

Conditional Design Flood Hydrograph Derivation Considering Spatially Heterogeneous Rainfall and Nonlinear Nonstationary Routing

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Contents of this file

Text S1 to S5

Figures S1 to S5

Tables S1 to S6

Supplementary Text

Text S1 Net Rainfall Intensity Classification, Reliability Assessment of Conditional Responses, and Conditional Unit Hydrograph Refinement Method、

To ensure the reproducibility of the conditional unit hydrograph construction procedure, this section further describes the classification of net rainfall intensity, the reliability assessment of conditional net rainfall-rapid surface runoff response functions, and the specific procedure for refining the Nash unit hydrograph based on conditional response characteristics.

(1) Conditional Classification and Net Rainfall Intensity Thresholds

Net rainfall intensity classes were determined by comparing several candidate schemes, including percentiles of nonzero net rainfall intensity, approximately equal-interval classification, cumulative net rainfall proportions, and fixed thresholds. Considering the effective sample size within each interval, the amplitude of the nonlinear response function (NRF), and the proportion of positive responses, 1, 5, and 10 mm/h were selected as candidate thresholds for comparing response characteristics and reliability among different net rainfall intensity intervals. The comparison of the candidate classification schemes is presented in Table S1. These classifications are used solely to diagnose net rainfall response characteristics and reliability and do not correspond to meteorological rainfall-intensity categories.

During the reliability assessment, the two antecedent wetness states were combined with four net rainfall intensity intervals, $0 < P_e < 1$, $1 \leq P_e < 5$, $5 \leq P_e < 10$, and $P_e \geq 10\text{mm/h}$, yielding eight diagnostic conditions. Sample support and NRF reliability were evaluated separately for each condition, as shown in Table S2. Based on the overall variations in NRF response amplitude and identifiability among the different intervals, 5 mm/h was ultimately selected as the net rainfall intensity threshold. Net rainfall was therefore classified into lower net rainfall intensity ($P_e < 5\text{mm/h}$) and higher net rainfall intensity ($P_e \geq 5\text{mm/h}$).

For the final conditional response identification, the two net rainfall intensity classes were combined with the lower (L) and higher (H) antecedent wetness states to form four final conditions, $C_{c,k}$, where $c \in \{L, H\}$ and $k \in \{\text{Low}, \text{High}\}$. Using the ERRA joint deconvolution framework described in Section 2.1.2, the net rainfall-rapid surface runoff response function, $\text{NRF}_{c,k}(\tau)$, was identified for each final condition and subsequently used to construct the conditional Nash unit hydrographs.

(2) Reliability Assessment of Conditional NRFs

Because the effective sample size may decrease for some combinations after jointly classifying

antecedent wetness state and net rainfall intensity, the reliability of the response under each condition was evaluated before using the NRF to refine the unit hydrograph. The evaluation metrics included the number of effective nonzero ERRA samples, the maximum absolute response amplitude within the main response period, and the proportion of positive responses. The number of effective nonzero samples under condition C_i is denoted by n_i . The maximum absolute response amplitude of the smoothed conditional NRF is defined in Eq. (S1-1):

$$A_i = \max_{0 \leq \tau \leq m} |NRF_{i,smoothed}(\tau)| \quad (S1-1)$$

The proportion of positive responses is defined in Eq. (S1-2):

$$\rho_i = \frac{\sum_{\tau=0}^m I[NRF_{i,smoothed}(\tau) > 0]}{N_\tau} \quad (S1-2)$$

where $I(\cdot)$ is the indicator function, m is the maximum lag within the main response period, and N_τ is the corresponding number of discrete lag intervals. Greater effective sample support, a larger NRF response amplitude, and a higher proportion of positive responses indicate stronger identifiability and stability of the conditional response. Based on the NRF response characteristics under the different classification schemes, $A_i > 0.01$ and $\rho_i > 0.50$ were adopted as criteria for response reliability, together with the number of effective nonzero net rainfall samples to assess the degree of sample support under each condition. The evaluation results for all condition combinations are presented in Table S2.

(3) Lag-Parameter Refinement under Lower Net Rainfall Intensity ($P_e < 5\text{mm/h}$)

According to the reliability assessment and net rainfall intensity classification described above, the NRFs under $P_e < 5\text{mm/h}$ generally exhibit relatively weak response amplitudes, and their local shapes are more susceptible to fluctuations arising from deconvolution. Therefore, the local NRF shape is not used directly to refine the unit hydrograph. Instead, the response centroid is used to adjust the time scale of the Nash unit hydrograph. For conditions under which the response centroid can be reliably identified, the centroid lag under condition C_i is defined in Eq. (S1-3):

$$Lag_i = \frac{\sum_{\tau=0}^m \tau \cdot NRF_{i,smoothed}(\tau)}{\sum_{\tau=0}^m NRF_{i,smoothed}(\tau)} \quad (S1-3)$$

where $NRF_{i,smoothed}(\tau)$ is the smoothed nonlinear nonstationary net rainfall-surface runoff response function under condition C_i , τ is the lag time, and m is the maximum response lag.

The centroid lag of the composite Nash unit hydrograph is denoted by Lag_{med} .

A lag-time scaling factor is then constructed and used to adjust the scale parameter of the composite Nash unit hydrograph, as shown in Eqs. (S1-4) and (S1-5):

$$\lambda_i = \frac{Lag_i}{Lag_{med}} \quad (S1-4)$$

$$K_i = K_{med} \cdot \lambda_i \quad (S1-5)$$

where λ_i is the lag-time scaling factor under condition C_i , K_i is the refined scale parameter, and K_{med} is the scale parameter of the composite Nash unit hydrograph. When $\lambda_i > 1$, the unit hydrograph becomes broader, its peak decreases, and its time to peak is delayed. When $\lambda_i < 1$, the unit hydrograph becomes narrower, its peak increases, and the response occurs earlier.

Accordingly, the parametrically refined unit hydrograph under lower net rainfall intensity is expressed in Eq. (S1-6):

$$u_{corr,i}(\tau) = \frac{1}{K_i \Gamma(n_{med})} \left(\frac{\tau}{K_i} \right)^{n_{med}-1} e^{-\frac{\tau}{K_i}} \quad (S1-6)$$

where $u_{corr,i}(\tau)$ is the refined unit hydrograph under condition C_i , τ is the lag time, K_i is the refined Nash unit hydrograph scale parameter under condition C_i , n_{med} is the shape parameter of the composite Nash unit hydrograph, and $\Gamma(n_{med})$ is the Gamma function. This approach preserves the smooth and continuous characteristics of the Nash unit hydrograph while representing differences in routing responses under lower net rainfall intensity through adjustment of the time scale, thereby reducing the influence of local NRF fluctuations on unit hydrograph shape refinement. If the NRF response under a lower-net-rainfall-intensity condition is too weak for the response centroid to be reliably identified, centroid-based scale adjustment is not imposed.

(4) Shape Refinement under Higher Net Rainfall Intensity ($P_e \geq 5\text{mm/h}$)

For conditions with $P_e \geq 5\text{mm/h}$ that pass the NRF reliability assessment, both the response amplitude and temporal response pattern are relatively stable. Therefore, the relative response characteristics represented by the NRF can be used to refine the shape of the composite Nash unit hydrograph. First, the smoothed conditional NRF is normalized by its mean to construct a dimensionless conditional correction factor, as shown in Eq. (S1-7):

$$f_{NRF,i}(\tau) = \frac{NRF_{i,smoothed}(\tau)}{\text{mean}[NRF_{i,smoothed}(\tau)]} \quad (S1-7)$$

where $NRF_{i,smoothed}(\tau)$ is the smoothed net rainfall-rapid surface runoff response function under condition C_i , and $f_{NRF,i}(\tau)$ is the corresponding dimensionless conditional correction factor used to characterize the relative response strength at different lag times.

Taking the composite Nash unit hydrograph $u_{med}(\tau)$ as the baseline, $f_{NRF,i}(\tau)$ is introduced to refine its temporal shape, as shown in Eq. (S1-8):

$$u_{corr,i}(\tau) = u_{med}(\tau) \cdot f_{NRF,i}(\tau) \quad (S1-8)$$

where $u_{corr,i}(\tau)$ is the refined unit hydrograph under condition C_i , and $u_{med}(\tau)$ is the composite Nash unit hydrograph. This approach uses the relative temporal variations captured by a reliable NRF to conditionally adjust the peak magnitude, time to peak, and recession behavior of the composite unit hydrograph, thereby representing differences in routing responses under different antecedent wetness states and higher net rainfall intensity conditions.

(5) Area Normalization

To ensure that the refined conditional unit hydrographs satisfy the water-balance requirement that a unit depth of net rainfall corresponds to a unit depth of runoff, the refined unit hydrograph $u_{corr}(\tau)$ is normalized by its area, as shown in Eq. (S1-9):

$$u_{corr,norm}(\tau_j) = \frac{u_{corr,i}(\tau_j)}{\sum_{j=1}^N u_{corr,i}(\tau_j) \Delta \tau} \quad (S1-9)$$

where $u_{norm,i}(\tau)$ denotes the final conditional unit hydrograph under condition C_i , N is the number of discrete time intervals of the unit hydrograph, and $\Delta \tau$ is the computational time step. Through area normalization, the conditional unit hydrographs retain their relative differences in temporal shape while satisfying the water-balance constraint, and can therefore be used in the subsequent conditional routing calculations.

After area normalization, four types of conditional unit hydrographs are ultimately obtained: L-lower net rainfall intensity, L-higher net rainfall intensity, H-lower net rainfall intensity, and

123 H-higher net rainfall intensity. These conditional unit hydrographs are then used in the dynamic
124 state-dependent routing calculations described in Section 2.5.2 of the main text.
125

Text S2 Joint Frequency Analysis and Scale Derivation of Design Rainfall Based on Copula Function

(1) Marginal distribution fitting

Before constructing the Copula-based joint distribution model of P and I_1 , the marginal distributions of the two variables must first be determined. Marginal distributions describe the probability characteristics of individual random variables and serve as the basis for multivariate joint distribution modeling (Papalexiou et al., 2021). Considering that total rainfall depth and short-duration rainfall intensity are generally non-negative, right-skewed, and characterized by extended upper tails, this study selects the Lognormal, Gamma, Weibull, Exponential, Log-logistic, and three-parameter lognormal (LN_3) distributions as candidate models, which are fitted to P and I_1 , respectively.

To identify the optimal marginal distributions, the fitting performance of the candidate distributions is comprehensively evaluated using the Kolmogorov–Smirnov (K-S) test, Anderson-Darling (A-D) test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Smaller K-S and A-D statistics indicate better agreement between the theoretical and empirical distributions, whereas lower AIC and BIC values indicate a better balance between goodness of fit and model complexity (Fan et al., 2022). After comprehensive comparison of these criteria, the distribution functions with the best fitting performance are selected as the marginal distribution models for P and I_1 .

(2) Construction of the Copula-based joint distribution

After determining the marginal distributions of P and I_1 , a Copula function is further used to construct their joint probability distribution. Copula functions can link the marginal distributions of multiple random variables into a joint distribution, thereby characterizing the dependence structure and joint distribution characteristics among variables (Xiao, 2024). In the modeling procedure, P and I_1 are first transformed into uniform variables on the interval $[0,1]$ based on their optimal marginal distributions. Then, the Frank, Gumbel, and Clayton Copulas are selected as candidate models to fit the dependence structure between the two variables. The Copula parameter θ is determined using Kendall's rank correlation coefficient method and maximum likelihood estimation. The fitting performance is comprehensively evaluated using the K-S test, A-D test, AIC, and BIC, and the optimal Copula function is finally selected as the joint distribution model of P and I_1 .

(3) Derivation of joint design rainfall magnitude

Based on the optimal marginal distributions and the Copula-based joint distribution model, the design total rainfall depth P_T and design maximum 1 h rainfall intensity $I_{1,T}$ are derived for different return periods. In this study, return periods of 20, 100, 200, 500, 2,000, and 10,000 years are selected as representative cases. Here, P_T controls the total magnitude of the design storm, while $I_{1,T}$ constrains the short-duration peak intensity. This method can simultaneously account for the dependence between total rainfall depth and short-duration rainfall intensity, thereby providing a common set of design-magnitude constraints for each return period. These constraints are subsequently combined with a common representative rainfall pattern to construct the 96-h design rainfall hyetograph used for both L and H scenarios.

Text S3. Construction of the Spatial Rainfall Allocation Template

To characterize the temporal variation in the spatial distribution of design rainfall, a common time-varying spatial rainfall allocation template was constructed using all historical heavy rainfall events. The catchment was divided into K spatial subregions, with the area fraction of the k -th subregion denoted by a_k , satisfying $\sum_{k=1}^K a_k = 1$. For the j -th historical heavy rainfall event, the hourly mean rainfall in the k -th subregion is denoted by $p_{k,j}(t)$. Accounting for differences in subregion area, the normalized cumulative contribution of the k -th subregion to the catchment-total rainfall up to time t is defined by Eq. (S3-1):

$$C_{k,j}(t) = \frac{a_k \sum_{\tau=1}^t p_{k,j}(\tau)}{\sum_{h=1}^K a_h \sum_{\tau=1}^{D_j} p_{h,j}(\tau)} \quad (\text{S3-1})$$

where $C_{k,j}(t)$ denotes the normalized cumulative rainfall contribution of the k -th subregion up to time t during the j -th event; D_j is the effective rainfall duration of the event; and a_k is the area fraction of the k -th spatial subregion.

Each event was subsequently mapped onto a common dimensionless time axis x , and the increments in cumulative contribution between adjacent time intervals, $\Delta C_{k,j}(x_i)$, were calculated. The rainfall allocation ratio of the k -th subregion during the i -th dimensionless time interval is given by Eq. (S3-2):

$$r_{k,j}(x_i) = \frac{\Delta C_{k,j}(x_i)}{\sum_{h=1}^K \Delta C_{h,j}(x_i)}, \quad k = 1, 2, \dots, K \quad (\text{S3-2})$$

where $r_{k,j}(x_i)$ represents the rainfall allocation proportion of the k -th spatial subregion within dimensionless time interval x_i for the j -th event and satisfies $\sum_{k=1}^K r_{k,j}(x_i) = 1$.

To reduce the influence of periods with negligible rainfall on the estimation of spatial allocation ratios, time intervals for which the sum of cumulative-contribution increments across all subregions was below a prescribed threshold were excluded from the statistical analysis, and only time points supported by a sufficient number of valid events were retained. The median spatial allocation ratio at each time interval was then used to construct a representative trajectory. After interpolation of missing values, smoothing, and time-step-wise normalization, the final common spatial allocation template $r_k(x)$ was obtained, satisfying $\sum_{k=1}^K r_k(x) = 1$. Finally, $r_k(x)$ was interpolated onto the common 96 h design rainfall time axis to obtain $r_k(t)$, which was used as input for the spatial-response temporal adjustment described in Section 2.4.2.

Text S4 Surface Runoff Generation Mechanism and Net Rainfall Calculation Based on SCS-CN Model

The Soil Conservation Service Curve Number (SCS-CN) model describes rainfall-runoff transformation based on rainfall depth, initial abstraction, and potential maximum soil water retention. Owing to its simplicity and computational efficiency, it is widely used for catchment runoff estimation (Ajith and Barik, 2026). Its basic form is given in Eq. (S4-1):

$$Q = \begin{cases} \frac{(P - I_c)^2}{P - I_c + S}, & P > I_c \\ 0, & P \leq I_c \end{cases} \quad (S4-1)$$

where Q is the cumulative surface runoff depth, P is the cumulative rainfall depth, I_c is the initial abstraction, and S is the potential maximum soil water retention. The relationship between I_c and S is given in Eq. (S4-2):

$$I_c = \lambda S \quad (S4-2)$$

where λ is the initial abstraction coefficient, which was set to 0.15 in this study based on trial calculations, and S is determined from the Curve Number (CN). The CN value reflects the combined effects of land-use type, hydrologic soil group, and antecedent wetness conditions. A larger CN indicates a lower potential water-storage capacity and a greater tendency for runoff generation.

To characterize the initial antecedent wetness condition at the beginning of each flood event or design storm, the cumulative rainfall during the preceding 5 days, denoted by the 5-day Antecedent Precipitation Index ($API_{5,0}$), was used for classification. Because all selected flood events occurred during the local growing season, the SCS-CN growing-season Antecedent Moisture Condition (AMC) classification criteria were adopted (Nageswara Rao, 2020). Specifically, $API_{5,0} < 35.56\text{mm}$, $35.56 \leq API_{5,0} \leq 53.34\text{mm}$, and $API_{5,0} > 53.34\text{mm}$ correspond to AMC I, AMC II, and AMC III, respectively. The baseline CN values were determined from the lookup tables provided in the National Engineering Handbook (Amatya et al., 2022), and the CN values under different antecedent moisture conditions were adjusted using the corresponding standard conversion relationships (Afrasiabikia et al., 2025). The detailed AMC classification criteria are provided in Table S4.

After the initial AMC class and corresponding CN value were determined for each flood event or design storm, the CN value was held constant throughout the individual event. The cumulative rainfall series was then input into the SCS-CN model to calculate cumulative surface runoff depth, and the hourly net rainfall series P_e was obtained from differences in cumulative runoff depth between successive time steps. This net rainfall series was subsequently used as input to the conditional Nash unit hydrographs for routing calculations. The rolling $API_{5,t}$ during the design storm was not used to dynamically adjust the CN value; instead, it was used only in the subsequent routing calculation to determine the antecedent wetness state at each time step and select the corresponding conditional unit hydrograph.

Table S4: Classification of Antecedent Moisture Conditions (AMC)

Antecedent moisture condition	Five-day antecedent precipitation during the dormant season (mm)	Five-day antecedent precipitation during the growing season (mm)
AMC I (dry)	<12.70	<35.56
AMC II (normal)	12.70~27.94	35.56~53.34
AMC III (wet)	>27.94	>53.34

Text S5 Subsurface Slow Flow Routing Mechanism and Parameter Calibration Based on Linear Reservoir Model

The SCS-CN runoff generation calculation and dynamically selected conditional unit hydrographs are mainly used to simulate the rapid surface response under design rainfall conditions, whereas groundwater regulation and the slow release of deep interflow may lead to slow-response characteristics during the flood recession stage. Therefore, based on surface runoff simulation, a subsurface runoff recharge and routing module is introduced to provide a simplified representation of slow-flow contributions during the flood process.

At the hydrological event scale, the spatially corrected design rainfall is converted into net rainfall through the SCS-CN model and then further transformed into surface runoff. The portion that is not immediately converted into surface runoff can be regarded as the combined result of infiltration, interflow detention, and groundwater recharge processes (Geetha et al., 2007). Based on the water balance relationship, the difference between the corrected areal rainfall and net rainfall is defined as the rainfall loss term, which is then converted into subsurface recharge through a subsurface recharge coefficient, as shown in Equations (S5-1) and (S5-2).

$$L^{(s_0)}(t) = P_{eff}^{(s_0)}(t) - P_e^{(s_0)}(t) \quad (S5-1)$$

$$R_g^{(s_0)}(t) = c_g L^{(s_0)}(t) \quad (S5-2)$$

where $P_{eff}^{(s_0)}(t)$ is the corrected areal rainfall under initial antecedent wetness background s_0 , $P_e^{(s_0)}(t)$ is the corresponding catchment net rainfall, and $L^{(s_0)}(t)$ is the rainfall loss term that is not immediately converted into surface runoff; $R_g^{(s_0)}(t)$ is the subsurface recharge, and c_g is the subsurface recharge coefficient.

Considering the pronounced lag and slow-release characteristics of groundwater and deep interflow processes (Ghaseminejad and Uddameri, 2020), which can be represented by linear-reservoir behavior at the catchment scale (Savenije, 2018), a linear reservoir model is adopted to simulate the subsurface runoff routing process, as shown in Equation (S5-3).

$$Q_b^{(s_0)}(t) = k_b Q_b^{(s_0)}(t-1) + (1 - k_b) R_g^{(s_0)}(t) \quad (S5-3)$$

where $Q_b^{(s_0)}(t)$ is the subsurface runoff at time t under initial antecedent wetness background s_0 ; $R_g^{(s_0)}(t)$ is the corresponding subsurface recharge; and k_b is the subsurface runoff memory coefficient, which is used to characterize the storage attenuation and slow-release capacity of the subsurface system.

The parameters c_g and k_b are calibrated after baseflow separation of typical historical flood hydrographs using the Lyne-Hollick (LH) digital filtering method (Narimani, 2023). The baseflow process separated by the LH method is used as the reference series, and c_g and k_b are adjusted so that the simulated subsurface runoff process is close to the reference baseflow in both magnitude and shape. The parameters are calibrated separately for each historical flood

event, and the median values of the parameter set are adopted as representative catchment parameters. The initial subsurface runoff condition is also determined based on the LH separation results. The median initial subsurface runoff values under dry and wet antecedent conditions are calculated separately and used as the representative initial values for the corresponding design scenarios.

The initial subsurface runoff condition is also determined based on the LH separation results. Historical flood events are grouped according to their initial antecedent wetness backgrounds using the event-start $API_{5,0}=35.66$ mm threshold. The median initial subsurface runoff values for the lower (L) and higher (H) initial antecedent wetness background groups are then

calculated separately and used as the representative initial conditions $Q_{b,0}^{(s_0)}$ for the corresponding design scenarios.

References

- A.V., A., Barik, D.K., 2026. A novel approach for the SCS-CN method by updating curve numbers for the antecedent soil moisture conditions (ASMCs) and improving its performance. *Water Resources Management* 40, 46. <https://doi.org/10.1007/s11269-025-04452-8>.
- Afrasiabikia, P., Parvaresh Rizi, A., Brocca, L., 2025. Improving the SCS-CN method based on adjusting the main parameters using rainfall-runoff data. *Journal of Hydrology: Regional Studies* 62, 102899. <https://doi.org/10.1016/j.ejrh.2025.102899>.
- Amatya, D.M., Walega, A., Callahan, T.J., Morrison, A., Vulava, V., Hitchcock, D.R., Williams, T.M., Epps, T., 2022. Storm event analysis of four forested catchments on the Atlantic coastal plain using a modified SCS-CN rainfall-runoff model. *Journal of Hydrology* 608, 127772. <https://doi.org/10.1016/j.jhydrol.2022.127772>.
- Amatya, D.M., Walega, A., Callahan, T.J., Morrison, A., Vulava, V., Hitchcock, D.R., Williams, T.M., Epps, T., 2022. Storm event analysis of four forested catchments on the Atlantic coastal plain using a modified SCS-CN rainfall-runoff model. *Journal of Hydrology* 608, 127772. <https://doi.org/10.1016/j.jhydrol.2022.127772>.
- Fan, Y.R., Shi, X., Duan, Q.Y., Yu, L., 2022. Towards reliable uncertainty quantification for hydrologic predictions, part II: Characterizing impacts of uncertain factors through an iterative factorial data assimilation framework. *Journal of Hydrology* 612(C), 128136. <https://doi.org/10.1016/j.jhydrol.2022.128136>.
- Geetha, K., Mishra, S.K., Eldho, T.I., Rastogi, A.K., Pandey, R.P., 2007. Modifications to SCS-CN method for long-term hydrologic simulation. *Journal of Irrigation and Drainage Engineering* 133(5), 475-486. [https://doi.org/10.1061/\(ASCE\)0733-9437\(2007\)133:5\(475\)](https://doi.org/10.1061/(ASCE)0733-9437(2007)133:5(475)).
- Ghaseminejad, A., Uddameri, V., 2020. Physics-inspired integrated space-time artificial neural networks for regional groundwater flow modeling. *Hydrology and Earth System Sciences* 24 (12), 5759-5779. <https://doi.org/10.5194/hess-24-5759-2020>.
- Nageswara Rao, K., 2020. Analysis of surface runoff potential in an ungauged basin using basin parameters and the SCS-CN method. *Applied Water Science* 10, 47. <https://doi.org/10.1007/s13201-019-1129-z>.
- Narimani, R., Jun, C., Nezhad, S.M., Bateni, S.M., Lee, J., Baik, J., 2023. The role of climate conditions and groundwater on baseflow separation in Urmia Lake Basin, Iran. *Journal of Hydrology: Regional Studies* 47, 101383. <https://doi.org/10.1016/j.ejrh.2023.101383>.
- Papalexiou, S.M., Serinaldi, F., Porcu, E., 2021. Advancing space-time simulation of random fields: From storms to cyclones and beyond. *Water Resources Research* 57, e2020WR029466. <https://doi.org/10.1029/2020WR029466>.
- Savenije, H.H.G., 2018. Linking Darcy's equation to the linear reservoir. *Hydrology and Earth System Sciences* 22, 1911-1916. <https://doi.org/10.5194/hess-22-1911-2018>.
- Xiao, H., Zhang, J., Fang, H., 2024. A Copula-based framework for joint encounter and state evolution analysis of urban short-duration rainstorm characteristics. *Journal of Hydrology* 631, 130823. <https://doi.org/10.1016/j.jhydrol.2024.130823>.

Supplementary Figure

Figure S1

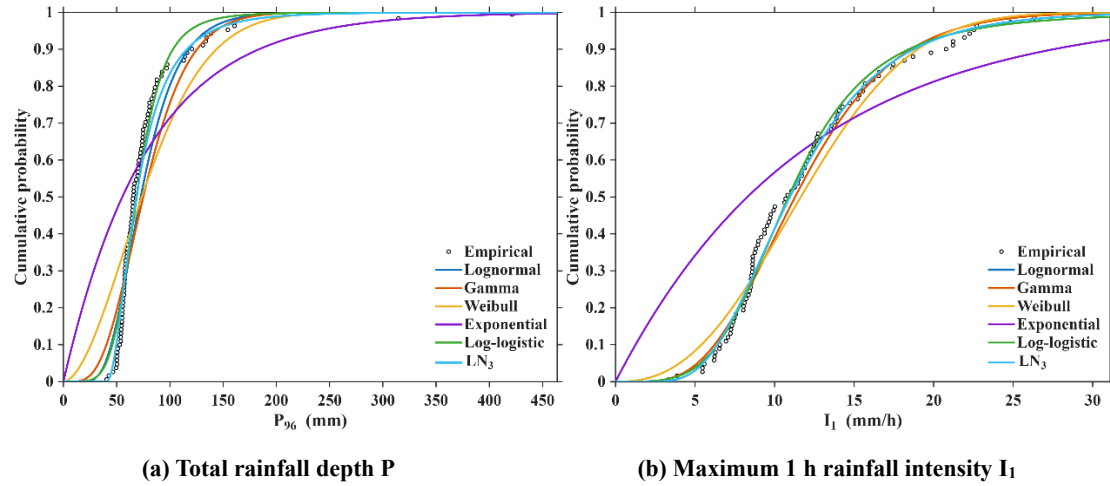


Figure S1: Marginal distribution fitting results of the design rainfall characteristic variables

Figure S2

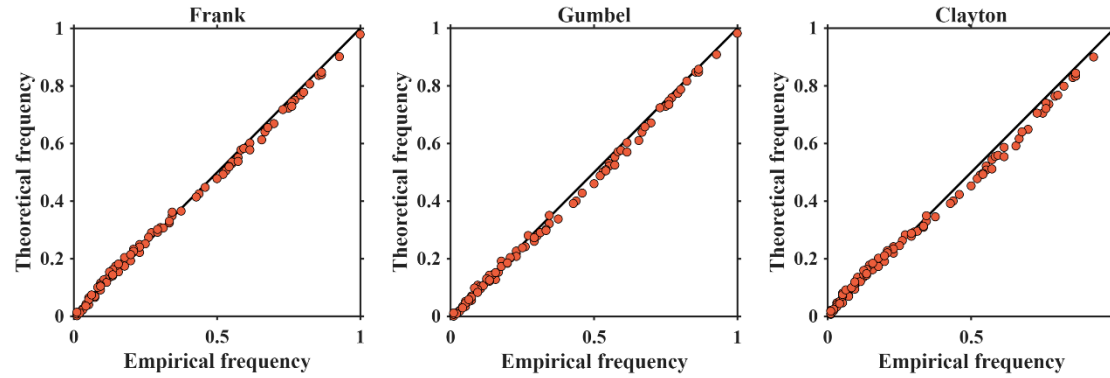


Figure S2: Joint distribution fitting results of the design rainfall characteristic variables

Figure S3

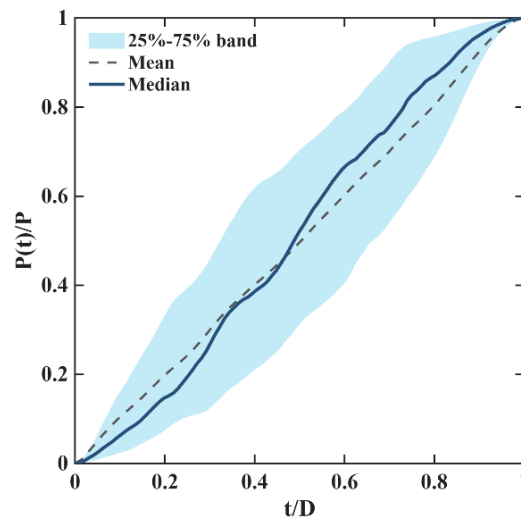


Figure S3: Representative dimensionless cumulative rainfall pattern derived from all historical strong-rainfall events

Figure S4

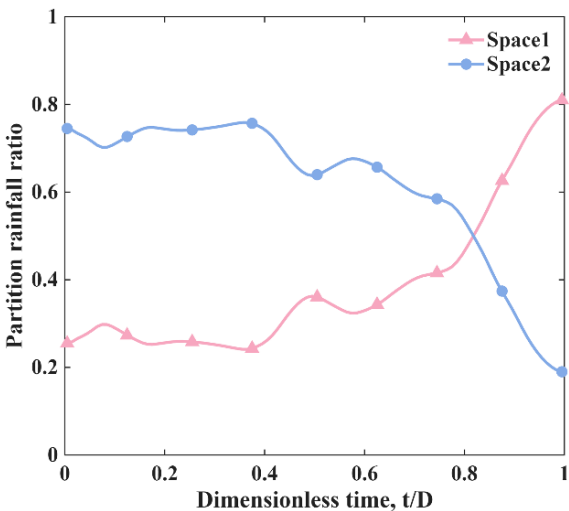


Figure S4: Representative time-varying spatial rainfall allocation template derived from all historical strong-rainfall events

Figure S5

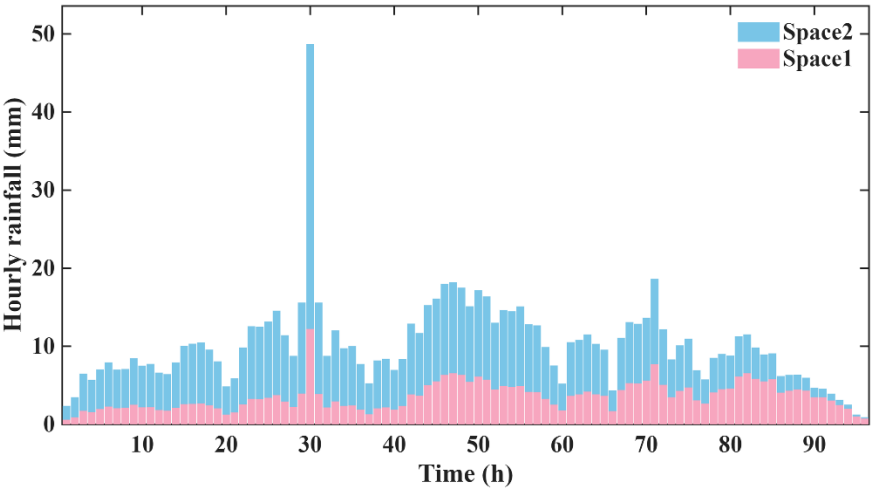


Figure S5: Area-weighted rainfall contributions of the spatial subregions derived from the common spatial rainfall allocation template (T=10,000 a)

Supplementary Table

Table.S1

Table S1: Comparison of ERA Response Reliability under Different Net Rainfall Intensity Classification Schemes

Classification scheme	Threshold-setting method	Net rainfall intensity interval, P_e (mm/h)	Effective nonzero ERA samples	Maximum absolute response amplitude (A_i)	Positive response proportion (ρ_i)	NRF reliability
Scheme 1	Percentiles of nonzero net rainfall intensity (P80, P90, P95, P97)	$P_e < 4.21$ ($< P_{80}$)	581	0.001	0.290	Unreliable
		$4.21 \leq P_e < 6.66$ (P_{80} - P_{90})	115	0.009	0.645	Unreliable
		$6.66 \leq P_e < 8.97$ (P_{90} - P_{95})	117	0.012	0.484	Unreliable
		$8.97 \leq P_e < 11.20$ (P_{95} - P_{97})	106	0.045	0.774	Reliable
		$P_e \geq 11.20$ ($\geq P_{97}$)	61	0.171	1	Reliable
Scheme 2	Automatically determined approximate equal intervals	$P_e < 2.12$	503	0.002	0	Unreliable
		$2.12 \leq P_e < 4.26$	80	0.003	1	Unreliable
		$4.26 \leq P_e < 6.42$	100	0.010	0.677	Unreliable
		$6.42 \leq P_e < 8.89$	126	0.011	0.516	Unreliable
		$P_e \geq 8.89$	172	0.118	1	Reliable
Scheme 3	Cumulative net rainfall proportion (20%, 50%, 80%)	$P_e < 2.12$	503	0.001	0.903	Unreliable
		$2.12 \leq P_e < 5.69$	143	0.003	0.516	Unreliable
		$5.69 \leq P_e < 10.64$	261	0.017	0.742	Reliable
		$P_e \geq 10.64$	74	0.155	1	Reliable
Final scheme	Fixed thresholds (1, 5, and 10 mm/h)	$0 < P_e < 1$	410	0.001	0.452	Unreliable
		$1 \leq P_e < 5$	201	0.002	0.452	Unreliable
		$5 \leq P_e < 10$	255	0.013	0.742	Reliable
		$P_e \geq 10$	115	0.146	1	Reliable

Table.S2

Table S2: Sample Support and Reliability Assessment of NRFs under Different Antecedent Wetness States and Net Rainfall Intensity Conditions

Antecedent wetness state	Net rainfall intensity interval, P_e (mm/h)	Effective nonzero ERA samples, n_i	Maximum absolute response amplitude, A_i	Positive response proportion, ρ_i	NRF reliability
Lower (L, $API_{5,T} < 35.56\text{mm}$)	$0 < P_e < 1$	240	0.001	0.40	Unreliable
	$1 \leq P_e < 5$	120	0.002	0.42	Unreliable
	$5 \leq P_e < 10$	140	0.011	0.67	Reliable
	$P_e \geq 10$	60	0.120	0.95	Reliable
Higher (H, $API_{5,T} \geq 35.56\text{mm}$)	$0 < P_e < 1$	170	0.002	0.52	Unreliable
	$1 \leq P_e < 5$	81	0.004	0.53	Unreliable
	$5 \leq P_e < 10$	115	0.018	0.82	Reliable
	$P_e \geq 10$	55	0.180	1.00	Reliable

Table.S3

Table S3: Marginal distribution fitting results for total rainfall depth P and maximum 1 h rainfall intensity I₁

Variable	Distribution	K-S	A-D	AIC	BIC
P (mm)	Lognormal	0.16	5.02	919.78	924.89
	Log-logistic	0.13	2.75	899.61	904.71
	Gamma	0.21	7.49	951.68	956.78
	LN₃*	0.05	0.29	853.21	860.87
	Weibull	0.28	10.65	988.38	993.49
	Exponential	0.45	19.44	1035.38	1037.94
I ₁ (mm/h)	Lognormal*	0.05	0.22	492.70	497.81
	Log-logistic	0.05	0.23	493.41	498.52
	Gamma	0.07	0.30	493.96	499.07
	LN ₃	0.06	0.20	494.38	502.04
	Weibull	0.11	1.17	506.03	511.14
	Exponential	0.34	16.49	597.04	599.59

Table.S4

Table S4: Copula fitting results for the joint distribution of total rainfall depth P and maximum 1 h rainfall intensity I₁

Copula	K-S	A-D	AIC	BIC
Frank*	0.0569	0.0060	-0.65	1.90
Gumbel	0.0594	0.0061	-0.26	2.30
Clayton	0.0631	0.0062	5.59	8.15

Table.S5

Table S5: Bootstrap Percentile Statistics of Design Flood Characteristics under Different Return Periods and Antecedent Wetness States

Return period (a)	State	Peak discharge			Time to peak			Flood volume		
		Q ₀₅ /(m ³ /s)	Q ₅₀ /(m ³ /s)	Q ₉₅ /(m ³ /s)	Q ₀₅ /h	Q ₅₀ /h	Q ₉₅ /h	Q ₀₅ /(10 ⁸ m ³)	Q ₅₀ /(10 ⁸ m ³)	Q ₉₅ /(10 ⁸ m ³)
20	L	2827.3	3247.6	3839.9	86	86	86	5.724	6.570	7.793
	H	5232.6	5917.4	7670.4	57	59	80	9.486	10.504	11.921
100	L	5376.3	6305.4	8817.1	66	84	85	10.039	11.954	14.948
	H	10623.9	12612.2	15023.3	57	58	59	16.066	18.511	21.988
200	L	6732.5	8714.2	12018.8	69	83	89	12.225	14.661	18.675
	H	12939.4	15291.3	18524.9	56	57	58	18.431	21.616	26.158
500	L	8953.7	12254.3	16142.6	68	82	84	14.727	18.423	24.085
	H	15926.6	18922.1	23580.6	56	57	57	21.713	25.907	32.145
2000	L	12178.0	16084.7	22100.9	65	78	79	19.051	24.687	33.589
	H	20148.8	24969.9	31774.3	57	57	58	26.598	32.786	42.315
10000	L	15282.8	20604.0	29270.9	75	75	89	24.236	32.516	46.303
	H	25074.1	31815.0	42816.5	55	56	56	32.311	41.180	55.644

Note: Q₀₅, Q₅₀, and Q₉₅ denote the 5th, 50th, and 95th percentiles, respectively, of the corresponding flood characteristic metrics obtained from the 1,000 event-level paired Bootstrap ensembles.

Table.S6

Table S6: Bootstrap Percentile Statistics of Antecedent Wetness Sensitivity Metrics for Different Return Periods

Return period (a)	H/L peak discharge ratio			Advance in time to peak	Flood volume increase		
	Q ₀₅	Q ₅₀	Q ₉₅	Median (h)	Q ₀₅	Q ₅₀	Q ₉₅
20	1.825	1.887	2.010	24	51.3	59.9	67.2
100	1.634	1.950	2.012	25	45.3	54.0	61.6
200	1.497	1.755	2.001	26	38.3	47.4	53.6
500	1.437	1.542	1.838	25	31.7	40.6	49.2
2,000	1.410	1.542	1.686	20	24.3	32.8	41.2
10,000	1.444	1.544	1.674	19	18.6	26.6	34.8

Note: All metrics were calculated from paired L/H results obtained from the same Bootstrap resampling.