



*Supplement of*

**Divergent responses of streamflow reanalysis errors to precipitation reanalysis errors modulated by catchment heterogeneity**

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## **Sect. S1: Selection of case-study catchments**

The case-study catchments are selected according to criteria that account for reanalysis performance, observational data availability and hydroclimatic diversity. Specifically, candidate catchments are required to have Nash–Sutcliffe efficiency (NSE) greater than 0.5 for the GloFAS-ERA5 streamflow reanalysis relative to observations (Michailovsky et al., 2023; Hwang and Devineni, 2022; Li et al., 2025). This criterion ensures that the reanalysis captures streamflow dynamics with reasonable skill, thereby reducing the likelihood that the diagnosed responses are driven primarily by poor streamflow simulation (Jiang et al., 2022; Mai et al., 2022). To further limit the influence of data gaps on the estimation of annual reanalysis errors and regression coefficients, only catchments with less than 5% missing streamflow observations are retained.

Among catchments satisfying these general criteria, the rain-dominated case study is selected from those with the snow fraction below 0.1 and statistically significant regression coefficient for precipitation reanalysis error ( $p < 0.05$ ). These criteria are used to identify catchments in which variations in streamflow reanalysis error are primarily associated with precipitation errors, with minimal influence from snow-related processes. By contrast, the snow-dominated case study is selected from catchments with the snow fraction greater than 0.3 and statistically significant regression coefficients for both precipitation and temperature reanalysis errors ( $p < 0.05$ ). These criteria are used to identify catchments in which variations in streamflow reanalysis error reflect the combined influence of precipitation errors and snow processes related to temperature. The two selected catchments therefore provide contrasting examples for presenting the divergent responses under rain-dominated and snow-dominated hydrological regimes.

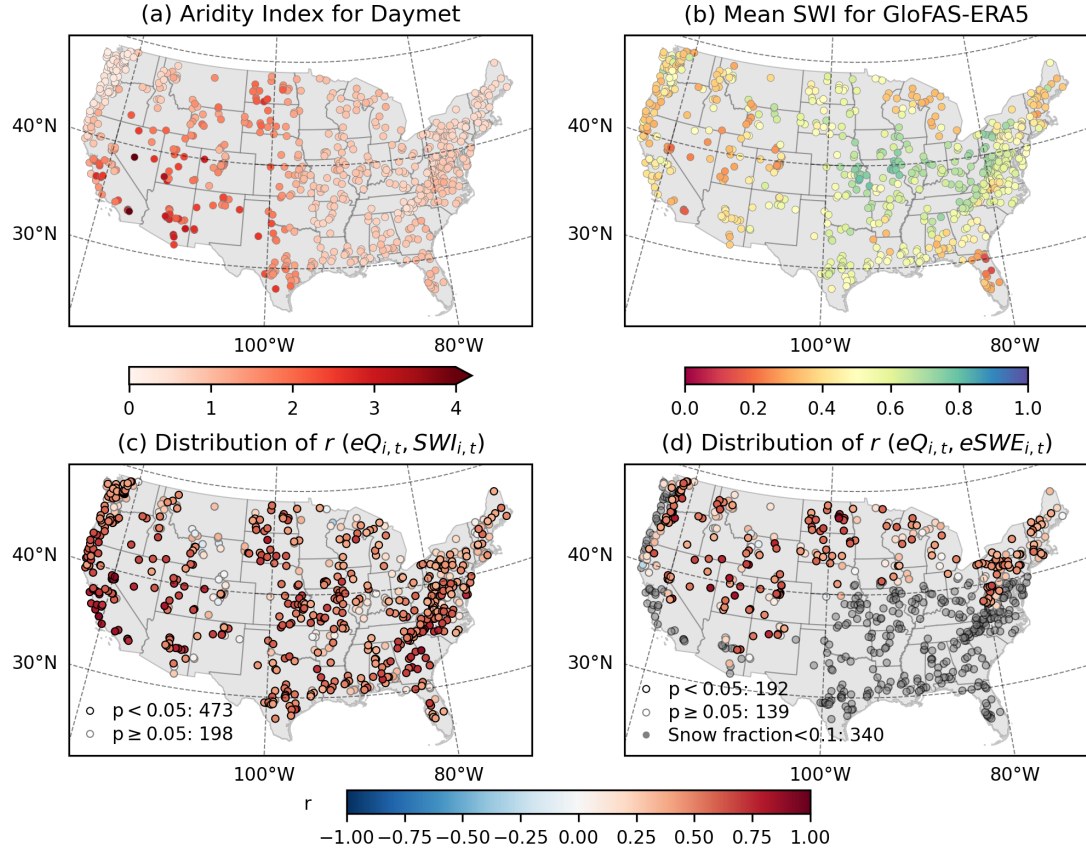
## Sect. S2: Sensitivity analysis using normalized errors

To examine whether the positive relationships between streamflow and precipitation reanalysis errors persist after reducing the influence of hydroclimatic magnitude, the sensitivity analysis is performed using normalized root-mean-square errors (NRMSEs) (Li et al., 2026; Meng and Zhao, 2025; Ambika et al., 2025). For each catchment and hydrological year, the streamflow and precipitation RMSEs are normalized by the corresponding annual mean of observations. The NRMSEs of streamflow ( $neQ_{i,t}$ ) and precipitation ( $neP_{i,t}$ ) are calculated as:

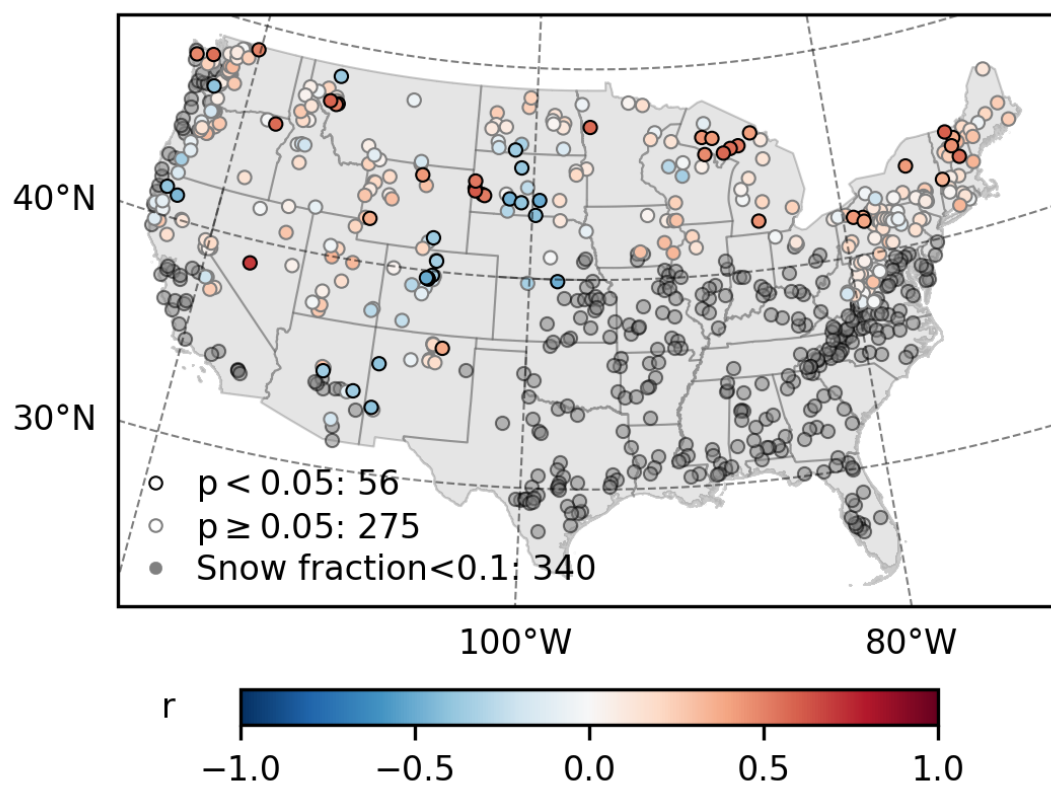
$$\begin{cases} neQ_{i,t} = \frac{\sqrt{\frac{1}{n_{i,t}} \sum_{d=1}^{n_{i,t}} (Q_{i,t,d} - \hat{Q}_{i,t,d})^2}}{\frac{1}{n_{i,t}} \sum_{d=1}^{n_{i,t}} Q_{i,t,d}} \\ neP_{i,t} = \frac{\sqrt{\frac{1}{n_{i,t}} \sum_{d=1}^{n_{i,t}} (P_{i,t,d} - \hat{P}_{i,t,d})^2}}{\frac{1}{n_{i,t}} \sum_{d=1}^{n_{i,t}} P_{i,t,d}} \end{cases} \quad (S1)$$

where  $\hat{Q}_{i,t,d}$  and  $\hat{P}_{i,t,d}$  respectively denote the streamflow and precipitation reanalysis for catchment  $i$  on day  $d$  of hydrological year  $t$ ;  $Q_{i,t,d}$  and  $P_{i,t,d}$  represent the corresponding observations, respectively;  $n_{i,t}$  is the number of data pairs in hydrological year  $t$  for catchment  $i$ . Both  $neQ_{i,t}$  and  $neP_{i,t}$  are dimensionless and represent the reanalysis errors relative to the corresponding observed hydroclimatic magnitude. For some arid catchments, the annual mean observed streamflow can be zero because of prolonged zero-flow conditions, making the corresponding ratio in Eq. (S1) undefined. In such cases, the zero annual mean is replaced by the average of the annual mean observed streamflow over all available hydrological years.

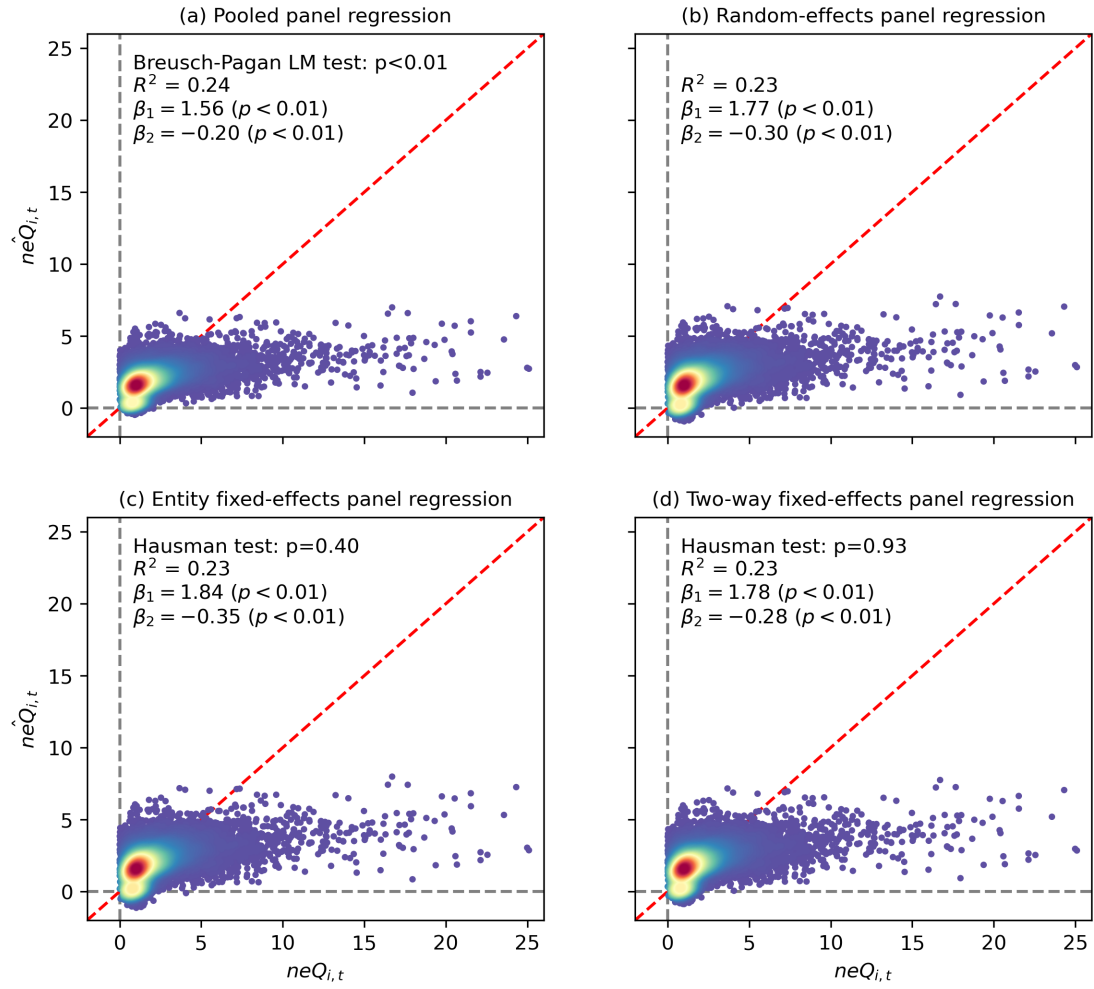
For the sensitivity analysis,  $neQ_{i,t}$  and  $neP_{i,t}$  are substituted for the streamflow RMSE ( $eQ_{i,t}$ ) and precipitation RMSE ( $eP_{i,t}$ ), respectively, in the catchment-specific linear regression and panel regression models described in Eqs. (3) to (9). The temperature-error term is retained in its original form. The results of the sensitivity analysis are shown in Figs. S3 and S4. The normalization is used here only for sensitivity analysis rather than as a replacement for the analysis of RMSE. First, annual mean streamflow can approach zero in arid and intermittent catchments, causing normalized streamflow errors to become very large and numerically unstable in low-flow years. Second, the physical interpretation of NRMSE depends on the selected normalization scale and is less direct than that of RMSE. In the main analysis, RMSE retains the physical magnitude and units of the reanalysis error, allowing the regression coefficients to be interpreted directly in terms of changes in precipitation and streamflow errors.



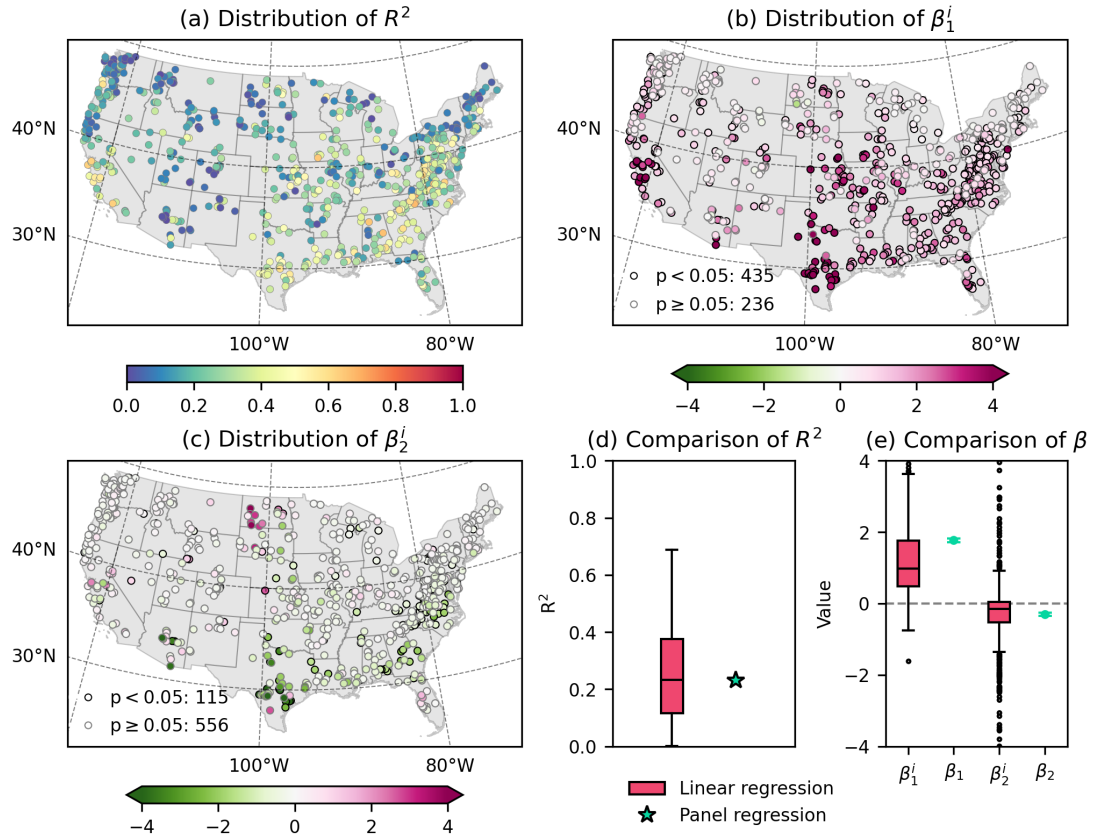
**Figure S1.** Spatial distribution of (a) aridity index for Daymet, (b) mean soil wetness index (SWI) from the GloFAS-ERA5 dataset and (c-d) Pearson's correlation coefficients of streamflow reanalysis error to SWI and to snow depth water equivalent (SWE) error. The eSWE represents the RMSE of SWE from the GloFAS-ERA5 dataset by hydrological year using the SWE from the Daymet dataset as reference data.



**Figure S2.** Pearson's correlation coefficients ( $r$ ) between precipitation reanalysis errors and temperature reanalysis errors on cold days (Daymet temperature  $\leq 0^\circ\text{C}$ ) by hydrological year.



**Figure S3.** As for Fig. 3, but for normalized root-mean-square error (NRMSE).



**Figure S4.** As for Fig. 4, but for normalized root-mean-square error (NRMSE).

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