



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

Jing Feng^{1,2}, Jiacheng Duan¹, Jianzhu Li¹, Hongdong Song³, Bin Wang³, Xu Chen⁴, Hao Wang²

¹State Key Laboratory of Hydraulic Engineering Intelligent Construction and Operation, Tianjin University, Tianjin 300350, China

²State Key Laboratory of Simulation and Regulation of Water Cycle in River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China

³Hebei Baoding Hydrological Survey and Research Center, Baoding 071000, China

⁴Hydrographic Bureau, Haihe River Water Conservancy Commission, MWR, Tianjin 300170, China

Correspondence to: Jiacheng Duan (jchngduan@tju.edu.cn)

Abstract. Design flood hydrographs are jointly influenced by the spatial distribution of rainfall, antecedent wetness states, and catchment runoff generation and routing responses. Taking the XDY Basin as the study area, this study develops a conditional design flood hydrograph derivation framework that accounts for spatially heterogeneous rainfall and nonlinear nonstationary routing. Ensemble Rainfall-Runoff Analysis (ERRA) is used to identify rainfall-runoff responses under different antecedent wetness states, net rainfall intensities, and spatial subregions, based on which state-dependent unit hydrographs are constructed. Joint frequency analysis of 96 h total rainfall depth (P96) and maximum 1 h rainfall intensity, together with a common representative rainfall pattern and spatial-response correction, is then used to derive design flood hydrographs under lower (L) and higher (H) antecedent wetness states. For a given return period, the L and H scenarios use the same design rainfall input. The results show that higher antecedent wetness and greater net rainfall intensity produce stronger runoff responses and earlier flood peaks. In the incremental model-structure comparison, the mean Nash-Sutcliffe efficiency (NSE) increased from 0.744 to 0.874. Compared with the L scenario, the H scenario increased peak discharge by 54.4%-100.0%, advanced the time to peak by 19-27 h, and increased flood volume by 26.6%-59.9%. Event-level paired Bootstrap analysis indicates that statistical uncertainty is concentrated mainly around the rising limb and main flood peak, while the effects of antecedent wetness exhibit good sample stability. The proposed framework provides process-based information for design flood review, flood-control safety assessment, and flood risk analysis.

Key words: Conditional design flood hydrograph; Spatially heterogeneous rainfall; Nonlinear nonstationary routing; State-dependent unit hydrograph



29 1 Introduction

30 Flooding is one of the major natural hazards threatening catchment flood-control safety and the stable operation of hydraulic
31 engineering systems, often causing severe casualties and economic losses (Ham et al., 2023). With changes in extreme rainfall
32 and evolving catchment surface conditions, reservoir inflow flood hydrographs have become increasingly complex, posing
33 greater challenges to flood-control operation, spillway capacity reassessment, flood risk analysis, and emergency management
34 (Guo et al., 2024). Design flood hydrographs are an important basis for flood-control project planning, design, and operation.
35 In addition to peak discharge and flood volume, they should reasonably characterize the time to peak, rising and recession
36 limbs, and overall hydrograph shape. For large and medium-sized reservoirs with flood-control functions, the rationality of
37 design flood hydrographs directly affects reservoir operation schemes, release control, and downstream flood-control safety
38 (Hu et al., 2024). Therefore, improving the ability of design flood hydrographs to represent actual rainfall-runoff generation
39 and routing mechanisms is of both scientific and engineering significance.

40 Design flood studies have gradually expanded from traditional typical-flood amplification and design storm-unit hydrograph
41 methods to regional flood frequency analysis, multivariate joint distributions, nonstationary frequency analysis, machine
42 learning, and climate-change scenario assessment (Hu et al., 2023; Zalnezhad et al., 2023). For example, Jarajapu et al. (2022)
43 combined regional flood frequency analysis with machine-learning models to estimate flood characteristics for different return
44 periods, while Yin et al. (2017) used Copula functions to characterize the dependence structure among flood variables. These
45 studies have extended design flood estimation from the perspectives of regionalization, multivariate probabilistic analysis, and
46 data-driven modeling, but most still focus on characteristic quantities such as peak discharge, flood volume, or specific flood
47 quantiles. By contrast, design storm-runoff generation and routing modeling remains an important approach for deriving
48 complete design flood hydrographs, and its results are jointly influenced by design rainfall structure, antecedent catchment
49 conditions, and rainfall-runoff response mechanisms. Previous studies have separately considered rainfall spatial distribution,
50 antecedent wetness, and state-dependent runoff generation and routing responses; however, their integrated and consistent
51 representation throughout the complete design flood derivation process remains limited.

52 Design rainfall is a key input to design flood hydrograph derivation, and its frequency magnitude, temporal structure, and
53 spatial distribution jointly affect flood response characteristics (Li et al., 2017). Conventional methods generally determine
54 design rainfall depth through univariate frequency analysis and construct design rainfall hyetographs using representative
55 rainfall patterns or equal-ratio amplification (Qian et al., 2020). With the development of multivariate frequency analysis,
56 increasing attention has been paid to the dependence among rainfall characteristics such as total rainfall depth and short-
57 duration rainfall intensity. Multivariate joint analysis can provide a more reasonable representation of the dependence among
58 different rainfall characteristics (Jhong and Tung, 2018). For example, Yin et al. (2017) performed bivariate analysis using
59 Copula functions and constructed design rainfall hyetographs. In addition to temporal structure, the spatial distribution of
60 rainfall also affects catchment flood responses. The same catchment-average rainfall depth may produce different outlet runoff
61 hydrographs under different rainfall-location patterns (Moghisai et al., 2024). Therefore, design rainfall construction should not



only reasonably represent rainfall magnitude and temporal distribution, but also account for spatial rainfall heterogeneity and differences in runoff responses among different subregions.

In addition to rainfall input, catchment routing response is another key factor controlling the shape of design flood hydrographs. Owing to its simple structure and clear physical interpretation, the unit hydrograph method has been widely used to transform design storms into design flood hydrographs (Grum et al., 2023). In particular, the Nash instantaneous unit hydrograph can parsimoniously represent catchment routing lag and storage attenuation (Yan et al., 2015). However, conventional unit hydrograph methods generally assume that the routing response remains stable, whereas actual responses may vary with antecedent wetness states and net rainfall intensity (Vormoor et al., 2016). The Ensemble Rainfall-Runoff Analysis (ERRA) proposed by Kirchner (2024) provides a means of identifying differences in rainfall-runoff responses under varying hydrological conditions. In this study, nonstationary routing specifically refers to event-scale state-dependent and time-varying routing responses associated with changes in antecedent wetness and net rainfall intensity, rather than nonstationarity in long-term flood frequency distributions. Constructing unit hydrographs from the conditional response characteristics identified by ERRA can therefore provide a more explicit representation of nonlinear and nonstationary catchment routing.

In summary, substantial progress has been made in design flood studies involving multivariate rainfall characteristics, spatial heterogeneity, antecedent wetness, and nonlinear rainfall-runoff responses. However, the coordinated representation of these factors throughout the complete design flood derivation process, as well as the distinction between state sensitivity and statistical uncertainty, still requires further investigation. Accordingly, this study develops a conditional design flood hydrograph derivation framework with four main components: (1) ERRA is used to identify rainfall-runoff response differences under different hydrological conditions and to construct state-dependent unit hydrographs; (2) joint frequency analysis of the 96 h total rainfall depth (P_{96}) and maximum 1 h rainfall intensity is combined with a common representative rainfall pattern and spatial-response correction to construct design rainfall hyetographs; (3) the Soil Conservation Service Curve Number (SCS-CN) runoff generation model, dynamic state-dependent routing, and a subsurface runoff model are coupled to derive conditional design flood hydrographs under lower (L) and higher (H) antecedent wetness states, with the H scenario representing relatively adverse antecedent conditions and the L scenario serving as a reference; and (4) historical flood simulation, incremental model-structure comparison, and event-level paired Bootstrap analysis are conducted to evaluate model performance and quantify the propagation of statistical uncertainty. The proposed framework provides process-based information for design flood review, flood-control safety assessment, and flood risk analysis.

2 Methods

2.1 Rainfall-Runoff Response Distribution Based on ERRA

Catchment rainfall-runoff responses exhibit pronounced nonlinear, state-dependent, and spatially heterogeneous characteristics (Kojima and Tani, 2025). To identify these response characteristics, Ensemble Rainfall-Runoff Analysis (ERRA) is adopted. ERRA was proposed by Kirchner, with a mathematical basis in deconvolution and unmixing methods for nonlinear,



94 nonstationary, and spatially heterogeneous systems (Kirchner, 2024). Within this framework, the input, output, and
95 conditioning variables are specified according to the research objectives to identify nonlinear conditional responses and multi-
96 input spatial responses. The resulting response characteristics are then used to support subsequent conditional routing
97 representation and design flood hydrograph derivation.

98 2.1.1 ERRA Ensemble Deconvolution and Response Estimation

99 ERRA uses the statistical relationships between input and output time series at different lag times to identify the mean lagged
100 runoff response to rainfall through ensemble deconvolution and to jointly estimate the response coefficients at each lag time
101 (Kirchner, 2024). For discrete time series, the basic formulation is given by Eq. (1):

$$102 \quad Q_t = \alpha + \sum_{\tau=0}^m \beta_{\tau} P_{t-\tau} + \varepsilon_t \quad (1)$$

103 where Q_t is the runoff at time t ; $P_{t-\tau}$ is the rainfall input lagged by τ time steps; m is the maximum response lag; β_{τ} is the
104 regression coefficient corresponding to lag τ ; α is the intercept; and ε_t is the residual term. For a computational time step of
105 Δt , the corresponding runoff response distribution (RRD) can be derived from the estimated regression coefficients.

106 ERRA jointly estimates the response coefficients at different lag times using least-squares deconvolution. Residual
107 autocorrelation correction is applied to reduce the influence of temporal correlation on the estimates, while the standard errors
108 of the response coefficients are used to evaluate the stability of the identified responses. Unlike a conventional unit hydrograph,
109 the integral of the RRD is not constrained a priori to unity; instead, its magnitude and temporal distribution mainly characterize
110 the response strength and lag structure between rainfall input and runoff output. Therefore, the RRD is not directly treated as
111 a unit hydrograph in this study. Instead, its response characteristics are extracted for the subsequent construction and refinement
112 of the routing model.

113 In the implementation, multiple historical flood events are standardized to an hourly time step. Sufficiently long intervals with
114 no rainfall and no rapid runoff are inserted between concatenated events to prevent overlap of lagged responses from adjacent
115 events. All valid time steps are then jointly incorporated into the ERRA deconvolution analysis.

116 2.1.2 Identification of Conditional Net Rainfall-Rapid Surface Runoff Responses

117 ERRA can identify variations in runoff responses with rainfall intensity and antecedent hydrological conditions through
118 nonlinear deconvolution and conditional analysis (Kirchner, 2024). To focus on the rapid routing process following the
119 generation of net rainfall, net rainfall P_e is used as the input and rapid surface runoff Q_q as the output. The net rainfall is
120 calculated from the corrected catchment-average rainfall using the Soil Conservation Service Curve Number (SCS-CN) model,
121 whereas rapid surface runoff is separated from the observed total reservoir inflow using the Lyne-Hollick (LH) digital filtering
122 method.



To characterize the dynamic variation in antecedent wetness during a flood event, the cumulative areal rainfall over the preceding 120 h is calculated for each valid time step t , as expressed in Eq. (2):

$$API_{5,t} = \sum_{j=1}^{120} P_{t-j} \quad (2)$$

where $API_{5,t}$ denotes the 5-day Antecedent Precipitation Index (API_5) and excludes rainfall at the current time step. It is updated hourly throughout the event. The 5-day cumulative rainfall is adopted as the antecedent wetness indicator to maintain consistency with the conventional definition of Antecedent Moisture Condition (AMC) in the SCS-CN model, which is based on rainfall during the preceding 5 days, while allowing the antecedent wetness state to be updated dynamically at an hourly time step. Because all flood events in the study area occurred during the growing season, the SCS-CN growing-season AMC classification criterion is adopted, and the boundary of 35.56 mm between AMC I and AMC II is used as the threshold for the two-state classification (Nageswara Rao, 2020):

$$c_t = \begin{cases} L, & API_{5,t} < 35.56 \\ H, & API_{5,t} \geq 35.56 \end{cases} \quad (3)$$

where L and H denote the lower and higher antecedent wetness states, respectively. It should be noted that this rolling indicator is used for conditional rapid-routing response identification in ERRA and for dynamic routing-state determination in subsequent design flood simulations, but not for dynamically adjusting the runoff-generation parameters of the SCS-CN model. The curve number (CN) is determined according to the initial antecedent wetness condition at the beginning of each event and remains unchanged throughout the event.

The nonlinear effect of net rainfall intensity is analyzed using a continuous piecewise approach. Different segmentation schemes are compared by considering both the number of valid samples and the characteristics of the nonlinear response function (NRF). Candidate breakpoints of 1, 5, and 10 mm/h are examined. Based on the response reliability assessment, 5 mm/h is ultimately selected as the classification threshold, dividing net rainfall into lower-intensity ($P_e < 5$ mm/h) and higher-intensity ($P_e \geq 5$ mm/h) classes. Details of the classification and reliability assessment are provided in Text S1.

Following the continuous piecewise nonlinear deconvolution and conditional-response framework of Kirchner (2024), the rapid runoff response under different combinations of antecedent wetness states and net rainfall intensities is expressed as Eq. (4):

$$Q_{q,t} = \alpha + \sum_{c \in C} \sum_{k=1}^K \sum_{\tau=0}^m \beta_{c,k,\tau} P'_{e,c,k,t-\tau} + \varepsilon_t \quad (4)$$

where $C = \{L, H\}$ is the set of antecedent wetness states; K is the number of continuous net-rainfall-intensity segments; $P'_{e,c,k,t-\tau}$ is the net rainfall variable corresponding to the k -th continuous segment under antecedent wetness state c , lagged by τ time steps; and $\beta_{c,k,\tau}$ is the corresponding response coefficient at lag τ . The remaining symbols are defined as above.

The Nonlinear Response Function (NRF) under different antecedent wetness states and net rainfall intensities is jointly constructed from the segmented response coefficients. The reliability of each conditional response is evaluated using the



number of nonzero net rainfall samples, NRF response magnitude, proportion of positive responses, and standard errors of the response coefficients. The resulting NRFs are used to characterize variations in rapid routing responses with net rainfall intensity and antecedent wetness state and provide the basis for the subsequent construction of conditional Nash unit hydrographs.

2.1.3 Identification of Spatially Heterogeneous Rainfall-Runoff Responses

ERRA can identify differences in the runoff responses of rainfall occurring at different spatial locations to catchment outlet runoff through multi-input deconvolution and unmixing (Kirchner, 2024). Considering the potentially strong correlations among rainfall series from different rain gauges, Thiessen polygon control areas are first used as the basic spatial units. These units are then aggregated by jointly considering inter-station rainfall correlations, principal component analysis, the spatial locations of rain gauges, and catchment surface characteristics, thereby reducing collinearity among inputs and improving the identifiability of spatial responses. Assuming that the catchment is divided into S spatial units, with the rainfall series of each unit denoted by $P_{s,t}$, the multi-input deconvolution and unmixing formulation of Kirchner (2024), with total catchment outlet runoff Q_t as the response variable, can be expressed as Eq. (5):

$$Q_t = \alpha + \sum_{s=1}^S \sum_{\tau=0}^m \beta_{s,\tau}(\tau) P_{s,t-\tau} + \varepsilon_t \quad (5)$$

where $P_{s,t-\tau}$ is the rainfall input from the s -th spatial unit lagged by τ time steps; $\beta_{s,\tau}$ is the response coefficient of the corresponding spatial unit at lag τ ; S is the number of spatial units; and the remaining symbols are defined as above. For a computational time step of Δt , the rainfall-runoff response distribution of the s -th spatial unit can be expressed as $RRD_s(\tau) = \frac{\beta_{s,\tau}}{\Delta t}$.

Rainfall inputs from all spatial units and their lagged terms are jointly estimated within the same regression framework, allowing the runoff responses associated with rainfall from different regions to be separated. The resulting spatial RRDs are used to compare differences among regions in response magnitude, time to peak, and response duration. The standard errors of the response coefficients are further used to evaluate the stability of the identified spatial responses, providing a basis for the subsequent spatial correction of design rainfall.

2.2 Construction of Conditional Unit Hydrographs

2.2.1 Construction of the Baseline Unit Hydrograph (Nash IUH)

The Nash Instantaneous Unit Hydrograph (Nash IUH), proposed by Nash in 1957 based on the theory of cascaded linear reservoirs, is a classical catchment routing model. Owing to its clear physical interpretation, limited number of parameters, and computational simplicity, it has been widely applied in catchment routing simulation and design flood hydrograph derivation (Nash, 1957). According to instantaneous unit hydrograph theory, the Nash IUH can be expressed as Eq. (6):



$$u(0, t) = \frac{1}{K\Gamma(n)} \left(\frac{t}{K}\right)^{n-1} e^{-\frac{t}{K}} \quad (6)$$

where $u(0, t)$ is the instantaneous unit hydrograph; n is the number of linear reservoirs; K is the storage constant of the linear reservoirs, representing the characteristic catchment routing time; and $\Gamma(n)$ is the Gamma function.

2.2.2 Conditional-Response-Driven Unit Hydrograph Refinement

To characterize differences in catchment routing responses under different antecedent wetness states and net rainfall intensities, a family of conditional unit hydrographs, $UH(C_i)$, is constructed using the composite Nash unit hydrograph $u_{med}(\tau)$ as the baseline and the conditional net rainfall-surface runoff response function $NRF_i(\tau)$ identified by ERRA. Here, C_i denotes a condition jointly defined by antecedent wetness state and net rainfall intensity.

First, $NRF_i(\tau)$ under each condition is smoothed and nondimensionalized to obtain a conditional correction factor that characterizes the relative response strength at different lag times. Because routing characteristics differ between net rainfall intensity classes, a classified refinement strategy is adopted. Under lower net rainfall intensity conditions, the scale parameter of the Nash unit hydrograph is primarily adjusted according to the centroid lag time of the conditional response function to represent delays or broadening of the routing process. Under higher net rainfall intensity conditions, the conditional correction factor is used directly to modify the shape of the composite unit hydrograph, thereby representing the more concentrated routing response associated with greater net rainfall intensity. Finally, the refined unit hydrographs are area-normalized to obtain the final conditional unit hydrographs, as expressed in Eq. (7). Detailed formulations for constructing $u_{corr,i}(\tau)$ under lower and higher net rainfall intensity conditions are provided in Text S1.

$$UH(C_i, \tau) = \frac{u_{corr,i}(\tau_j)}{\sum_{j=1}^N u_{corr,i}(\tau_j) \Delta\tau} \quad (7)$$

where $UH(C_i, \tau)$ is the conditional unit hydrograph under condition C_i ; $u_{corr,i}(\tau)$ is the unit hydrograph refined using the conditional response; τ is the lag time; $\Delta\tau$ is the computational time step; and N is the number of discrete lag-time intervals of the unit hydrograph.

2.3 Design Rainfall Construction

2.3.1 Joint Distribution Modeling of Design Rainfall Magnitude

Based on the hourly areal rainfall series during the flood season in the XDY Basin, independent rainfall events are identified using 24 consecutive hours without effective rainfall as the event-separation criterion. For each event, the total rainfall depth and the maximum 1 h, 12 h, and 24 h rainfall depths are calculated. Referring to the *Grades of Precipitation* standard issued by the National Meteorological Center, strong rainfall events are selected when the total rainfall depth is ≥ 50 mm and at least one of the following criteria is satisfied: maximum 1 h rainfall ≥ 8 mm, maximum 12 h rainfall ≥ 15 mm, or maximum 24 h rainfall ≥ 25 mm. The selected events are then standardized to a 96 h window. Events shorter than 96 h are zero-padded at the



end, whereas for events longer than 96 h, the continuous 96 h period with the maximum cumulative rainfall is extracted. The 96 h total rainfall depth P_{96} and maximum 1 h rainfall intensity I_1 are then recalculated while preserving their event-wise pairing.

Marginal distributions are fitted separately to P_{96} and I_1 , and a Copula function is used to establish their joint distribution. Based on the resulting joint distribution, the design total rainfall depth P_T and maximum 1 h rainfall intensity $I_{1,T}$ are determined for different return periods. Details of the distribution fitting and joint frequency analysis are provided in Text S2.

2.3.2 Construction of the Representative Rainfall Pattern and Design Rainfall Hyetograph

After determining the design rainfall magnitude, a common representative temporal rainfall pattern is constructed based on all historical strong rainfall events. The effective rainfall duration of each event is extracted and normalized to dimensionless time $x \in [0, 1]$. The dimensionless cumulative rainfall curves are then interpolated onto a common time axis, and the median cumulative curve $y(x)$ across all events is adopted as the common representative rainfall pattern.

The design rainfall duration is uniformly set to 96 h. For a given return period T , the cumulative design rainfall process is reconstructed from the common representative rainfall pattern and the design total rainfall depth P_T , as expressed in Eq. (8):

$$P_T(t) = P_T \cdot y\left(\frac{t}{96}\right) \quad (8)$$

where $P_T(t)$ is the cumulative design rainfall depth at time t , and $y(t/96)$ is the cumulative rainfall fraction at the corresponding dimensionless time. The cumulative rainfall process is differenced at an hourly time step to obtain the initial design rainfall series, which is then adjusted under the dual constraints of total rainfall depth and maximum 1 h rainfall intensity, as expressed in Eq. (9):

$$\begin{cases} \sum_{t=1}^{96} P_T^0(t) = P_T \\ \max_t P_T^0(t) = I_{1,T} \end{cases} \quad (9)$$

where $P_T^0(t)$ denotes the adjusted hourly design rainfall, and $I_{1,T}$ denotes the design maximum 1 h rainfall intensity corresponding to return period T . During the adjustment, the timing of the main peak and the overall temporal structure are preserved, yielding a 96 h baseline design rainfall hyetograph $P_T^0(t)$ that satisfies the constraints of the total design rainfall P_T and the maximum 1 h rainfall intensity $I_{1,T}$. The subsequent spatial-response adjustment only modifies the temporal distribution of rainfall without changing the above design-magnitude constraints.

2.4 Spatial Correction of Design Rainfall Hyetographs Based on Spatial Heterogeneity

2.4.1 Construction of the Spatial Rainfall Allocation Template

According to the analysis in Section 2.1.3, rainfall occurring in different spatial subregions exhibits different responses at the catchment outlet. To characterize the dynamic variation in the spatial distribution of design rainfall, a common time-varying



spatial allocation template was constructed using all historical heavy rainfall events. For each historical event, the hourly contribution of each subregion to the catchment-average rainfall was calculated by accounting for differences in subregion area and then mapped onto a common dimensionless time axis. The hourly allocation ratios from all events were statistically summarized, and their median trajectories were adopted as the representative spatial allocation template $r_k(x)$, satisfying Eq. (10):

$$\sum_{k=1}^K r_k(x) = 1 \quad (10)$$

where $r_k(x)$ denotes the area-weighted contribution ratio of the k -th spatial subregion to the catchment-average rainfall at dimensionless time x , and K is the total number of spatial subregions. This template represents the time-varying distribution of rainfall among different subregions rather than a fixed event-total rainfall proportion for each subregion. Details of the calculation procedure are provided in Supplementary Text S3.

2.4.2 Temporal Adjustment of Design Rainfall Based on Spatial Response-Efficiency Weights

Based on the spatial rainfall allocation template, differences in the runoff responses of rainfall occurring in different subregions are further considered. Using the spatially heterogeneous rainfall-runoff response distributions $R_k(\tau)$ obtained in Section 2.1.3, the positive component of each response distribution is integrated to obtain the response-efficiency index E_k , which is then normalized to derive the response-efficiency weight β_k for the k -th spatial subregion, as shown in Eq. (11):

$$E_k = \sum_{\tau=0}^m R_k^+(\tau) \Delta t, \quad \beta_k = \frac{E_k}{\sum_{j=1}^K E_j} \quad (11)$$

where E_k is the spatial response-efficiency index; $R_k^+(\tau)$ is the positive component of the response distribution for the k -th spatial subregion; m is the maximum response lag; and β_k is the corresponding response-efficiency weight, with $\sum_{k=1}^K \beta_k = 1$. Because β_k represents the relative contribution of rainfall in different subregions to runoff response at the catchment outlet, whereas catchment-average rainfall is defined with respect to the subregion area fraction a_k , a dimensionless spatial-response modulation factor is introduced:

$$M(t) = \sum_{k=1}^K \frac{\beta_k}{a_k} r_k(t) \quad (12)$$

where a_k is the area fraction of the k -th spatial subregion and $r_k(t)$ is its spatial rainfall contribution ratio at time t . The factor $M(t)$ represents only the relative hydrological effectiveness of different spatial rainfall distributions at each time step and is not used as an absolute scaling factor for the design rainfall magnitude.

Let $P_T^0(t)$ denote the baseline design rainfall hyetograph obtained in Section 2.3.2, with the main rainfall peak occurring at t_p . Under the prescribed design-frequency constraints, $M(t)$ is used to adjust the relative rainfall allocation during non-peak periods, yielding the spatial-response-adjusted design rainfall hyetograph defined by Eq. (13):



$$P_T^*(t) = \begin{cases} I_{1,T}, & t = t_p, \\ (P_T - I_{1,T}) \frac{P_T^0(t)M(t)}{\sum_{\tau \neq t_p} P_T^0(\tau)M(\tau)}, & t \neq t_p. \end{cases} \quad (13)$$

where $P_T^*(t)$ is the spatial-response-adjusted hourly design rainfall for return period T . The method redistributes rainfall among non-peak periods according to the spatial rainfall allocation and subregional response efficiencies while preserving the total design rainfall P_T and the maximum 1 h rainfall intensity $I_{1,T}$, such that $\sum_{t=1}^{96} P_T^*(t) = P_T$, $P_T^*(t_p) = I_{1,T}$. The resulting design rainfall hyetograph is subsequently used as the common rainfall input for runoff-generation and routing simulations.

2.5 Simulation of Runoff Generation and Routing Processes

2.5.1 Runoff Generation Calculation Based on the SCS-CN Model

The SCS-CN model describes the transformation of rainfall into runoff based on the relationships among rainfall depth, initial abstraction, and potential maximum soil retention. Owing to its parsimonious parameterization and computational convenience, it has been widely applied to estimate surface runoff generation at the catchment scale (Ajith and Barik, 2026). The basic formulation is provided in Text S4.

For a given return period, the L and H antecedent wetness states use the same spatial-response-corrected design rainfall, while differences in antecedent wetness are represented solely through different initial runoff-generation conditions. The L and H states adopt the CN values corresponding to AMC I and AMC III, respectively, and these values remain unchanged throughout the 96 h design storm event. The hourly design rainfall is accumulated and input into the SCS-CN model to calculate cumulative runoff, which is then differenced to obtain the hourly net rainfall process $P_e^{(s_0)}(t)$, where s_0 denotes the initial antecedent wetness state.

2.5.2 Dynamic Routing Calculation Using State-Dependent Unit Hydrographs

After obtaining the hourly net rainfall process $P_e^{(s_0)}(t)$ corresponding to the initial antecedent wetness state s_0 , state-dependent unit hydrographs are used to calculate direct surface runoff. To remain consistent with the conditional-response identification in ERRA, the antecedent wetness state during the design storm is not fixed at its initial condition but is dynamically updated according to the hourly rolling $API_{5,T}$. Following the classification criterion in Section 2.1.2, the antecedent wetness state $c(t)$ at time t is determined using a threshold of 35.56 mm. Meanwhile, the net rainfall intensity class $k(t)$ is determined from the hourly net rainfall intensity using a threshold of 5 mm/h.

Accordingly, the net rainfall at each time step is routed using the conditional unit hydrograph corresponding to $c(t)$ and $k(t)$ at the time when that net rainfall occurs. The direct surface runoff process is expressed as Eq. (14):

$$Q_q^{(s_0)}(t) = \sum_{\tau=0}^m P_e^{(s_0)}(t - \tau) u_{c(t-\tau), k(t-\tau)}(\tau) \quad (14)$$



where $Q_q^{(s_0)}(t)$ is the direct surface runoff at time t under the initial antecedent wetness state s_0 ; $P_e^{(s_0)}(t - \tau)$ is the net rainfall depth at time $t - \tau$; $c(t - \tau)$ is the antecedent wetness state determined from the rolling $API_{5,t-\tau}$ at that time step; $k(t - \tau)$ is the corresponding net rainfall intensity class; $u_{c(t-\tau), k(t-\tau)}(\tau)$ is the conditional unit hydrograph for the corresponding state combination; τ is the lag time; and m is the maximum response duration of the unit hydrograph.

2.5.3 Simulation of Subsurface Slow Flow and Total Runoff Composition

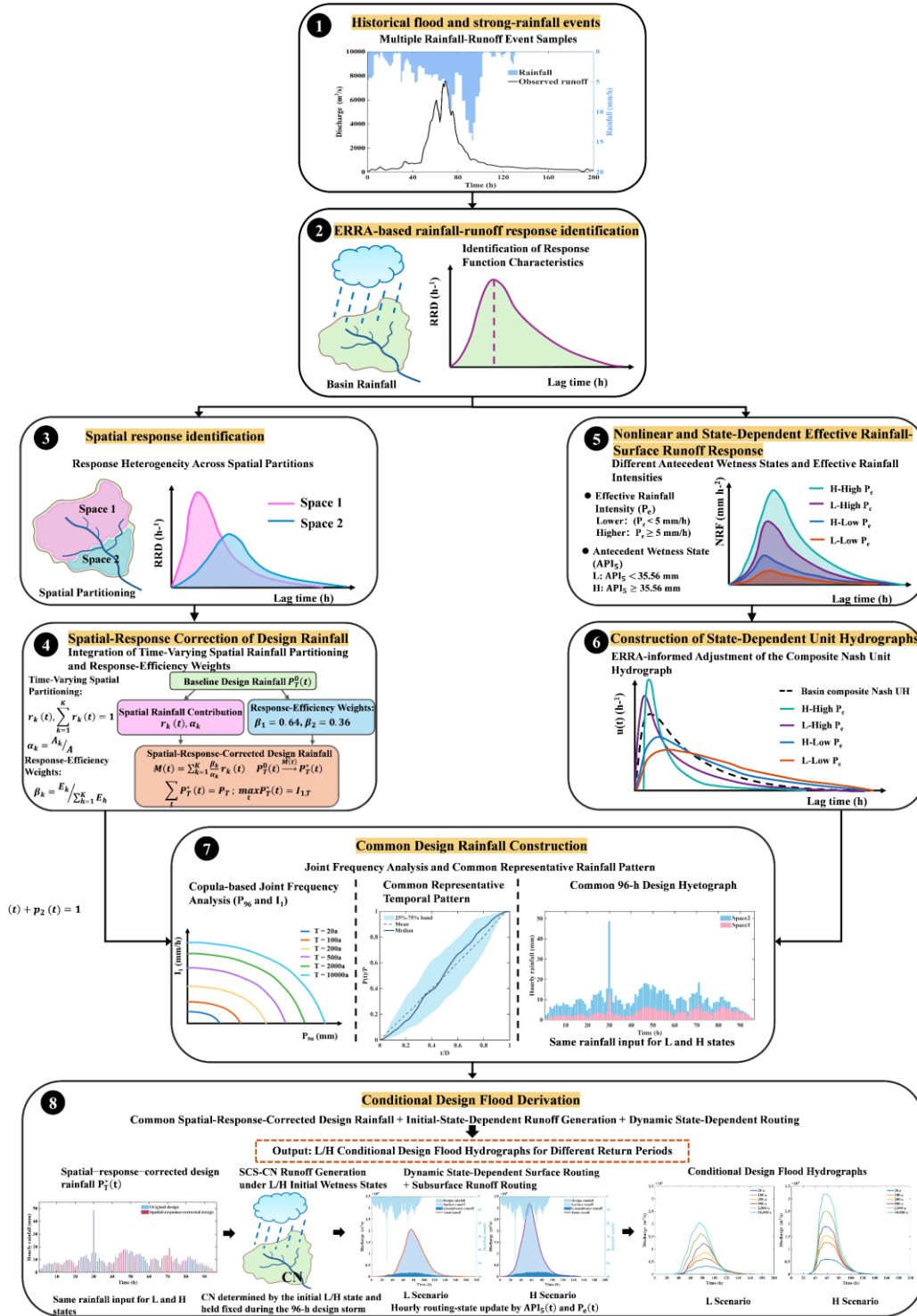
To represent the slow-response process during the flood recession stage, the contribution of subsurface slow flow is further considered in addition to direct surface runoff. Parameters of the linear reservoir model are calibrated based on the Lyne-Hollick (LH) baseflow separation results for representative historical flood events, and subsurface runoff is simulated using the linear reservoir method. The subsurface slow flow and direct surface runoff are then superimposed at each time step to obtain the total design flood hydrograph, as expressed in Eq. (15):

$$Q^{(s_0)}(t) = Q_q^{(s_0)}(t) + Q_b^{(s_0)}(t) \quad (15)$$

where $Q^{(s_0)}(t)$ is the total runoff at time t under the initial antecedent wetness state s_0 ; $Q_q^{(s_0)}(t)$ is the direct surface runoff; and $Q_b^{(s_0)}(t)$ is the subsurface slow flow. Details of parameter calibration and recursive computation for the subsurface slow-flow component are provided in Text S5.

2.6 Derivation of Conditional Design Flood Hydrographs

The conditional design flood hydrograph derivation framework developed in this study consists of four main components: rainfall-runoff response identification, construction of conditional unit hydrographs, construction of spatially corrected design rainfall, and coupled simulation of runoff generation and routing processes, as illustrated in Fig. 1.



312

313 **Figure 1: Framework for Conditional Design Flood Hydrograph Derivation**



314 2.7 Antecedent Wetness Sensitivity and Design Flood Uncertainty Analysis

315 2.7.1 Antecedent Wetness Sensitivity Analysis

316 To quantitatively evaluate the effects of antecedent wetness on conditional design flood hydrographs, the design flood
317 hydrographs corresponding to the lower (L) and higher (H) antecedent wetness states are compared in pairs under the same
318 return period and identical design rainfall input. The relative increase in peak discharge, advance in time to peak, and relative
319 increase in flood volume are used as the primary sensitivity metrics, as expressed in Eq. (16):

$$320 \quad \begin{cases} \Delta Q_p = \frac{Q_{p,H} - Q_{p,L}}{Q_{p,L}} \times 100\% \\ \Delta T_p = T_{p,L} - T_{p,H} \\ \Delta V = \frac{V_H - V_L}{V_L} \times 100\% \end{cases} \quad (16)$$

321 where $Q_{p,L}$ and $Q_{p,H}$ are the peak discharges under the L and H states, respectively; $T_{p,L}$ and $T_{p,H}$ are the corresponding times
322 to peak; and V_L and V_H are the corresponding flood volumes. A positive ΔT_p indicates that the flood peak under the H state
323 occurs earlier than that under the L state. By comparing these metrics across different return periods, the effects of antecedent
324 wetness on peak discharge, flood volume, and response timing are evaluated. Because the L and H states use the same design
325 rainfall input, their differences primarily reflect the effects of antecedent wetness conditions and the associated runoff
326 generation and routing responses.

327 2.7.2 Uncertainty Interval Analysis of Design Flood Hydrographs

328 Bootstrap is a statistical method that constructs empirical ensembles through repeated resampling from a finite sample (Zahran
329 et al., 2022). In this study, an event-level Bootstrap approach is adopted to quantify the propagation of uncertainty associated
330 with historical strong-rainfall samples and joint frequency estimation into the derived design flood hydrographs, and to assess
331 the robustness of antecedent wetness sensitivity results. Complete historical strong-rainfall events are treated as the resampling
332 units, and $B=1000$ resamples with replacement are generated while preserving the within-event pairing between P_6 and I_1 .
333 For each Bootstrap sample, the marginal distributions and Copula parameters are re-estimated, and the resulting uncertainty is
334 propagated through design rainfall construction and runoff generation and routing calculations to obtain an ensemble of design
335 flood hydrographs for each return period. Within each resampling realization, the L and H states use the same design rainfall
336 sample to ensure paired comparability.

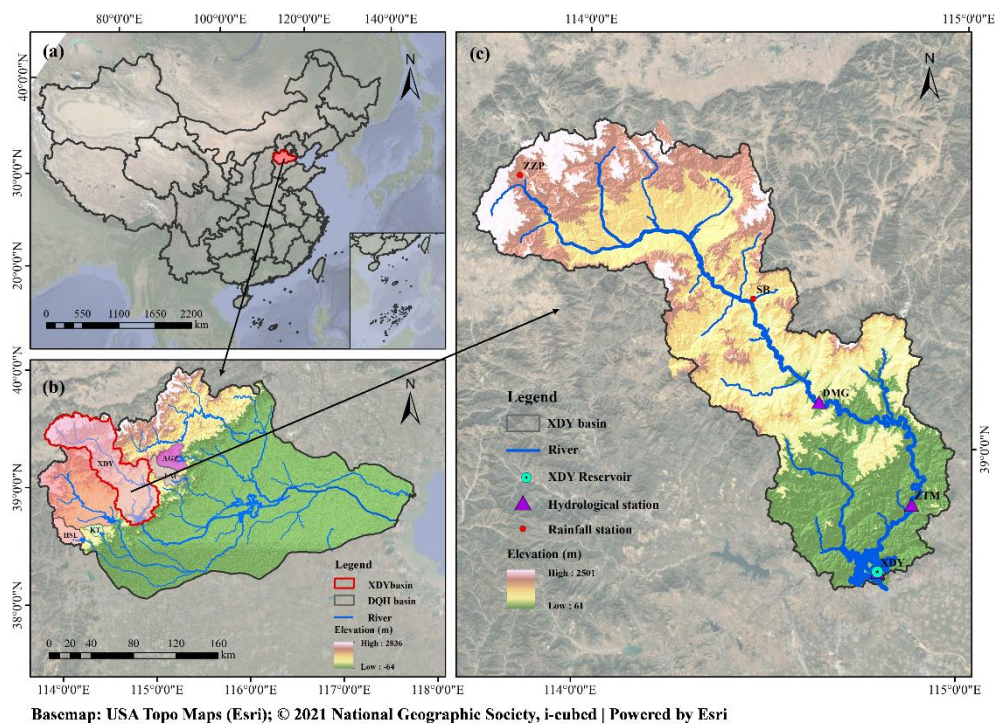
337 The 5th, 50th, and 95th percentiles are calculated for hourly discharge, peak discharge, time to peak, and flood volume. The
338 percentile distributions of the paired L/H peak-discharge ratio, advance in time to peak, and relative increase in flood volume
339 are also calculated to characterize statistical uncertainty and the sample robustness of the sensitivity results. Finally, the L and
340 H antecedent wetness sensitivity scenarios are jointly presented with the Bootstrap 5th-95th percentile ranges within each state,
341 thereby distinguishing scenario sensitivity from statistical uncertainty and providing more complete process-based information
342 for design flood review and flood risk analysis.



343 **3. Study Area and Data Sources**

344 The Daqing River is one of the major river systems in the Haihe River Basin. It originates on the eastern foothills of the
345 Taihang Mountains and consists of northern and southern branches upstream of Dongdian, where six large mountainous
346 reservoirs are distributed. In this study, the catchment controlled by the XDY Reservoir, located in the upper reaches of the
347 Tang River on the southern branch of the Daqing River system, is selected as the study area (Fig. 2). The XDY Reservoir
348 controls a catchment area of 4,420 km² and has a total storage capacity of 1.258×10⁹ m³, including a flood-regulation storage
349 capacity of 8.79×10⁸ m³ and a flood-control storage capacity of 3.13×10⁸ m³. It is a large (Class I) multipurpose reservoir
350 primarily designed for flood control, while also serving water supply, irrigation, and hydropower generation. Both its
351 controlled catchment area and total storage capacity are relatively large within the region.

352 As shown in Fig. 2, the catchment controlled by the XDY Reservoir is characterized by substantial topographic relief, complex
353 land-surface conditions, long routing pathways, and pronounced spatial variability, resulting in heterogeneous spatial rainfall
354 distribution. Meanwhile, catchment wetness varies dynamically with antecedent rainfall and water-storage conditions, causing
355 flood responses to exhibit pronounced nonlinear and nonstationary characteristics. Therefore, conventional design flood
356 methods based on a fixed response structure may not adequately represent the spatiotemporal variability of rainfall-runoff
357 relationships in this catchment.



358 **Figure 2: Schematic Map of the XDY Basin and Distribution of Hydrological Stations**
359

360 **Note: Basemap credit: USA Topo Maps (Esri); copyright © 2021 National Geographic Society, i-cubed.**



The data used in this study primarily comprise two categories: hydrometeorological data and basic geospatial data. The hydrometeorological data include the catastrophic “63.8” flood event of 1963, hourly rainfall records from five rainfall and hydrological stations in the XDY Basin during the flood seasons (June–September) from 1974 to 2025, and the corresponding hourly inflow discharge records of the XDY Reservoir. A total of 27 flood events and 96 strong rainfall events were extracted. The basic geospatial data include the Digital Elevation Model (DEM), land-use, and soil-texture data. The DEM data were obtained from the publicly available ASTER Global Digital Elevation Model V003 dataset at a spatial resolution of 30 m (Abrams et al., 2020). Land-use data were obtained from the ESRI Global 10 m Land Use/Land Cover dataset (ESRI10) (Karra et al., 2021), and soil-texture data were obtained from the SoilGrids 2.0 global soil information dataset at a spatial resolution of 250 m (Poggio et al., 2021).

4. Results

4.1 Identification of Conditional Response Structures Based on ERRA

4.1.1 Identification of Nonlinear and Nonstationary Net Rainfall–Surface Runoff Responses

Based on the hourly net rainfall and rapid surface runoff series from historical flood events, ERRA is used to identify differences in runoff responses under different antecedent wetness states and net rainfall intensities. Antecedent wetness is characterized by the hourly rolling $API_{5,t}$ and classified into lower (L) and higher (H) states using the 35.56 mm boundary between AMC I and AMC II under the SCS-CN growing-season criterion. Candidate breakpoints of 1, 5, and 10 mm/h are first examined to assess response reliability. The results show that the NRF response is generally weak and less identifiable when $P_e < 5\text{ mm/h}$, whereas both response magnitude and stability improve markedly when $P_e \geq 5\text{ mm/h}$. Therefore, 5 mm/h is adopted as the final threshold for net rainfall intensity, dividing the net rainfall process into lower-intensity ($P_e < 5\text{ mm/h}$) and higher-intensity ($P_e \geq 5\text{ mm/h}$) classes. Combined with the two antecedent wetness states, four hydrological conditions are defined. The corresponding NRFs are shown in Fig. 3, while the segmentation diagnostics and reliability assessment are provided in Tables S1–S2.

Based on this classification, the net rainfall–rapid surface runoff responses under the four conditions are identified, as shown in Fig. 3. The NRF curves differ markedly among the conditions. Overall, higher net rainfall intensity produces a greater response magnitude and a more concentrated response, while under the same net rainfall intensity, the response under the H state is generally stronger than that under the L state. These results indicate that rapid routing responses following net rainfall generation in the XDY Basin are jointly regulated by net rainfall intensity and dynamically varying antecedent wetness, exhibiting pronounced nonlinear and nonstationary characteristics.

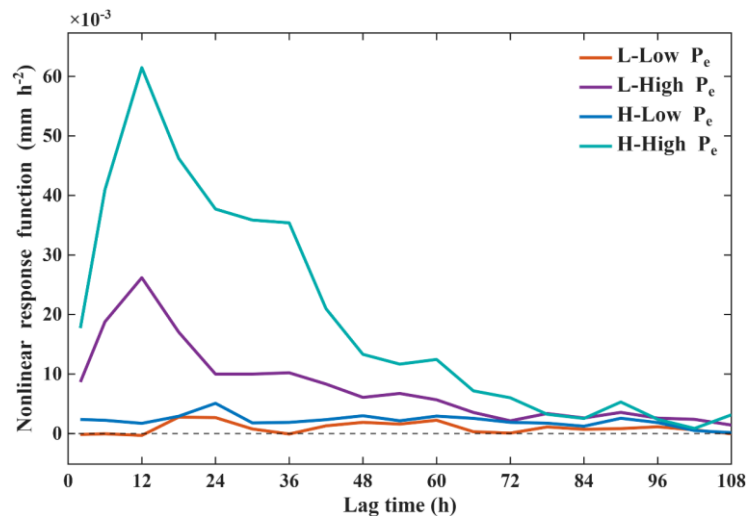


Figure 3: Net Rainfall-Surface Runoff Response Curves under Different Hydrological Conditions

4.1.2 Identification of Spatially Heterogeneous Rainfall-Runoff Responses

Building on the nonlinear and nonstationary net rainfall-surface runoff responses identified in Section 4.1.1, the effects of uneven spatial rainfall distribution on runoff responses are further examined. Based on 27 rainfall events recorded by five rain gauges and the corresponding reservoir inflow data, the multi-station rainfall series are introduced as input variables into the rainfall-runoff response analysis framework to identify differences in the contributions of rainfall from different regions to the outlet runoff process.

As shown in Fig. 4, the area surrounding the ZZP station is located in the upper part of the catchment, with relatively high elevation, longer routing pathways, predominantly loamy soils, and a mixed land-use pattern consisting mainly of grassland, cropland, and woodland. In contrast, the remaining stations are mostly located in the middle and lower reaches of the catchment, where the terrain is relatively lower and closer to the reservoir inlet, the soils are mainly clay loam, and woodland is the dominant land-use type. Considering the differences in rainfall-runoff responses together with catchment topography, soil properties, and land-use characteristics, the SB station is used as the boundary to divide the catchment into two spatial subregions: the area upstream of SB is defined as Space 1, whereas the area at and downstream of SB is defined as Space 2, as shown in Fig. 4(d).

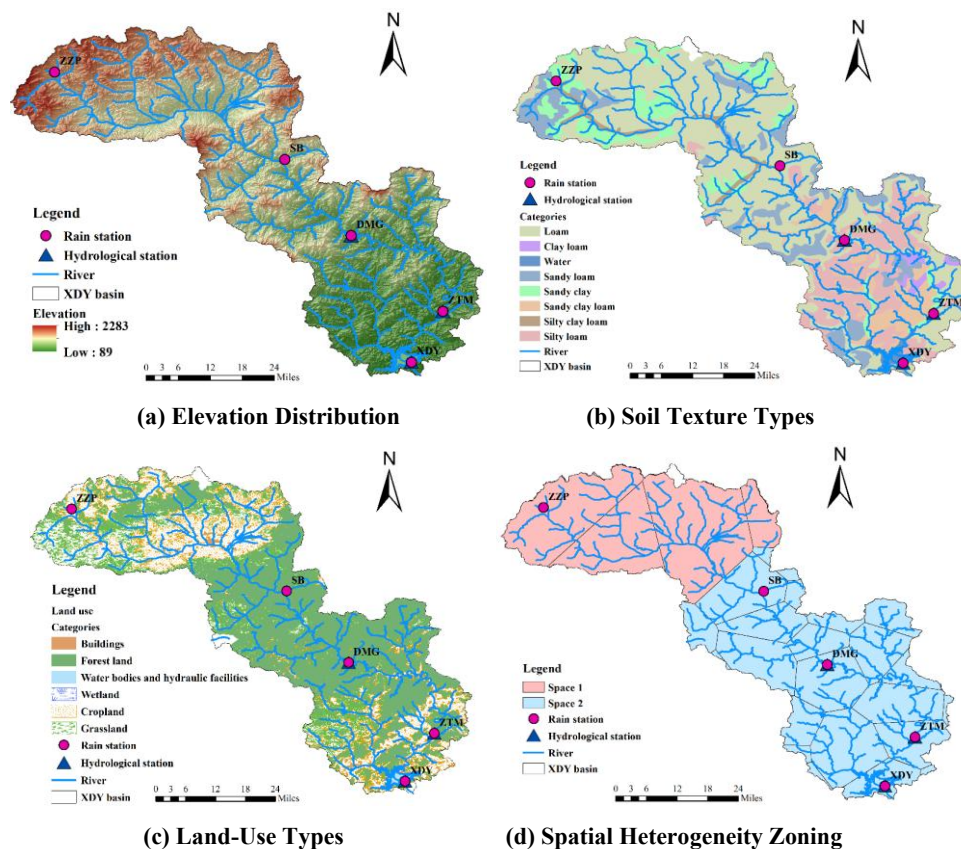


Figure 4: Catchment Surface Characteristics of the XDY Basin

On this basis, the rainfall processes of the two spatial subregions are calculated separately and used as inputs to the rainfall-runoff regression equation to establish rainfall-runoff response relationships that account for spatial heterogeneity. As shown in Fig. 5 and Table 1, the response distributions of Space 1 and Space 2 differ markedly. Space 1 exhibits a greater maximum response magnitude and a more concentrated overall response, with shorter T_{50} , T_{90} , and T_{95} . In contrast, Space 2 reaches its response peak earlier but shows a weaker response magnitude and a substantially longer recession tail. These differences indicate pronounced spatial heterogeneity in rainfall-runoff response within the catchment. The spatial response efficiency weights are further calculated using the method described in Section 2.4.2, yielding values of 0.64 and 0.36 for Space 1 and Space 2, respectively. These weights represent the relative contributions of rainfall from different spatial subregions to outlet runoff responses and are subsequently used for the spatial correction of design rainfall hyetographs.

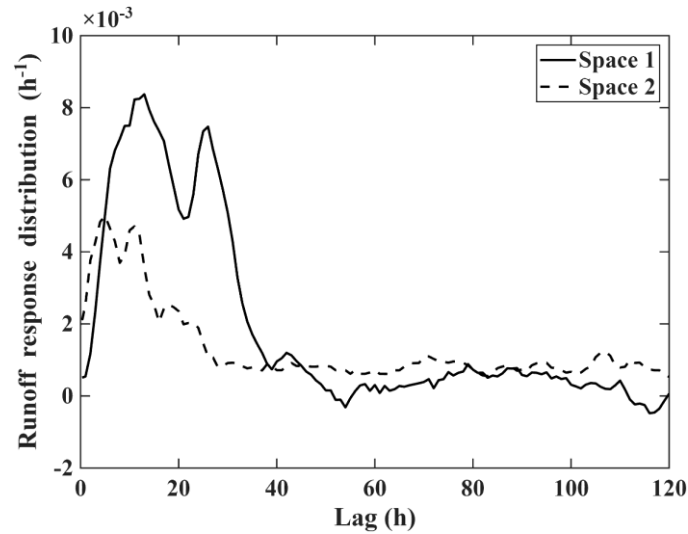


Figure 5: Rainfall-Runoff Response Distributions of Space 1 and Space 2

Table 1: Characteristic Metrics of Spatially Heterogeneous Rainfall-Runoff Response Distributions

Metric	Space 1	Space 2
Maximum response intensity (RRD_{max}, h^{-1})	0.0084	0.0050
Time to peak (T_p, h)	13	5
50% response time (T_{50}, h)	19	24
90% response time (T_{90}, h)	47	102
95% response time (T_{95}, h)	82	110

4.2 Construction of Conditional Unit Hydrographs and Simulation of Surface Runoff Generation and Routing

4.2.1 Runoff Generation Calculation Based on the SCS-CN Model

The SCS-CN model is used for runoff generation calculation, with the initial abstraction coefficient λ set to 0.15. The spatially corrected catchment-average rainfall is used as input, and the 5-day cumulative rainfall prior to the onset of each event, $API_{5,0}$, is used to characterize the initial antecedent wetness condition. Because all flood events in the study area occurred during the growing season, the SCS-CN antecedent moisture condition classification criteria are adopted. Specifically, $API_{5,0} < 35.56$ mm, $35.56 \leq API_{5,0} \leq 53.34$ mm, and $API_{5,0} > 53.34$ mm are classified as AMC I, AMC II, and AMC III, respectively, and the corresponding CN values are used for runoff generation calculation. The CN values for different land-use types and the composite catchment-average CN values are listed in Table 2.

Here, $API_{5,0}$ is used only to determine the initial antecedent wetness condition of each event and its corresponding CN value, whereas the rolling $API_{5,t}$ described in Section 2.1.2 is updated hourly throughout the flood event and used for identifying conditional rapid-routing responses. Therefore, the CN value remains unchanged during an individual flood event and is not dynamically adjusted according to $API_{5,t}$. The resulting net rainfall process P_e , calculated using the SCS-CN model, is subsequently used as input to the conditional Nash unit hydrograph routing calculation.



Table 2: CN Values under Different Antecedent Moisture Conditions in the XDY Basin

Land-use type	Area (km ²)	Weight	CN _{AMC II}	CN _{AMC I}	CN _{AMC III}
Woodland	2385.96	53.98%	60	40	80
Cropland	1124.88	25.45%	65	45	85
Grassland	834.54	18.88%	53	32	75
Building area	65.70	1.49%	69	51	86
Water bodies and water conservancy facilities	8.92	0.20%	100	100	100
Average	—	—	60.16	39.99	80.41

Note: All flood events analyzed in this study occurred during the flood season (June–September), corresponding to the growing season in the SCS-CN model. CN_{AMC I}, CN_{AMC II}, and CN_{AMC III} denote the curve numbers under dry, normal, and wet antecedent moisture conditions, respectively.

4.2.2 Parameter Calibration of the Nash Instantaneous Unit Hydrograph Model

The Nash Instantaneous Unit Hydrograph (Nash IUH) model is adopted to represent the rapid routing process of the catchment. Because the observed total discharge contains a baseflow component, whereas the unit hydrograph is primarily used to characterize the surface runoff response, baseflow separation is performed prior to unit hydrograph calibration using the Lyne–Hollick (LH) method described in Section 2.5.3, and the surface runoff component Q_q is extracted. The separation results show that the net rainfall volume is generally consistent with the rapid runoff volume at the event scale, while baseflow accounts for a certain proportion of the total runoff, indicating that unit hydrograph calibration based on baseflow separation is reasonable. For the 27 representative flood events, the Nash unit hydrograph shape parameter n and scale parameter K are calibrated separately. To obtain stable representative catchment parameters, the median values of the parameter sets $\{n_i, K_i\}$ are adopted, and the maximum lag time is set to $t_{\max} = 108$ h to construct the composite Nash unit hydrograph. The resulting representative parameters are $n_{\text{med}} = 1.3$ and $K_{\text{med}} = 20$, corresponding to a time to peak of approximately 6 h, as shown in Fig. 6.

4.2.3 Construction of State-Dependent Unit Hydrographs Based on Nonlinear and Nonstationary Responses

As indicated by the ERRAs in Section 4.1.1, the net rainfall–surface runoff response varies markedly with antecedent wetness state and net rainfall intensity. Therefore, following the method described in Section 2.2.2, state-dependent unit hydrographs are constructed for the four combinations of the L and H antecedent wetness states and lower and higher net rainfall intensity classes.

As shown in Fig. 6, with increasing antecedent wetness and net rainfall intensity, the unit hydrograph peak gradually increases, the time to peak advances, and the runoff response becomes more concentrated. The strongest response occurs under the H-higher net rainfall intensity condition, followed by the L-higher net rainfall intensity and H-lower net rainfall intensity conditions, whereas the L-lower net rainfall intensity condition exhibits the weakest and most delayed response. These results indicate that the state-dependent unit hydrographs can effectively characterize nonlinear and nonstationary routing responses under different hydrological conditions, providing a basis for the subsequent derivation of conditional design flood hydrographs.

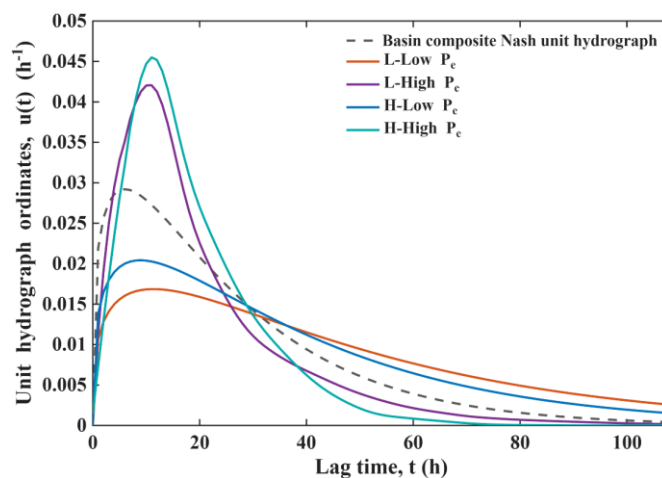


Figure 6: State-Dependent Unit Hydrographs under Different Hydrological Conditions

4.3 Derivation of Design Rainfall Hyetographs

4.3.1 Determination of Design Rainfall Magnitudes for Different Return Periods

Following the method described in Section 2.3.1, a total of 96 historical strong rainfall events are selected. The 96 h total rainfall depth P_{96} and maximum 1 h rainfall intensity I_1 within the standardized 96 h event window are extracted as the design variables. The Lognormal, Gamma, Weibull, Exponential, Log-logistic, and three-parameter lognormal (LN_3) distributions are selected as candidate marginal distributions and comprehensively evaluated using the Kolmogorov-Smirnov (K-S) test, Anderson-Darling (A-D) test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The results are shown in Fig. S1 and Table S3. The LN_3 distribution is selected for P_{96} , with parameters $\xi = 37.52$, $\mu_{ln} = 3.43$, and $\sigma_{ln} = 0.73$, whereas the Lognormal distribution is selected for I_1 , with parameters $\mu_{ln} = 2.39$ and $\sigma_{ln} = 0.42$.

The joint distribution of P_{96} and I_1 is further fitted using the Frank, Gumbel-Hougaard, and Clayton Copulas. As shown in Fig. S2 and Table S4, the Frank Copula provides the best overall fit, with a parameter of $\theta = 3.20$, and is therefore selected to characterize the dependence between the two variables. Based on the joint frequency analysis, the design total rainfall depth P_T and maximum 1 h rainfall intensity $I_{1,T}$ corresponding to different return periods are determined, as summarized in Table 3.

Table 3: Design 96 h Total Rainfall Depth P_{96} and Maximum 1 h Rainfall Intensity I_1 for Different Return Periods

Return period (a)	P (mm)	I_1 (mm/h)
20	302.82	20.28
100	455.36	29.10
200	526.47	35.97
500	622.72	39.56
2,000	777.87	43.94
10,000	966.43	48.71



4.3.2 Construction of Conditional Design Rainfall Hyetographs

The statistical characteristics of the dimensionless cumulative rainfall patterns derived from the 96 historical strong rainfall events are shown in Fig. S3. Their overall temporal structures are relatively consistent, providing the basis for determining a common representative temporal rainfall pattern. Based on the design total rainfall depth P_T and maximum 1 h rainfall intensity $I_{1,T}$ for different return periods listed in Table 3, the corresponding 96 h design rainfall hyetographs are constructed, as shown in Fig. 7.

As shown in Fig. 7, both the design total rainfall depth and peak rainfall intensity increase with increasing return period, whereas the main peak position, principal rainfall concentration period, and overall temporal structure remain nearly unchanged. This indicates that differences among design rainfall hyetographs for different return periods are primarily reflected in rainfall magnitude. For a given return period, the L and H antecedent wetness states use exactly the same design rainfall input, ensuring that subsequent differences in flood responses primarily reflect the effects of antecedent wetness and the associated runoff generation and routing conditions.

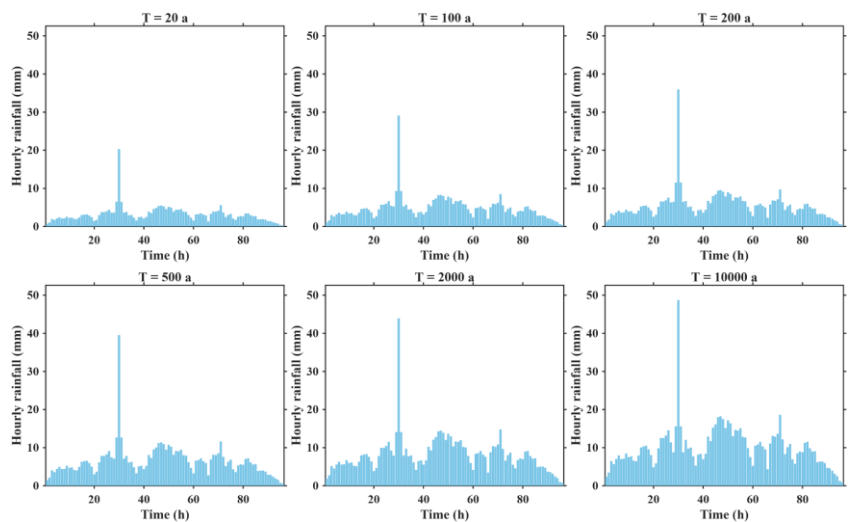


Figure 7: Common Design Rainfall Hyetographs for Different Return Periods

4.3.3 Adjustment of the Design Rainfall Hyetograph Based on Spatially Heterogeneous Rainfall-Runoff Responses

As shown in Section 4.1.2, clear differences exist between the rainfall-runoff responses of Space 1 and Space 2. A common time-varying spatial rainfall allocation template was constructed using all historical heavy rainfall events (Fig. S4). The results show that the relative contribution of Space 2 is higher during the early stage of rainfall, whereas the contribution of Space 1 gradually increases and eventually exceeds that of Space 2 during the later stage, indicating pronounced time-varying spatial allocation characteristics within the design rainfall process.

Further incorporating the spatial differences in rainfall-runoff response, the response-efficiency weights of Space 1 and Space 2 were determined as 0.64 and 0.36, respectively. After accounting for the area fractions of the two subregions, a spatial-

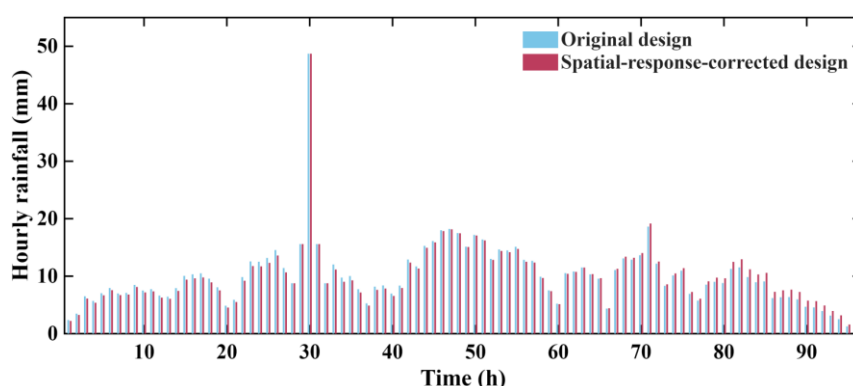


Figure 8: Comparison of Design Rainfall Hyetographs Before and After Spatial-Response Adjustment (T=10,000 a)

4.4 Derivation of Conditional Design Flood Hydrographs

4.4.1 Surface-Subsurface Runoff Composition and Analysis of Typical Hydrographs

Under the same design rainfall input, the surface runoff, subsurface runoff, and total runoff hydrographs under the L and H antecedent wetness states are compared. Surface runoff is generated using the SCS-CN model and routed using state-dependent unit hydrographs, with the routing state dynamically determined according to the rolling $API_{5,t}$ and hourly net rainfall intensity. Subsurface runoff is simulated using a linear reservoir model. Based on the Lyne-Hollick (LH) baseflow separation results from representative historical flood events, the subsurface recharge coefficient and subsurface runoff memory coefficient are calibrated as $c_g = 0.15$ and $k_b = 0.975$, respectively. The simulated subsurface runoff is then superimposed on the surface runoff to obtain the total runoff hydrograph.

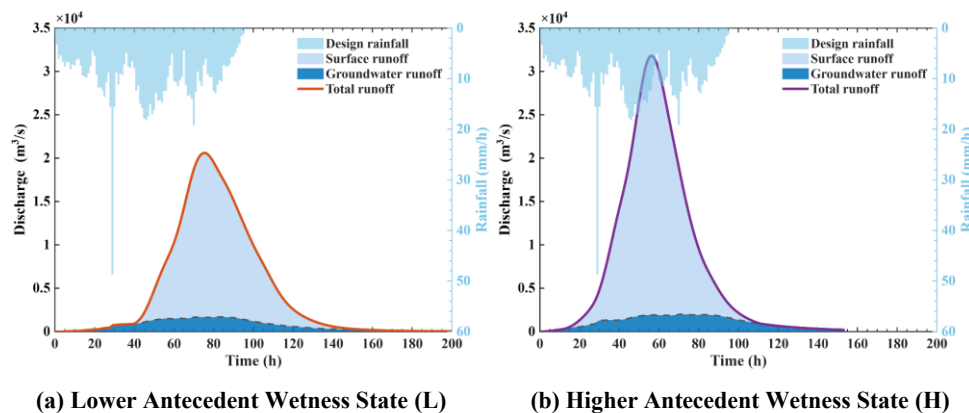
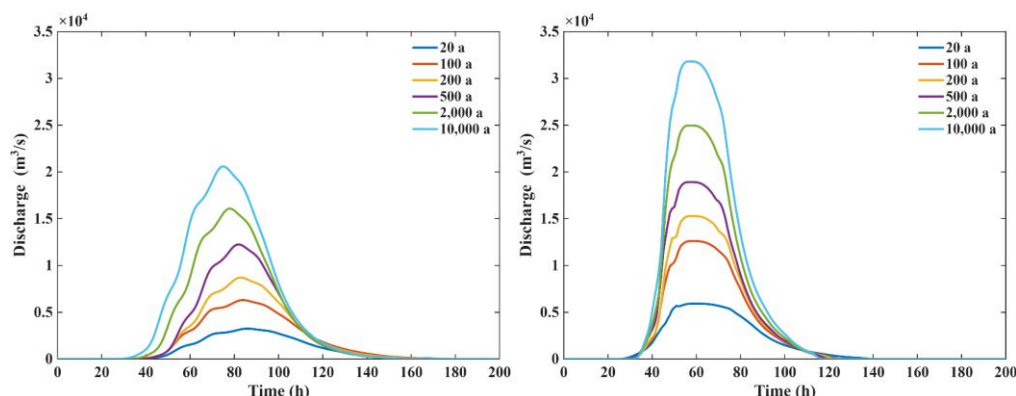


Figure 9: Comparison of Runoff Components in Typical Design Flood Hydrographs under Different Antecedent Wetness States (T=10,000 a)

Taking the 10,000-year return period as an example, the runoff components and total flood hydrographs are shown in Fig. 9. Under both antecedent wetness states, the flood hydrographs are dominated by surface runoff, whereas subsurface runoff varies more gradually and mainly contributes to the recession stage. Under the L state, the total runoff peak is approximately 2.06×10^4 m^3/s and occurs at about 75 h, with a relatively smooth hydrograph. Under the H state, the peak discharge increases to approximately 3.18×10^4 m^3/s and occurs earlier, at about 56 h, resulting in a more concentrated flood peak. These results indicate that, under the same design rainfall conditions, a higher antecedent wetness state enhances both runoff generation and rapid routing responses, leading to a markedly larger and earlier flood peak.

4.4.2 Characteristics of Conditional Design Flood Hydrographs under Different Antecedent Wetness States

The conditional design flood hydrographs under the L and H antecedent wetness states for different return periods are shown in Fig. 10, and the corresponding characteristic metrics are summarized in Table 4. As the return period increases, both peak discharge and flood volume increase continuously under the two states, while the time to peak generally occurs earlier. Meanwhile, the hydrograph shapes differ markedly between the two states: the L-state hydrographs are relatively smoother and broader, whereas the H-state hydrographs exhibit higher peaks, more concentrated responses, and earlier times to peak. As shown in Table 4, under the L state, peak discharge increases from $3247.6 \text{ m}^3 \text{ s}^{-1}$ for the 20-year return period to $20,604.0 \text{ m}^3 \text{ s}^{-1}$ for the 10,000-year return period, while flood volume increases from 6.570×10^8 to $32.516 \times 10^8 \text{ m}^3$. Under the H state, peak discharge increases from 5917.4 to $31,815.0 \text{ m}^3 \text{ s}^{-1}$, and flood volume increases from 10.504×10^8 to $41.180 \times 10^8 \text{ m}^3$. For the same return period, the H state generally exhibits a larger peak discharge and flood volume, together with an earlier time to peak, indicating that antecedent wetness can markedly influence both the magnitude and shape of design flood hydrographs.



(a) Lower Antecedent Wetness State (L) (b) Higher Antecedent Wetness State (H)

Figure 10: Conditional Design Flood Hydrographs for Different Return Periods under Different Antecedent Wetness States

Table 4: Characteristic Metrics of Conditional Design Flood Hydrographs under Different Antecedent Wetness States

Antecedent wetness state	Return period (a)	Peak discharge (m³/s)	Time to peak (h)	Flood volume (10⁸ m³)
Lower antecedent wetness state (L)	20	3247.6	86	6.570
	100	6305.4	84	11.954
	200	8714.2	83	14.661
	500	12,254.3	82	18.423
	2,000	16,084.7	78	24.687
	10,000	20,604.0	75	32.516
Higher antecedent wetness state (H)	20	5917.4	59	10.504
	100	12,612.2	58	18.511
	200	15,291.3	57	21.616
	500	18,922.1	57	25.907
	2,000	24,969.9	57	32.786
	10,000	31,815.0	56	41.180

Note: All design flood hydrographs were standardized to a unified duration of 200 h.

4.5 Sensitivity and Uncertainty Analysis of Conditional Design Flood Hydrographs

4.5.1 Antecedent Wetness Sensitivity Analysis

Under identical design rainfall conditions, antecedent wetness has a pronounced influence on design flood responses. As shown in Table 5, the higher antecedent wetness state (H) produces larger peak discharges and flood volumes and earlier flood peaks across all return periods. Compared with the lower antecedent wetness state (L), the H scenario increases peak discharge by 54.4%-100.0%, advances the time to peak by 19-27 h, and increases flood volume by 26.6%-59.9%. In addition, the peak width is smaller under the H scenario than under the L scenario, indicating a faster and more concentrated flood response under higher antecedent wetness conditions.

As the return period increases, the relative effects of antecedent wetness on flood volume and peak timing generally decrease. The increase in flood volume declines from 59.9% for the 20-year return period to 26.6% for the 10,000-year return period, while the advance in time to peak decreases from 27 h to 19 h. By contrast, although peak-discharge sensitivity varies



nonlinearly with return period, the increase remains approximately 54%-55% over the 500-10,000-year range. These results indicate that, as design rainfall magnitude increases, rainfall itself increasingly dominates the overall flood volume and response timing, whereas antecedent wetness continues to exert a strong influence on extreme peak discharge.

Table 5: Sensitivity of Conditional Design Flood Hydrographs to Antecedent Wetness State for Different Return Periods

Return period (a)	Increase in peak discharge (%)	Advance in time to peak (h)	Increase in flood volume (%)
20	82.2	27	59.9
100	100.0	26	54.9
200	75.5	26	47.4
500	54.4	25	40.6
2,000	55.2	21	32.8
10,000	54.4	19	26.6

4.5.2 Uncertainty Analysis of Design Flood Hydrographs

Based on 1,000 event-level paired Bootstrap samples, ensembles of design flood hydrographs are obtained for the L and H antecedent wetness states at different return periods. The time-varying 5th, 50th, and 95th percentile hydrographs are shown in Fig. 11, while the percentile statistics of peak discharge, time to peak, and flood volume for each state are provided in Table S5. The L and H scenarios represent antecedent wetness sensitivity scenarios rather than the lower and upper bounds of uncertainty. Overall, uncertainty is concentrated mainly along the rising limb and around the main flood peak. The 5th-95th percentile ranges of peak discharge and flood volume generally widen with increasing return period, indicating that uncertainty arising from historical-event sampling and statistical estimation of design rainfall can propagate into the derived design flood hydrographs.

The paired L/H results obtained from the same Bootstrap samples are summarized in Table S6. Across the different return periods, the median H/L peak-discharge ratio ranges from 1.54 to 1.95, with the 5th percentile consistently greater than 1. The median advance in time to peak under the H state relative to the L state ranges from 19 to 26 h. The median increase in flood volume decreases from 59.9% for the 20-year return period to 26.6% for the 10,000-year return period, with the 5th percentile remaining greater than 0. These results indicate that the effects of antecedent wetness on peak discharge, peak timing, and flood volume are robust to event-sample variability. The L/H comparison represents sensitivity to antecedent wetness state, whereas the 5th-95th percentile range within each state represents statistical uncertainty. These percentiles are empirical percentiles of the Bootstrap ensemble under the specified model structure and parameter settings and should not be interpreted as statistical confidence intervals.

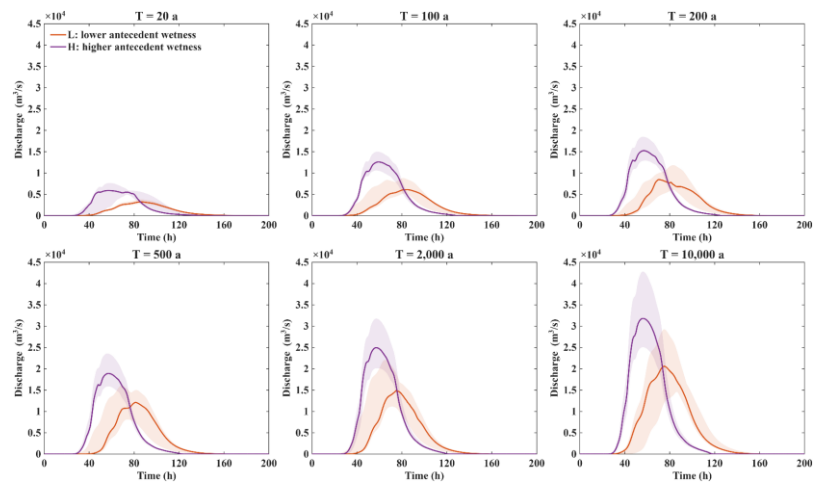


Figure 11: Bootstrap Uncertainty Ranges of Design Flood Hydrographs under Different Return Periods and Antecedent Wetness States

5. Discussion

5.1 Comparison between Conditional Design Flood Hydrographs and the Conventional Single Design Flood Hydrograph

According to the flood-control planning of the XDY Reservoir, the current design flood standard corresponds to a 500-year return period, while the check flood standard corresponds to a 10,000-year return period. The corresponding standard design flood hydrographs are shown in Fig. 12. As indicated by Fig. 12 and Table 6, the conditional design flood hydrographs under different antecedent wetness states differ markedly from the existing standard hydrographs.

For both the 500-year and 10,000-year return periods, the peak discharge under the L state is lower than that of the existing standard hydrograph, and the time to peak occurs later. In contrast, the peak discharge under the H state is slightly higher than the existing standard, the time to peak occurs earlier, and the flood volume is larger. These results indicate that, under the same design rainfall conditions, the lower antecedent wetness state is associated with weaker runoff generation and routing responses, whereas the higher antecedent wetness state enhances runoff generation and rapid routing, resulting in a more adverse combination of peak discharge and flood volume.

Overall, the existing standard hydrograph represents a single engineering design scenario, whereas the conditional design flood framework further characterizes differences in peak discharge, flood volume, time to peak, and hydrograph shape under different antecedent wetness states. It therefore provides richer process-based information for design flood review and flood risk scenario analysis.

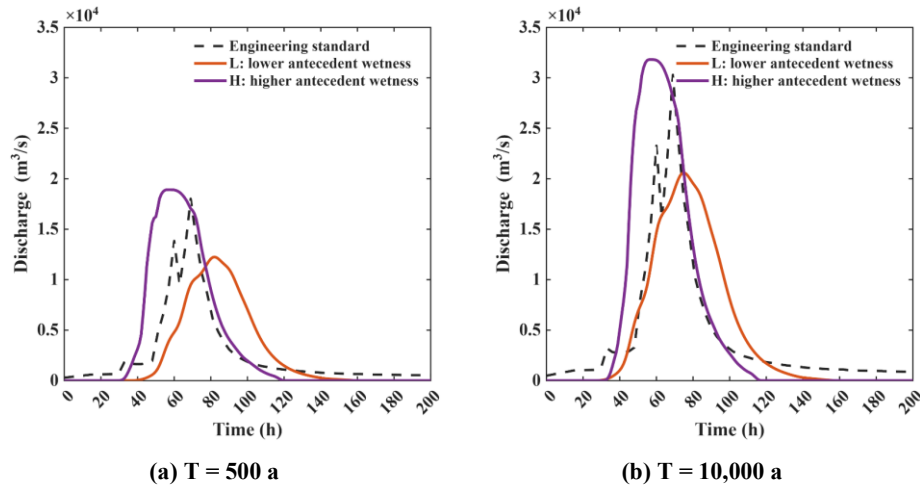


Figure 12: Comparison of Conditional Design Flood Hydrographs with the Existing Standard Hydrographs for Representative Return Periods

Table 6: Comparison of Characteristic Metrics between Conditional Design Flood Hydrographs and Existing Design Standards for Representative Return Periods

Return period (a)	Scenario	Peak discharge (m³/s)	Time to peak (h)	Flood volume (10 ⁸ m³)
500	Existing standard	18021	69	19.25
	L state	12254	82	18.42
	H state	18922	57	25.91
10000	Existing standard	30300	69	32.37
	L state	20604	75	32.52
	H state	31815	56	41.18

5.2 Model Applicability and Structural Validation

5.2.1 Validation Using Historical Extreme Flood Simulations

To evaluate the applicability of the developed runoff generation and routing model to historical extreme floods, two major flood events, 19630801 and 20230728, are selected for simulation. The model adopts the spatial response relationships, conditional unit hydrographs, and runoff generation and routing parameters determined uniformly in the preceding analyses. No event-specific recalibration or parameter adjustment is performed during validation, thereby avoiding the influence of event-specific tuning on model evaluation. The spatial-heterogeneity-corrected catchment-average rainfall is used as input, and the simulated and observed flood hydrographs are compared in Fig. 13.

Model performance is evaluated using the relative peak discharge error ΔP_c , time-to-peak error ΔT_c , relative flood volume error ΔR_c , and Nash-Sutcliffe efficiency (NSE). As shown in Table 7, the NSE values for the two flood events are 0.80 and 0.85, respectively, while the time-to-peak error is 0 h for both events. The relative peak discharge errors are 1.24% and 8.83%, and the relative flood volume errors are 26.89% and 14.62%, respectively. These results indicate that, under a unified parameter setting, the model can reasonably reproduce the flood peaks, times to peak, and overall hydrograph variations of the two



historical extreme flood events, providing event-scale evidence of model applicability for the subsequent derivation of conditional design flood hydrographs.

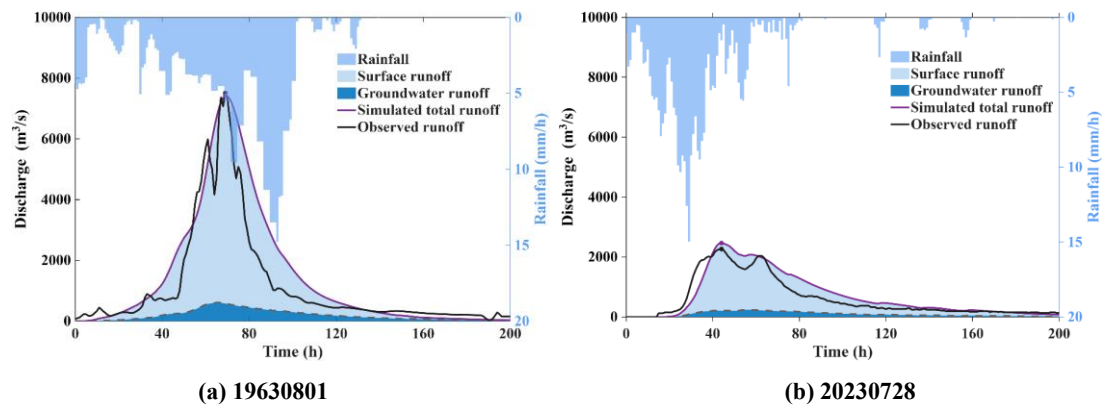


Figure 13: Rainfall-Runoff Simulations of Historical Extreme Flood Events Using the Coupled Model

Table 7: Performance Evaluation Metrics for Historical Extreme Flood Simulations

Flood event	NSE	Flood volume error (ΔR_c) (%)	Peak discharge error (ΔP_c) (%)	Time-to-peak error (ΔT_c) (h)
19630801	0.80	26.89	1.24	0
20230728	0.85	14.62	8.83	0

5.2.2 Incremental Comparison of Model Structures

To quantitatively evaluate the incremental contribution of each methodological component to flood simulation performance, five historical flood events representing different antecedent wetness states and rainfall intensity levels are selected, and four runoff generation and routing schemes, M0-M3, are established. M0 uses Thiessen-weighted areal rainfall and the Nash unit hydrograph. M1 introduces spatial-response-corrected rainfall. M2 further incorporates an RRD-based unit hydrograph refinement, while M3 additionally introduces nonlinear state-dependent unit hydrographs. Model performance is evaluated using NSE, $|\Delta P_c|$, $|\Delta R_c|$, and $|\Delta T_c|$. All schemes use a unified parameter setting, and the results are shown in Fig. 14. Comparison between M0 and M1 shows that the spatially heterogeneous rainfall correction increases NSE by 0.05-0.08 across the five events and reduces flood volume errors in all cases, with the largest error decreasing from 22.22% to 8.13%. After further introducing the RRD-based unit hydrograph refinement, M2 generally achieves additional improvements in peak discharge, flood volume, and time-to-peak errors. Compared with M2, M3 further reduces peak discharge and flood volume errors for all events, while the time-to-peak error is further improved by 1-2 h for three events. Overall, from M0 to M3, the mean NSE across the five events increases from 0.744 to 0.874, the mean absolute peak discharge error decreases from 13.67% to 6.80%, the mean absolute flood volume error decreases from 18.31% to 6.45%, and the mean absolute time-to-peak error decreases from 3.8 h to 1.4 h. These results indicate that both spatially heterogeneous rainfall correction and state-dependent routing improve the simulation of key flood characteristics, including peak discharge, flood volume, and time to peak, with the complete M3 model showing the best overall simulation performance.

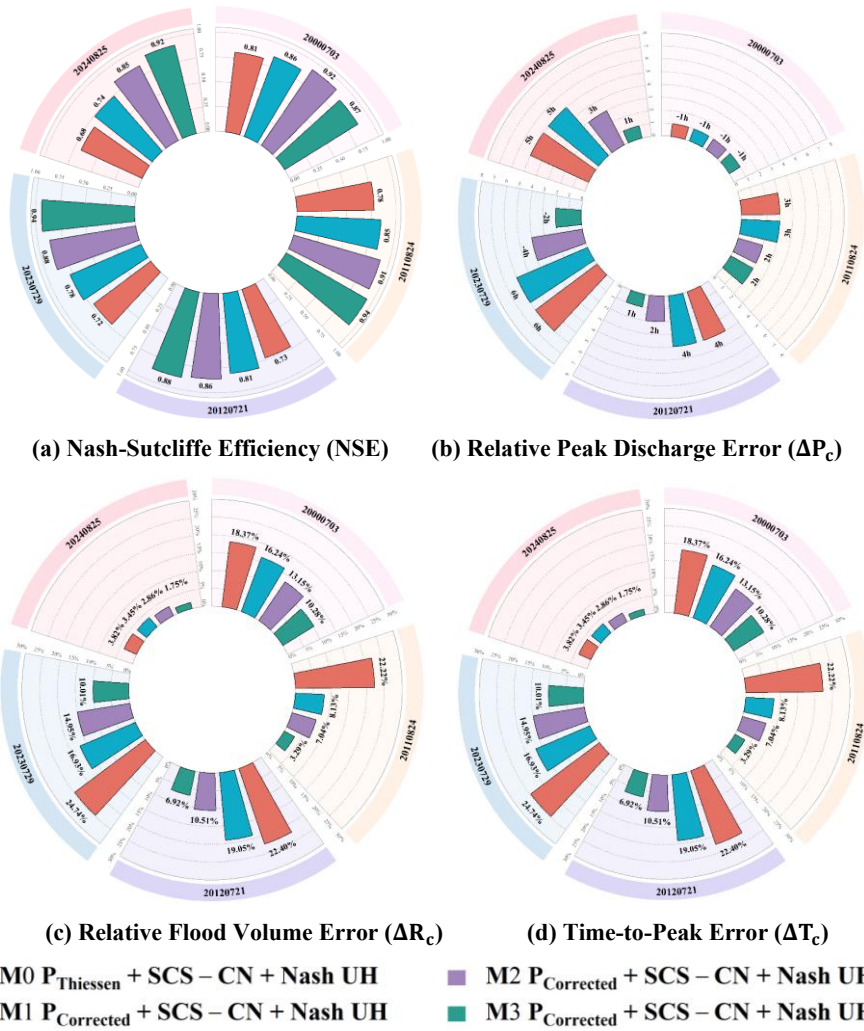


Figure 14: Comparison of Historical Flood Simulation Performance among the M0-M3 Incremental Model Structures

5.3 Limitations and Future Research

Although the conditional design flood hydrograph derivation method developed in this study can represent differences in flood responses under varying antecedent wetness states and catchment response conditions, several limitations remain and warrant further investigation.

First, the classification of antecedent wetness states is still relatively simplified. In actual catchments, wetness varies continuously and is influenced by multiple factors, including antecedent rainfall, soil moisture, groundwater level, and catchment storage conditions. In this study, antecedent wetness is generalized into lower and higher states, which facilitates engineering application and interpretation but cannot fully characterize differences in runoff generation and routing under



intermediate wetness conditions. Future studies could incorporate soil moisture, antecedent precipitation indices, groundwater levels, and related information to develop continuous or multi-level indicators of antecedent wetness. Second, this study mainly uses event-level Bootstrap analysis to characterize the propagation of uncertainty associated with historical strong-rainfall samples and joint frequency estimation. Future work could further incorporate parameter uncertainty and model structural uncertainty to provide a more comprehensive assessment of uncertainty in design flood hydrographs. In addition, the proposed framework is validated only in the XDY Basin, and its applicability under different climatic, topographic, and land-surface conditions remains to be further examined. Comparative applications across different types of catchments could be conducted to evaluate the regional applicability and transferability of the method. Finally, the engineering performance of conditional design flood hydrographs requires further evaluation. This study mainly analyzes differences among scenarios in terms of peak discharge, flood volume, and hydrograph shape, without further coupling the results with reservoir operation or flood risk models. Future studies could use conditional design flood hydrographs as inputs to reservoir operation and risk assessment models to quantitatively evaluate their effects on indicators such as maximum reservoir water level, maximum release discharge, and downstream flood risk, thereby further assessing their engineering applicability.

5.4 Engineering Implications of Conditional Design Flood Hydrographs

The primary purpose of engineering design floods is to determine hydrological loads that are critical to flood-control safety (Tramblay et al., 2024; Kim et al., 2026). For a given design storm, antecedent wetness can markedly affect runoff generation, peak discharge, and time to peak. Accordingly, engineering design often adopts a higher antecedent wetness state to represent relatively adverse conditions. However, the catchment does not necessarily remain highly wet before every extreme rainfall event. Although using only a wet antecedent scenario may provide a conservative estimate, it cannot adequately reflect the sensitivity of design floods to variations in antecedent conditions or their corresponding engineering implications (Poudel et al., 2026; Guo et al., 2022).

Therefore, both lower (L) and higher (H) antecedent wetness scenarios are retained in this study. The H scenario represents the flood response under relatively adverse antecedent conditions, whereas the L scenario serves as a reference for quantifying the effects of antecedent wetness on peak discharge, flood volume, and time to peak, as well as for evaluating the conservativeness of assuming a wet antecedent condition. In practical reservoir operation, the L scenario may also provide useful information for avoiding excessive prerelease or unnecessary reservation of flood-control storage, thereby helping balance flood-control safety and water-resource utilization.

On this basis, the conditional design flood framework further incorporates statistical uncertainty within each antecedent wetness state. For flood-control safety checks, greater attention may be given to the H scenario and its adverse flood response. For design flood review, comparison of reservoir operation schemes, and risk analysis, the L and H scenarios can be considered together with their corresponding uncertainty ranges. In this way, conditional design flood hydrographs can provide more targeted process-based information for flood-scenario selection and risk identification under different engineering objectives.



689 6. Conclusions

690 Taking the XDY Basin as the study area, this study develops a conditional design flood hydrograph derivation method that
 691 accounts for spatially heterogeneous rainfall and nonlinear nonstationary routing. Conditional rainfall-runoff responses are
 692 identified using ERRA, and design flood hydrographs under different antecedent wetness states, together with their statistical
 693 uncertainty, are derived by integrating state-dependent unit hydrographs, spatially corrected design rainfall, and event-level
 694 paired Bootstrap analysis. The main conclusions are as follows.

695 (1) Rainfall-runoff responses in the XDY Basin exhibit pronounced state dependence and spatial variability. Increases in net
 696 rainfall intensity and antecedent wetness both strengthen and concentrate rapid runoff responses, while clear differences in
 697 runoff response are also observed among different spatial subregions.

698 (2) State-dependent unit hydrographs can characterize the nonlinear and nonstationary features of catchment routing. As net
 699 rainfall intensity and antecedent wetness increase, the unit hydrograph peak becomes higher and the time to peak occurs earlier.
 700 From M0 to M3, the mean NSE increases from 0.744 to 0.874. The NSE values for the two historical extreme flood events are
 701 0.80 and 0.85, respectively, indicating good model applicability.

702 (3) A design rainfall hyetograph framework is constructed that jointly accounts for rainfall magnitude, temporal structure, and
 703 spatial response differences. Design rainfall magnitude is determined through joint frequency analysis of total rainfall depth
 704 and maximum 1 h rainfall intensity, and spatial correction is then conducted by combining a representative rainfall pattern
 705 with regional response differences. For a given return period, the L and H states use the same design rainfall input.

706 (4) Antecedent wetness has a pronounced influence on conditional design flood hydrographs. Compared with the L state, the
 707 H state increases peak discharge by 54.4%-100.0%, advances the time to peak by 19-27 h, and increases flood volume by
 708 26.6%-59.9%. As the return period increases, the increase in flood volume and the advance in time to peak generally decrease.

709 (5) Event-level paired Bootstrap results indicate that statistical uncertainty is concentrated mainly along the rising limb and
 710 around the main flood peak, and generally expands with increasing return period. The paired L/H results further show that the
 711 effects of antecedent wetness are robust to event-sample variability. The conditional design flood framework can therefore
 712 represent both state sensitivity and statistical uncertainty, providing support for flood-control safety assessment, design flood
 713 review, and reservoir operation risk analysis.

714 Code and data availability

715 The rainfall and hydrological datasets used in this study were provided by the Hydrographic Bureau of the Haihe River Water
 716 Conservancy Commission, MWR, and the Hebei Baoding Hydrological Survey and Research Center. These datasets are
 717 subject to access restrictions imposed by the data providers and therefore cannot be publicly deposited. Researchers interested
 718 in accessing the original datasets may contact the corresponding author; access may be granted subject to approval by the
 719 respective data providers. The model code developed in this study is available from the corresponding author upon reasonable
 720 request.



721 **Supplement link**

722 The supplement related to this article is available online at: [link to be inserted by Copernicus].

723 **Author contributions**

724 Jing Feng was responsible for the conceptualization and methodological design of the study, model development, programming,
725 data processing, model simulations, analysis of the results, visualization, and preparation of the original manuscript. Jiacheng
726 Duan contributed to the conceptualization and methodological design of the study, supervised the research, and contributed to
727 the review and revision of the manuscript. Jianzhu Li contributed to the study design and methodological guidance and was
728 responsible for supervision, project administration, and funding acquisition, as well as reviewing and revising the manuscript.
729 Hongdong Song contributed to the collection, organization, and verification of hydrological data and supported the analysis
730 and interpretation of catchment hydrological processes. Bin Wang contributed to the collection and organization of
731 hydrological data and data quality control and participated in the discussion and validation of the results. Xu Chen contributed
732 to the collection and organization of hydrological and catchment-related data and supported the design flood analysis and
733 validation of the results. Hao Wang supervised the research and contributed to discussions on the study design and to the
734 review and revision of the manuscript. All authors reviewed and approved the final version of the manuscript.

735 **Competing interests**

736 The authors declare that they have no conflict of interest.

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