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Article

County-Level Flash Flood Warning Framework Coupled with Disaster-Causing Mechanism

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Abstract: Climate change has intensified the risk of extreme precipitation, while mountainous areas are constrained by complex disaster mechanisms and difficulties in data acquisition, making it challenging for existing critical rainfall threshold accuracy to meet practical needs. Therefore, this study focuses on Yunnan Province as the research area. Based on historical flash flood events, and combining remote sensing data and measured data, 12 causative factors are selected from four aspects: terrain and landforms, land use, meteorology and hydrology, and population and economy. A combined qualitative and quantitative method is employed to analyze the relationship between flash floods and triggering factors, and to calibrate the parameters of the RTI (Rainfall Threshold Index) model. Meanwhile, machine learning is introduced to quantify the contribution of different causative factors and identify key causative factors of flash floods. Based on this, a parameter η coupling the causative mechanism is proposed to optimize the RTI method, and develop a framework for calculating county-level critical rainfall thresholds. The results show that: (1) Extreme rainfall, elevation, slope, and other factors are direct triggers of flash floods, and the high-risk areas for flash floods are mainly concentrated in the northeast and southeast of Yunnan Province. (2) The intraday rainfall has the highest correlation with the accumulated rainfall of the previous ten days; the critical cumulative rainfall ranges from 50 mm to 400 mm. (3) The county-level critical rainfall threshold for Yunnan Province is relatively accurate. These findings will provide theoretical references for improving flash flood early warning methods.

Keywords: flash flood; triggering factors; RTI; critical rainfall threshold; Yunnan province

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1. Introduction

Global climate warming has led to an increase in extreme precipitation, resulting in one of the most severe flood disasters—flash floods. Flash floods occur mainly in mountainous areas with complex terrain, caused by heavy rainfall, and can trigger disasters such as debris flows and landslides [1]. They are characterized by their suddenness, short duration, rapid onset, and high destructiveness [2], causing serious damage to the national economy, people's lives, and property. For example, on 21 August 2023, a major flash flood disaster in Luga Town, Jinyang County, Sichuan Province, China, resulted in 52 deaths and missing persons. In July 2022, heavy rain-induced floods in multiple regions of Iran caused over 100 deaths and missing. Therefore, how to enhance flood disaster resilience, especially improving the accuracy of key measures for flash flood early warning and forecasting, has become a focal point in the field of disaster risk reduction.

Since the 20th century, both domestic and international research has been conducted on the prevention of flash flood disasters, primarily focusing on its core technology of early warning and forecasting. The United States established the Flash Flood Guidance System (FFGS) in 1969, which is currently one of the most widely used flash flood warning systems in the world [3]. Japan, being prone to various geological disasters, has conducted extensive research on landslide and debris flow warnings. For example, in 1984, the Japanese government established guidelines for determining critical rainfall thresholds for debris flow disasters. In addition, the Sediment Disaster Prevention Law, implemented since 2001, actively promotes the establishment of sediment disaster monitoring and early warning systems [4]. In 1990, scholars in Taiwan, China, proposed that an early warning system is a primary condition for debris flow prevention. Since 2000, the Taiwan Soil and Water Conservation Bureau has utilized a debris flow warning system to establish a mechanism and platform for issuing debris flow warnings. In mainland China, research on flash flood disaster warnings started relatively late [5]. In 2006, following the State Council's approval of the "National Plan for Flood and Debris Flow Disaster Prevention", a comprehensive strategy for flash flood disaster prevention was established, emphasizing a "prevention-first, integrated prevention and control, emphasis on non-engineering measures, and a combination of non-engineering and engineering measures" approach to flash flood disaster prevention [6].

Early warning indicators are critical values derived from rainfall information and disaster conditions for specific disaster prevention objects. They generally include three types: critical rainfall, critical water level, and critical flow rate [7–9]. Currently, research on early warning indicators has become more refined. The determination methods have evolved from complete empirical approaches to semi-empirical and semi-theoretical methods, and further, to dynamic early warning. Static early warning indicator analysis involves various methods, including statistical induction, empirical analysis, and hydrological methods. It mainly analyzes the correspondence between rainfall elements and flash flood disasters. These methods are simple to calculate and widely applied in operational settings [10,11]. Dynamic critical rainfall thresholds take into account real-time soil moisture. When the peak flow at the watershed's outlet section reaches the flow threshold, the required rainfall amount is estimated. Bournas et al. [12] used the Flash Flood Guidance (FFG) method in Greece to predict flash floods, conducting sensitivity analysis on threshold runoff and soil moisture conditions, which allowed for advanced warning time. Ye et al. [13] utilized the Xin'anjiang model to obtain the dynamic critical rainfall threshold for flash floods and successfully applied it in the Pihe Basin in Anhui Province. Liu et al. [14] proposed a flash flood dynamic critical rainfall warning method based on a distributed hydrological model, and successfully applied it in the Suichuan River Basin. Furthermore, some experts have attempted to employ both hydrodynamic models and machine learning. Tufano et al. [15] used a two-dimensional hydrodynamic model to generate flood inundation maps and obtained the risk range by overlaying the layers. Janizadeh et al. [16] utilized various machine learning methods to assess flash flood susceptibility in the Tafresh watershed in Iran. He established a geographic spatial database containing 320 historical flood events. Combining this database with eight selected flood-influencing factors, he found that the Average Decision Tree (ADT) method outperformed other methods. In summary, research on dynamic critical rainfall thresholds in China started relatively late. The purely empirical method, despite lacking clear physical mechanisms, has relatively low data requirements and is commonly applied in un-gauged areas. The semi-empirical and semi-theoretical methods are in a developmental stage, with the primary approaches currently being the water level–flow inverse method and the comprehensive multi-factor rainfall warning index method.

The water level–flow inverse method primarily involves simulating flood processes using different hydrological models to determine the critical flood level. Subsequently, by considering cross-sectional characteristics and the hydrological-flow relationship, the critical flow is obtained, allowing for the reverse calculation of the warning rainfall. Then, considering the cross-sectional characteristics and the hydrological–flow relationship, the critical flow is obtained, allowing for the reverse calculation of the warning rainfall. For example, Zhang et al. [17] established the water level–flow relationship using the Manning formula. Subsequently, they introduced the HEC-HMS model to reverse calculate the critical rainfall for flash flood disasters in small watersheds. Yuan et al. [18] analyzed the influence of antecedent soil moisture conditions (ASMC) and rainfall patterns on critical rainfall and calculated the critical rainfall thresholds corresponding to different scenarios. Rainfall is the main triggering factor for flash floods, including rainfall amount, intensity, and duration. Flash floods are closely related to factors such as intraday rainfall, antecedent rainfall, and rainfall intensity. The triggering rainfall (intensity) is an essential factor [19]. L. Alfieri et al. [20], based on the European Precipitation Index for Catchments (EPIC), determined the threshold for extreme accumulated rainfall in flash flood-prone small watersheds, and this threshold demonstrates good predictive accuracy. The Rainfall Triggering Index (RTI) method, proposed by Jan [21], is a mudflow disaster defense method that has been successfully applied in practice. This method primarily takes into consideration rainfall factors related to flash floods, such as rainfall intensity, antecedent rainfall, and accumulated rainfall, to determine the warning indicators.

Relevant researchers often concentrate on small watersheds, using their historical flood events to determine warning indicators through the construction of critical area maps or empirical frequency methods. They also explore the application of the RTI model. Nam et al. [22] predicted landslides and mudflows by calculating rainfall triggering indices that reflect accumulated rainfall and rainfall intensity, and provided real-time forecasts using rainfall information. Guo et al. [23] calculated the composite warning indicators for the Beizhangdian small watershed, and subsequently determined the critical values corresponding to different warning information. Peng et al. [24] employed the rainfall-driven index method, at the village level, to establish the relationship between rainfall intensity and effective accumulated rainfall. Ma et al. [25] introduced the rainfall triggering index β and, based on different triggering factors, used either the RTI method or the I-D method to analyze the accumulated warning rainfall in Yunnan Province. Obviously, the RTI model has been applied in China and has achieved certain early warning effectiveness.

The RTI method not only considers multiple rainfall factors but also improves the linear I-R model. It has low data requirements and mainly infers critical rainfall based on the relationship between flash floods and rainfall. However, this method focuses too much on flash floods' driving factors and ignores the influence of regional geography, hydrology, er al., resulting in less-than-ideal practical early warning effectiveness. In recent decades, researchers, both domestically and internationally, have conducted in-depth studies on the concept, formation, development, and evolution of flash flood disasters. They mainly analyze key influencing factors such as rainfall characteristics, topography, soil types, and vegetation cover to enhance the accuracy of defense against flash flood disasters. With the continuous development of modern science and technology, high-resolution remote sensing data are widely used to explore the characteristics of study areas and watersheds prone to flash flood disasters for risk assessment. Subraelu. et al. [26] combined eight satellite image-derived parameters to predict the flash flood-vulnerable zones in Arid Region, Fujairah City, UAE. Mohamed et al. [27] explored methods for determining the weights of hazard and vulnerability factors, such as topography, geology, and hydrology, utilized to calculate the risk of flash floods in Egypt. Hamid. et al. [28] digitized ten factors, including elevation, slope, land use, terrain wetness index, etc., and then created a flash flood map to estimate the flash flood sensitivity. The underlying surface parameters are an important basis for flash flood risk prediction. Satellite remote sensing can provide effective basic information for data-deficient areas, which is advantageous in reducing the uncertainty of early warnings [29].

Remote sensing data alleviate the constraints of the natural environment, expanding the scope of data collection and providing valuable foundational information for data-deficient areas [30]. Ruzza et al. [31] evaluated the potential of Sentinel-1 SAR imagery in tracking floods during flood events in the Philippines. El-Magd et al. [32] utilized Landsat-8 imagery and other remote sensing data to explore the impact of flash floods on industrial areas. Bui et al. [33] utilized a GIS database, combined with 12 influencing factors, to construct a prediction model and validated it. With the development of modern information technology, how to integrate remote sensing data to explore the disaster mechanisms of flash floods, thereby improving the accuracy of traditional warning methods, is a crucial issue that urgently needs to be addressed in flash flood disaster defense efforts. Therefore, this study focuses on Yunnan as the research area, utilizing historical flash flood events, combined with remote sensing data and field measurements. Through quantifying the contributions of triggering factors in flash floods, the study introduces the coupling factor η for disaster mechanisms to optimize and improve the RTI method. Subsequently, a framework for calculating county-level critical rainfall threshold for flash floods has been developed. Yunnan is a region prone to flash floods in China. With the increasing frequency of extreme weather events in the future, improving the accuracy of flash flood warning in Yunnan Province can provide theoretical references for coping with future disasters. This research will provide theoretical reference and insights for the ongoing flash flood disaster defense efforts in China.

2. Study Area and Data

2.1. Research Area

Yunnan is located in the southwestern border of China, between 97°31′ E and 106°12′ E longitude and 20°08′ N and 29°16′ N latitude, with a total area of 394,100 km^2, accounting for 4.1% of the total national area. It has 16 prefecture-level administrative regions and 129 county-level administrative regions. The total population is 48.583 million, with a population density of 123.3 people per square kilometer, and a GDP of CNY 2.3223 trillion. Yunnan is located on a low-latitude plateau, characterized by many mountains, high mountains, steep slopes, and complex topography. The annual rainfall ranges from 100 mm to 1500 mm, with more rain in the south and less in the north, distinct wet and dry seasons, and uneven distribution of precipitation in time and space, especially concentrated in the wet season.

Influenced by topography, landforms, climate, etc., Yunnan frequently experiences small-scale regional heavy rainstorms and single-point heavy rainstorms, making it a heavily flash flood-affected area in China. In summer, Yunnan is greatly affected by the southwest and southeast monsoons, with a high occurrence of short-term regional heavy rainfall and sustained low-intensity rainfall, making it susceptible to serious flash floods. According to data from 2011 to 2016, more than 350 people died or went missing due to flash floods. Over 90% of these flash floods occurred between the months of June and September, with July being the most frequent month for such disasters, accounting for approximately 45% of the annual flash flood events. The areas with higher density of flash flood occurrences are mainly in the northeast, northwest, and southeast. Among them, Honghe Prefecture and Zhaotong City experienced a higher number of flash flood incidents (Figure 1).

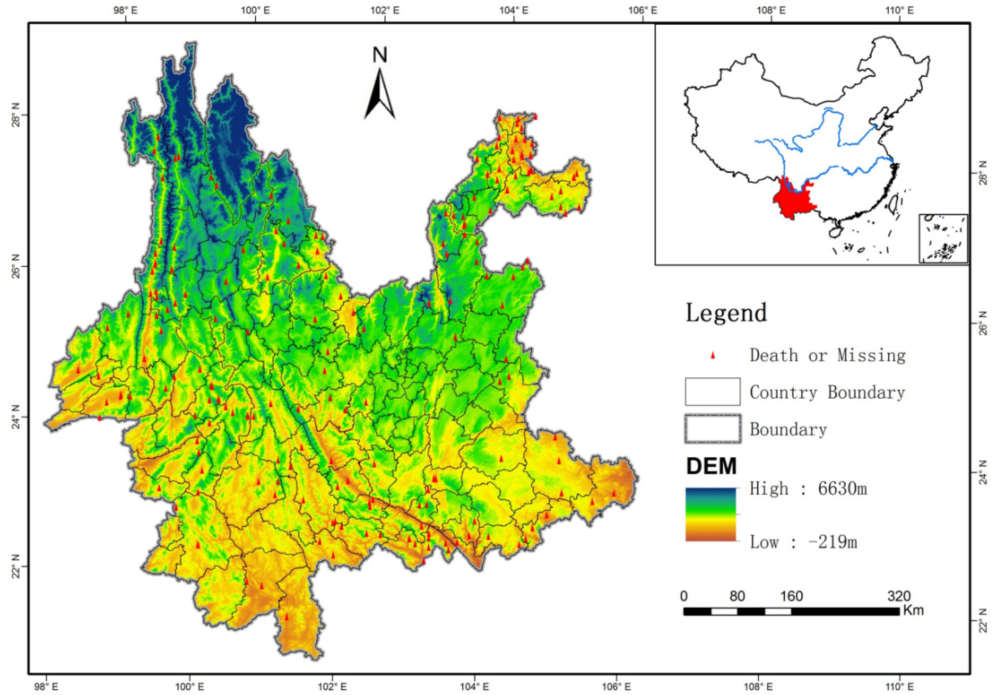

Figure 1. Location of the research area and distribution of flash floods (2011–2016).

2.2. Data

The flash flood disasters mainly come from officially authorized and verified statistics, including information from the Ministry of Water Resources and various provincial water resources departments. This study is primarily constrained by insufficient data. There was a higher occurrence of flash floods in Yunnan Province from 2011 to 2016; we compiled flash flood disaster data for Yunnan Province from 2011 to 2016, including the occurrence time, location, and the number of missing and deceased individuals. Simultaneously, we collected the intraday 24 h accumulated rainfall data for each event, along with the corresponding rainfall intensity, to analyze the rainfall before and after flash flood occurrences. The geomorphic type is primarily classified based on elevation, including plains, plateaus, hills, and mountains. Additionally, subcategories such as small, medium, large, and extreme are further defined based on the degree of undulation. Table 1 shows the factors causing flash flood and their data sources.

Table 1. Factors causing flash flood and their data sources.

Characteristics	Name	Source
Topographic	Digital Elevation Model (DEM)	Shuttle Rador Topography Mision (SRTM)
Topographic	Slope	Shuttle Rador Topography Mision (SRTM)
Topographic	Geomorphic type	Chinese Academy of Sciences Resource and Environmental Science Data Center
Land	Soil type	Chinese Academy of Sciences Resource and Environmental Science Data Center
Land	Soil Texture	Chinese Academy of Sciences Resource and Environmental Science Data Center
Land	Land use status	Chinese Academy of Sciences Resource and Environmental Science Data Center
Meteorological	Maximum 3 h rainfall	Chinese Meteorological Dataset
Meteorological	Maximum 24 h rainfall	Chinese Meteorological Dataset
Hydrological	Distribution of water systems	Chinese Vector Format Datasets
Socio-economic	Population	Chinese Academy of Sciences Resource and Environmental Science Data Center
Socio-economic	Gross Domestic Product (GDP)	Chinese Academy of Sciences Resource and Environmental Science Data Center

3. The County-Level Flash Flood Warning Framework Coupled with the Disaster-Causing Mechanism

3.1. The Framework for the County-Level Critical Rainfall Threshold

This article focuses on the calibration and optimization of the RTI model, mainly using remote sensing data and measured data to introduce the parameter η associated with causative mechanisms, in order to address the insufficient consideration of causative factors in the traditional RTI model. The study develops a framework for county-level critical rainfall warning thresholds. Specifically, to overcome the limitation of the traditional RTI model that mainly focuses on rainfall factors, we propose a coupled disaster-causing mechanism parameter, η. This involves initially standardizing influencing factors such as terrain and landforms, land use, meteorology and hydrology, and population and economy. Subsequently, η is obtained through a weighted process, leading to the improvement of the cumulative rainfall (Pa) to ηPa. This modification aims to present an enhanced RTI model. The research area is Yunnan Province, where 12 key causative factors are identified. A combined qualitative and quantitative method is used to analyze the relationship between flash floods and triggering factors. Machine learning is used to quantify the contribution of causative factors, and the parameter η is proposed to modify the previous n-day cumulative rainfall Pa to ηPa. As the flash flood triggering index β for most events in Yunnan Province is greater than 5, the preceding rainfall is chosen as the independent variable, and the rainfall on the current day is taken as the dependent variable for regression analysis. The preceding rainfall days, denoted as i, are determined using the maximum linear correlation.

The RTI cumulative probability is calculated using the Weibull empirical frequency method. The lower and upper bounds of the rainfall warning are established as the lower bound line (RTI_{10}) and upper bound line (RTI_{90}), respectively. These bounds divide the possibility of flash flood occurrence into high, moderate, and low categories. The warning value for Yunnan Province is set as RTI_{50}, and R_{50} is taken as the critical rainfall indicator R_c. The range of warning rainfall for Yunnan Province is determined accordingly. Finally, using ArcGIS 10.8, the critical rainfall thresholds in Yunnan Province are divided at the county level, obtaining the flash flood warning thresholds for each county. This contributes to the development of a framework for calculating county-level critical rainfall threshold. The specific approach is shown in Figure 2.

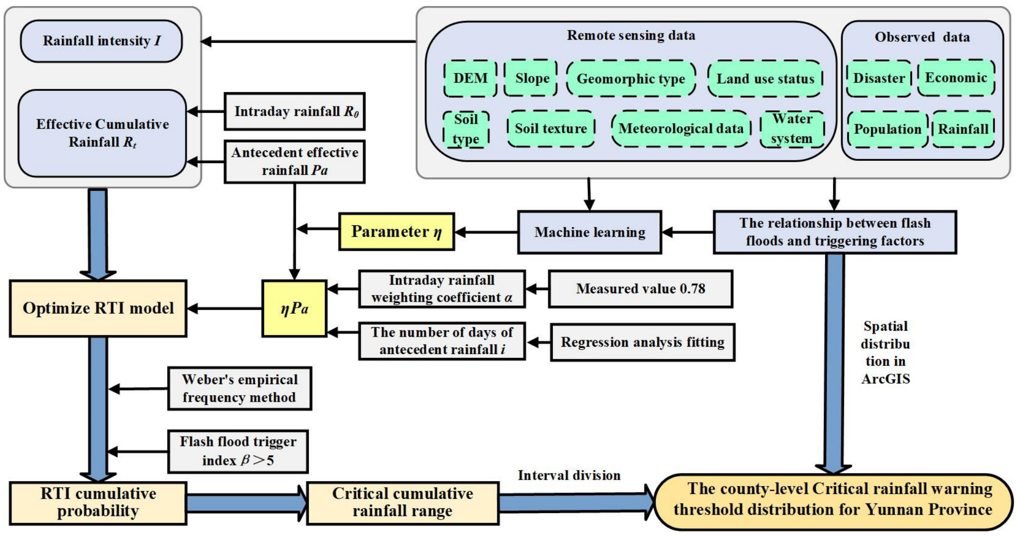

Figure 2. The framework for calculating county-level critical rainfall threshold.

3.2. RTI Model and Parameter Calibration Method

Flash flood disasters are primarily associated with heavy rainfall. First, we refer to the definition of rainfall events as outlined by Jan et al. [21]. Rainfall events are primarily determined based on the magnitude of hourly rainfall. The start time of rainfall is considered when it exceeds 4 mm, and the end time is when it is less than 4 mm and continues so for 6 h. The peak of the hourly rainfall represents the flash flood occurrence. The rainfall preceding the onset of this rainfall is referred to as antecedent rainfall. The division of rainfall events is depicted in Figure 3.

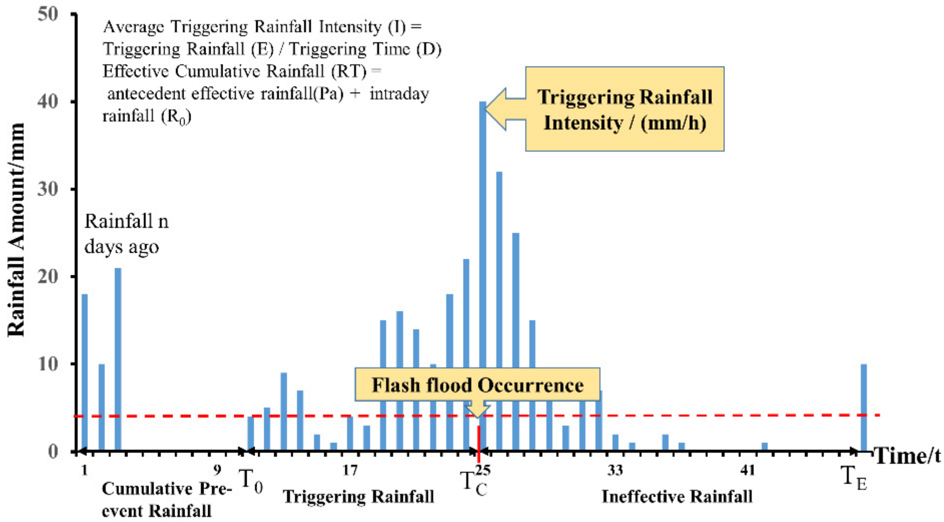

Figure 3. Rainfall event division diagram.

The RTI model, proposed by Jan et al. [21], is a method for determining the indicators for flash flood warnings by considering factors related to flash floods such as rainfall intensity, antecedent rainfall, and accumulated rainfall. It is currently widely operationalized in disaster defense efforts. The model is the product of two indicators: rainfall intensity (I) in mm/h and accumulated rainfall (R_t) in mm. The specific equation is as follows:

$$\mathrm{RTI} = I \times R_t \tag{1}$$

$$R_t = R_0 + Pa = R_0 + \sum_{i=1}^{n} \alpha^i R_i = \sum_{i=0}^{n} \alpha^i R_i \tag{2}$$

where:

I: rainfall intensity in mm/h.
R_t: the accumulated rainfall before the occurrence of a flash flood in mm.
R_0: the accumulated rainfall from the start of rainfall to the occurrence of the flash flood in mm.
Pa: the accumulated rainfall in the n days before the start of the flash flood in mm.
i: the number of days used to calculate the pre-event rainfall.
α: the intraday rainfall weighting coefficient.

Indeed, this model only takes into account rainfall factors, while flash floods are the result of multiple factors combined. Elevation, slope, land use, etc. play a pivotal role in triggering flash floods. Therefore, we propose the parameter η that couples with the disaster-causing mechanism. This parameter primarily improves the accumulated rainfall Pa to ηPa, resulting in an enhanced RTI model. The specific calculation equation is as follows:

$$\eta = \frac{w_1 f_1 + w_2 f_2 + \cdots + w_i f_i}{f_1 + f_2 + \cdots + f_i} \tag{3}$$

where:

f_i: the average value of the i-th disaster-causing factor;
w_i: the weight of the i-th disaster-causing factor.

When calculating η, obtain disaster-causing factor information and analyze it through remote sensing data, typically selecting no more than 15 factors, and obtain their disaster-causing weights using machine learning. Then, the standardized processing is conducted, and the weighted sum is obtained. After determining the rainfall driving indicators, the lower and upper boundary lines for flash flood rainfall warnings are established. The probability of a flash flood occurrence is determined based on a linear relationship, calculated using the following equation:

$$\mathrm{RTI}_p = \mathrm{RTI}_{10}\left(\frac{P-0.1}{0.8}\right)(\mathrm{RTI}_{90} - \mathrm{RTI}_{10}) \tag{4}$$

where:

RTI_P: the RTI value when the probability of a flash flood occurrence is P%.

The RTI of historical rainfall events (including both flash flood and non-flash flood events) are sorted in ascending order. RTI_{10} is the value at the 10th percentile, calculated using the Weber method [21]. RTI_{90} is the value at the 90th percentile. The probability of a flash flood occurrence is then divided into different zones. when the RTI value for a rainfall event is less than RTI_{10}, the likelihood of a flash flood occurrence is low, whereas if it exceeds RTI_{90}, it indicates a high probability of a flash flood event. Combined with the analysis of disaster-causing factors, the warning value is set at RTI_{50}, where R_{50} is RTI_{50} divided by 10 mm/h. The warning rainfall range is determined using a 50 mm interval. Finally, the county's warning indicators are obtained by combining the above with ArcGIS 10.8.

In addition, this study also references the flash flood trigger index β proposed by Ma et al. [25], which categorizes factors that trigger flash floods into short-term heavy rainfall-induced and sustained low-intensity rainfall-induced factors. The calculation equation is as follows:

$$\beta = R/R_0 \tag{5}$$

where:

R: the effective accumulated rainfall;
R_0: the intraday rainfall.

4. Results and Analysis

4.1. Analysis of Disaster Causal Factors

4.1.1. Topography and Landforms

Topographic factors are important factors that trigger flash floods. Yunnan is located in the transitional zone from the Qinghai–Tibet Plateau to the Yungui Plateau and Sichuan Basin, with higher elevations in the northwest and lower elevations in the southeast, gradually decreasing in altitude from north to south. According to Figure 4a–c, mountains and plateaus account for 94% of the total area. The eastern part of Yunnan is mainly composed of the Yungui Plateau, with an average elevation of around 2000 m. The terrain is relatively gentle, characterized by rolling low hills. The northwest and northeast are the southern extensions of the Qinghai-Tibet Plateau, with a distribution of large and medium-sized undulating mountains and valleys, featuring significant differences in elevation. The south gradually becomes gentler, with elevations ranging from 800 m to 1000 m. Approximately 40% of the province's mountainous areas have slopes greater than 25°, while in the northwest and northeast, this figure can reach 60% to 90%. Except for the relatively gentle terrain in the east, where the frequency of flash floods is low, other regions are characterized by mountainous areas with high elevations and a high risk of flash floods.

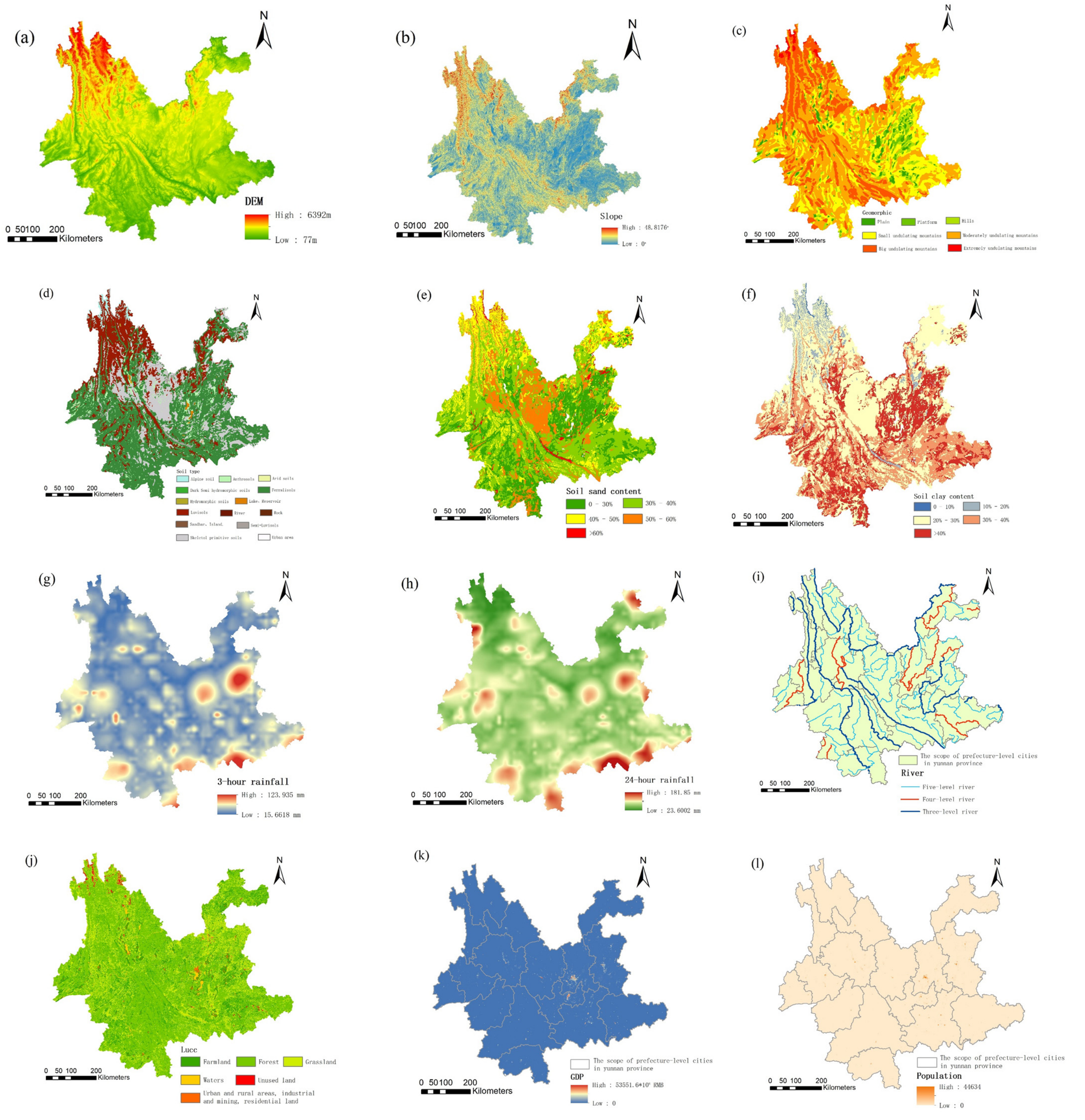

Figure 4. Distribution of factors influencing flash flood. (**a**) DEM, (**b**) slope, (**c**) geomorphic type, (**d**) soil type, (**e**) soil sand content, (**f**) soil clay content, (**g**) 3 h rainfall, (**h**) 24 h rainfall, (**i**) water system, (**j**) land use status, (**k**) GDP, (**l**) population.

4.1.2. Soil and Land Use

Loose soil and soil composition are the material source conditions for flash floods. Soil types and land use reflect the impact of human activities on flash floods. Figure 4d–f depict the soil conditions in Yunnan. Yunnan has various soil types, with ferrallisols, luvisols, and skeletol primitive soils accounting for approximately 92% of the total soil area. Ferralisols account for about 55%, mainly distributed in the southwest and east. The main soil types in this region are red soil and red-yellow soil. Humans have converted gentle slopes such as valley slopes into cultivated land, resulting in low vegetation cover and low organic matter content, making the soil prone to erosion and disintegration. Leaching soils belong to forest soils and are mostly distributed in the high mountains of northwest and northeast Yunnan. The forest coverage is high, making it less susceptible to erosion and loss from heavy rainfall. In terms of soil texture, the majority of soils have a sand content of about 20% to 40%, mainly distributed in northwest and northeast Yunnan, accounting for about 40% to 60%. Most of the land used for agriculture, residential purposes, etc., which has good water retention and is less prone to erosion, is located in soils with a clay content greater than 40%. However, human activities have reduced the soil's erosion resistance.

4.1.3. Meteorology and Hydrology

Rainfall and rainfall intensity are important water sources and driving conditions for flash floods. Among them, the 24 h rainfall can reflect the distribution of rainfall, and the 3 h rainfall can reflect the rainfall intensity. Combined with Figure 4g–i, the maximum 24 h rainfall ranges from 25 mm to 180 mm, while most areas have a 24 h rainfall of 50 mm to 100 mm. Yunnan has abundant rainfall during the flood season, especially in the eastern and southern basins, where heavy rainfall often occurs, leading to flash flood disasters. The range of 3 h rainfall is 16 mm to 124 mm, and its spatial distribution is basically consistent with the distribution of 24 h rainfall. Obviously, the combination of rainfall and rainfall intensity results in more localized and short-duration heavy rainfall, which can trigger flash flood disasters. Yunnan has a dense river system, with high mountains and canyons in the west, characterized by large drops and large changes in water flow. Therefore, during flash floods, river water levels rise rapidly. Meantime, the density of the river system is high, and there are many streams with flash flood potential.

4.1.4. Population and Economy

Population and economic characteristics mainly reflect the distribution of human settlements and social property, which can provide a preliminary assessment of affected people and the extent of economic losses after flash floods. Combined with Figure 4j–l, the population distribution is more concentrated in the east and less in the west. From a topographical perspective, areas with gentle terrain in valleys and basins have a higher population density. The population in the northwest accounts for only 1.97% of the total population, indicating significant differences in population distribution. Economic and population distribution exhibit a positive correlation in spatial terms. In a few counties in eastern and central Yunnan, the economic development level is relatively high, and the population is concentrated. However, economic development lags behind population growth. Conversely, in the southwestern and southeastern regions, the situation is reversed, with a concentration of population and relatively lower economic development.

The occurrence of flash floods is influenced by highly complex environmental factors, with various triggering factors interacting. Firstly, rainfall serves as a water source and driving force for flash floods; extreme 24 h rainfall often occurs during heavy rain events with high precipitation intensities, and is related to slope conditions of the terrain. Terrain and topography are fundamental factors triggering flash floods, while complex geological conditions exacerbate internal factors of flash floods [34]. In flash flood-prone areas, the terrain usually has steep slopes, significant longitudinal channel gradients, and watershed shapes that promote the convergence of water flow. Areas with significant terrain changes and steep slopes have a higher risk of flash floods. Based on the above research results, the frequency of flash floods is higher in the southeastern and northeastern regions of Yunnan Province. This is primarily due to the lower elevation, dense population, and significant human activities in these areas, which accelerate the occurrence of flash floods. For example, although there are many high-altitude mountainous areas in the northwest of Yunnan Province, the occurrence of flash floods is relatively low. However, the terrain in this region undergoes significant changes, with high channel gradients and valley slopes. Additionally, soil type is directly related to the occurrence of flash flood disasters. The southeast of China is dominated by red soil, which is extensively cultivated, leading to a decrease in soil fertility and poor soil aggregation. The northeastern region has high sand content in the soil and thick soil layers. Excessive development of red soil by human activities has resulted in reduced particle cohesion and increased loose materials, making it more prone to flash floods.

Human activities and economic development also play a key role in triggering flash floods, affecting land use and resulting in low vegetation coverage. Furthermore, economically underdeveloped areas often lack adequate defense measures and complete early warning systems, making it difficult to take timely and effective measures to reduce disaster losses. Considering the above influencing factors, it is evident that the northwestern region of China has significant terrain changes and a lower frequency of flash floods. This is mainly due to lower rainfall, higher elevations, and greater forest coverage, with minimal human influence. On the other hand, Nujiang Prefecture in the southwest is at higher risk of flash floods due to location on windward slopes, significant terrain changes, and abundant precipitation. The central region has gentle slopes, resulting in a lower risk of flash floods.

4.2. Critical Warning Indicators for Flash Flood Disasters

4.2.1. Rainfall Triggering Index (RTI)

First, divide the rainfall events; that is, calculate the 1 h rainfall intensity in flash flood events. Then, calculate the effective accumulated rainfall (R_t), which includes antecedent accumulated rainfall and event-specific accumulated rainfall. The previous rainfall affects the soil moisture content, which in turn affects the soil's permeability, pore water pressure, and shear strength. The closer the soil is to saturation, the less rainfall is required to trigger a flash flood. To calculate the RTI (Rainfall Triggering Index) for each flash flood event, you should gather the accumulated rainfall for the preceding 10 days and the rainfall on the day of the event. Then, multiply the effective accumulated rainfall by the rainfall intensity.

In the RTI model, the main parameters involved are α, i, and η. α is the intraday rainfall weighting coefficient, which is related to factors such as soil moisture content and underlying surface conditions. In this case, the measured value of α is 0.78 [35]. The parameter i represents the number of days of antecedent rainfall, and it is determined through a multiple regression analysis. η is primarily determined through machine learning by analyzing the disaster contributions of triggering factors, selecting key triggering factors, standardizing them, calculating the multi-year average values of these triggering factors, and finally using Equation (3) to compute it.

Based on the above research, historical flash flood events and corresponding rainfall factors are further organized to calculate the β index. Since the majority of flash flood events in Yunnan Province have β values greater than 5, this study mainly considers the influence of previous rainfall. Taking the accumulated rainfall in the previous period as the independent variable and the rainfall on the day as the dependent variable, linear functions (Y = aX + b), exponential functions (Y = ae$^{\mathrm{bX}}$), logarithmic functions (Y = alnx + b), and power functions (Y = aX$^{\mathrm{b}}$) are used for regression analysis. The correlation between the rainfall on the day and the accumulated rainfall in the previous period is shown in Table 2, with i representing the value corresponding to the maximum coefficient of determination (R^2). Clearly, the accumulated rainfall in the previous 10 days has a significant impact on flash flood occurrences. The linear correlation between Pa_{10} and the rainfall on the day is the strongest, and the relationship is expressed as:

$$Pa_{10} = 6.3979R_0 + 11.247 \tag{6}$$

Table 2. Correlation between intraday rainfall and accumulated rainfall.

	Pa_1	Pa_2	Pa_3	Pa_5	Pa_6	Pa_7	Pa_9	Pa_{10}	Pa_{12}	Pa_{13}
Linear functions	0.4192	0.7746	0.7684	0.7819	0.7801	0.7961	0.8004	0.8020	0.8001	0.8017
Exponential functions	\	\	0.4959	0.6164	0.6034	0.6162	0.6530	0.6540	0.6538	0.6494
Logarithmic functions	0.2275	0.3779	0.3870	0.3960	0.4026	0.4209	0.4112	0.4099	0.4098	0.4082
Power functions	\	\	0.3551	0.4441	0.4292	0.4505	0.4690	0.4662	0.4626	0.4578

4.2.2. Calculation of Warning Indicators

After calculating the RTI for each flash flood event, combined with the critical zone analysis of the possibility of flash flood occurrence, warning thresholds are established. Firstly, events that meet the condition $\beta > 5$ are selected, and the RTIs are arranged in ascending order. The Weber empirical frequency method is used to calculate the accumulated frequency of the RTI at 10% as RTI_{10}. Events with accumulated frequencies less than 10% are excluded. Similarly, the RTI at 90% is taken as RTI_{90}. The results are RTI_{10} = 60 mm^2/h and RTI_{90} = 1300 mm^2/h. The possibility of flash flood occurrence is divided into three zones: when the RTI of a precipitation event is $<RTI_{10}$, the possibility of flash flood occurrence is very low; when $RTI_{10} < RTI < RTI_{90}$, it belongs to the intermediate possibility zone of flash flood occurrence; when $RTI > RTI_{90}$, the possibility of flash flood occurrence is very high. The RTIs for flash flood events are shown in Figure 5.

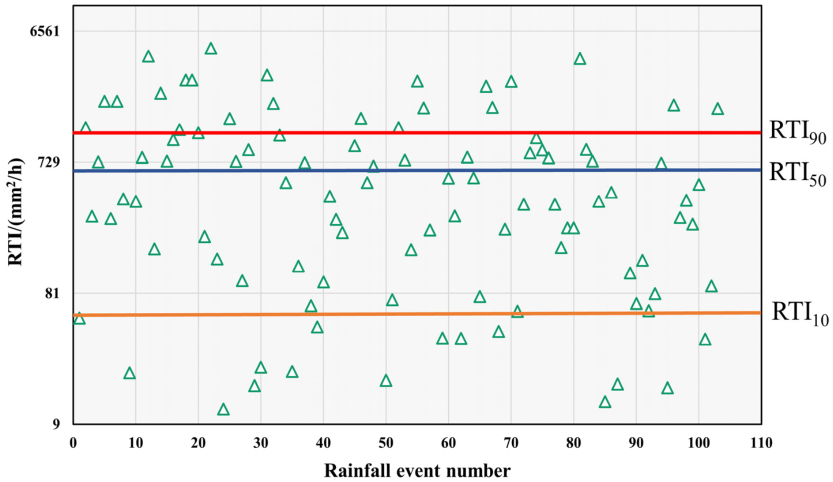

Figure 5. Distribution of RTI values for flash flood events.

According to Equation (4), RTI_{50} is obtained as 680 mm^2/h and RTI_{70} as 990 mm^2/h. Through comprehensive analysis, RTI_{50} is determined as the warning indicator. Then, RTI_{50} is divided by 10 mm/h to obtain the critical rainfall warning indicator R_c (mm), where R_{50} is 68 mm. Consequently, the critical accumulated rainfall range is determined to be 50 mm to 400 mm, with an interval of 50 mm and divided into 8 intervals. The critical zone is shown in Figure 6.

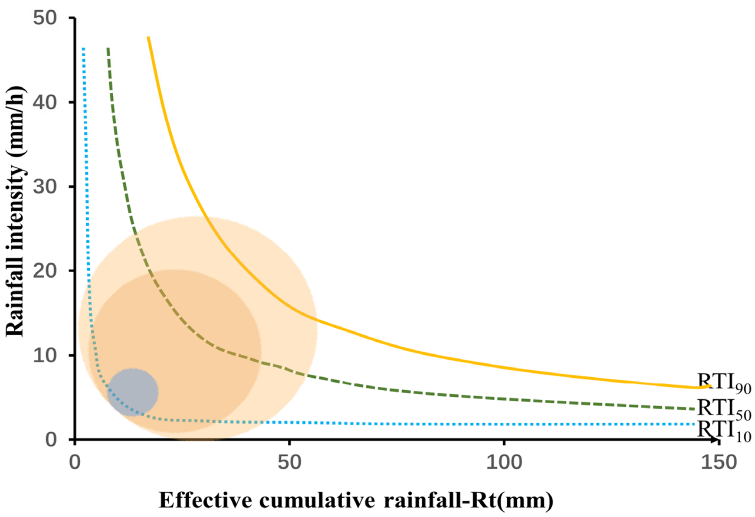

Figure 6. Zoning map of flash flood occurrence probability.

4.3. Determination of County-Level Flash Flood Warning Indicators

Based on the characteristics of the disaster-causing factors, a flash flood risk zoning is established. The high-risk areas include the northeastern and southeastern regions of Yunnan Province, while the moderate-risk areas are in the northwestern and southwestern regions. The remaining areas have relatively low risk. Chinese flood disaster defense is organized at the county level. For practical convenience, based on the improved RTI model, this study, after obtaining gridded critical rainfall data for flash floods in Yunnan Province, integrates county-level administrative boundary data. It utilizes the zonal statistics tool in ArcGIS 10.8 to calculate the grid mean values for different counties. This approach aims to derive the critical rainfall thresholds for each county in Yunnan Province. Eight rainfall ranges from 50 mm to 400 mm are divided into counties, establishing the county-level critical rainfall warning index in Yunnan Province, as shown in Figure 7. Among these, there are more than thirty high-risk flash flood counties, primarily located in the northeastern part of Zhaotong City, the southeastern regions of Wenshan Prefecture, and Honghe Prefecture. The counties with higher flash flood risks include Suijiang County, Shuifu County, and Yanjin County in the northeast of Yunnan; Pingbian County, Maguan County, and Hekou County in the southeast of Yunnan; Changning County and Lancang County in the western part; and Bijiang County and Gongshan County in the northwest of Yunnan.

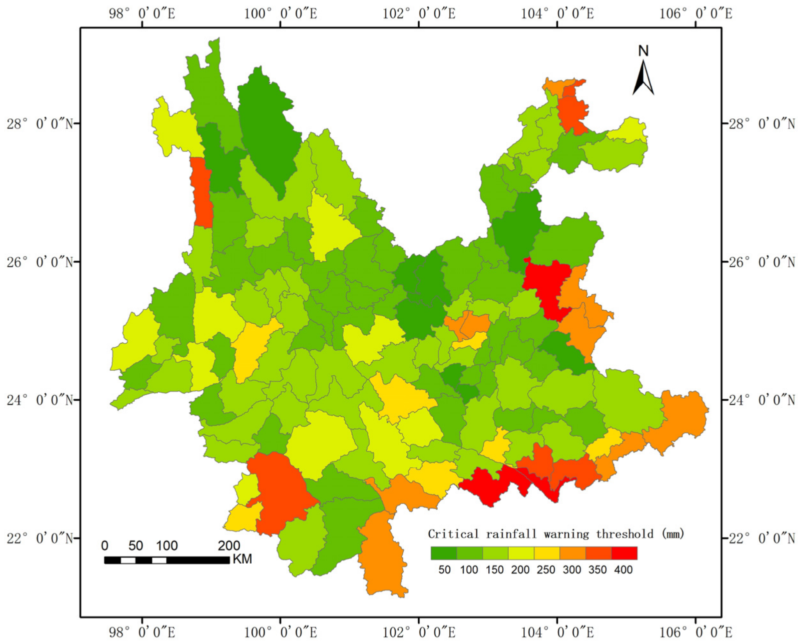

Figure 7. The county-level critical rainfall threshold for Yunnan Province.

In conjunction with the RTI, most of the flash flood high-risk counties have relatively low critical rainfall warning thresholds. When these thresholds are reached, it is necessary to issue corresponding warnings to mitigate the losses caused by flash flood disasters.

5. Conclusions

This study explores the correlation between flash floods and triggering factors and qualitatively analyzes the focus areas with high flash flood risk. Taking into account regional variations in influencing factors, an improved RTI method is developed by incorporating the disaster mechanism parameter η, leading to the development of a county-level critical rainfall warning model; in conjunction with the analysis of warning thresholds, the critical rainfall warning indices for Yunnan Province's counties have been established. Complex influencing factors provide the driving conditions, material conditions, and precipitation conditions for flash flood disasters. The northeastern and southeastern regions of Yunnan

Province have a higher risk of flash floods. Rainfall factors directly trigger flash flood disasters. The county-level critical rainfall warning model, which incorporates disaster mechanisms, exhibits a high level of accuracy. The accumulated rainfall in the ten days before a flash flood event has the highest correlation with the rainfall on the day of the event. The accumulated rainfall mainly affects soil moisture content, permeability, etc. The critical rainfall warning range for Yunnan is from 50 mm to 400 mm, and this range is used to determine county-level flash flood critical rainfall warning indices. There are more than 30 high flash flood risk counties (areas) with low critical rainfall warning indices, indicating a high risk of flash flood occurrences in mountainous areas.

In the future, we will further delve into the mechanisms of flash flood disasters, quantitatively identify triggering factors, and, in combination with the latest multi-event flash flood incidents, revise critical accumulated rainfall values. This is to provide a theoretical foundation for improving flash flood disaster defense strategies.

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Data Availability Statement: This dataset an only be used by contacting the author. Requests to access these datasets should be directed to Meihong Ma, mamh@tjnu.edu.cn.

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