Reviewer 1

The submission reads like a project report rather than a research article. It is mainly because the proposed method seems to be tailored for the case study, instead of being general for different case studies.

Response: This manuscript aims to present a generalized framework to improve reservoir storage forecasting for operational use and decision-making across river basins. Although the case study is conducted in the Nueces Basin, the proposed events selection, ensemble modeling and post-processing methods in the study can be applied for streamflow and reservoir inflow forecasting in other river basins. In particular, as reservoir management in the Nueces River Basin is the decisive factor behind the evolving water crisis in Corpus Christi, the first major US city that could declare water emergency, our case study at this hot spot could have broad implications to the reservoir management and water resources planning of other cities with high water vulnerability in arid and semi-arid regions.

The study framework uses a set of ensemble members derived from historical catchment conditions, enabling reproducible model setup and consistent assessment of flow dynamics. The number of ensemble members can vary depending on the variability of initial and antecedent conditions, but the overall methodology remains adaptable across hydrological settings. Furthermore, the integration of the ensemble model and post-processing techniques enhances the applicability in data scarce regions by allowing flexible model resolution. The application in the Nueces Basin can effectively illustrate these capabilities and highlight the challenges of reservoir storage systems worldwide, demonstrating the practicality and robustness of the proposed framework.

Rather than relying on historical rainfall time series, recent years witnessed extensive applications of precipitation forecasts to streamflow forecasting. Below are a few examples:

- Robertson, D. E., D. L. Shrestha, and Q. J. Wang. "Post-processing rainfall forecasts from numerical weather prediction models for short-term streamflow forecasting." Hydrology and Earth System Sciences 17, no. 9 (2013): 3587-3603.
- Li, Ming, Q. J. Wang, James C. Bennett, and David E. Robertson. "Error reduction and representation in stages (ERRIS) in hydrological modelling for ensemble streamflow forecasting." Hydrology and Earth System Sciences 20, no. 9 (2016): 3561-3579.
- Bennett, James C., Quan J. Wang, David E. Robertson, Andrew Schepen, Ming Li, and Kelvin Michael. "Assessment of an ensemble seasonal streamflow forecasting system for Australia." Hydrology and Earth System Sciences 21, no. 12 (2017): 6007-6030.

Given the increasing availability of precipitation forecasts, the authors are suggested to consider precipitation forecasts in their proposed method. Otherwise, the proposed method can be outdated.

Response: We appreciate the insightful comments. The suggested articles are very helpful, and we will incorporate them into the revised manuscript. The utilization of quantitative precipitation forecasts (QPFs) to force hydrologic models has become the prevailing approach for generating ensemble flow predictions (Zhang et al., 2025). The NOAA medium-range QPFs used in this study have been widely used as key inputs in operational streamflow forecasting in the United States and form a core component of the National Water Model. This is similar to studies in other parts of the world that use ECMWF precipitation forecasts to drive hydrologic models.

Regarding historical rainfall patterns, there exist analog methods for selecting similar precipitation events in the past. Given that analog methods are missing in the sections of introduction and methods, the authors are suggested to improve the rainfall part in their proposed methods.

Below please find two papers on analog methods.

- Junk, C., Delle Monache, L. and Alessandrini, S., 2015. Analog-based ensemble model output statistics. Monthly Weather Review, 143(7), pp.2909-2917.
- Horton, P., 2019. AtmoSwing: Analog technique model for statistical weather forecastING and downscalING (v2. 1.0). Geoscientific Model Development, 12(7), pp.2915-2940.

Response: We appreciate the reviewer's comment and will include analog methods in the revision, highlighting the selection, comparison, and assimilation of analog years in the context of operational forecasting and how they can be used to enhance storage forecast skill.

The study model setup is based on a representative range of historical events that resemble past hydrological conditions. In the revision, analog year will be incorporated to enhance systematic selection of historical rainfall events. We will improve the selection process for ensemble members by combining the analog rainfall years with the variability of initial catchment conditions (such as soil moisture status), and the magnitude of the precipitation to historical patterns. The revised approach will incorporate the concept of analog-based reasoning in a flexible and condition-based operational forecasting framework with consideration of the similarity of the NOAA medium-range QPFs. This can complement conventional analogue-event methods by improving analogue-regime and teleconnection matching, thereby reducing forecast uncertainty and enhancing simulation reliability (Wood and Lettenmaier, 2006).

Meteorological input uncertainty is usually assumed to represent the largest sources of uncertainty in hydrologic forecasting, but the uncertainties in initial conditions, structure, and parameters of the hydrologic models can also be significant (Cloke and Pappenberger, 2009; Zhang et al., 2025). An improved understanding of such factors will contribute to the advances in multi-model and super-ensemble methods for reservoir inflow forecasts (Dion et al., 2021; Thebault et al., 2025). In this study, a weighted configuration will be developed to adaptively provide more representative and accurate results after the probabilistic distribution evaluation of the ensemble members. Ensemble members will be weighted according to their similarity to forecasted atmospheric patterns and antecedent soil moisture conditions, with greater weights assigned to members that better reproduce hindcast forecasts of wet and dry regimes. The weighted forecast is represented as:

$$F_w = \sum_{i=1}^{n} w_i f_i$$

where w_i denotes the weight assigned to ensemble member i and f_i is the corresponding forecast (Hamill et al., 2006; Demargne et al., 2014).

References:

Cloke, H. L., & Pappenberger, F. (2009). Ensemble flood forecasting: A review. *Journal of hydrology*, *375*(3-4), 613-626.Dion, P., Martel, J. L., & Arsenault, R. (2021). Hydrological ensemble forecasting using a multi-model framework. *Journal of Hydrology*, *600*, 126537.

Demargne, J., Martyn Clark, Eric Wood, et al. (2014). The science of NOAA's Hydrologic Ensemble Forecast Service. *Journal of Hydrology, 519*, 3552–3567.

Dion, P., Martel, J. L., & Arsenault, R. (2021). Hydrological ensemble forecasting using a multi-model framework. *Journal of Hydrology*, *600*, 126537.

Hamill, T. M., & Whitaker, J. S. (2006). *Probabilistic quantitative precipitation forecasts based on reforecast analogs*. Monthly Weather Review.

Thébault, C., Perrin, C., Legrand, S., Andréassian, V., Thirel, G., & Delaigue, O. (2025). What can be expected from a semi-distributed multi-model approach for streamflow forecasting? Tailoring the structure and size of a super-ensemble on the Rhône basin. *Journal of Hydrology*, *661*, 133589.

Wood, A. W., & Lettenmaier, D. P. (2006). *A test bed for new seasonal hydrologic forecasting approaches in the western United States*. Bulletin of the American Meteorological Society, 87(12), 1699–1712.

Zhang, J., Li, W., & Duan, Q. (2025). Quantifying the contributions of hydrological pre-processor, post-processor, and data assimilator to ensemble streamflow prediction skill. *Journal of Hydrology*, *651*, 132611.