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Study on the Early Warning and Forecasting of Flash Floods in Small Watersheds Based on the Rainfall Pattern of Risk Probability Combination

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Abstract: Flash floods cause great harm to people's life 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. This paper proposes a novel rainfall pattern based on total rainfall and peak rainfall intensity, i.e., the rainfall pattern of risk probability combination (RPRPC). To determine the joint distribution function with the best fitting effect, copula functions are introduced and optimized. On this basis, the HEC-HMS

hydrological model is used to simulate the rainfall-runoff process, a trial algorithm is used to calculate the critical rainfall (CR), and an 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 (TRP) and that the HEC-HMS model can be applied to small watersheds in hilly areas. Additionally, the influence of antecedent soil moisture condition (ASMC) and rainfall pattern on critical rainfall varies with the change of peak rainfall intensity and rainfall duration. Finally, the O-G-P early warning mode is effective and provides a valuable reference for the early warning and forecasting of flash floods in small watersheds in hilly areas.

Keywords: Flash floods · copula function · rainfall pattern of risk probability · critical rainfall · early warning mode

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 (Karbasi 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 hydrologic models have been applied to simulate and forecast flash 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. These hydrological models take into account the hydrometeorological and watershed characteristics of the study area, which can well simulate the hydrological process when flash floods occur. Rainfall is an important factor affecting the accuracy of hydrological models in flood simulation (Diederer 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 et al. (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. Zocatelli 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 mountainous or 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. Hou et al. (2017) uncovered the quantitative relationship between rainfall pattern and the degree of waterlogging by simulating the waterlogging process under different rainstorm conditions with different recurrence periods and peak ratio. 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 mountainous and 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 HEC-HMS hydrological model, this method is applied to flash floods early warning and forecasting. The main contributions of this paper can be summarized as follows:

(1) A novel rainfall pattern design method based on risk probability combination is proposed, which takes into account the uncertainty of rainfall events. In this method, the uncertainty of rainfall is considered through a probability analysis of rainfall characteristic parameters, and copula theory is used to construct the joint distribution function of rainfall characteristic parameters.

(2) Based on the RPRPC, the HEC-HMS model is used to simulate the rainfall-runoff process in a small watershed, and the trial algorithm is used to calculate the CR threshold space in a multi-scenario mode.

(3) Based on the current flood control capacity and CR threshold space of disaster prevention objects, an effective early warning mode including optimistic, general, and pessimistic (O-G-P) forecasting of flash floods is established. This early warning mode considers the disaster prevention experience and risk preference of early warning decision makers, and provides a new method of early warning and forecasting 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 flash floods, CR calculation and early warning mode establishment. Section 3 introduces the case study and data sources. The results and analysis are shown in Section 4. Finally, Section 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.

Fig.1 Schematic diagram of flash flood early warning and forecasting based on the RPRPC

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

probability analysis of total rainfall and peak rainfall intensity, when the peak rainfall intensity exceeds a value corresponding to a certain probability P_B and when 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).

$$F_{y|x_{p_A}}(X, Y) = P(Y \geq y | X \geq x_{p_A}) = \frac{1 - F_Y(y) - F_X(x_{p_A}) + F(x_{p_A}, y)}{1 - F_X(x_{p_A})} \quad (1)$$

$$(P_A, P_B) = (P(X \geq x_{p_A}), P(Y \geq y | X \geq x_{p_A})) \quad (2)$$

Where X and Y denote the total rainfall and the peak rainfall intensity, respectively. x_{p_A} 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

kernel density 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 γ , Kendall rank correlation coefficient τ , and Spearman rank correlation coefficient ρ , 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 Criteria (AIC) and Bayesian Information Criteria (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 Section 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.

Fig.2 Calculation flow chart for the rainfall distribution for each time period

(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 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).

$$\bar{d}_n = (d_{n,1} + d_{n,2} + \dots + d_{n,ns} + \dots + d_{n,NS-1} + d_{n,NS}) / NS \quad (n \neq m) \quad (3)$$

(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).

$$L_n = \bar{d}_n / \sum_{n=1}^N \bar{d}_n \quad n \neq m \quad (4)$$

(6) Total rainfall H_{P_A} and peak rainfall intensity H_{P_B} , with the risk probability combination (P_A, P_B) , can be calculated based on the copula function optimized in Section 2.1.2.

(7) Calculate the rainfall of each time period outside t_m based on H_{pA} , H_{pB} 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).

$$H_n = L_n \cdot (H_{pA} - H_{pB}) \quad n \neq m \quad (5)$$

$$R_n = H_n / \sum_{n=1}^N H_n \quad n = 1, 2, 3, \dots, N \quad (6)$$

$$\sum_{n=1}^N R_n = 1 \quad (7)$$

2.2 Simulation of flash floods based on the HEC-HMS hydrological model

Considering the flexibility and applicability of the rainfall-runoff relationship, the HEC-HMS model was used to simulate the rainfall-runoff process in a small watershed (Laouacheria and Mansouri 2015). The HEC-HMS model is a distributed hydrological model, and has been developed by the United States Army Corps of Engineers' Hydrologic Engineering Center. In order to fully consider the uneven spatial distribution of rainfall and the complex underlying surface, the model is closely combined with 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 hydrological model is mainly composed of four modules: basin module, meteorological module, control specifications module and time-series data module. Of these modules, the basin module is the model generalization of the rainfall-runoff process, including rainfall loss, direct runoff, base flow and channel confluence. The function of the meteorological module is to analyze meteorological elements in the rainfall-runoff process. The control specifications module contains all of the time control information for the model. The time-series data module is mainly used to store rainfall, evaporation, runoff and other data. Each rainfall-runoff

process simulation will call the above four modules. Details of the model structure and module invocation are given in the HEC-HMS Technical Reference Manual (USACE-HEC 2000).

The HEC-HMS model is flexible due to its modular approach. According to the measured data and watershed conditions, an appropriate combination of methods can be selected to calculate the rainfall-runoff relationship. The parameters of the HEC-HMS model can then be calibrated by using the measured data in the study area. By comparing the measured and simulated values of the flood, the best simulation parameters are determined. The appropriate method combination selection process and parameter calibration process can be referred to in Ref. (Du et al. 2012; Zelelew and Langon 2020).

2.3 Critical Rainfall Calculation

According to the RPRPCs, which are generated using the methods proposed in Section 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.

Fig.3 Flowchart of the trial algorithm for critical rainfall

(1) The HEC-HMS model is constructed using the method mentioned in Section 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 water level-flow relationship for the control channel in the study area, the disaster flood flow Q_z is determined according to the measured disaster water level.

(4) Q_m and Q_z are compared. If the deviation satisfies the requirement of calculation accuracy (i.e., $|Q_m - Q_z| \leq \delta$), 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 antecedent soil moisture condition (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.

Fig. 4 Schematic diagram of early warning mode establishment

3 Case Study

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.

Fig. 5 Schematic diagram of the Xinxian watershed

Table 1 characteristics of the study area

Watershed	Area (km ²)	River length (m)	Mean slope	Typical river section	Source of flood date	Source of rainfall date
Xinxian	274	39.27	0.018	Caohezu	Xinxian hydrology station (1967-2018)	Sidian rainfall station (1968-2018)

The data used in this paper includes GIS data, rainfall data and flood 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 flood data were provided by the hydrological bureau of Henan. The time resolution was considered as 1 h. After the division of rainfall events, there were 44 rainfall events with a total duration of 12 h, which accounted for the largest proportion of the total rainfall events.

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 2 and Table 3.

Table 2 The results of K-S test for marginal distribution

Characteristic parameters	K-S test	
	Calculated	Critical value
Total rainfall	0.106	0.2006
Peak rainfall intensity	0.114	

Table 3 The correlation coefficients between total rainfall and rainfall peak intensity

Characteristic parameters	Correlation coefficients			
	γ	τ	ρ	Reference value
Total rainfall	0.822	0.806	0.876	0.8
Peak rainfall intensity				

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 both 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 γ , Kendall rank correlation coefficient τ , and Spearman rank correlation coefficient ρ , 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 4 and Table 5.

Table 4 The results of K-S test for the joint distribution function

Copula Functions	K-S test	
	Calculated	Critical value
Gumbel	0.1255	0.2006
Clayton	0.1104	
Frank	0.1182	

Table 5 Evaluation of goodness of fit for three copula functions

Copula Functions	Criteria		
	RMSE	AIC	BIC
Gumbel	0.0457	-268.4659	-266.6817
Clayton	0.0520	-257.0868	-255.3026
Frank	0.0409	-278.2837	-276.4995

According to Table 4, 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 5, all evaluation values of the Frank function were the smallest for the three evaluation criteria of fitting goodness, which shows that the goodness of fit of the Frank function was 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 were adopted to carry out the calculation of the basin module. These included the initial and constant method, the soil conservation service unit hydrography method, the recession curve method and the Muskingum method. Ten typical 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 6.

Table 6 Simulation results of the floods

State	Number	Peak flow(m^3/s)		Flood volume(10^6m^3)		NSE
		Simulated	Measured	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	5.8	5.4	0.861
	19960714	966.1	935	30.9	29.6	0.926
	20040718	347	339	2.8	2.9	0.887

It can be seen that all the relative deviation between the simulated value and the measured value of the peak flow and 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. 6.

Fig.6 Comparison of rainfall patterns:(a) rainfall 20040718 (b) rainfall 20080816 (c) rainfall 20160701

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 (8). The approach degrees of the rainfall patterns for the three rainfall events are shown in Table 7.

$$e = 1 - \sqrt{\frac{1}{N} \cdot \sum_{n=1}^N (z_n - y_n)^2} \quad (8)$$

Where e is the approach degree, N is the total number of time periods; z_n is the rainfall proportion

of the n th time period for the measured rainfall; y_n is the rainfall proportion of the n th time period for the RPRPC.

Table 7 Approach degree of three rainfall events

Rainfall number	20040718	20080816	20160701
Approach degree	0.981	0.951	0.966

It can be seen that the approach degrees between the RPRPC and measured rainfall are all greater than 0.95, indicating that the RPRPC is in good agreement with the measured rainfall. 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 is compared with time-interval characteristic rainfall (TICR) (Park and Chung, 2020) . and the deviation degree (National Mountain Flood Prevention and Control Group, 2016) has also been calculated according to Eq (9). The results are shown in Table 8.

$$DD = |(CR - TICR) / TICR| \times 100\% \quad (9)$$

Where DD is the deviation degree.

Table 8 Deviation degree results between CR and TICR

Rainfall number	ASMC (mm)	Early-warning Time(h)	TICR (mm)	CR (mm)	DD (%)
20140718	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	0.5Wm	3	75	68	9.3
		6	96	109	13.5
		12	269	237	11.9

Note: Wm denotes the saturated soil moisture

It can be observed that all the deviations for different combinations of ASMC and early warning

time are less than 15%, which meets the accuracy requirements. The deviation results prove that the CR based on the RPRPC has a high reliability.

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 the RPRPC 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 Fig. 7 and Fig. 8, respectively.

Fig. 7 Rainfall pattern collection:(a) (0.02, P_B); (b) (0.05, P_B); (c) (0.1, P_B)

Fig. 8 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

Based on Fig. 8, the maximum CR threshold for 12 h, 6 h, and 3 h are 73~163 mm, 53~101 mm, 41~61 mm, respectively. 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. 7. 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. It can be concluded that that the longer the regulation and storage time is, the smaller the influence of the ASMC on CR will be.

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 Section 2.4. The results are shown in Fig. 9.

Fig. 9 (a) Optimistic early warning mode; (b) General early warning mode; (c) Pessimistic early warning mode

Rainfall 201607001 in Caohezu is 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 the China Meteorological Agency, the rainstorm grade in Xinxian on 1st July 2016 was heavy rainfall, so the G mode was used for early warning. The ASMC for this rainfall was 0.5Wm. The corresponding early warning information is shown in Fig. 10.

Fig. 10 Warning information chart for the G mode of Caohezu for heavy rainfall on 1th July 2016

Comparing the accumulated rainfall in various EWTPs and the CR line, the 3 h accumulated rainfall exceeded the G-3 CR line during the 4th 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 early warning signal had been issued at 09:00 through the O-G-P early warning mode. The warning time is therefore 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) Copula function can be used to determine the joint distribution function of total rainfall and peak rainfall intensity. The RPRPC design method based on copula function is a novel and practical method. The simulated rainfall processes based on the RPRPC are more accurate than those based on the traditional rainfall pattern.

(2) The flood peak and flood volume of the watershed simulated by the HEC-HMS model are very close to the measured flood data, which proves that the simulation results of the rainfall-runoff process are reasonable and reliable. The HEC-HMS model has good performance in the simulation of flash floods in a small watershed in a hilly area.

(3) Both ASMC and rainfall pattern have an impact on CR. 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.

(4) The O-G-P early warning mode, which considers decision makers' experience in disaster prevention and risk preference, is effective. It can provide effective information for 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, we will study the uncertainty of multimodal rainfall patterns based on this study, thereby determining the accurate critical rainfall and further improving the accuracy of the early warning of flash floods.

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Figures

Figure 1

Schematic diagram of flash flood early warning and forecasting based on the RPRPC

Figure 2

Calculation flow chart for the rainfall distribution for each time period

Figure 3

Flowchart of the trial algorithm for critical rainfall

Figure 4

Schematic diagram of early warning mode establishment

Figure 5

Schematic diagram of the Xinxian watershed Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 6

Comparison of rainfall patterns:(a) rainfall 20040718 (b) rainfall 20080816 (c) rainfall 20160701

Figure 7

Rainfall pattern collection:(a) (0.02, PB); (b) (0.05, PB); (c) (0.1, PB)

Figure 8

Critical rainfall :(a) PA=0.02, EWTP=12 h; (b) PA =0.02, EWTP=6 h; (c) PA =0.02, EWTP=3 h; (d) PA =0.05, EWTP=12 h; (e) PA =0.05, EWTP=6 h; (f) PA =0.05, EWTP=3 h; (g) PA =0.10, EWTP=12 h; (h) PA =0.10, EWTP=6 h; (i) PA =0.10, EWTP=3 h

Figure 9

(a) Optimistic early warning mode; (b) General early warning mode; (c) Pessimistic early warning mode

Figure 10

Warning information chart for the G mode of Caohezu for heavy rainfall on 1th July 2016