## The GSQM-SST framework to project future rainfall extremes



### **Stochastic Storm Transposition (SST)**



Fig. 2. (a) Transposition domain for a region surrounding New Orleans, Louisiana along the southern United States Gulf Coast. (b) Peak 72-hour rainfall map for Hurricane Harvey in August 2017, based on Stage IV gage-corrected radar rainfall data (Lin, 2011). (c) to (e) three possible random transpositions of Hurricane Harvey rainfall which produce little, no, and extreme rainfall over New Orleans, respectively. (f) Example 72-hour IDF curve for New Orleans generated using the RainyDay software (Section 4.4); shaded area portrays the spread of 100 distinct realizations, each consisting of 1000 annual rainfall maxima.

# Supplementary

# Gamma-based spatial quantile mapping (2.2. GSQM) (ii) Future climate (4.4) Future IDFs (4.6)

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## Rainfall-temperature scaling

- • $S_{MAR}$  is up to 3.6%, lower than 7%
- •Sample size: 20 years
- Hook structure

# **GSQM** and **SST** parameters

- Other marginal distribution
- Underestimation from  $S_{R99}$
- Assumption in future SST

- Simple and efficient
- •Need to consider dynamic factors

### **Code Access**

[1] Zou, W., & Peleg, N. (2025). Gamma-based Spatial Quantile Mapping (GSQM) of heavy storm in Beijing, China [Software]. Zenodo. https://doi.org/10.5281/zenodo.15046546 [2] Wasko, C., & Sharma, A. (2014). Quantile regression for investigation scaling of extreme precipitation with temperature. Water Resources Research, 50(4), 3608-3614. [3] Peleg, N. et al., (2022). Mapping storm spatial profiles for flood impact assessments. Advances in Water Resources, 166, 104258.



$$Rp = WAR \cdot S_{WAR}$$

$$(y) = G[R(x, y), a, b].$$

$$\frac{1}{CV^2}, b = MAR \cdot CV^2$$

$$Q > 99, a_p, b_p] = R99 \cdot S_{R99},$$

$$\frac{1}{(CV \cdot S_{CV})^2} \quad b_p = (MAR \cdot S_{MAR}) \cdot (CV \cdot S_{CV})^2.$$

$$(y) = G_p^{-1}[Q(x, y), a_p, b_p].$$