Study on the early warning and forecasting of flash floods in small watersheds based on the rainfall pattern of risk probability combination

Lu Lu1 · Wenlin Yuan1 · Chengguo Su1 · Qianyu Gao2 · Denghua Yan1,3 · Zening Wu1

Accepted: 3 July 2021 / Published online: 14 July 2021 © The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2021

Abstract
Flash floods cause great harm to people's lives and property safety. Rainfall is one of the main causes of flash floods in small watersheds. The uncertainty of rainfall events results in inconsistency between the traditional single rainfall pattern and the actual rainfall process, which poses a great challenge for the early warning and forecasting of flash floods. To carry out the effective flash flood early warning and forecasting, this paper proposes a novel rainfall pattern by coupling total rainfall and peak rainfall intensity based on copula functions, i.e., the rainfall pattern of risk probability combination (RPRPC). On this basis, the Hydrologic Engineering Center-Hydrologic Modeling System (HEC-HMS) hydrological model is used to simulate the rainfall-runoff process, the trial algorithm is used to calculate the critical rainfall (CR), and the optimistic-general-pessimistic (O–G–P) early warning mode considering the decision maker's risk preference is proposed. The small watershed of Xinxian in Henan province, China, is taken as a case study for calculation. The results show that the RPRPC is feasible and closer to the actual rainfall process than the traditional rainfall pattern, Frank copula function is the best for determining the joint distribution function of total rainfall and peak rainfall intensity, and the HEC-HMS model can be applied to small watersheds in hilly areas. Additionally, both RPRPC and antecedent soil moisture condition (ASMC) have influence on CR, and the variation of RPRPC will change the influence of ASMC on CR. Finally, the effectiveness of O–G–P early warning mode is verified.

Keywords Copula function · Critical rainfall · Early warning mode · Flash flood · Rainfall pattern of risk probability combination

1 Introduction
Flash floods refer to a sudden rise of the water level (within a few hours or less) together with a significant peak discharge which are caused by heavy rainfall (Braud et al. 2014). In China, flash floods generally refer to brief, intense surface runoff caused by short-term heavy rainfall in small, hilly watersheds below several hundred square kilometers, with a response time of a few hours or less. With global climate change, extreme rainfall events occur frequently, and flash floods have become one of the most significant natural hazards (Morin et al. 2009; Han et al. 2015; Hosseini et al. 2020), causing the greatest loss of human life and economic damage (Karbari et al. 2018; Gaume et al. 2009). According to statistics taken over many years, the casualties of China's flash floods account for approximately 70% of the casualties of flood disasters (Ministry of Water Resources, P.R.C. 2020). Hence it is necessary to carry out high-accuracy early warning and prediction of flash floods for disaster prevention and damage reduction.
Several indicators have been used to evaluate the susceptibility and severity of flash floods, such as the flash-flood potential index (FFPI) (Smith 2003), flashiness (Saharia et al. 2017) and critical rainfall (CR) (Kuo et al. 2018). Of these indexes, CR is the most widely used in the early warning of flash floods (Hapuarachchi et al. 2011; Kong et al. 2020), therefore, its accurate determination is key (Norbiato et al. 2009). Statistical induction based on data-driven methods, and the hydrology and hydraulics method (HHM) which is based on hydrology theory, are commonly used methods to calculate CR (Liu 2019). However, the physical mechanism involved in the occurrence for flash floods is ignored in statistical induction, so the CR obtained in most cases cannot be directly applied (Chen 2013). Therefore, HHM is adopted in the current early warning and forecasting of flash floods. The flash flood guidance (FFG), developed by the American Hydrological Research Center, is widely used in the USA (Norbiato et al. 2009). Based on FFG, many studies have improved CR accuracy from the perspective of hydrological models for simulating rainfall-runoff processes (Seo et al. 2013; Clark et al. 2014). This indicates that the hydrological model based on the rainfall-runoff process has become an important part of CR calculation.

The hydrological model can well consider the meteorological environment and hydrological characteristics of the watershed and reflect the rainfall-runoff process. Many models have been applied to simulate flood processes (Adamovic et al. 2016; Zhang et al. 2019). Ivanescu and Drobot (2016) used a hydrological-hydraulic model which coupled MIKE SHE with MIKE 11 to determine the rainfall thresholds and transformation coefficients from hourly rainfall to other durations in the early warning of flash floods. Douinot et al. (2016) assessed the applicability of the FFG method on French Mediterranean catchments using the MARINE hydrological model. To avoid flood risks, Burgan and Icaga (2019) adopted Adaptive Hydraulics model and the Finite Element Surface Water Modeling System to perform flood analysis of the Akarcay basin before the flood. Rainfall is an important factor affecting the accuracy of hydrological models in flood simulation (Diederen and Liu 2020; Klongvessa et al. 2018). Due to the randomness of rainfall, its distribution in time and space is not uniform, which has a great impact on hydrological simulation. Carreau and Bouvier (2016) used daily data from eight rain gauge stations in the Gardon River catchment in Anduze, France, to make an accurate characterization of the spatial variability of flood-risk rainfall. Zoccatelli et al. (2010) used a spatial rainfall metric to clarify the dependence between spatial rainfall organization, basin morphology and runoff response. However, because the spatial scale of a small watershed in a hilly area is small, only the time scale of rainfall is studied during the research process.

The change in rainfall over time is called the rainfall pattern, which reflects the time distribution of rainfall events. The rainfall pattern has a great influence on the flood process (Máca and Torfs 2009; Tao et al. 2017). Since the 1940s, many rainfall patterns have been proposed, such as model rainfall patterns (Yuan et al. 2019a), the Chicago rainfall pattern (Keifer and Chu 1957) and the P&C rainfall pattern (Pilgrim and Cordery 1975), which are applied in the calculation of urban floods. With the development of modern hydrology theory, the study of rainfall pattern has been rapidly developed. Forestieri et al. (2016) calculated and analyzed the flood processes of different designed rainstorm patterns in the Sicilian basin, and obtained an early warning mechanism which was suitable for different rainfall patterns. Pedrozo-Acuna et al. (2017) analyzed and studied the flash floods caused by different rainfall patterns in Tabasco, Mexico, and established an early warning and forecasting response mechanism for these different rainfall patterns. By simulating the waterlogging process under different rainstorm conditions with different recurrence periods and peak ratio, Hou et al. (2017) uncovered the quantitative relationship between rainfall pattern and the degree of waterlogging. Yuan et al. (2019b) proposed four rainfall patterns based on the different rain peak positions in a designed rainfall pattern to calculate CR. Park and Chung (2020) proposed three-day rainfall patterns to better reproduce the characteristics of rainfall events. Although the above studies enrich the study of rainfall patterns, most of them adopt fixed rainfall patterns. Moreover, these studies seldom considered the uncertainty of the temporal distribution in rainfall events. They also ignored the influence of the uncertainty of the characteristic parameters of rainfall in the calculation of runoff yield and conflux for a watershed. With the intensification of climate change, the sudden frequency of rainfall events increases, which intensifies the uncertainty of the rainfall pattern. Therefore, the uncertainty of rainfall pattern in small watersheds must be considered in the early warning and forecasting of flash floods. Furthermore, most of the above rainfall pattern studies are applicable to urban areas, but few are applicable to small watersheds in the hilly areas.

In view of the mentioned operational hydrology problems with the early warning and forecasting of flash floods, a novel design method for the rainfall pattern of risk probability combination (RPRPC) is proposed in this paper. Combined with the Hydrologic Engineering Center-The Hydrologic Modeling System (HEC-HMS) hydrological model, this method is applied to flash flood early warning and forecasting. The main contributions of this paper can be summarized as follows:
(1) A novel and practical rainfall pattern design method, based on risk probability combination of total rainfall and peak rainfall intensity, is proposed to calculate the CR of flash flood. This method can well consider the uncertainty of rainfall pattern and the probability characteristics of rainfall characteristic parameters by coupling total rainfall and peak rainfall intensity, which reflects the change of CR caused by uncertainty of rainfall pattern and improves the accuracy of flash flood early warning and forecasting.

(2) The HEC-HMS model, which fully considers the underlying surface conditions of the watershed, is applied to simulate the rainfall-runoff process in the flash flood early warning and forecasting in the small watershed of hilly area, which is beneficial to obtain a more actual CR. In addition, the CR under multiple rainfall pattern scenarios is calculated by the trial algorithm.

(3) An early warning mode of flash floods including optimistic state, general state, and pessimistic state (O-G-P) is established to issue the effective early warning signal. This early warning mode considers the disaster prevention experience and risk preference of early warning decision makers, which provides a new method for early warning and forecasting of flash floods in small watersheds.

The remainder of this paper is structured as follows. Section 2 introduces the methodology, including the design method of the RPRPC, simulation of rainfall-runoff process, CR calculation and early warning mode establishment. Section 3 introduces the study area and data analysis. The results and analysis are shown in Sect. 4. Finally, Sect. 5 outlines the conclusions of the study.

2 Methodology

In this section, the design method of the RPRPC, the CR calculation method based on the HEC-HMS model, and the flash flood early warning mode are described in detail. It should be noted that this study only focuses on unimodal rainfall. The overall process diagram of this study is shown in Fig. 1.

2.1 Design method for the rainfall pattern of risk probability combination

2.1.1 The definition of rainfall pattern of risk probability combination

Risk probability combination is the basis of the design method for the RPRPC, hence the definition of risk probability combination will be introduced first. For rainfall events, rainfall characteristic parameters can quantitatively describe the rainfall time distribution characteristic. Based on the feature extraction and analysis from the actual rainfall process, total rainfall and peak rainfall intensity are implemented to describe the rainfall characteristics (Marc et al. 2020; Palynchuk and Guo 2011). The total rainfall indicates the sum of rainfall for each time period, and the peak rainfall intensity refers to the maximum rainfall over all time periods. Based on the statistics data of rainfall events, the probability analysis of total rainfall and peak rainfall intensity are carried out. When the peak rainfall intensity exceeds a value corresponding to a certain probability $P_B$ and the total rainfall exceeds a value corresponding to a probability $P_A$, the risk probability combination can be defined as $(P_A, P_B)$. Hence the risk probability is treated as a conditional probability, as shown in Eq. (1). The rainfall pattern corresponding to $(P_A, P_B)$ is called the rainfall pattern of risk probability combination (RPRPC), as shown in Eq. (2).

$$\begin{align*}
F_y(x|y_A) &= P(Y \geq y|X \geq x_P) \\
&= \frac{1 - F_Y(y) - F_X(x_P) + F(x_P, y)}{1 - F_X(x_P)} \quad (1)
\end{align*}$$

$$\begin{align*}
(P_A, P_B) &= (P(X \geq x_{PA}), P(Y \geq y|X \geq x_{PA})) \quad (2)
\end{align*}$$

where $X$ and $Y$ denote the total rainfall and the peak rainfall intensity, respectively. $x_P$ denotes the total rainfall corresponding to $P_A$, $F_X(x)$, $F_Y(y)$ and $F(x, y)$ are the distribution functions of total rainfall, the distribution function of peak rainfall intensity, and the joint distribution function of total rainfall and peak rainfall intensity, respectively. These distribution functions will be discussed in detail in the next section.

2.1.2 Copula function optimization

In the previous section, the determination of the joint distribution function is an important part of the RPRPC calculation. Copula functions have the ability to connect different marginal distribution functions together (Kao and Govindaraju 2010; Thong et al. 2019). However, there are many kinds of copula functions, and different copula functions have different fitting effects. Therefore, copula functions must be optimized. Copula function optimization steps are shown below.

(1) In this research, the Pearson-III distribution was used to fit the total rainfall. Nonparametric distribution estimation was adopted to determine the distribution of peak rainfall intensity. The Kolmogorov–Smirnov (K-S) test method was used to test the marginal distribution functions of total rainfall and peak rainfall intensity.

(2) Three correlation coefficients, including the Pearson linear correlation coefficient $\gamma$, Kendall rank correlation coefficient $\tau$, and Spearman rank correlation coefficient $\rho$, were selected to analyze the correlation between the total rainfall and the peak rainfall intensity.
(3) The copula function parameters (i.e., Gumbel, Clayton and Frank) were estimated using the correlation index method, and the fitting quality of the joint distribution function was tested using the K-S test.

(4) The goodness of fitting for the three copula functions was evaluated by Root Mean Square Error (RMSE), Akaike Information Criterions (AIC) and Bayesian Information Criterions (BIC). Then, the copula function with the best fitting quality was selected as the joint distribution function.

### 2.1.3 Rainfall distribution for each time period

According to the optimal copula function in Sect. 2.1.2, the total rainfall and peak rainfall intensity can be determined using risk probability combination. Then, the rainfall distribution process for a rainfall event can be obtained, and the specific steps are as follows, and summarized in Fig. 2.

1. Collect the rainfall data for the study area, and classify the actual rainfall data according to the classification principle of rainfall events (Yuan et al. 2019a).
2. Select the rainfall events with a total duration \( N \) which account for the largest proportion of all rainfall events as the initial sample \( IS \).
3. Take the time period with the most occurrences of rainfall peak counted from \( IS \) as the rainfall peak position of the RPRPC \( t_m \) in the study area. Then, select the rainfall events whose rainfall peak position is equal to \( t_m \) in the actual rainfall data as the new sample \( NS \).
4. Calculate the rainfall percentage \( d_{n, NS} \) of each time period for each rainfall in \( NS \). Then, the average rainfall percentage \( \bar{d}_n \) of each time period outside \( t_m \) can be obtained, as shown in Eq. (3).

\[
\bar{d}_n = \frac{d_{n,1} + d_{n,2} + \cdots + d_{n,NS-1} + d_{n,NS}}{NS} (n \neq m)
\]

(3)

5. Take the time periods outside \( t_m \) as a whole and calculate the proportion for the average rainfall percentage in the sum of the average rainfall percentage \( L_n \) according to Eq. (4).

\[
L_n = \frac{\bar{d}_n}{\sum_{n=1}^{N} \bar{d}_n} n \neq m
\]

(4)

6. Total rainfall \( H_{PA} \) and peak rainfall intensity \( H_{PB} \), with the risk probability combination \( (P_A, P_B) \), can be calculated based on the copula function optimized in Sect. 2.1.2.
(7) Calculate the rainfall of each time period outside \(t_m\) based on \(H_{P_a}\), \(H_{P_b}\) and \(L_n\), as shown in Eq. (5). Then determine the rainfall percentage \(R_n\) of each time period, including \(t_m\) in the RPRPC, as shown in Eq. (6)-(7).

\[
H_n = L_n \cdot (H_{P_a} - H_{P_b}) n \neq m
\]

\[
R_n = H_n \left/ \sum_{n=1}^{N} H_n \right. \quad n = 1, 2, 3, \cdots, N.
\]

\[
\sum_{n=1}^{N} R_n = 1
\]

2.2 Simulation of rainfall-runoff process based on the HEC-HMS hydrological model

Considering the flexibility and applicability of the rainfall-runoff process, the HEC-HMS model was used to simulate the rainfall-runoff process in a small watershed of hilly area. The HEC-HMS model is a semi-distributed hydrological model (Kumar and Bhattacharjya 2020), and has been developed by the United States Army Corps of Engineers’ Hydrologic Engineering Center. This model is mainly composed of four modules: basin module, meteorological module, control specifications module and time-series data module. Details of the model structure and module invocation are given in the HEC-HMS Technical Reference Manual (USACE-HEC 2000). In order to fully consider the uneven spatial distribution of rainfall and the complex underlying surface, the model is closely combined with Geographic Information System (GIS) technology to divide the study area into several sub-basins based on the natural water separation lines, and the rainfall-runoff process is then simulated. The HEC-HMS simulates the rainfall-runoff process based on the separate modules to represent each part of the rainfall-runoff process, including net rainfall, direct runoff, base flow and channel confluence. Therefore, it is necessary to select reasonable methods to calculate the above four parts. The methods selected for each part are described in detail in the following sections.

2.2.1 Initial and constant method

The method used to calculate the net rainfall in this paper was the Initial and Constant method (Zema et al. 2017). This method defines two stages for the rainfall loss process including initial loss and later loss, as shown in Eq. (8).

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

where \(P_{et}\) denotes the net rainfall at time period \(t\). \(P_a\) denotes the antecedent soil moisture condition (ASMC), which is an indicator of soil moisture. \(P_t\) denotes the rainfall at time period \(t\). \(P_i\) denotes the rainfall of each time period from the rainfall beginning to the last time period of the current time period. \(f_c\) denotes the maximum infiltration capacity of soil.
2.2.2 Soil conservation service unit hydrograph method

Soil Conservation Service Unit Hydrograph method (Elfeki et al. 2020) was used for the direct runoff in this paper because it required only one parameter, i.e., lag time. The lag time parameter can be obtained through calibrating the model based on the measured data. For ungauged catchments, the lag time parameter is estimated by flow confluence time (Abushandhi and Merkel 2013), as shown in Eq. (9).

\[ t_p = 0.6t_c \]  
\[ (9) \]

where \( t_p \) is the lag time parameter, \( t_c \) is the flow confluence time.

2.2.3 Recession method

Base flow refers to the minimum river depth over which additional runoff accumulates. In the current study, recession method (Knebl et al. 2005) was used to calculate the base flow. The principle of this method is that the relationship between the base flow and the initial base flow at any moment is shown in Eq. (10).

\[ Q_t = Q_t^m \]  
\[ (10) \]

where \( Q_t \) denotes the flow threshold at time period \( t \), \( Q_t^m \) denotes the base flow for the initial time period and \( R \) denotes attenuation coefficient. Both \( Q_t \) and \( R \) are obtained from the observed flow hydrograph.

2.2.4 Muskingum method

Muskingum method (Niazkar and Afzali 2016) was used to calculate the channel confluence process. The basic parameters of this method are the specific gravity factor of flow and the evolution time of flood wave in the river. The calculation process is shown in Eq. (11)-(13).

\[ Q_2 = C_0I_2 + C_1I_1 + C_2Q_t \]  
\[ (11) \]

\[ \begin{cases} C_0 = (0.5\Delta t - Kx)/(K - Kx + 0.5\Delta t) \\ C_1 = (0.5\Delta t + Kx)/(K - Kx + 0.5\Delta t) \\ C_2 = (K - Kx - 0.5\Delta t)/(K - Kx + 0.5\Delta t) \end{cases} \]  
\[ (12) \]

\[ C_0 + C_1 + C_2 = 1 \]  
\[ (13) \]

where \( K \) denotes the evolution time of flood wave in the channel, which reflects the reach propagation time under the condition of steady flow. \( x \) denotes the specific gravity factor, which reflects the wedge accumulation and regulation capacity of the reach. \( Q_t \) and \( Q_2 \) denote the outflow of the lower section at the start and end times, respectively. \( I_1 \) and \( I_2 \) denote the inflow of the upper section at the start and end times, respectively.

2.3 Critical rainfall calculation

According to the RPRPCs, which are generated using the methods proposed in Sect. 2.1, a trial algorithm is used to calculate the critical rainfall corresponding to different RPRPCs. The flow chart of the trial algorithm is shown in Fig. 3. The specific steps are summarized as follows.

1. The HEC-HMS model is constructed using the method mentioned in Sect. 2.2.

2. Assuming an initial rainfall \( R \), the rainfall of each time period in the RPRPC is input into the established HEC-HMS model to simulate the rainfall-runoff process. The peak flow \( Q_m \) is then obtained.

3. Through the analysis of the rating curve for the control channel in the study area, the disaster flow \( Q_d \) is determined according to the measured disaster water level.

4. \( Q_m \) and \( Q_d \) are compared. If the deviation satisfies the requirement of calculation accuracy (i.e., \( |Q_m - Q_d| \leq \delta \)), the trial calculation is finished. If the accuracy is not satisfied, adjust the assumed rainfall and repeat the trial calculation until the accuracy requirement is satisfied. At this point, \( R \) is the critical rainfall.

2.4 Optimistic-general-pessimistic early warning mode

Limited by rainfall uncertainty, if the uncertainty of the CR for flash floods is fully considered, the workload of the early warning process will be greatly increased. In order to reduce the complexity of the early warning process as much as possible and take into account the rainfall uncertainty, a risk preference early warning mode based on the RPRPC is proposed in this paper. The process of constructing the flash flood early warning mode can be summarized as the following steps.

1. Based on an analysis of the current flood control capacity of the disaster prevention target, and assuming the same frequency for rainfall and flooding, the range of risk probability combination in the study area is determined. The rainfall pattern collection of the RPRPCs is then determined.

2. The CR scatterplot is drawn for different combinations of early warning time periods (EWTP) and ASMC in different RPRPCs. The points under the three-dimensional coordinates of the scatterplot are projected to two-dimensional coordinates. The early warning mode diagram for different risk preferences are then made, as shown in Fig. 4. In this early warning mode, the optimistic, general and pessimistic (O-G-P) modes are, respectively, the upper limit, the mean value and the lower limit of the CR threshold space.
(3) The appropriate early warning mode is selected based on the rainfall grades from authoritative numerical forecast information. Generally, the rainstorm grades are divided into rainstorm, heavy rainfall, and extraordinary heavy rainfall, which correspond to the optimistic, general and pessimistic modes, respectively.

(4) The ASMC is determined according to previous rainfall events. Early warning signals that remind people to evacuate immediately are then issued according to the
sliding comparison between cumulative rainfall and CR in different EWTPs.

3 Case study

3.1 Study area

Xinxian, a small watershed located in Xinyang city, Henan Province, China and which forms part of the Huaihe river basin, has been selected as the study area (as shown in Fig. 5). This watershed has a high West and low East, a large drop, and a high land vegetation coverage, resulting in the generation of surface runoff and surges of flash floods. The main geomorphological features of the watershed are shown in Table 1.

3.2 Data analysis

The data used in this paper includes GIS data, rainfall data and flow data. The GIS data, including the digital elevation model, land use and soil maps were collected from the National Geomatics Center of China. The measured rainfall data and flow data were provided by the hydrological bureau of Henan. Rainfall duration, rainfall peak position, total rainfall and peak rainfall intensity have great influence on RPRPC, hence it is necessary to analyze their statistical properties and distribution characteristics.

According to the analysis of the rainfall data of Sidian rainfall station, the proportion of rainfall events with various durations is shown in Table 2. It can be seen from Table 2 that the rainfall duration with 9 ~ 12 h accounted for the largest proportion, which is 43.86%. After comprehensive consideration of the characteristics for rainfall events, the duration of rainfall is set as 12 h and the time resolution is considered as 1 h in this study. After statistics, there were 44 rainfall events with a total duration of 12 h.

In the selected 44 rainfall events, rainfall peak position, total rainfall and peak rainfall intensity are analyzed. The proportion of rainfall peak position in each time period is shown in Table 3. It can be seen that the proportion of rainfall peak position in the fourth time period is the highest, so the fourth time period is selected as the rainfall peak position of RPRPC. In RPRPC, the calculation of rainfall in each time period is based on the proportion. However, the total rainfall of each rainfall event is 1 in terms of proportion, hence only the data of peak rainfall intensity is statistically analyzed, as shown in Fig. 6.

4 Results and discussion

4.1 Joint distribution function optimization

In this paper, the Pearson-III distribution and the kernel density estimation method have been selected to determine the marginal distribution of total rainfall and peak rainfall intensity, respectively. The rationality of the selected marginal distribution function was verified by K-S test. The fitting quality of these two marginal distribution functions was evaluated, and the correlations between total rainfall and peak rainfall intensity were analyzed. The results are shown in Table 4 and Table 5.
The significance level of the K-S test was set as $\alpha = 0.05$. When $n = 44$, the corresponding critical value was 0.2006. The K-S test results of both the total rainfall and peak rainfall intensity were smaller than the critical value. These results indicate that the Pearson-III distribution and the kernel density estimation method are feasible for simulating the marginal distribution of total rainfall and peak rainfall intensity, respectively. According to the correlation results, all correlation coefficients, including Pearson linear correlation coefficient $r$, Kendall rank correlation coefficient $\tau$, and Spearman rank correlation coefficient $\rho$, were greater than reference value 0.8, which signifies a strong positive correlation between the total rainfall and peak rainfall intensity. Therefore, the copula function can be used to construct the joint distribution function of the total rainfall and peak rainfall intensity.

Then, three copula functions (i.e., Gumbel, Clayton and Frank) were selected to optimize the best copula function. The rationality of the three copula functions was verified by K-S test, and the goodness of fit of the three copula functions were evaluated by RMSE, AIC and BIC Criterion. The results are shown in Table 6 and Table 7.

According to Table 6, the K-S test statistic of each copula function is smaller than the critical value, with $\alpha = 0.05$ and $n = 44$. This indicates that all the three copula functions can be used to establish a joint distribution for total rainfall and peak rainfall intensity. According to Table 7, all evaluation values of the Frank function were the smallest for the three evaluation criterions of fitting goodness, which shows that the goodness of fit of the Frank function is the best. Therefore, the Frank function was selected as the joint distribution function.

### 4.2 Hydrological model application assessment

Based on the digital elevation data of the study area, the HEC-HMS model was established. Considering the hydrological characteristics of the study area, the flexibility of the model, and the simplicity of parameter calibration, a combination of methods described in Sect. 2.2 was adopted to carry out the calculation of the rainfall-runoff process. Ten rainfall events and corresponding floods were selected...
from the watershed, in which seven floods were used for parameter calibration and three floods were used for verification. The results are shown in Table 8.

It can be seen that all the relative deviations between the simulated value and the measured value of the peak flow and the flood volume were less than 20%. Moreover, the Nash–Sutcliffe efficiencies (NSEs) (Jain and Sudheer 2008), which has often been used to evaluate the effectiveness of hydrological models, were greater than 0.8. The above results prove that the calculated model is reasonable and reliable, and that the HEC-HMS model can be effectively applied in this watershed.

4.3 Rationality analysis of the RPRPC

According to the statistical rainfall data, three rainfall events were selected to verify the rationality of the application of the RPRPC in the early warning and forecasting of flash floods. By determining the total rainfall and peak rainfall intensity of the three measured rainfall events, the corresponding risk probability combination was determined through the Frank copula function. Then, the corresponding RPRPC was calculated by Eq. (3)-(7). In addition, the RPRPC was compared with the traditional rainfall pattern (TRP) which is widely used in China (Lin et al. 2005). The TRP is a simplified single rainfall pattern, and is usually determined based on the typical rainfall process in the rainstorm handbook of the region. The results of different rainfall patterns are shown in Fig. 7.

It can be seen that the differences between the TRP and measured rainfall are very large, especially for the rainfall peak position and peak rainfall intensity. The reason for this is that, in the calculation of the TRP, the rainfall peak position was set backward and the peak rainfall intensity is set high based on the consideration of engineering safety. Compared to the TRP, the RPRPC is obviously less different to the measured rainfall. The three RPRPCs all have the same rainfall peak positions as the measured rainfall, and the peak rainfall intensity differs by very little. Besides, all three RPRPCs have a single rainfall peak with a forward rainfall peak position, which is the same as the corresponding measured rainfall. Therefore, the RPRPC has the characteristic of maintaining trend consistency with the measured rainfall.

(1) Approach degree analysis

The approach degree (Liu et al. 2019), which is commonly used in rainfall pattern research to describe the degree of rainfall pattern conformity, was used to analyze the rationality of the RPRPC, as shown in Eq. (14). The approach degrees of the rainfall patterns for the three rainfall events are shown in Table 9.

\[ e = 1 - \sqrt{\frac{1}{N} \sum_{n=1}^{N} (z_n - y_n)^2} \]  

(14)

where \( e \) is the approach degree, \( N \) is the total number of time periods; \( z_n \) is the rainfall proportion of the time period \( n \) in the measured rainfall; \( y_n \) is the rainfall proportion of the time period \( n \) in the RPRPC.

It can be seen that the approach degrees between the measured rainfall and the corresponding RPRPC are all greater than 0.95, which indicates that the temporal sequence of rainfall proportion in RPRPC is close to the temporal sequence of rainfall proportion in measured rainfall. The rainfall levels of the three rainfall events are different, but the approach degrees are more than 0.95, indicating that RPRPC can adapt to different rainfall levels. This also proves the rationality of the RPRPC to a certain extent.

(2) CR analysis

The CR for different EWTPs is calculated in this section based on the RPRPC. Moreover, CR was compared with time-interval characteristic rainfall (TICR) (Park and Chung, 2020), and the deviation degree (DD, National
Mountain Flood Prevention and Control Group, 2016) was calculated according to Eq. (15). The results are shown in Table 10.

\[ DD = \left| \frac{(CR - TICR)}{TICR} \right| \times 100\% \quad (15) \]

It can be observed that all the DDs between TICR and CR are less than 15% under different early-warning time in each rainfall, which indicates that the CR calculated based on RPRPC has good reliability in different early-warning time. The rainfall levels of the three rainfall events are different, but all the DDs in the three rainfall events are less than 15%, which indicates that CR calculated based on RPRPC has high accuracy under different rainfall levels. The results of DDs in different early-warning time and different rainfall levels show that CR based on RPRPC has high reliability, that is, RPRPC is reasonable in the calculation of CR.

In summary, the comparison between the measured rainfall and the TRP shows that the trend characteristics of the RPRPC are reasonable. Numerical results show that the RPRPC is reasonable in terms of approach degree and CR. These results fully demonstrate that the RPRPC proposed in this paper has good reliability and can be applied to the early warning and forecasting of flash floods.

### 4.4 Analysis of the influence of RPRPC and ASMC on critical rainfall

According to ASMC analysis in Xinxian, ASMC can be divided into three states: drought (0.2Wm), normal (0.5Wm) and wet (0.8Wm). Taking into account the current flood control capacity of Caohezu (i.e., once every 10 years), the uncertainty of the rainfall pattern and the state of the ASMC, the HEC-HMS model and the trial algorithm were used to calculate CR with different rainfall patterns and ASMCs. The corresponding calculation results for rainfall pattern and CR are shown in Figs. 8 and 9, respectively.

Based on Fig. 9, in the same RPRPC, the larger the ASMC is, the smaller the CR is. The reason is that the ASMC is large, which means the soil moisture content is

---

### Table 8 Simulation results of the floods

| State   | Number          | Peak flow (m³/s) | Flood volume (10⁶m³) | NSE |
|---------|-----------------|------------------|----------------------|-----|
|         |                 | Simulated        | Measured             |     |
| Calibration | 19820719 | 766.0            | 761.0                | 33.4 | 28.8 | 0.933 |
|         | 19870705 | 1007.8           | 1060.0               | 47.7 | 40.3 | 0.860 |
|         | 19910703 | 822.8            | 980.0                | 43.9 | 47.4 | 0.922 |
|         | 19990627 | 301.4            | 309.0                | 13.5 | 15.6 | 0.883 |
|         | 20030708 | 550.8            | 539.0                | 24.5 | 25.3 | 0.939 |
|         | 20080816 | 759.9            | 749.0                | 41.2 | 39.3 | 0.801 |
|         | 20130526 | 170.0            | 166.0                | 7.9  | 8.3  | 0.923 |
| Validation | 19850713 | 209.3            | 191.0                | 5.8  | 5.4  | 0.861 |
|         | 19960714 | 966.1            | 935.0                | 30.9 | 29.6 | 0.926 |
|         | 20040718 | 347.0            | 339.0                | 2.8  | 2.9  | 0.887 |

### Table 9 Approach degree of three rainfall events

| Rainfall number | 20040718 | 20080816 | 20160701 |
|-----------------|----------|----------|----------|
| Approach degree | 0.981    | 0.951    | 0.966    |

---

Fig. 7 Comparison of rainfall patterns: a rainfall 20,040,718 b rainfall 20,080,816 c rainfall 20,160,701

Fig. 8 Comparison of rainfall patterns: a rainfall 20040718 b rainfall 20080816 c rainfall 20160701
large and is easy to generate runoff. On this basis, the amount of rainfall required to reach the disaster flow is small, hence the CR is small. In addition, the maximum CR threshold for 12 h, 6 h, and 3 h are 73 ~ 163 mm, 53 ~ 101 mm, 41 ~ 61 mm, and the corresponding CR maximum variations are 90 mm, 48 mm, and 20 mm, respectively. These variations indicate that rainfall pattern has a great influence on CR. When the risk probability of the total rainfall is constant, the CR curves for 0.2Wm, 0.5Wm and 0.8Wm in Caohezu gradually converge with the increasing risk probability of peak rainfall intensity. The reason for this is that the larger the risk probability of the peak rainfall intensity is, the smaller the peak rainfall intensity is. Then, the role of the rainfall peak is weakened in the whole temporal distribution of rainfall, and the rainfall pattern gradually changes to a uniform rainfall pattern, as shown in Fig. 8. Uniform rainfall allows the regulation and storage function of the watershed to be brought into full play, and thus the influence of ASMC on CR is reduced. For the three EWTPs, the CR curves for 12 h are the most concentrated while the CR curves for 3 h are the most dispersed, which indicates that the longer the regulation time and storage time are, the less impact ASMC has on CR.

### 4.5 Analysis of the effectiveness for the early warning mode

The current flood control capacity of Caohezu is once every 10 years. Based on the assumption of the same frequency for rainfall and flooding, the range of risk probability combination in the study area is \((P_A < 0.1, \ P_B < 0.1)\). The corresponding O–G–P early warning mode has been calculated using the steps in Sect. 2.4. The results are shown in Fig. 10.

Rainfall 20160701 in Caohezu was taken as an example for verifying the effectiveness of the O–G–P early warning mode in the early warning of flash floods. According to the weather forecasting of China Meteorological Administration, the rainstorm grade in Xinxian on July 1, 2016 was heavy rainfall, so the G mode was used for early warning. The corresponding early warning information is shown in Fig. 11.

Comparing the accumulated rainfall in various EWTPs and the CR line, the 3 h accumulated rainfall exceeded the G-3 CR line during the fourth time period, and an early warning signal was issued immediately. According to the results of the flood investigation, the disaster time of formation caused by rainfall 20160701 was 10:00, and the

---

**Table 10** Deviation degree results between CR and TICR

| Rainfall number | ASMC (mm) | EWTP (h) | TICR (mm) | CR (mm) | DD (%) |
|-----------------|-----------|----------|-----------|---------|--------|
| 20040718        | 0.2Wm     | 3        | 71        | 78      | 9.8    |
|                 |           | 6        | 124       | 130     | 4.8    |
|                 |           | 12       | 177       | 160     | 9.6    |
| 20080816        | 0.5Wm     | 3        | 62        | 67      | 8.1    |
|                 |           | 6        | 100       | 107     | 7.0    |
|                 |           | 12       | 146       | 133     | 8.9    |
| 20160701        | 0.8Wm     | 3        | 75        | 68      | 9.3    |
|                 |           | 6        | 96        | 109     | 13.5   |
|                 |           | 12       | 269       | 237     | 11.9   |

Wm denotes the saturated soil moisture

---

![Fig. 8 Rainfall pattern collection: (a) (0.02, \(P_B\)); (b) (0.05, \(P_B\)); (c) (0.1, \(P_B\))](image)
early warning signal was issued at 09:00 through the O–G–P early warning mode. Therefore, the early warning time is 1 h, which provides sufficient time for people to transfer. These results show that the O–G–P mode is effective in the early warning and forecasting of flash floods.

5 Conclusion

In this paper, a novel and practical rainfall pattern design method, which considers the uncertainty of rainfall pattern based on copula function, is presented through the risk probability combination of total rainfall and rainfall peak intensity. It is then applied to calculate the critical rainfall of flash floods, combined with the HEC-HMS hydrological model and trial algorithm. Through the combination of RPRPCs and ASMCs, the critical rainfall threshold space was obtained. On this basis, an O–G–P early warning mode considering the disaster prevention experience and risk preference of decision makers was developed. According to the obtained results, the main conclusions are summarized as follows.

1. The simulated rainfall processes based on the RPRPC are more accurate than those based on the traditional rainfall pattern. Moreover, the approach degrees between RPRPC and the actual rainfall are all greater than 0.95, and the deviation degrees of the critical rainfall are all

---

**Fig. 9** Critical rainfall: a $P_A = 0.02$, EWTP = 12 h; b $P_A = 0.02$, EWTP = 6 h; c $P_A = 0.02$, EWTP = 3 h; d $P_A = 0.05$, EWTP = 12 h; e $P_A = 0.05$, EWTP = 6 h; f $P_A = 0.05$, EWTP = 3 h; g $P_A = 0.10$, EWTP = 12 h; h $P_A = 0.10$, EWTP = 6 h; i $P_A = 0.10$, EWTP = 3 h
less than 0.15. The RPRPC is reasonable and can effectively reflect the real rainfall process.

(2) In the evaluation results of fitting goodness for three copula functions, all the evaluation values of Frank function are the smallest, Frank copula function is the best for determining the joint distribution function of total rainfall and peak rainfall intensity.

(3) The relative deviations between the simulated results and the measured data in terms of the peak flow and the flood volume are all less than 0.2. In addition, all NSEs are greater than 0.8. It is reasonable and reliable to simulate rainfall-runoff process by the HEC-HMS model, and the HEC-HMS model has good performance in the simulation of rainfall-runoff process in a small watershed of hilly area.

(4) Both ASMC and rainfall pattern have impacts on CR. In the same RPRPC, the larger the ASMC is, the smaller the CR is. However, when the total rainfall in the RPRPC is constant, the decrease in peak rainfall intensity will weaken the influence of ASMC on CR. In addition, the increase of rainfall duration will also weaken the influence of ASMC on CR.

(5) An early warning signal was issued 1 h before the flash flood occurred. The O–G–P early warning mode is effective and can provide the information of flash flood early warning combined with rainfall forecasting information.

It should be noted that the design method of the RPRPC proposed in this study is only applicable to the calculation of unimodal rainfall pattern, which may not cover all the possible rainfall patterns in the study area. In the future, the uncertainty of multimodal rainfall patterns based on this study will be studied further, thereby determining the accurate critical rainfall and further improving the accuracy of the early warning of flash floods.

Acknowledgements The work described in this paper was supported by National Natural Sciences Foundation of China (No.51779229) and Scientific Research Projects of Henan Province (No.202102310296).

Author contributions All authors contributed to the study conception and design. Methodology, Writing—Review & Editing were performed by Lu Lu. Software, Writing—Original Draft, Validation, Funding acquisition were performed by Wenlin Yuan. Conceptualization, Supervision, Project administration, Writing—Review & Editing were performed by Chengguo Su. Investigation was performed by Qianyu Gao. Data Curation was performed by Denghua Yan. Formal analysis was performed by Zening Wu.

Funding The work described in this paper was supported by National Natural Sciences Foundation of China (No.51779229) and Scientific Research Projects of Henan Province (No.202102310296), the recipients of both fundings was Wenlin Yuan.

Data availability The data and material used in this paper are available.

Code availability The software application and custom code used in this paper are available.
Declarations

Conflicts of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

Abushandhi 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 27:2391–2409. 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

Braud I, Ayral PA, Bouvier C, Branger F, Delrieu G, Le JC, Nord G, Vandervaeve JP, Anquetin S, Adamovic M, Andrieu J, Batiot C, Boudevillain B, Brunet P, Carreau J, Confolonad A, Didon-Lescot JF, Domergue JM, Douvinet J, Dramais G, Freydier R, Gérard S, Haza 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

Burgan HI, Icaga Y (2019) Flood Analysis Using Adaptive Hydraulics (ADH) Model in the Akarcay Basin. Tek Dergi 30:9029–9051

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

Chen WS (2013) A review of rainfall thresholds for triggering flash floods. Adv Water Sci 24:901–908

Clark RA, Gourley JJ, Flamig ZL, Hong Y, Clark E (2014) CONUS-wide evaluation of national weather service flash flood guidance products. Weather Forecast 29:377–392. https://doi.org/10.1175/WAF-D-12-00124.1

Diederien 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

Doupinet A, Roux H, Garambois PA, Larnier K, Labat D, Dautres 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

Elfeki A, Masoud M, Basahi J, Zaidi S (2020) A unified approach for hydrological modelling of arid catchments for flood hazards assessment: case study of wadi Itwad, southwest of Saudi Arabia. Arab J Geosci 13:490. https://doi.org/10.1007/s12517-020-05430-7

Forestieri A, Caracciolo D, Arnone E, Noto LV (2016) Derivation of rainfall thresholds for flash flood warning in a Sicilian basin using a hydrological model. Procedia Engineering 154:818–825. https://doi.org/10.1016/j.proeng.2016.07.413

Gaume E, Bain V, Bernardara P, Newinger O, Barbuc M, Bateman A, Blaskovicova L, Bloshgl H, Borgia M, Dumitrescu A, Daliakovoulos I, Garcia J, Irimiescu A, Kohnova S, Koutoulis A, Marchi L, Matreata S, Medina V, Preciso E, Sempere-Torres D, Stanca 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, Nabiour N, Shamsirband S, Darabi H, Haghhighi 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

Hou JM, Guo KH, Wang ZL, Jing HX, Li DL (2017) Numerical simulation of design storm pattern effects on urban flood inundation. Adv Water Sci 28:820–828

Ivanescu V, Drobot R (2016) Deriving rain threshold for early warning based on a coupled hydrological-hydraulic model. Math Model Civil Eng 12:10–21. https://doi.org/10.1515/mmce-2016-0014

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)

Kao SC, Govindaraju RS (2010) A copula-based joint deficit index for droughts. J Hydrol 380:121–134. https://doi.org/10.1016/j.jhydrol.2009.10.029

Karbas M, Shokooohi A, Saghaftian 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

Keiper CJ, Chu HH (1997) Synthetic storm pattern for drainage design. J Hydraulics Division ASCE 83:1–25

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 32:2871–2877. 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 Manag 75:325–336. 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

Kumar D, Bhattacharjya RK (2020) Evaluating two GIS-based semi-distributed hydrological models in the Bhagirathi-Alkhnanda River catchment in India. Water Policy 22:991–1014. https://doi.org/10.2166/wp.2020.159

Kuo HL, Lin GW, Chen CW, Saito H, Lin CW, Chen H, Chao WA (2018) Evaluating critical rainfall conditions for large-scale landslides by detecting event times from seismic records. Nat Hazards Earth Syst Sci 18:2877–2891. https://doi.org/10.5194/nhess-18-2877-2018

Lin GF, Chen LH, Kao SC (2005) Development of regional design hyetographs. Hydrol Process 19:937–946. 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

Liu YY, Wang Y, Liu HW, Du LG, Liu S, Chai FX (2019) Study on temporal distribution of precipitation in Beijing city during flood period based on dynamic. J China Hydrol 39:74–77

Máca P, Torfs P (2009) The influence of temporal rainfall distribution in the flood runoff modelling. Soil Water Res 4:S102–S110

Marc O, Stumpf A, Malet JP, Gosset M, Uchida T, Chiang SH (2020) Initial insights from a global database of rainfall-induced

landslide inventories: the weak influence of slope and strong influence of total storm rainfall. Earth Surf Dyn 6:903–922.

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

Morin E, Jacoby Y, Navon S, Bet-Halachmi E (2009) Towards flash-flood prediction in the dry Dead Sea region utilizing radar rainfall information. Adv Water Resour 32:1066–1076. https://doi.org/10.1016/j.advwatres.2008.11.011

National Mountain Flood Prevention and Control Group (2016) Technical requirements for inspection and verification of mountain flash flood early-warning indicators. National Mountain Flood Prevention and Control Group, Beijing

Niazkar M, Afzali SH (2016) Application of new hybrid optimization technique for parameter estimation of new improved version of Muskingum model. Water Resour Manag 30:4713–4730. https://doi.org/10.1007/s11269-016-1449-9

Norbiato D, Borgia 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

Palynchuk BA, Guo YP (2011) A probabilistic description of rain storms incorporating peak intensities. J Hydrol 409:71–80. https://doi.org/10.1016/j.jhydrol.2011.07.040

Park H, Chung G (2020) A nonparametric stochastic approach for disaggregation of daily to hourly rainfall using 3-Day rainfall patterns. Water 12:2306. https://doi.org/10.3390/w12082306

Pedrozo-Acuna A, Moreno G, Mejia-Estrada P, Paredes-Victoria P, Brenu-Naranjo JA, Meza C (2017) Integrated approach to determine highway flooding and critical points of drainage. Transport Res Part D-Transport Environ 50:182–191. https://doi.org/10.1016/j.trd.2016.11.004

Pilgrim DH, Corderly J (1975) Rainfall temporal patterns for design floods. J Hydraulics Division ASCE 101:81–95

Saharia M, Kistetter PE, Vergara H, Gourley JJ, Hong Y, Giroud M (2017) Mapping flash flood severity in the United States. J Hydrometeorol 18:397–411

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 49:1296–1307. https://doi.org/10.1111/jawr.12087

Smith G (2003) Flash flood potential: determining the hydrologic response of ffmp basins to heavy rain by analyzing their physiographic characteristics. A white paper available from the NWS Colorado Basin River Forecast Center web site at http://www.cbrfc.noaa.gov/papers/ffp_w.pdf

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

Thong NH, Deo RC, Mushfaq S, Kath J, Khan S (2019) Copula statistical models for analyzing stochastic dependencies of systemic drought risk and potential adaptation strategies. Stoch Environ Res Assess 33:779–799. https://doi.org/10.1007/s00477-019-01662-6

USACE-HEC (2000) Hydrologic modeling system HEC-HMS technical reference manual. US army corps of engineers, hydrologic engineering centre (HEC), Davis, USA

Yuan WL, Liu MQ, Wan F (2019) Study on the impact of rainfall pattern in small watersheds on rainfall warning index of flash flood event. Nat Hazards 97:665–682. https://doi.org/10.1007/s11069-019-03666-5

Yuan WL, Liu MQ, Wan F (2019b) 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

Zema DA, Labate A, Martino D, Zimbone SM (2017) Comparing different infiltration methods of the HEC-HMS model: the case study of the mesima torrent (Southern Italy). Land Degrad Dev 28:294–308. https://doi.org/10.1002/ldr.2591

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

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

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.