the downstream reservoir catchment (i.e., intermediate catchment in Fig 2b) to explore the quantify the relative contributions of upstream reservoirs and local drainage catchment on water quality (e.g., algae contributions and water color) of downstream reservoir by tracking temperature and nutrient flows from upstream reservoirs and intermediate catchments (e.g., Hou et al., 2022; Yang et al., 2022).

We envision that Res-CN with its comprehensive and extensive attributes can provide strong supports to a wide range of applications and disciplines. Firstly, our two types of catchments along with their catchment-level attributes allow investigations within individual catchments and interconnected river networks. For example, as illustrated in Figure 2, users may quantify the relative contributions of upstream reservoirs and local drainage catchment on water quality (e.g., algae contributions and water color) of downstream reservoir by tracking temperature and nutrient flows from upstream reservoirs and intermediate catchments (e.g., Hou et al., 2022; Yang et al., 2022). Besides, water and sediment transfer can be also more accurately simulated in such a spatially explicit context if appropriate approaches are used. Machine-learning methods make it possible to predict reservoir storage change at 1- to 3-month lead from reservoir upstream attributes and time-series of reservoir states (Tiwari et al., 2019).

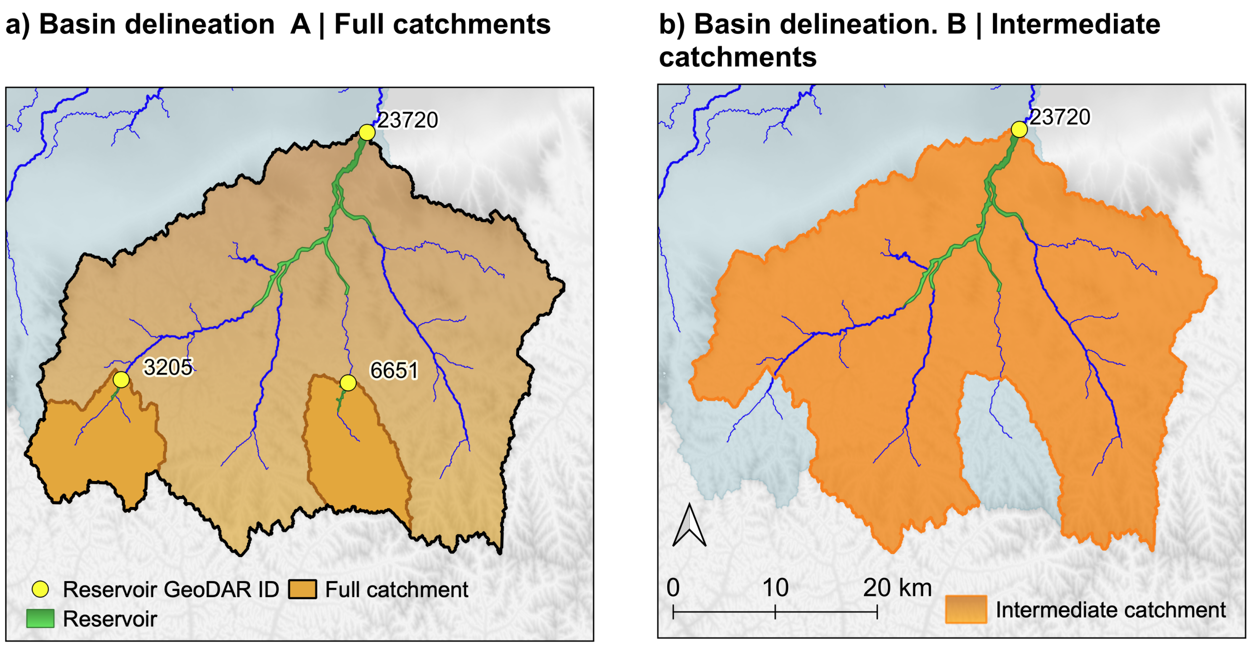

Figure 2. An example of the types of catchment delineations in Res-CN. (a) Catchment delineation A: full catchments, which are defined as the entire area contributing to a reservoir. In plot (a), full catchment of reservoir 23720 overlaps with that of reservoir 3205 and that of 6651. (b) Catchment delineation B: intermediate catchment. In plot (b), all upstream contributing areas of the upstream reservoirs (3205 and 6651) are removed from the full catchment of reservoir 23720, thus, we get the intermediate catchment of reservoir 23720 (in black boundary). Background in light blue indicates other catchments not shown in this example. Source of background: MERIT Hydro and MERIT DEM (Yamazaki et al., 2019).

Other Comments

L243: there's no need to mention computational time, unless you can provide details on the platform because it is highly platform dependent.

Reply: Thank for your comment, we have rephrased it:

This algorithm can correct the river networks by analyzing the gradients of flow accumulations along the rivers and can rapidly delineate catchments.

L365~L370: I suggest that the author should place these introductions after L358 (GRSAD and RealSAT) to make the content more cohesive.

Reply: I completely agree with you and appreciate your constructive feedback. These sentences are positioned after L358 is to enhance the cohesiveness of the overall content.

We compare these datasets with in situ water levels and altimetric measurements as well as other areal datasets (GRSAD and RealSAT). RealSAT generated 681,137 monthly Lake-surface area maps from Landsat images during 1984-2015 using an ORBIT (Ordering-Based Information Transfer) approach that has been validated on 94 large reservoirs. As opposed to RealSAT, which generated new static lake polygons from water occurrence data, GRSAD used existing static surface water polygons, HydroLAKES and GRanD, to create monthly areas for 6,817 global reservoirs based on Landsat images over the last 35 years.

L381~L382: Why the time period of reservoir storage variation is from 1984 to 2020, not 1984~2021?

Reply: Upon careful review of the information, we have identified an error in our manuscript. The correct date range should be 1984-2021 instead of what was previously stated. We apologize for any confusion this may have caused. However, we want to assure you that the rest of the manuscript, including Table 2, contains accurate information. We have corrected the mistake in Line 381-382.

L395: Please explain the two peak values of in-situ in 2021 (Figure.7 and Figure.8).

Reply: For the figure 7: Yes, we add more explanations and discussed the uncertainties as well as limitations in this section. Please also note that for Fig. 7 panels 9-12, our data indeed captured the large peak values for most reservoirs (2, 0.5, 0.2 km^3).

Main text: The Res-CN database provides monthly reservoir water storage anomaly for 3254 Chinese reservoirs during 1984-2020 using DEM's area-storage model, along with their detailed evaluation reports (see Section of data availability).

The remotely sensed storage anomalies generally agree with the observations represented by the statistical metrics, although some large discrepancies occur in peak values.

The uncertainties in storage anomalies are primarily attributed to three sources, i.e., the altimetric water level, water surface area estimations from Landsat and Sentinel-2 images, and the error resulting from their combination (the hypsometric curve). Fig. S10 provides an example that illustrates how the uncertainties in satellite datasets propagate to storage anomalies. According to Shen et al. (2022), the primary source of error in storage anomaly is water surface area and the hypsometric curve. Regarding the water surface area, after applying the algorithm developed by Donchyts et al. (2022), these errors and impacts can be reduced to a large extent. Meanwhile, we employed five hypsometric relationships, and the one with the highest R^2 value for further use. For more than 80 % reservoirs, the R^2 values are greater than 0.5, providing a strong foundation for storage anomaly estimates. Nonetheless, the current satellite sensors have limitations, as evidenced by the significant discrepancies observed in peak values (Figure 7). The increasing temporal resolution and data accuracy of satellite datasets, such as the SWOT mission, will likely improve the accuracy of storage anomaly estimates in the future.

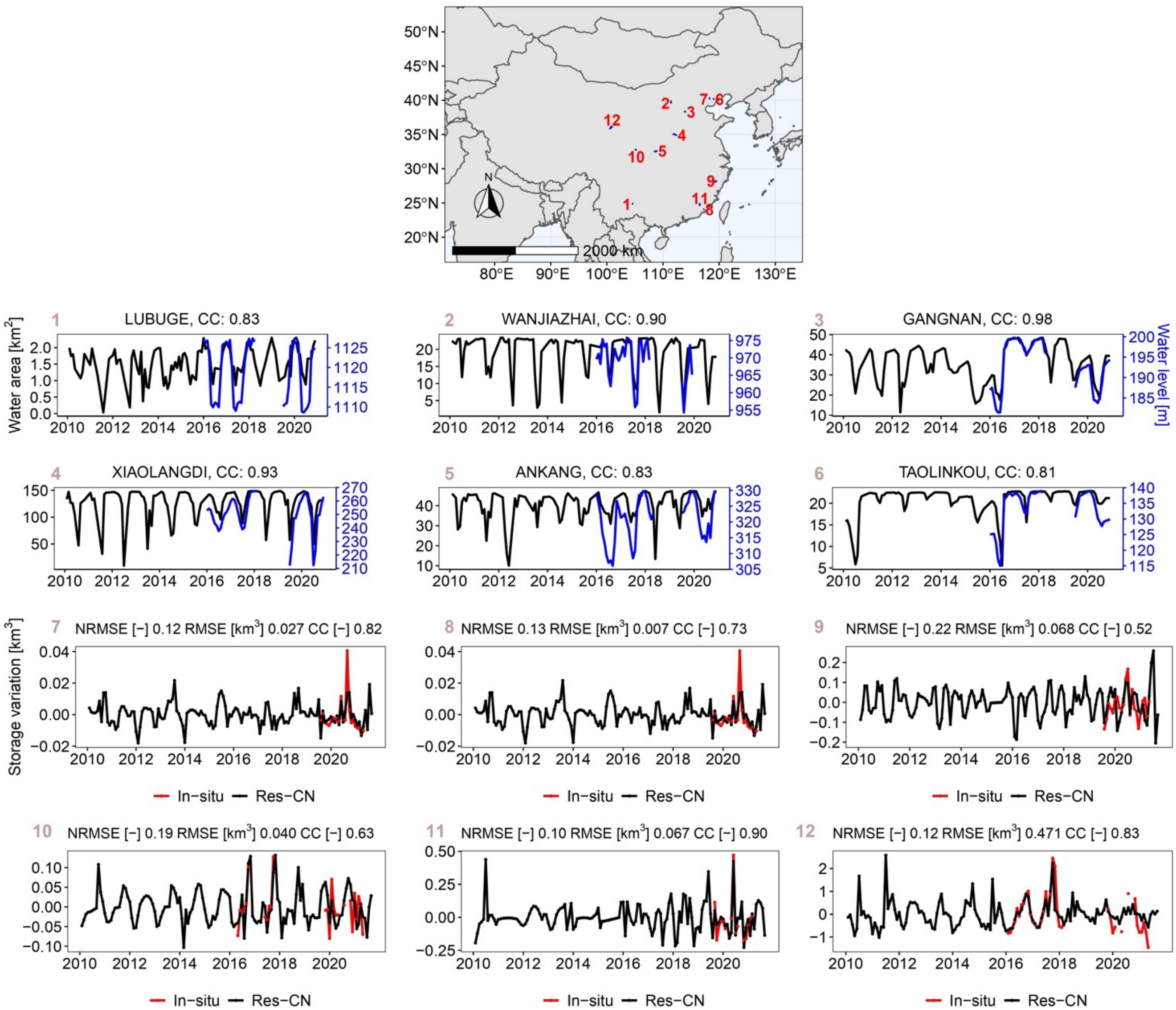

Figure 7. Time series of water surface area and storage anomaly in selected reservoirs. RMSE (km^3), NRMSE, and CC values are given at the top of each subplot when in situ observations available. Note that: time series of water surface area and storage anomaly of the remaining reservoirs are available in our datasets.

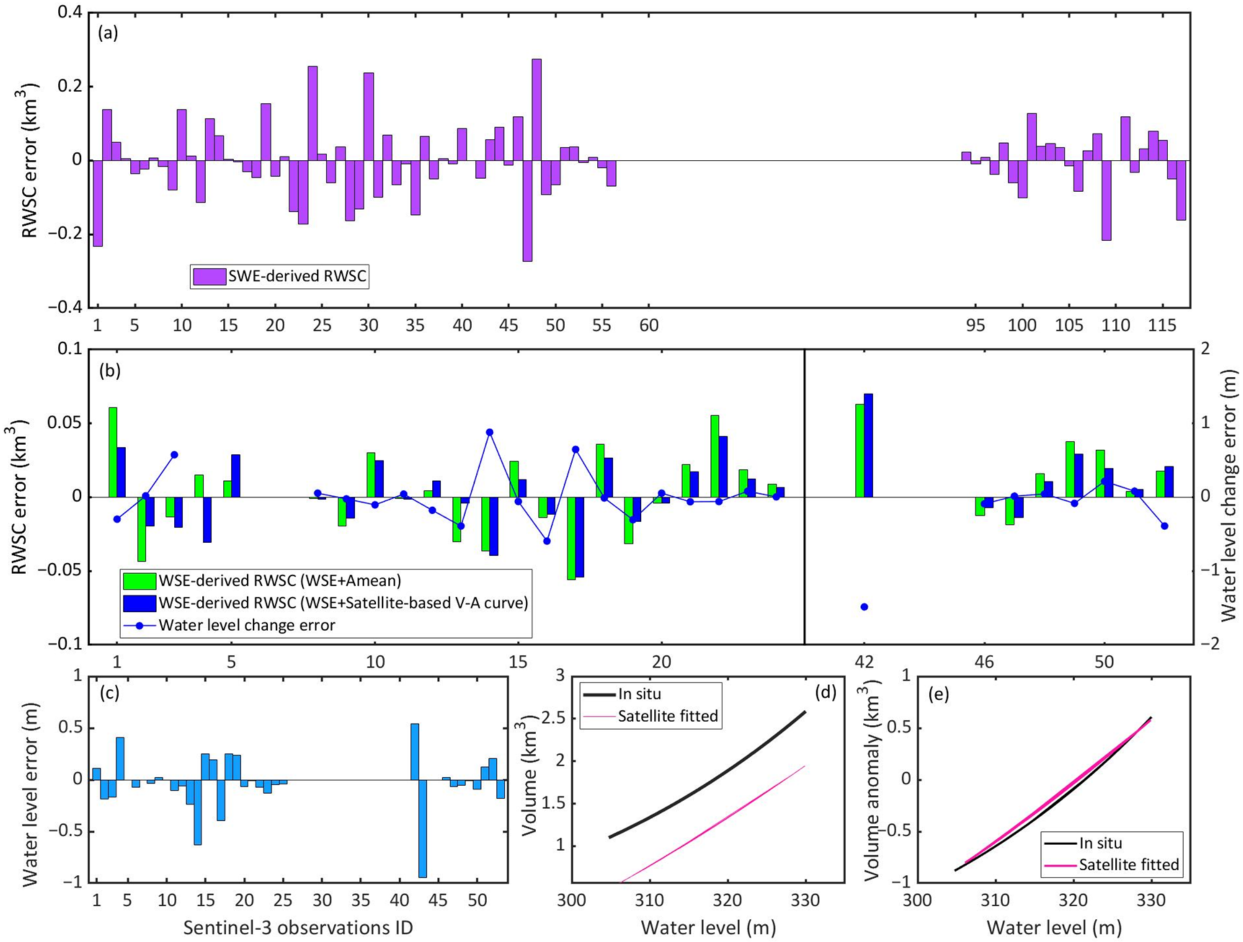

Figure S10. Graphs showing an example that illustrates how the uncertainties in satellite datasets propagate to storage anomalies. Error series and relationships of reservoir elevation-storage. Error series of (a) SWE-derived RWSC (i.e., storage anomaly), (b) WSE-derived RWSC and water level change, (c) WSE (i.e., water level). (d) and (e) Relationships of elevation-storage. The numbers on the x-axis (a, b, c) refer to the IDs of SWE, WSE, and WSE change observations, respectively. For more details about the propagation process, please find the reference Shen et al., (2020): https://doi.org/10.3390/rs14040815.

For Figure 8: We revised the figure 8 and re-create figure s11 for validation. Please find our revised text below:

Res-CN provides monthly reservoir evaporation values for 3254 Chinese reservoirs during 1984-2021. Detailed validations of the algorithm can be found in Zhao et al. (2019; 2022) and Tian et al., (2021). The validation of simulated evaporation at an annual scale from Tian et al. (2022) at 47 reservoirs was summarized in Fig. S11 through a literature review. The results in Fig. S11 indicate that the modeled average annual evaporation rates match well with the observed rates. Specifically, the percent bias (PBIAS), Nash-Sutcliffe efficiency (NSE), and root-mean-square error (RMSE) were found to be 0.02%, 0.82, and 11.2 mm, respectively. This high level of agreement suggests that the Penman method is a reliable approach for calculating reservoir evaporation rates in China. Fig. S12 shows the long-term mean meteorological variables that were used to calculate the evaporation rates.

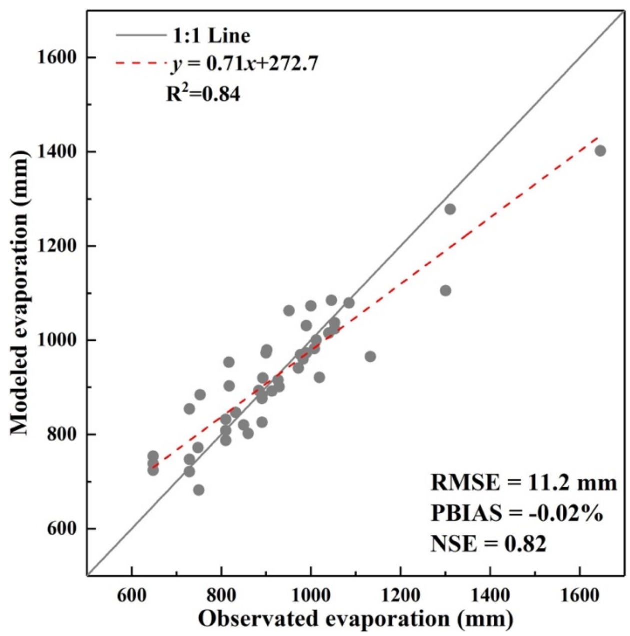

Figure S11. Observed and modeled average annual evaporation for 47 reservoirs (Tian et al., 2021).

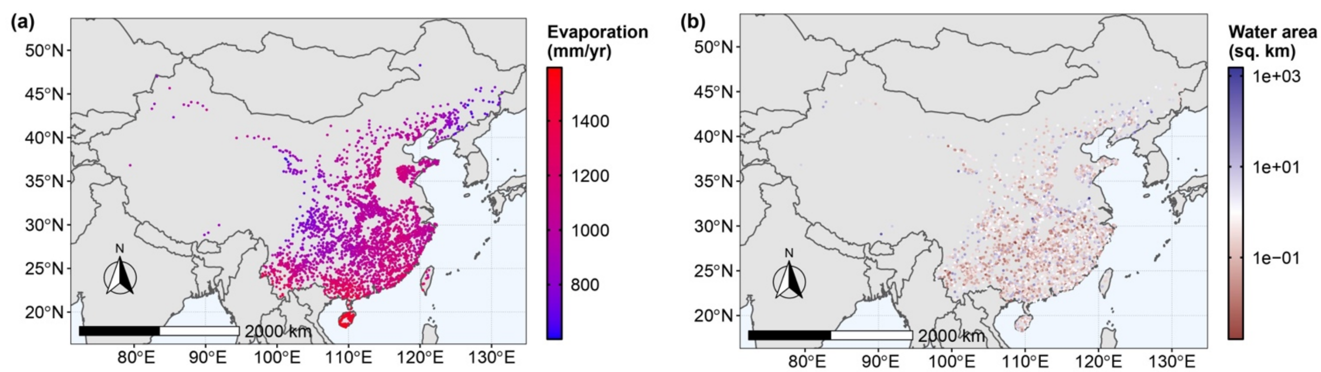

Figure 8. Validation of reconstructed monthly reservoir evaporation values. (a) Long-term mean evaporation rates and (b) water surface areas during 1984-2020.

References:

Tian, W., Liu, X., Wang, K., Bai, P., & Liu, C. (2021). Estimation of reservoir evaporation losses for China. Journal of Hydrology, 596, 126142. https://doi.org/10.1016/j.jhydrol.2021.126142

Zhao, G., and Gao, H.: Estimating reservoir evaporation losses for the United States: Fusing remote sensing and modeling approaches, Remote Sens. Environ., 226, 109-124, https://doi.org/10.1016/j.rse.2019.03.015, 2019.

Zhao, G., Li, Y., Zhou, L., and Gao, H.: Evaporative water loss of 1.42 million global lakes. Nat. Commun., 13, 3686, https://doi.org/10.1038/s41467-022-31125-6, 2022.

L425: Please confirm that the time period is 1984-2020.

Reply: The correct date range should be 1984-2021 instead of what was previously stated. We apologize for any confusion this may have caused. We have corrected the mistake in this Line.

L437: When the author first introduced the MERIT-river database, please add citations.

Reply: We used the MERIT-Hydro database (Yamazaki et al., 2019) to calculate stream density and length within a catchment.

References:

Yamazaki, D, Ikeshima, D, Sosa, J, Bates, P. D., Allen, G. H., and Pavelsky, T. M.: MERIT Hydro: A high-resolution global hydrography map based on latest topography dataset, Water Resour. Res., 55, 5053-5073, https://doi.org/10.1029/2019WR024873, 2019.

L463~L464: Why the time period is different between here (1990~2018) and L456 (1980~2020)?

Reply: We updated the metrics based on all available data, and revised it:

We calculated nine attributes for NSCD based on meteorological data between 1 October 1990 and 30 September 2020 to reflect aspects of climatic characteristics.

L524: Why the color of Fig.11i is red?

Reply: We have thoroughly examined the figure in question, as well as all the other figures in the manuscript, and have confirmed that it is accurate. We apologize for any confusion or misunderstanding that may have arisen, and we hope that this clarification has helped to address any concerns.