Response to the topic editor:

(1) One of my original comments was regarding how the limitations of using NDWI to classify water, such as issues related to high turbidity, shadows, the presence of aquatic vegetation, mixed land-water pixels, and seasonal vegetation cover, are addressed. In your response, you mention that the locally-adjusted Contrast Limited Adaptive Histogram Equalization (CLAHE, Reza, 2004) method can address all these issues. However, I think the authors should be cautious in asserting that CLAHE can effectively address all these challenges based on the method's underlying principle.

A: Yes, you are right. We want to clarify that while CLAHE applied to NDWI images does not specifically correct for high turbidity, shadows, aquatic vegetation, mixed land-water pixels, or seasonal vegetation effects—this remains a limitation of our study. However, CLAHE is intended to standardize reflectance values and reduce noise in NDWI-based water detection, helping to mitigate challenges such as varying illumination conditions and subtle spectral differences that could lead to partial misclassification of water pixels. We have now added a sentence in the revised manuscript to state these limitations explicitly.

Please also see Line 527-529:

"*Please note that CLAHE applied to NDWI images does not specifically correct for high turbidity, shadows, aquatic vegetation, mixed land-water pixels, or seasonal vegetation effects—this remains a limitation of our study.*"

(2) The temporal resolution of the reservoir storage time series is unclear. Given that this study leverages both Landsat and Sentinel-2 data, the temporal frequency should be higher than what is currently stated. It may be helpful to clarify this point in the time series figures to provide better explanation.

A: Thank you, we completely understand your concern. However, although we leveraged both Landsat and Sentinel-2 data and a robust cloud-effect removal algorithm, the estimation was still not possible for the images with more than 80% cloud coverage. We have also thought of combining a series of individual Landsat and Sentinel-2 images to generate surface water maps potentially up to a biweekly time period. However, many reservoirs do not fit in a single tile of Landsat and/or Sentinel-2, because of the shape and location of the reservoir. This leads to many no-data (missing) pixels over the reservoir, making image enhancement and gap-filling more challenging, and sometimes unrealistic. Therefore, we decided not to go for individual tiles of Landsat and Sentinel-2. Rather, we compromised slightly with the temporal frequency of the images and opted for using the image composites at 10-day intervals.

(3) Please increase the font in Figure 1, it's hard to read for now.

A: We have increased the font in Figure 1 to the best possible and updated the manuscript accordingly. Please see:

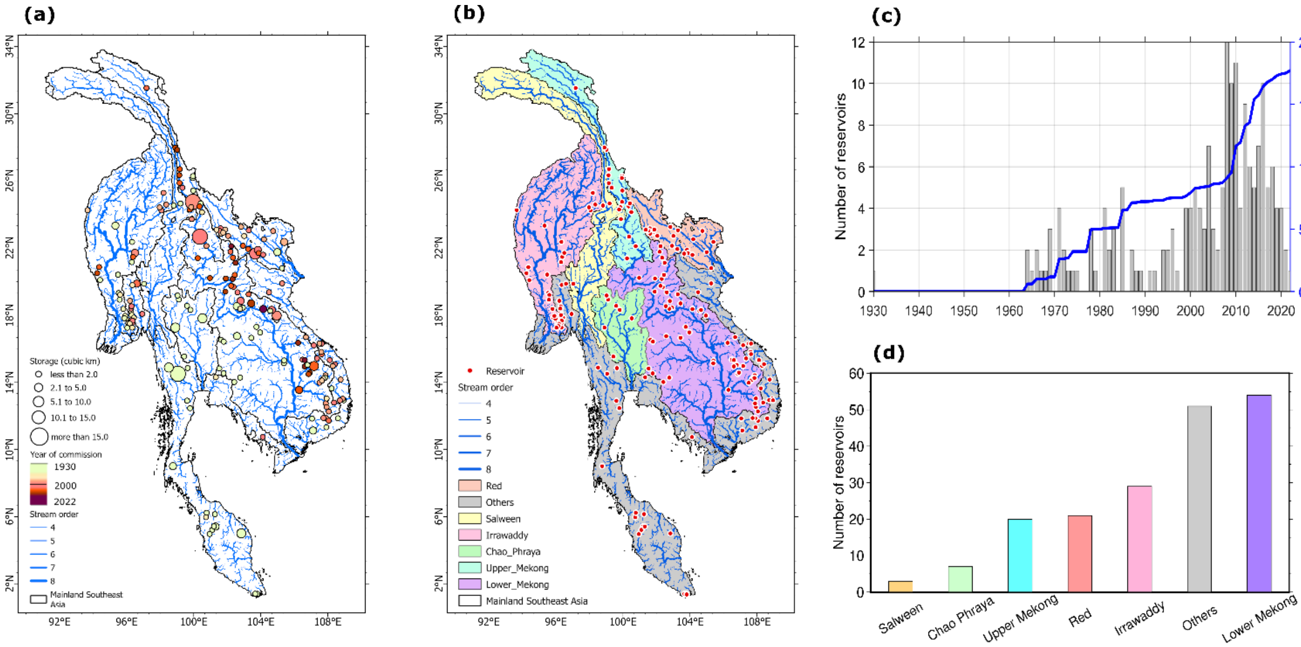

Figure 1: Spatial distribution and evolution of reservoirs in Mainland Southeast Asia. (a) Map showing reservoir storage volume (km^3), where the size of the circle is proportional to the reservoir capacity while the colour represents the year of commission of the reservoirs. (b) Basin-wise distribution of reservoir location (red dots), stream network in the respective catchments, and stream order. (c) Number of reservoirs built per year and their corresponding cumulative storage capacity. (d) Basin-wise total number of reservoirs built until 2023.

(4) Statement 'Water frequency' is not very accurate in Figure 3, maybe 'Flood frequency'.

A: The term 'water frequency' here refers to how often water is present in a given pixel (area) within the reservoir, as explicitly stated in Lines 214-216. Since 'flood frequency' has a distinct meaning in hydrology—one that is less relevant to the reservoir's water surface dynamics—we believe 'water frequency' is the more appropriate term to describe the probability of water presence in the reservoir.

Lines 214-216:

"*The FREQ layer is created by making a composite of all binary NDWI images (more than 200 images from the Landsat and Sentinel collections), whose cloud percentage is less than 20% (i.e., clear sky condition) and by dividing it by the total number of selected images (cloud percentage <20%). We multiply the FREQ layer by 100 to get the percentage of water present at each pixel.*"