Study on the Uncertainty of Critical Rainfall for Flash Floods in Small Watersheds Based on the Random Rainfall Pattern

Wenlin Yuan  
Zhengzhou University; Key Laboratory of Lower Yellow River Channel and Estuary Regulation, M.W.R.

Lu Lu  
Zhengzhou University

Hanzhen Song (songhanzhen1994@163.com)  
Yellow River Engineering Consulting Co Ltd

Xiang Zhang  
Key Laboratory of Lower Yellow River Channel and Estuary Regulation, M.W.R.; Yellow River Institute of Hydraulic Research, YRCC

Linjuan Xu  
Key Laboratory of Lower Yellow River Channel and Estuary Regulation, M.W.R.; Yellow River Institute of Hydraulic Research, YRCC

Chengguo Su  
Zhengzhou University

Meiqi Liu  
Zhengzhou University

Denghua Yan  
Zhengzhou University; China Institute of Water Resources and Hydropower Research

Zening Wu  
Zhengzhou University

Research Article

Keywords: Flash floods, uncertainty, critical rainfall, random rainfall pattern, early warning model

Posted Date: December 23rd, 2021

DOI: https://doi.org/10.21203/rs.3.rs-1186032/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License
Study on the uncertainty of critical rainfall for flash floods in small watersheds based on the random rainfall pattern

Wenlin Yuan\textsuperscript{a,b}, Lu Lu\textsuperscript{a}, Hanzhen Song\textsuperscript{c}*, Xiang Zhang\textsuperscript{b,d}, Linjuan Xu\textsuperscript{b,d}, Chengguo Su\textsuperscript{a}, Meiqi Liu\textsuperscript{a}, Denghua Yan\textsuperscript{a,e}, Zening Wu\textsuperscript{a}

\textsuperscript{a} School of Water Conservancy Engineering, Zhengzhou University, Zhengzhou, 450001, China.
\textsuperscript{b} Key Laboratory of Lower Yellow River Channel and Estuary Regulation, MWR, Zhengzhou, 450003, China.
\textsuperscript{c} Yellow River Engineering Consulting Co., Ltd, Zhengzhou, 450003, China.
\textsuperscript{d} Yellow River Institute of Hydraulic Research, YRCC, Zhengzhou, 450003, China.
\textsuperscript{e} Water Resources Department, China Institute of Water Resources and Hydropower Research, Beijing, 100038, China.

Corresponding author, Hanzhen Song, songhanzhen1994@163.com

Abstract: Flash floods cause great harm to people's lives and property safety. Rainfall is the key factor which induces flash floods, and critical rainfall (CR) is the most widely used indicator in flash flood early warning systems. Due to the randomness of rainfall, the CR has great uncertainty, which causes missed alarms when predicting flash floods. To improve the early warning accuracy for flash floods, a random rainfall pattern (RRP) generation method based on control parameters, including the comprehensive peak position coefficient (CPPC) and comprehensive peak ratio (CPR), is proposed and an early warning model with dynamic correction based on RRP identification is established. The rainfall-runoff process is simulated by the HEC-HMS hydrological model, and the CR threshold space corresponding to the RRP set is calculated based on the trial algorithm. Xinxian, a small watershed located in Henan Province, China, is taken as the case study. The results show that the method for generating the RRP is practical and simple, and it effectively reflects the CR uncertainty caused by the rainfall pattern uncertainty. The HEC-HMS model is proved to have good application performance in the Xinxian watershed. Through sensitivity analysis, the effect of the
antecedent soil moisture condition, CPPC, and CPR are compared. The proposed early warning model is practical and effective, which increases the forecast lead time.

**Keywords**: Flash floods; uncertainty; critical rainfall; random rainfall pattern; early warning model

## 1 Introduction

Flash floods refer to the flooding disaster caused by rainfall with a short duration in hilly areas, excluding landslides and debris flows (Braud et al., 2014). Flash floods are characterized by their sudden occurrence and short duration, which can cause casualties and loss of property (Karbasi et al., 2018; Gaume et al., 2009). With worldwide environmental change, extreme precipitation events happen every now and again, and flash floods have perhaps become the most common natural hazard (Han et al., 2015; Hosseini et al., 2020). Statistics have long indicated that the number of casualties in China caused by flash floods represent roughly 70% of the casualties of all flood catastrophes (Ministry of Water Resources, P.R.C., 2020). Hence, it is important to carry out high-precision flash flood forecasting to ensure the safety of people's lives and property.

Critical rainfall (CR) refers to the minimum magnitude of rainfall at which a flash flood occurs, which is one of the most effective indicators for the early warning of flash floods (Hapuarachchi et al., 2011; Kong et al., 2020). Therefore, the accurate and effective determination of critical rainfall has become an important issue in early warning for flash floods (Norbilato et al., 2009). In the early stages, a data-driven method is often used to calculate the CR. However, this method is based purely on statistical data, which ignores the physical mechanism of flash flood, so the CR is less consistent with the real-life natural disaster scenario (Liu, 2019). Hydrology and hydraulics methods can fully consider the hydrological characteristics of a watershed, which is embraced in current flash flood
early warning and forecasting systems. The flash flood guidance (FFG) framework, created by the American Hydrologic Research Center, has made a great contribution to the early warning of flash floods and has been widely used in the USA (Norbato et al., 2009). Many investigations have been completed using the FFG to work on hydrological models for the simulation of the rainfall-runoff interaction and improving the accuracy of CR (Norbato et al., 2008; Seo et al., 2013; Costache, 2019).

With the development of 3S technology (i.e., remote sensing, geography information systems and global positioning systems), the topography, soil and vegetation data become richer. In view of such a wealth of data, the calculation of rainfall-runoff processes based on hydrological processes and hydraulics has gradually been established for the calculation of CR.

Hydrological modelling can well consider hydrometeorological conditions and watershed characteristics and simulate rainfall-runoff processes. Therefore, numerous hydrological models are used in simulations and flash flood forecasting (Bodoque et al., 2016; Adamovic et al., 2016; Zhang et al., 2019). Nguyen et al. (2020) studied the parameter calibration strategy of the modelloidrologicosemi-distribuito in continuo-2 layers (MISDc-2L) and used it to simulate the flash floods in a small watershed of the Huaihe River Basin in China. Zhai et al. (2018) employed the China Flash Flood hydrological model to reenact the flash flood processes which included hydrographs, peak flow discharges and occurrence times in three mountainous watersheds of southern China. Li et al. (2019) implemented the Topography-based hydrological model to obtain flash flood hydrographs with different peaks and return periods in a mountainous basin of South China. Rainfall has an important effect on the accuracy of hydrological models when simulating flood processes (Diederen and Liu, 2020; Klongvessa et al., 2018; Cha and Lee, 2021). Because of the random characteristic of rainfall, the spatial and temporal distribution of rainfall is not uniform, which enormously affects the
simulation results of hydrological models. Many studies have investigated the influence of rainfall spatial distribution on hydrological models (Douinot et al., 2016; Carreau and Bouvier, 2016; Zoccatelli et al., 2010). However, the spatial size of a small watershed within a mountainous region is small, hence the rainfall temporal distribution is mainly considered in this study.

The distribution of rainfall over time is defined as the rainfall pattern. The rainfall pattern does not directly affect the CR, but indirectly affects it by affecting soil moisture content and the flood process. Yinglan et al. (2018) studied the law of how soil moisture content changes under different rainfall conditions (i.e., advanced rainfall pattern, delayed rainfall pattern, central rainfall pattern and uniform rainfall pattern) through rainfall simulation experiments. However, no further research has been carried out on the confluence process. Li et al. (2018) used the Chicago rainfall pattern, Huff rainfall pattern, and P&C rainfall pattern to simulate the flood process under different development conditions, and found that the rainfall pattern has a significant influence on the flood peak discharge. Tao et al. (2017) simulated rainfall experiments with four rainfall patterns: balanced type, incremental type, increasing type and decreasing type, and the results showed that the change of rainfall patterns has a great influence on the rainfall-runoff processes. Therefore, rainfall patterns should be taken into account in the prevention and control of natural disasters related to rainfall. In view of this, many studies on the construction of rainfall patterns have been carried out. Casas-Castillo et al. (2018) believe that rainfall events have high self-similarity in statistical law, hence, a method of proportional parameter scaling to design rainfall patterns was proposed, but the uncertainty of some characteristics in rainfall time distribution was ignored. To describe the randomness of urban rainfall temporal distribution, Thorndahl and Willems (2008) adopted Gaussian distribution to express the characteristic parameters of rainfall patterns. Fadhel et al. (2018) found that the peak rainfall was
highly sensitive to the total rainfall, but the association between the rainfall peak position and the total rainfall was not analyzed. Bezak et al. (2016), Rahmani et al. (2016), and Pradhan et al. (2017) have found that through the trend analysis of rainfall parameters and the optimization of the probability density function, the resulting CR threshold is more reasonable. However, it does not solve the problem that, due to the randomness of rainfall, the critical rainfall is not unique. Although there are many studies on rainfall patterns, there are few studies on the randomness of rainfall patterns in small watersheds in mountainous and hilly areas. With the intensification of environmental change, the abruptness and intensity of rainfall events are increasing, which leads to the increasing uncertainty of rainfall patterns. In addition, as far as we know, the existing studies have not combined rainfall pattern and CR organically to explore the response relationship between the randomness of the rainfall pattern and the CR.

Considering the aforementioned operational hydrology problems in the calculation of CR for flash flood early warning and forecasting systems, a novel approach for random rainfall pattern (RRP) design is put forward in this study. On this basis, the HEC-HMS hydrological model and the trial algorithm are adopted to obtain the CR. Finally, an early warning model based RRP and CR is established to carry out early warning and forecasting of flash floods. The novel contributions of this paper are summarized as follows.

(1) A novel design method of RRP is developed, which takes into account the uncertainty of rainfall events. In this method, the uncertainty of the rainfall pattern is considered through a combination of parameters, including the comprehensive peak position coefficient (CPPC) and comprehensive peak ratio (CPR), based on the transfer and diffusion principle of probability distribution.
Based on the RRP, the HEC-HMS model is utilized in the simulation of the rainfall-runoff process for a small watershed, and the trial algorithm is used to calculate the CR threshold space. Moreover, the effect of the peak position coefficient and peak ratio on the CR is quantitatively analyzed.

Based on the similarities in quantity and tendency, and the comprehensive similarity between the RRP and current rainfall, the RRP that is best suited to the current rainfall conditions is identified. Then an early warning model with dynamic correction based on RRP identification is proposed to carry out effective early warning for flash floods.

In the following section, Section 2 presents the methodology and the model, including the structure of the RRP, the calculation process of the rainfall-runoff process, detailed steps of the trial algorithm and the establishment of the early warning model. Section 3 describes an overview of the study area and the source of the data used. The results and discussion are displayed in Section 4. Finally, conclusions are drawn in Section 5.

2 Methodology

In this section, a complete flash flood early warning system including rainfall pattern module, rainfall-runoff module, CR module and early warning module is introduced. Rainfall patterns considering the randomness of rainfall are designed in the rainfall pattern module as input conditions for the hydrological model, and then the rainfall-runoff process is simulated by the rainfall-runoff module. Based on the hydrological model after debugging parameters, the CR module is used to calculate CR threshold space. Finally, a warning signal is issued through the early warning module. The general schematic diagram of this study is displayed in Fig. 1.
Since the establishment of the early warning model in this paper is mainly based on the CR in the RRP, it is very important to choose appropriate methods from all of the ones available when solving for the CR. In China, the typical rainfall pattern (TRP) recommended by the Storm and Flood Atlas is the most widely used to calculate CR (Lin et al., 2005). However, for engineering safety, the peak rainfall position is usually designed to be at the back of the TRP, which is greatly different from actual rainfall. In addition, the randomness of rainfall is ignored, therefore, the RRP is proposed for rainfall pattern design. This method not only follows the distribution law of regional rainfall, but also takes into account the uncertainty of rainfall. There are many flood simulation methods, such as the reasoning formula, unit line and hydrological model methods. The watershed module in the HEC-HMS model can truly reflect the underlying surface conditions, and the model has excellent application in northern China (Yuan et al., 2019; Zhang et al., 2021). Therefore, the HEC-HMS model is selected to simulate the rainfall-runoff process. The main CR calculation methods include the rainfall comparison method (RCM) and trial algorithm. The application of RCM assumes that rainfall and floods occur with the same frequency. This assumption deviates from the reality to a certain
extent. Thence the trial algorithm is selected to calculate the critical rainfall. Because this method takes the disaster flow as the target value, the results are obtained through continuous iterative calculation, which weakens the indirect influence of the intermediate process on the results.

2.1 Generating Random Rainfall Pattern

The generation of the RRP is not a totally random process, rather it is based on the principle of information transfer of a random variable density function. According to the measured data, the optimal distribution function \( f(b) \) of the random variable \( b \) is fitted, so that \( b \) creates a series of pseudo-random variables \( b' \) based on the original information distribution.

Set \( u \) denotes the sample from the parent \( v \), \( u=\{u_1, u_2, u_3, \ldots, u_i\} \) as knowledge samples and \( b \) as the characteristic variable of \( u \). Let's say that \( b \) is consistent with the distribution of \( f(b) \) and better reflects the distribution law of \( u \) in the threshold space of \( u \). Series \( b' \), generated by function \( f(b) \), denotes the simulated value under random conditions. Based on the above principles, the generation method of RRP using parameter control is developed. The specific steps of the RRP generation method are shown below and are summarized in Fig. 2.
Fig. 2 Flowchart of the RRP generation method

(1) Gather rainfall data, including information for rainfall which causes flash flood, and then establish a database.

(2) Determine the resolution of rainfall data including the total rainfall duration $T$ and temporal resolution $t$. $T$ is equal to the duration with the largest proportion of the duration in the total duration of the rainfall events. Based on $T$ and $t$, the total number of time periods $I$ can be obtained, which is equal to the ratio of $T$ to $t$.

(3) Extract all rainfall events with a total duration of $T$ from the database, and use $j$ to denote the number of these rainfall events. Then, a rainfall information matrix $P$ can be obtained, as shown in Eq. (1).

$$P = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1I} \\ P_{21} & O & \cdots & \cdots & P_{2I} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ P_{j1} & O & \cdots & O & P_{jI} \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix}$$ (1)
Where $P_{ji}$ denotes the rainfall in time period $i$ of rainfall event $j$, and $i$ denotes the number of time periods.

(4) Calculate the time distribution ratio matrix of rainfall $B$ based on $P$, as shown in Eq. (2).

At the same time, the peak position coefficient $R$ and the peak ratio matrix $B_{max}$ are calculated through Eqs. (3) and (4), respectively, as shown in Eq. (5).

\[ b_{ji} = \frac{P_{ji}}{P_j} \]  
\[ r_j = \frac{T_{ji}}{T_j} \]  
\[ b_{jmax} = \frac{P_{jmax}}{P_j} \]

\[ B = \begin{bmatrix} b_{j1} & b_{j2} & b_{j3} & \cdots & b_{ji} \\ b_{2j} & 0 & \cdots & \cdots & \cdots \\ b_{3j} & 0 & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ b_{ij} & b_{j2} & b_{j3} & \cdots & b_{ji} \end{bmatrix} \quad R = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \cdots \\ r_j \end{bmatrix} \quad B_{max} = \begin{bmatrix} b_{1max} \\ b_{2max} \\ \cdots \\ b_{jmax} \end{bmatrix}

Where $b_{ji}$ denotes the ratio of rainfall in time period $i$ to the total rainfall in rainfall event $j$. $r_j$ denotes the peak position coefficient of rainfall event $j$. $b_{jmax}$ denotes the peak ratio of rainfall event $j$. $T_{ji}$ denotes the time period of rainfall with peak position in rainfall event $j$. $T_j$ denotes the total duration of rainfall event $j$. $P_{jmax}$ denotes the rainfall with peak position in rainfall event $j$. $P_j$ denotes the total rainfall of rainfall event $j$.

(5) Take each column of data in $B$ as the information set for each time period $B_i$, and select different distribution functions to fit $B_i$. After that, select the distribution function with the highest fitting accuracy as the ideal distribution function $f_i(b)$ of $B_i$.

(6) For each $B_i$, take $\min\{b_{i1}, b_{i2}, b_{ij}\}$ as the lower limit and $\max\{b_{i1}, b_{i2}, b_{ij}\}$ as the upper limit, respectively. Then, the boundary conditions of $B_i$ can be expressed as $g_i \subseteq [b_{imin}, b_{imax}]$. 
(7) Pseudo-random number sequences $B_i'$ are randomly generated, which satisfies the distribution function $f(b)$ and the boundary conditions in step (6). Combined with Eq. (6), the RRP is generated.

$$b_{j1} + b_{j2} + b_{j3} + \ldots + b_{j_n} = 1$$

(8) Calculate the comprehensive peak position coefficient $r$ and the comprehensive peak ratio $b_{max}$ through Eqs. (7) and (8), and use both of them as control parameters for screening out the eligible random rainfall pattern set $(r, b_{max})$.

$$r = \frac{\sum_{j=1}^{n} w_j \cdot r_j}{n}$$

$$b_{max} = \frac{\sum_{j=1}^{n} w_j \cdot b_{j_{max}}}{n}$$

Where $w_j$ denotes the ratio of the number of rainfall events with the same peak position to the sample.

2.2 Simulating Rainfall-runoff Process

The HEC-HMS model is a physically-based and conceptual semi-distributed model, which has been developed by the United States Army Corps of Engineers’ Hydrologic Engineering Center. The HEC-HMS hydrological model is composed of four modules including a meteorological module, control operation module, time series data module, and basin module. The hydrometeorological elements of each sub-basin are determined by the meteorological module. The start and end time of the simulated rainfall-runoff process and the time step of the simulation are set through the control operation module. The time series module is used to input hydrological data such as flood and rainfall.
The core module of the HEC-HMS model is the basin module. It can be generalized into four sub-modules: net rainfall (i.e., rainfall loss), direct runoff, base flow and channel confluence. There are various methods for the calculation of each sub-module in the basin module, and the appropriate selection process for combining methods can be referred to in Ref. (USACE-HEC, 2000; Du et al., 2012; Zelelew and Langon, 2020). The method combinations used in this study are detailed below.

(1) Calculation for net rainfall

The initial constant rate method is the most widely used in calculating net rainfall. This method includes two parts of rainfall loss calculation, namely the initial loss and later loss, as shown in Eq. (9).

\[
P_{et} = \begin{cases} 
0, & \sum P_i < P_a \\
(P_i - f_c), & \sum P_i > P_a, P_i > f_c \\
0, & \sum P_i > P_a, P_i < f_c 
\end{cases}
\]  

(9)

Where \( P_{et} \) represents the net rainfall at time \( t \), \( P_a \) is the antecedent soil moisture condition (ASMC), which is an indicator of soil moisture. \( P_i \) denotes the cumulative rainfall from \( t \) to \( t + \Delta t \). \( P_i \) denotes the cumulative rainfall, and \( f_c \) means the maximum infiltration capacity of the soil.

(2) Calculation for direct runoff

In this study, the Soil Conservation Service Unit Hydrograph method is chosen to calculate direct runoff since this method includes just one parameter (i.e., lag time), as shown in Eqs. (10)-(11). For ungauged catchments, the lag time can be estimated based on the flow concentration time (Abushandi and Merkel, 2013).

\[
U_p = C \frac{A}{T_p}
\]  

(10)

\[
t_{lag} = 0.6 \ell_c
\]  

(11)

Where \( U_p \) denotes the unit hydrograph peak flow, \( T_p \) denotes the peak time fraction of the unit
hydrograph peak flow, \( A \) denotes the area of the catchment area, \( C \) denotes the conversion coefficient, \( t_{lag} \) denotes the lag time parameter, and \( t_c \) denotes the flow concentration time.

(3) Calculation for base flow

The base flow calculation process points to the recharge process of groundwater and soil flow to the river channel. Exponential recession is a base flow separation model with exponential decay, which contains the initial flow, threshold flow and recession constant, as shown in Eq. (12). In current studies, the base flow is calculated by the exponential recession method (Knebl et al., 2005).

\[
Q_t = Q_0^{e^{Rt}}
\]  

(12)

Where \( Q_0 \) denotes the initial base flow at the beginning of the simulation. \( Q_t \) denotes the threshold flow at time \( t \), and \( R \) denotes the exponential decay constant. \( R \) depends on the source of base flow and can be estimated using an observed flow hydrograph. \( Q_t \) is also estimated by the observed flow hydrograph. At the recession limb, \( Q_t \) is well approximated by a straight line (USACE-HEC, 2008).

(4) Calculation for channel confluence

Muskingum, a channel flow calculation method, is based on the water balance equation and channel storage equation. There are only two parameters, the non-dimensional weighting factor and the movement time of the flood wave. Therefore, it is convenient to obtain the river outflow process from the flood simulation, as shown in Eqs. (13)-(14).

\[
I - Q = dW / dt
\]  

(13)

\[
W = K[xI + (1-x) \cdot Q]
\]  

(14)

Where \( I \) denotes the channel inflow, \( Q \) denotes the channel outflow, \( W \) denotes the storage capacity of the channel, \( x \) denotes a non-dimensional weighting factor, and \( K \) denotes the time
taken for the flood wave to pass along the section of river channel.

Based on Eqs. (13)-(14), the expression of the flow equation can be acquired, as shown in Eqs. (15)-(18).

\[ Q_2 = C_0 I_1 + C_1 I_2 + C_2 Q_1 \]  

(15)

\[ C_0 = \frac{0.5 \Delta t - Kx}{(0.5 \Delta t + K - Kx)} \]  

(16)

\[ C_1 = \frac{0.5 \Delta t + Kx}{(0.5 \Delta t + K - Kx)} \]  

(17)

\[ C_2 = \frac{-0.5 \Delta t + K - Kx}{(0.5 \Delta t + K - Kx)} \]  

(18)

Where \( I_1 \) and \( I_2 \) mean the inflow of the upper section at the beginning and finish time, respectively; \( Q_1 \) and \( Q_2 \) mean the outflow of the lower section at the beginning and finish times, respectively.

After determining the calculation method combination for the basin module, all kinds of data are input into relevant tools. The digital elevation model (DEM) data of the small watershed being studied is imported into ArcGIS to carry out depression filling, flow direction analysis, confluence accumulation analysis and watershed analysis using preprocessing tools in the HEC-GeoHMS module. Watershed merging, watershed division and river network merging are carried out by basin processing tools, and the river length, slope and longest confluence path are calculated by characteristics tools. The watershed model is imported into the HEC-HMS model by the HMS-Schematic tool, and the parameters are calibrated according to the rainfall and flood data. After that, different floods are selected to verify the parameters of the model, and the validated model is used in flood simulation.
2.3 Obtaining Critical Rainfall

The trial algorithm is adopted in the current study for calculating the CR of the flash flood corresponding to the RRP set. A flowchart of the trial algorithm is displayed in Fig.3. The detailed steps are shown below.

(1) Assume an initial rainfall $H$ which is the total rainfall of the rainfall event.

(2) To obtain the rainfall process, the time distribution of $H$ is obtained using the RRP designed in section 2.1.

(3) Specify the antecedent soil moisture condition (ASMC) (Yuan et al., 2021), which denotes the influence of the dry or wet conditions of the soil in the watershed before a rainfall on the runoff, and input it into the HEC-HMS model to calculate the deduction loss. The ASMCs of a rainy day and a rainless day are calculated through Eqs. (19) and (20), respectively.

$$P_{a,i} = KP_{a,i-1} + K^2 P_{a,i-2} + \Lambda + K^n P_{a,i-n}$$  \hspace{1cm} (19)
\[ P_{n,t+1} = KP_{n,t} \]  

Where \( P_{n,t} \) denotes the ASMC of day \( t \); \( n \) denotes the number of antecedent rainy days that affecting the runoff; \( K \) denotes the conversion coefficient.

(4) Import the hypothetical rainfall process into the HEC-HMS hydrological model to obtain the flood peak flow \( Q_f \).

(5) Calculate \( Q_e \) based on the measured disaster water level by using the rating curve, and then compare \( Q_e \) with \( Q_f \). If the deviation meets the required accuracy (i.e., \( |Q_e - Q_f| \leq \xi \)), finish the trial calculation. Otherwise, adjust the assumed rainfall and go to step (1) until the result meets the required accuracy. At this point, \( H \) is the CR. \( Q_e \) denotes the minimum peak flow needed to induce flash floods, which can be obtained through flood investigation.

2.4 Establishing an Early Warning Model Based on Rainfall Pattern Identification

Due to the randomness of rainfall patterns, taking the uncertainty fully into consideration when determining the CR may make the early warning process cumbersome. To simplify the early warning process and improve the early warning efficiency while considering the uncertainty of the rainfall pattern and issuing a warning signal which is suitable for current rainfall conditions, this study proposes an early warning model with dynamic correction based on RRP identification. The detailed early warning process is as follows.

(1) Determine the range of control parameters according to the statistics of the measured rainfall data and generate multiple RRP sets by using the method in Section 2.1.

(2) Calculate the CR for each RRP by using the methods described in Sections 2.2 and 2.3. Then, the rainfall of each time period in the RRP can be allocated according to the CR.
(3) Set the rainfall identification time period (ITP), which indicates the time period that needs to be compared in the early warning process up to the current period. As the rainfall process continues, the ITP will increase dynamically.

(4) Calculate the indices used to describe rainfall similarity corresponding to the ITP, including the quantity similarity index (QSI), tendency similarity index (TSI) and comprehensive similarity index (CSI) (Xiao et al., 2018), as shown in Eqs. (21)-(23). QSI denotes the difference in the cumulative amount of rainfall between the two rainfalls, TSI denotes the trend similarity of the two rainfalls over time, and CSI denotes the overall similarity of any two rainfall events.

\[
\begin{align*}
QSI &= \frac{Qua(X,Y) - Qua(X,Y)_{\text{cum}}}{Qua(X,Y)_{\text{cum}} - Qua(X,Y)_{\text{cum}}} \\
Qua(X,Y) &= \sum_{\text{itp}} X_{\text{itp}} - \sum_{\text{itp}} Y_{\text{itp}} \\
TSI &= \frac{Tre(X,Y) - Tre(X,Y)_{\text{cum}}}{Tre(X,Y)_{\text{cum}} - Tre(X,Y)_{\text{cum}}} \\
Tre(X,Y) &= \sum_{\text{itp}} \text{Score(itp)} \\
\text{Score(itp)} &= \begin{cases} 
1, & \text{con(itp)} \leq 0 \\
0, & \text{con(itp)} > 0 
\end{cases} \\
\text{con(itp)} &= (X_{\text{itp}} - X_{\text{itp-1}})/(Y_{\text{itp}} - Y_{\text{itp-1}})
\end{align*}
\]
(21)

\[
CSI = \alpha_1 \cdot QSI + \alpha_2 \cdot TSI
\]
(23)

Where \( X \) and \( Y \) mean the rainfall process in RRPs and the current rainfall process, respectively. \( Qua(X,Y) \) and \( Tre(X,Y) \) denote the quantity difference and the trend difference between \( X \) and \( Y \) in the ITP, respectively. \( \text{Score(itp)} \) and \( \text{Con(itp)} \) denote the accumulative unit step function and the trend consistency between \( X \) and \( Y \) in time period \( \text{itp} \), respectively. If the changes in trend of \( X \) and \( Y \) are the same (i.e., \( \text{Con(itp)} > 0 \)), then \( \text{Score(itp)} = 0 \). If the changes in trend of \( X \) and \( Y \) are opposite to each other (i.e., \( \text{Con(itp)} \leq 0 \)), then \( \text{Score(itp)} = 1 \). \( \alpha_1 \) and \( \alpha_2 \) denote the weights of the QSI and TSI in the CSI, respectively.
(5) Select the RRP with the highest similarity to the current rainfall and calculate the CRs for different early warning time periods based on this RRP.

(6) Compare the accumulated rainfall with the CR in the corresponding time period. If the accumulated rainfall is greater than CR, then an early warning signal will be issued immediately. At this point, the flash flood early warning is over. If the accumulated rainfall does not reach the CR, no warning signal will be issued and step (7) should be followed.

(7) As the current rainfall progresses, the ITP increases. Reset ITP=ITP+1 and return to step (3) until the current rainfall ends. If the accumulated rainfall does not reach CR with the corresponding time period until the end of the current rainfall, it indicates that no flash flood is caused by the current rainfall.

3 Case Study

3.1 Study Area

Xinxian, a mountainous and small watershed, located in the south of Henan Province, China, belongs to the Huaihe River basin, as shown in Fig.4. The control area of the Xinxian watershed is 274 km$^2$, the length of the main river stem is 39.37 km, the stream gradient is 0.003 and the maximum soil moisture content is 50 mm. This watershed has a humid climate, abundant rainfall, a complex underlying surface and fragile geological structure, which can easily cause surface runoff and flash floods. According to statistics, in recent years, several flash floods have occurred in Xiawan. In particular, the flash flood on July 1, 2016 was especially serious. Therefore, Xiawan has been selected as the representative disaster prevention object, and Xinxian has been selected as a typical small watershed in a mountainous area due to its tragic history of flash floods.
3.2 Source of Data

Data including rainfall data, flood data and GIS data were adopted in this study. The rainfall data and flood data were collected from the Hydrology Bureau of Henan. The flood data came from Xinxian hydrological station records from 1979 to 2018, and the rainfall data was obtained from Tangfan rainfall station from 1979 to 2018. A rainfall event can be judged by the principle of rainfall fields division (Gao, 2019), so the characteristics of the rainfall duration were analyzed according to the rainfall data and the results are displayed in Table 1. The results indicate that short duration rainfall, with rainfall duration of 1h to 6h, occupied the largest proportion of the total rainfall events. In addition, short-duration heavy rainfall is the main causal factor of flash floods. Therefore, after comprehensively considering the characteristics of rainfall and the warning time period, the total duration was set as 6h and the temporal resolution was set as 1h.
Table 1 Rainfall duration distribution in the study area

| Rainfall duration (h) | <1  | 1~3 | 3~6 | 6~12 | >12 |
|-----------------------|-----|-----|-----|------|-----|
| Proportion (%)        | 5.4 | 20.9| 46.5| 13.1 | 14.1|

The GIS data contains DEM data (Fig.4), soil maps (Fig.5a) and land use (Fig.5b), which were obtained from the National Geomatics Center of China. DEM data is the basic input condition of the HEC-HMS model; however, high-resolution DEM data is not available for open access in many places because of high cost and confidentiality requirements, leaving researchers with the freely available DEM data to carry out scientific studies. Many studies have demonstrated that appropriate low-resolution DEM data can be used for flood modeling (Masood and Takeuchi, 2012; Mishra et al., 2018), hence the 30m gridded DEM data collected for the Xinxian Watershed can be used for further analysis. As illustrated in Fig. 5a, there are three types of soil in the Xinxian watershed: coarse bone soil, yellow brown soil and paddy soil. The land use in the Xinxian Watershed is relatively homogenous, with surrounding forests on the hills and cultivated land along the river (Fig. 5b).

Fig. 5 (a) Soil maps and (b) land use in the Xinxian watershed
4 Results and Discussion

4.1 Distribution Function Optimization

Each column of data $B_i$ in the time distribution ratio matrix $B$ of rainfall was extracted and fitted with the Poisson distribution, Gauss distribution, Pareto distribution, Weibull distribution and Log Normal distribution. In order to ensure the accuracy of the fit results, two indicators consisting of the residual sum of squares (RSS) and coefficient of determination (CD) were selected for evaluating the goodness of fit. The results are shown in Table 2.

| Functions  | $B_1$ | $B_2$ | $B_3$ | $B_4$ | $B_5$ | $B_6$ |
|------------|-------|-------|-------|-------|-------|-------|
|            | RSS   | CD    | RSS   | CD    | RSS   | CD    | RSS   | CD    | RSS   | CD    | RSS   | CD    |
| Gauss      | 0.002 | 0.963 | 0.006 | 0.952 | 0.004 | 0.964 | 0.002 | 0.958 | 0.001 | 0.979 | 0.0 | 0.991 |
| Poisson    | 0.078 | 0.210 | 0.107 | 0.196 | 0.086 | 0.142 | 0.025 | 0.389 | 0.047 | 0.311 | 0.046 | 0.403 |
| Pareto     | 0.095 | 0.030 | 0.131 | 0.016 | 0.109 | 0.087 | 0.043 | 0.033 | 0.061 | 0.111 | 0.060 | 0.229 |
| Weibull    | 0.032 | 0.672 | 0.041 | 0.693 | 0.021 | 0.793 | 0.010 | 0.752 | 0.016 | 0.765 | 0.019 | 0.747 |
| Log Normal | 0.004 | 0.936 | 0.006 | 0.901 | 0.009 | 0.914 | 0.002 | 0.916 | 0.003 | 0.953 | 0.003 | 0.904 |

It can be seen that the RSS is smaller for the Gauss function and Log Normal function than for other distribution functions in each $B_i$, and all CDs are larger for the Gauss function and Log Normal function than for other distribution functions in each $B_i$. In addition, the RSS and CD for the Gauss function are very close to those of the Log Normal function, which indicates they both have similar fitting abilities. However, the RSS for the Gauss function is little smaller than it is for the Log Normal function, and the CD for the Gauss function is little larger than it is for the Log Normal function, which indicates that goodness of fit of the Gauss function is the best. Hence, the Gauss function was adopted as the distribution function for each $B_i$, and the fitting result of each $B_i$ is shown in Fig.6.
It can be seen that the Gauss function can well reflect the frequency distribution of six time periods. It should be noted that since the fitting of the distribution function is limited by the study area and has a certain relationship with the size of the sample space and the rules of rainfall event division, the same result cannot be guaranteed when the sample is expanded or the study area is changed. However, in the typical small watershed selected for this study, the distribution function is screened with a variety of distribution functions and evaluated by goodness of fit indices. Therefore, it is reliable to believe that the Gauss function is the optimal distribution function for the six time periods.

**4.2 Hydrological Model Application Assessment**

In view of the hydrological attributes of the investigation region and the adaptability of the model, the HEC-HMS model was calibrated through the method in Section 2.2. Ten typical floods in the watershed were selected to calibrate and verify the model, in which seven were calibrated and three were verified. The results were evaluated by the Nash-Sutcliffe efficiency (NSE) (Jain and Sudheer,
which is generally used to evaluate the simulation results of hydrological models, as displayed in Table 3.

| State         | Number      | Peak flow (m$^3$/s) | The time deviation of peak flow occurrence (h) | NSE  |
|---------------|-------------|---------------------|-----------------------------------------------|------|
|               |             | Observed            | Simulated                                    |      |
| Calibration   | 19820718    | 761.0               | 766.0                                         | 0.5  | 0.933 |
|               | 19850713    | 191.0               | 209.3                                         | 0.5  | 0.861 |
|               | 19870705    | 1061.0              | 1007.8                                        | 1.0  | 0.860 |
|               | 19910702    | 980.0               | 1001.2                                        | 0.5  | 0.942 |
|               | 19960714    | 935.0               | 960.1                                         | 1.0  | 0.926 |
|               | 19990627    | 309.0               | 301.4                                         | 0    | 0.883 |
|               | 20030708    | 539.0               | 550.8                                         | 0    | 0.939 |
| Validation    | 20040718    | 339.0               | 347.0                                         | 0    | 0.887 |
|               | 20080816    | 749.0               | 759.9                                         | 0.5  | 0.823 |
|               | 20130526    | 166.0               | 170.1                                         | 0.5  | 0.923 |

The results show that each relative deviation between the simulated value and the observed value is less than 15%, the time deviations of peak flow occurrence are less than 1 h, and all the NSEs are greater than 0.8, which indicate that the simulated results of this model are reliable and reasonable. Therefore, the HEC-HMS hydrological model has a good application in this small watershed, and the calibrated HEC-HMS hydrological model can be used to simulate the rainfall-runoff process.

4.3 Critical Rainfall Calculation

The peak ratio and peak position coefficient form the basis of the CPR and CPPC, respectively. Based on Eqs. (12) and (13), the peak ratio and peak position coefficient of each rainfall event was obtained. These values indicate the distribution of rainfall pattern parameters in the statistical sample.
space, as shown in Fig.7. The results indicate that most of the peak position coefficients are between 0.2 and 0.8, and most of peak ratio values are between 0.30 and 0.55. According to Eqs. (17) and (18), taking the proportion of rainfall fields with the same rainfall peak position to the total sample fields as $w$, then the CPPC is 0.50, and the CPR is 0.35. Therefore, $(0.50, b_{\text{max}})$ and $(r, 0.35)$ are the control conditions of the RRP set.

![Fig.7 Distribution of rainfall pattern parameters](image)

The determination of the early warning time period is important to the CR calculation. The confluence duration is usually considered as the longest early warning time period. The minimum warning periods in wet and dry regions are 1 h and 0.5 h, respectively. Xinxian has a wet climate with a confluence duration of almost 5.3 hours. Therefore, the early warning time period in Xinxian can be set to both 1h and 6h. The rainfall data in mountainous and hilly areas generally cover more than 1 h, so the rainfall pattern cannot be fully considered when calculating the 1h CR. Considering the rainfall data in Section 3, only the 6h CR is calculated in this section.

According to the range of control parameters in Section 4.1, $(0.50, b_{\text{max}})$ and $(r, 0.35)$ were set as the control conditions of the random rain pattern set, and six RRP sets including $(0.20, 0.35)$, $(0.50, 0.35)$, $(0.80, 0.35)$, $(0.50, 0.30)$, $(0.50, 0.40)$ and $(0.50, 0.50)$ were used to analyze the response relationship between the rainfall pattern and the CR. The independent parameter
A perturbation method was used to generate ten RRPs in each RRP set, and the rainfall patterns are shown in Fig.8.

**Fig.8** Schematic diagram for each RRP set: (a) (0.20,0.35), (b) (0.50,0.35), (c) (0.80,0.35), (d) (0.50,0.30), (e) (0.50,0.40), (f) (0.50,0.50).

Based on Fig.8, it can be seen that, except for the peak ratio and the peak position, the rainfall for other time periods varies in each RRP set, which verifies the diversity of the rainfall patterns in the RRP set. In fact, within the range of control parameters, if enough RRP sets are determined and enough RRPs are generated in each RRP set, there must be a rainfall whose rainfall pattern is the highly similar to the RRP.

Combined with the disaster flow, the CRs corresponding to the RRPs in Fig.8 were calculated
by the method in Section 2.3. In addition, taking into account the moisture of the soil, three ASMCs were set to $0.2\, Wm$ (dry), $0.5\, Wm$ (general) and $0.8\, Wm$ (wet), respectively, as shown in Fig.9.

![Graphs showing CR for each RRP set under different ASMCs](image)

Fig.9 CR for each RRP set under different ASMCs: (a) (0.20,0.35), (b) (0.50,0.35), (c) (0.80,0.35), (d) (0.50,0.30), (e) (0.50,0.40), (f) (0.50,0.50).

It can be seen that the CRs form a threshold space under each combination of RRP sets and ASMC, which provides a range for judging CR. Furthermore, the CR decreases under the same
rainfall pattern in the RRP set with the increase of the ASMC. The reason is that the larger the ASMC, the more water content in the soil. As a result, less rainfall is needed to form runoff, so the CR is smaller.

4.4 Effect of RRP on CR

4.4.1 Effect of CPPC on CR

Three RRP sets including (0.2, 0.35), (0.5, 0.35) and (0.8, 0.35) were used to study the effect of CPPC on CR. The results are shown in Table 4.

| ASMC  | CR threshold space (mm) |
|-------|-------------------------|
|       | \( r=0.2 \)              | \( r=0.5 \) | \( r=0.8 \) |
| \( 0.2W_m \) | 174-188                 | 137-158     | 124-132     |
| \( 0.5W_m \) | 167-177                 | 129-149     | 118-125     |
| \( 0.8W_m \) | 152-165                 | 123-140     | 112-118     |

It can be seen that the CR threshold space of various RRP sets showed obvious stepwise distributions. In cases where the CPPC is small (i.e., the proportion of rainfall in the initial stage of the rainfall event is large), the peak rainfall is small after rainfall loss such as infiltration, filling, and vegetation interception. Hence, the rainfall needed to reach the disaster flow would be large. With the increase of CPPC (i.e., the rainfall peak position shifting backwards), the rainfall loss at the peak position is relatively small, and the peak probability of flood formation was strong, hence the corresponding CR decreases. The CR fluctuation range is significantly larger than \( r=0.2 \) and \( r=0.8 \) when \( r=0.5 \), which indicates that the disaster scenario in the RRP set \( (0.5, b_{max}) \) is changeable, and the CR is uncertain and not easy to control. In addition, under the three ASMC conditions, the variation range of CR caused by \( r=0.2 \), \( r=0.5 \) and \( r=0.8 \) are 34\%, 33\% and 32\%, respectively. At the
same rainfall peak position, the variation range of CR caused by 0.2Wm, 0.5Wm and 0.8Wm are 19%, 22% and 15%, respectively. Therefore, it can be concluded that the peak position has more effect on CR compared to the ASMC.

### 4.4.2 Effect of CPR on CR

Combined with three soil moisture conditions (i.e., 0.2Wm, 0.5Wm and 0.8Wm), three RRP sets including (0.5,0.3), (0.5,0.4) and (0.50,0.5) were used to study the effect of CPR on CR. Table 5 presents the results.

| ASMC   | $b_{max}=0.3$   | $b_{max}=0.4$   | $b_{max}=0.5$   |
|--------|-----------------|-----------------|-----------------|
| 0.2Wm  | 159–175         | 134–149         | 118–125         |
| 0.5Wm  | 152–169         | 127–140         | 112–117         |
| 0.8Wm  | 146–157         | 120–132         | 106–110         |

As shown in Table 5, when the ASMC remains the same, the CR ranges corresponding to different CPRs are different. The smaller the CPR is, the greater the variation range of CR is, which indicates that the CPR plays a leading role in the flooding disaster. When the peak rainfall accounts for a large proportion of the total rainfall (i.e., CPR is large), the rainfall which can cause disaster is relatively stable, and the corresponding CR varies within a small range. For example, when CPR reaches 0.5, the CR tends to be stable, and the variation range of the CR is obviously reduced. On the contrary, due to the uncertainty of the factors affecting runoff production, the corresponding CR varies within a large range. In addition, under the three ASMC conditions, the variation ranges of CR caused by $b_{max}=0.2$, $b_{max}=0.5$ and $b_{max}=0.8$ are 33%, 34% and 33%, respectively. When CPRs remain the same, the variation ranges of CR caused by 0.2Wm, 0.5Wm and 0.8Wm are 17%, 19% and 15%, respectively. Thus, it is believed that the effect of the CPR on CR is much larger than that of the
ASMC. To sum up, the influence of rainfall pattern on CR is greater than the ASMC, and the CPPC and the CPR have the same degree of influence on the CR. In engineering practice, when compared with the ASMC, more attention should be paid to the identification of the rainfall pattern in order to obtain more accurate CR and early warning mode graphs.

4.5 Rationality Analysis of the early warning model based on RRP identification

The accurate identification of rainfall pattern is very important in the early warning of flash floods based on RRP. To verify the rationality of the dynamic correction early warning model proposed in this study, the measured rainfall data of 20160701 was selected for verification. Considering the complexity of calculation and the randomness of the rainfall pattern, the RRP set number was set to 60, and 20 RRPs were generated in each RRP set, numbered RT1-RT1200. Then, the rainfall pattern identification indexes were calculated according to Eqs. (21) and (22), and the results of the five RRPs with the best comprehensive, similar rainfall indexes are shown in Table 6 and Table 7. The early warning information is shown in Fig.10.

| RRP number | RRP set | QSI | TSI | CSI |
|------------|---------|-----|-----|-----|
| RT35       | (0.70,0.35) | 0.52 | 0   | 0.260 |
| RT21       | (0.70,0.35) | 0.53 | 0   | 0.265 |
| RT362      | (0.60,0.35) | 0.61 | 0   | 0.305 |
| RT128      | (0.50,0.45) | 0.72 | 0   | 0.360 |
| RT453      | (0.55,0.45) | 0.49 | 1   | 0.745 |

Table 6 The similarity index results where ITP is 2h

| RRP number | RRP set | QSI | TSI | CSI |
|------------|---------|-----|-----|-----|
| RT362      | (0.60,0.35) | 0.36 | 0   | 0.180 |
| RT35       | (0.70,0.35) | 0.43 | 0   | 0.215 |
| RT279      | (0.62,0.45) | 0.49 | 0   | 0.245 |
| RT479      | (0.60,0.40) | 0.39 | 1   | 0.695 |
| RT186      | (0.72,0.35) | 0.42 | 1   | 0.710 |

Table 7 The similarity index results where ITP is 3h
As can be seen from Table 6, the CSI of RT35 is the smallest value out of the five RRPs, which indicates that when the rainfall lasts for 2h, RT35 is most similar to the current rainfall. Then, the 2h CR was calculated according to RT35, and the 2h accumulated rainfall of the current rainfall was calculated, as shown in Fig.10. It can be seen that the 2h accumulated rainfall did not exceed the 2h CR line, hence, there was no need to issue an early warning signal. As the current rainfall continues, so does the ITP. When the current rainfall lasted for 3h (i.e., ITP=3h), the CSI of RT362 was the smallest, indicating that RT362 was the most similar to the current rainfall. Combined with Fig.10, the 3h accumulated rainfall of the current rainfall was compared with the 3h CR, and it was found that at 9:10 a.m., the 3h accumulated rainfall exceeded the 3h CR, and the early warning signal was immediately issued. Rainfall 20160701 from the measured data did cause a flash flood at 10:00 a.m., and based on the early warning model, the early warning signal was issued at 9:10 a.m., increasing the forecast lead time and leaving enough time for the transfer of people.

**Fig.10 Schematic diagram of early warning information**
5 Conclusions

Considering the randomness of the rainfall pattern, this study proposed a novel design method for RRP based on control parameters, including the CPPC and CPR, to study the uncertainty of CR for flash floods in small watersheds. The RRP and CR were then adopted in the establishment of an early warning model for flash floods. The rainfall-runoff process was simulated by the HEC-HMS model, and the CR was calculated by the trial algorithm. The developed method and model were applied to the early warning of flash floods in the Xinxian small watershed. Based on the obtained results and analysis, the conclusions of this study can be summarized as follows.

(1) The generation method of the RRP based on parameter control is a practical and simple method, and it presents a novel idea and an approach for investigating the uncertainty relationship between CR and rainfall pattern. The uncertainty of CR caused by the uncertainty of the rainfall pattern can be effectively controlled by solving the critical rainfall threshold space under the RRP set.

(2) The peak flow deviations are less than 15%, the time deviations of the peak flow occurrences are less than 1 h, and all the NSEs are greater than 0.8, which proves that the application of the HEC-HMS model in the rainfall-runoff process simulation of a small watershed is reasonable and reliable.

(3) Rainfall pattern has a greater effect on critical rainfall than the ASMC. The disaster scenario in \((0.5, b_{\text{max}})\) is changeable, difficult to control, and has a high frequency of occurrence, so this rainfall pattern can be considered the key rainfall pattern. \((r, b_{\text{max}} < 0.5)\) brings more uncertainty to the CR, but it belongs to the safe rainfall pattern, while \((r, b_{\text{max}} > 0.5)\) brings less uncertainty to the CR and belongs to the dangerous rainfall pattern.

(4) The early warning model with dynamic correction based on RRP identification is effective and practical. Before the occurrence of the flash flood, the early warning signal of the catastrophic
rainfall was issued 50 minutes in advance, which avoided loss of life and property.

It was assumed that the time periods are independent from each other in the random rainfall pattern, and all of them are single-peak rainfall patterns. Thus, it does not have the capacity to include each possible rainfall pattern of the region. Furthermore, the disaster mechanism of flash flood is complex, and there are many influencing factors. The coupling effect of multiple factors on the uncertainty response mechanism between the rainfall pattern and critical rainfall remains to be studied further.

**Ethical Approval**

All authors have seen and agreed with the contents of the manuscript and are looking forward to publishing this paper on “Water Resources Management” journal. We certify that the submission is original work and is not published at any other publications.

**Authorship Contributions**

All authors contributed to the study conception and design. **Wenlin Yuan**: Methodology, Writing - Review & Editing, Funding acquisition. **Lu Lu**: Software, Writing - Original Draft, Validation. **Hanzhen Song**: Conceptualization, Supervision. **Xiang Zhang**: Funding acquisition. **Linjuan Xu**: Project administration. **Chengguo Su**: Writing - Review & Editing. **Meiqi Liu**: Investigation, Data Curation. **Denghua Yan**: Data Curation. **Zening Wu**: Formal analysis.

**Funding**

The work described in this paper was supported by the National Natural Sciences Foundation of
China (No.51779229), the Open Project Foundation of the Key Laboratory of Lower Yellow River
Channel and Estuary Regulation (No.HHNS202002), Scientific Research Projects of Henan Province
(No.202102310296) and the Special Basic Research Fund for Central Public Research Institutes
(No.HKY-JBYW-2018-03, HKY-JBYW-2020-15).

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal
relationships that could have appeared to influence the work reported in this paper.

Code Availability

The code that supports the findings of this study is available from the corresponding author upon
reasonable request.

References

Abushandi E, Merkel B (2013) Modelling rainfall runoff relations using HEC-HMS and IHACRES for a single rain
event in an Arid region of Jordan. Water Resour. Manag. 27 (7),2391-2409. https://doi.org/10.1007/s11269-
013-0293-4.

Adamovic M, Branger F, Braud I, Kralisch S (2016) Development of a data-driven semi-distributed hydrological
model for regional scale catchments prone to Mediterranean flash floods. J. Hydrol. 541,173–189.
https://doi.org/10.1016/j.jhydrol.2016.03.032.

Bezak N, Šraj M, Mikoš M (2016) Copula-based IDF curves and empirical rainfall thresholds for flash floods and
rainfall-induced landslides. J. Hydrol. 541, 272-284. https://doi.org/10.1016/j.jhydrol.2016.02.058
Bodoque JM, Amerigo M, Diez-Herrero A, Garcia JA, Cortes B, Ballesteros-Canovas JA, Olcina J (2016) Improvement of resilience of urban areas by integrating social perception in flash-flood risk management. J. Hydrol. 541: 665-676. https://doi.org/10.1016/j.jhydrol.2016.02.005.

Braud I, Ayral PA, Bouvier C, Branger F, Delrieu G, Le JC, Nord G, Vandervaere JP, Anquetin S, Adamovic M, Andrieu J, Batiot C, Boudevillain B, Brunet P, Carreau J, Confoland A, Didon-Lescot JF, Domergue JM, Douvinet J, Dramais G, Freydier R, Gérard S, Huza J, Leblois E, Le OB, Le RB, Marchand P, Martin P, Nottale L, Patris N, Renard B, Seidel JL, Taupin JD, Vannier O, Vincendon B, Wijbrans A (2014) Multi-scale hydrometeorological observation and modelling for flash flood understanding. Hydrol. Earth Syst. Sci. 18, 3733–3761. https://doi.org/10.5194/hess-18-3733-2014.

Carreau J, Bouvier C (2016) Multivariate density model comparison for multi-site flood-risk rainfall in the French Mediterranean area. Stoch. Environ. Res. Risk Assess. 30, 1591-1612. https://doi.org/10.1007/s00477-015-1166-6.

Casas-Castillo MC, Llabrés-Brustenga A, Rius A, Rodríguez-Solà R, Navarro X (2018) A single scaling parameter as a first approximation to describe the rainfall pattern of a place: application on Catalonia. Acta Geophys. 66(3), 415-424. https://doi.org/10.1007/s11600-018-0122-5.

Cha SM, Lee SW (2021) Advanced hydrological streamflow simulation in a watershed using adjusted radar-rainfall estimates as meteorological input data. J. Environ. Manage. 277, 111393. https://doi.org/10.1016/j.jenvman.2020.111393.

Costache R (2019) Flash-flood potential assessment in the upper and middle sector of Prahova river catchment (Romania). A comparative approach between four hybrid models. Sci. Total Environ. 659:1115–1134. https://doi.org/10.1016/j.scitotenv.2018.12.397.

Dieder D, Liu Y (2020) Dynamic spatio-temporal generation of large-scale synthetic gridded precipitation: with
improved spatial coherence of extremes. Stoch. Environ. Res. Risk Assess. 34, 1369-1383. https://doi.org/10.1007/s00477-019-01724-9.

Douinot A, Roux H, Garambois PA, Larnier K, Labat D, Dartus D (2016) Accounting for rainfall systematic spatial variability in flash flood forecasting. J. Hydrol. 541, 359-370. https://doi.org/10.1016/j.jhydrol.2015.08.024.

Du JK, Qian L, Rui HY, Zuo TH, Zheng DP, Xu YP, Xu CY (2012) Assessing the effects of urbanization on annual runoff and flood events using an integrated hydrological modeling system for Qinhua River basin, China. J. Hydrol. 464, 127–139. https://doi.org/10.1016/j.jhydrol.2012.06.057.

Fadhel S, Rico-Ramirez MA, Han DW (2018) Sensitivity of peak flow to the change of rainfall temporal pattern due to warmer climate. J. Hydrol. 560: 546-559. https://doi.org/10.1016/j.jhydrol.2018.03.041.

Gao QY (2019) Study on Combination of Risk Probability Rainfall Threshold of Flash Flood in Small Watershed Based on Copula Function. Dissertation. School of Water Conservancy Engineering, Zhengzhou University.

Gaume E, Bain V, Bernardara P, Newinger O, Barbuc M, Bateman A, Blaskovicova L, Bloschl G, Borga M, Dumitrescu A, Daliakopoulos I, Garcia J, Irimescu A, Kohnova S, Koutroulis A, Marchi L, Matreata S, Medina V, Preciso E, Sempere-Torres D, Stancalie G, Szolgay J, Tsanis I, Velasco D, Viglione A (2009) A compilation of data on European flash floods. J. Hydrol. 367,70-78. https://doi.org/10.1016/j.jhydrol.2008.12.028.

Han LF, Xu YP, Pan GB, Deng XJ, Hu CS, Xu HL, Shi HY (2015) Changing properties of precipitation extremes in the urban areas, Yangtze River Delta, China, during 1957-2013. Nat. Hazards 79, 437-454. https://doi.org/10.1007/s11069-015-1850-3.

Hapuarachchi HAP, Wang QJ, Pagano TC (2011) A review of advances in flash flood forecasting. Hydrol. Process. 25, 2771-2784. https://doi.org/10.1002/hyp.8040.

Hosseini FS, Choubin B, Mosavi A, Nabipour N, Shamshirband S, Darabi H, Haghighi AT (2020) Flash-flood hazard assessment using ensembles and Bayesian-based machine learning models: Application of the simulated
annealing feature selection method. Sci. Total Environ. 711, 135161. https://doi.org/10.1016/j.scitotenv.2019.135161.

Jain SK, Sudheer KP (2008) Fitting of hydrologic models: A close look at the Nash-Sutcliffe index. J. Hydrol. Eng. 13, 981-986. https://doi.org/10.1061/(ASCE)1084-0699(2008)13:10 (981).

Karbasi M, Shokoohi A, Saghaian B (2018) Loss of life estimation due to flash floods in residential areas using a regional model. Water Resour. Manag. 32,4575-4589. https://doi.org/10.1007/s11269-018-2071-9.

Klongvessa P, Lu MJ, Chotpantarat S (2018) Response of the flood peak to the spatial distribution of rainfall in the Yom River basin, Thailand. Stoch. Environ. Res. Risk Assess. 32, 2871-2887. https://doi.org/10.1007/s00477-018-1603-4.

Knebl MR, Yang ZL, Hutchison K, Maidment DR (2005) Regional scale flood modeling using NEXRAD rainfall, GIS, and HEC-HMS/RAS: a case study for the San Antonio River Basin Summer 2002 storm event. J. Environ. Manage. 75 (4) 325–336. https://doi.org/10.1016/j.jenvman.2004.11.024.

Kong FZ, Huang W, Wang ZL, Song XM (2020) Effect of unit hydrographs and rainfall hyetographs on critical rainfall estimates of flash flood. Adv. Meteorol. 2020,2801963. https://doi.org/10.1155/2020/2801963.

Li JK, Deng CN, Li HE, Ma MH, Li YJ (2018) Hydrological Environmental Responses of LID and Approach for Rainfall Pattern Selection in Precipitation Data-Lacked Region. Water Resour. Manag. 32(10),3271–3284. https://doi.org/10.1007/s11269-018-1990-9.

Li WJ, Lin KR, Zhao TTG, Lan T, Chen XH, Du HW, Chen HY (2019) Risk assessment and sensitivity analysis of flash floods in ungauged basins using coupled hydrologic and hydrodynamic models. J. Hydrol. 572, 108–120. https://doi.org/10.1016/j.jhydrol.2019.03.002.

Lin GF, Chen LH, Kao SC (2005) Development of regional design hyetographs. Hydrol. Process. 19(4), 937-946. https://doi.org/10.1002/hyp.5550.
Liu MQ (2019) Study on rainfall early warning model of mountain flash flood based on characteristic rainfall patterns. Dissertation. School of Water Conservancy Engineering, Zhengzhou University.

Masood M, Takeuchi K (2012) Assessment of food hazard, vulnerability and risk of mid-eastern Dhaka using DEM and 1D hydrodynamic model. Nat. Hazards 61:757–770. https://doi.org/10.1007/s11069-011-0060-x

Ministry of Water Resources, P.R.C. (2020) The State Council Information Office held a press conference on flood and drought disaster prevention. The State Council Information Office, P.R.C. http://www.gov.cn/xinwen/2020-06/11/content_5518663.htm.

Mishra BK, Rafei Emam A, Masago Y, Kumar P, Regmi RK, Fukushi K (2018) Assessment of future food inundations under climate and land use change scenarios in the Ciliwung River Basin, Jakarta. J. Flood Risk Manag. 11:S1105–S1115. https://doi.org/10.1111/jfr3.12311

Nguyen NT, He W, Zhu YH, Lu HS (2020) Influence of Calibration Parameter Selection on Flash Flood Simulation for Small to Medium Catchments with MISDc-2L Model. Water. 12(11), 3255. https://doi.org/10.3390/w12113255.

Norbiato D, Borga M, Esposti SD, Gaume E, Anquetin S (2008) Flash flood warning based on rainfall thresholds and soil moisture conditions: An assessment for gauged and ungauged basins. J. Hydrol. 362(3-4):274-290. https://doi.org/10.1016/j.jhydrol.2008.08.023.

Norbiato D, Borga M, Dinale R (2009) Flash flood warning in ungauged basins by use of the flash flood guidance and model-based runoff thresholds. Meteorol. Appl. 16,65-75. https://doi.org/10.1002/met.126.

Pradhan AMS, Kang HS, Lee JS, Kim YT (2017) An ensemble landslide hazard model incorporating rainfall threshold for Mt. Umyeon, South Korea. Bull. Eng. Geol. Environ. 78(1), 131-146. https://doi.org/10.1007/s10064-017-1055-y.

Rahmani V, Hutchinson SL, Harrington JA, Hutchinson JMS (2016) Analysis of frequency and magnitude of
extreme rainfall events with potential impacts on flooding: a case study from the central United States. Int. J. Climatol. 36, 3578-3587. https://doi.org/10.1002/joc.4577.

Seo D, Lakhankar T, Mejia J, Cosgrove B, Khanbilvardi R (2013) Evaluation of operational National Weather Service Gridded Flash Flood Guidance over the Arkansas Red River Basin. J. Am. Water Resour. Assoc. 49(6):1296–1307. https://doi.org/10.1111/jawr.12087.

Tao WH, Wu JH, Wang QJ (2017) Mathematical model of sediment and solute transport along slope land in different rainfall pattern conditions. Sci. Rep. 7, 44082. https://doi.org/10.1038/srep44082.

Thorndahl S, Willems P (2008) Probabilistic modelling of over-flow, surcharge and flooding in urban drainage using the first-order reliability method and parameterization of local rain series. Water Res. 42 (1-2): 455-466. https://doi.org/10.1016/j.watres.2007.07.038.

USACE-HEC (2000) Hydrologic Modeling System HEC-HMS Technical Reference Manual. US Army Corps of Engineers, Hydrologic Engineering Centre (HEC), Davis, USA.

USACE-HEC (2008) Hydrologic modelling system (HEC-HMS)-application guide, US Army Corps of Engineers, Hydrologic Engineering Center, Davis, Calif.

Xiao ZL, Liang ZM, Liu XW, Liu LQ, Li BQ, Hu YM (2018) Research on advance prediction and flood warning based on similarity theory. Yellow River 40,20-23. https://doi.org/10.3969/j.issn.1000-1379.2018.06.005.

Yinglan A, Wang GQ, Sun WC, Xue BL, Kiem A (2018) Stratification response of soil water content during rainfall events under different rainfall patterns. Hydrol. Process. 32(20), 3128-3139. https://doi.org/10.1002/hyp.13250.

Yuan WL, Liu MQ, Wan F (2019) Calculation of critical rainfall for small-watershed flash floods based on the HEC-HMS hydrological model. Water Resour. Manag. 33, 2555–2575. https://doi.org/10.1007/s11269-019-02257-0.
Yuan WL, Tu XY, Su CG, Liu MQ, Yan DH, Wu ZN (2021) Research on the Critical Rainfall of Flash Floods in Small Watersheds Based on the Design of Characteristic Rainfall Patterns. Water Resour. Manag. 35 (10), 3297-3319. https://doi.org/10.1007/s11269-021-02893-5.

Zelelew DG, Langon S (2020) Selection of appropriate loss methods in HEC-HMS model and determination of the derived values of the sensitive parameters for un-gauged catchments in Northern Ethiopia. Int. J. River Basin Manag. 18, 127-135. https://doi.org/10.1080/15715124.2019.1672701.

Zhai XY, Guo L, Liu RH, Zhang YY (2018) Rainfall threshold determination for flash flood warning in mountainous catchments with consideration of antecedent soil moisture and rainfall pattern. Nat. Hazards 94 (2), 605–625. https://doi.org/10.1007/s11069-018-3404-y.

Zhang Y, Wang Y, Chen Y, Liang FG, Liu HP (2019) Assessment of future flash flood inundations in coastal regions under climate change scenarios-A case study of Hadahe River basin in northeastern China. Sci. Total Environ. 693, 133550. https://doi.org/10.1016/j.scitotenv.2019.07.356.

Zhang Y, Wang Y, Zhang YX, Luan QZ, Liu HP (2021) Multi-scenario flash flood hazard assessment based on rainfall-runoff modeling and flood inundation modeling: a case study. Nat. Hazards 105(1), 967-981. https://doi.org/10.1007/s11069-020-04345-6.

Zoccatelli D, Borga M, Zanon F, Antonescu B, Stancalie G (2010) Which rainfall spatial information for flash flood response modelling? A numerical investigation based on data from the Carpathian range, Romania. J. Hydrol. 394, 148-161. https://doi.org/10.1016/j.jhydrol.2010.07.019.