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Investigation of the functional relationship between antecedent rainfall and the probability of debris flow occurrence in Jiangjia Gully, China

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Abstract

A larger antecedent effective precipitation (AEP) indicates a higher probability of a debris flow (P_{df}) being triggered by subsequent rainfall. There are several scientific topics surrounding this qualitative conclusion that can be raised, including what kinds of variation rules do they follow, and whether there is a boundary limit. To answer these questions, Jiangjia Gully in Dongchuan, Yunnan province, China, was chosen as the study area, and a numerical calculation, rainfall scenario simulation, and Monte Carlo integration method were used to calculate the occurrence probability of debris flow under different AEP conditions and derive the functional relationship between P_{df} and AEP. The relationship between P_{df} and AEP can be quantified by a piecewise function, and P_{df} reaches a maximum value of 18.96% after the AEP exceeds 110 mm, indicating that debris flow in nature has an extremely small probability compared to the rainfall frequency. Data from 1094 rainfall events and 37 historical debris flow events were collected to verify the reasonability of the functional relationship. The results indicate that the first two stages of the piecewise function are highly correlated with the observation results. Our study confirms the correctness of the qualitative description of the relationship between AEP and P_{df}, clarifies that debris flow is a small probability event compared to rainfall frequency, and quantitatively reveals the evolution law of debris flow occurrence probability with AEP, which can provide a clear reference for the early warning of debris flows.

Keywords: Debris flow, antecedent effective rainfall, Dens-ID, Monte Carlo method

1 Introduction

The antecedent effective precipitation (AEP) is similar to a Trojan horse lurking inside a loose soil mass, which can cooperate with subsequent rainfall at any time to trigger debris flow in a gully. The AEP is equivalent to the preservation of precipitation in the soil mass before the triggering rainfall process; it represents the saturation degree of the loose soil mass (Segoni et al., 2018a; Leonarduzz and Molnar, 2020). Therefore, the soil moisture that has accumulated from antecedent rainfall since the beginning of a rainfall season has a significant influence on how new storm rainfall interacts with the loose soil mass within a gully (Fiorillo and Wilson, 2004; Long et al., 2020). If a loose solid material is provided by shallow landslides or channel erosion, its shear strength is decreased by an increase in AEP (Papa, et al., 2013; Senthilkumar et al., 2017; Liu et al., 2020), and in the subsequent rainfall process, the supply rate of solid material resources can be significantly enhanced (Wei et al., 2008; Bennett et al., 2014; Zhang et al., 2020). Additionally, increased AEP and moisture content have been shown to enhance surface rainfall-induced runoff in a variety of environments (Tisdall, 1951; Luk, 1985; Le Bissonnais et al., 1995; Castillo et al., 2003; Jones et al., 2017; Hirschberg et al., 2021). Thus, AEP plays an important role in the formation of debris

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

flows (Hong et al., 2018).

The rainfall threshold represents the degree of difficulty of debris flow triggered by rainfall (Marra et al., 2017). Investigations, such as the influence of AEP on the rainfall threshold, can be helpful in examining the relationship between AEP and debris flow occurrence. Currently, conclusions drawn from the analysis of the relationship between the AEP and rainfall threshold are relatively consistent, and there is a negative correlation between the AEP and rainfall conditions (such as daily rainfall) that trigger debris flows (Huang, 2013). AEP represents the degree of saturation of the loose soil mass (Zhao et al., 2019a; Abraham et al., 2021), and integrating soil moisture with rainfall thresholds has been proven effective in improving these thresholds (Segoni et al., 2018a; Zhao et al., 2019b; Abraham et al., 2020), as the antecedent moisture content plays a key role in the soil shear strength. Scholars have attempted to analyze the influence of antecedent soil moisture on the rainfall threshold triggering debris flow (Cui et al., 2007; Hu et al., 2015). Similar to the relationship between AEP and rainfall threshold, there is a negative correlation between antecedent soil moisture and triggering rainfall conditions (Chen et al., 2017). The above investigations on the AEP and antecedent soil moisture show that the AEP can significantly decrease the rainfall conditions that trigger a debris flow, which in turn means that debris flow is more likely to occur. Therefore, there is the following consensus in the field of debris flow: the greater the AEP, the higher the probability (P_{df}) of subsequent rainfall triggering the debris flow (De Vita et al., 2000; Bel et al., 2017). Therefore, discovering a specific function to describe this qualitative description is helpful in further demonstrating the above consensus, revealing a certain evolutionary law of debris flow with rainfall in nature. Long-term observational data may be used to achieve this purpose; however, the number of debris flow gullies with long-term observational data worldwide is less than

10 (Hürlimann et al., 2019). Even at a field site, such as Jiangjia Gully, it has been difficult to provide sufficient observational data to accomplish this goal for more than 60 years.

To quantify the evolution law of P_{df} with AEP variation, a numerical model that can correlate the rainfall parameters (I and D) with the debris flow density (Zhang et al., 2020; Long et al., 2020) was denoted as the Dens-ID model and was used to construct the rainfall intensity-duration (ID) threshold curve database for different AEP. The ID threshold curves with upper and lower bounds can delineate the closed region in the ID coordinate system, which represents the set of all rainfall conditions that can trigger debris flow at a certain AEP. Consequently, the probability of natural rainfall falling into a closed region is equivalent to P_{df}, which can then be calculated based on Monte Carlo integration. The next section introduces the basic information of study area including the rainfall and debris flow event data collected from the study area. The third section addresses how to establish the functional relationship between the AEP and P_{df} using the Dens-ID and Monte Carlo integration method. Section 4 and 5 discuss the results and state the conclusions of this study, respectively.

2 Study area

The Jiangjia Gully (JJG), a primary tributary of the Xiaojiang River, is located in the Dongchuan District of Kunming City, Yunnan Province, China (Fig.1). As shown in Fig.1, JJG has a drainage area of 48.6 km^2 with elevations ranging from 1040–3260 m. In this gully, the relative relief from the ridge to the valley reaches 500 m, and most of the slope gradient is greater than 25°. Slopes within JJG are covered by abundant loose soil with a thickness of more than ten meters. Shallow landslides are frequently triggered by intense rainfall processes in JJG, providing a large amount of solid materials for debris flow (Yang et al., 2022). The Menqian and Duozhao gullies,

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
Open Access
Discussions

shown in Fig.1, are the two main tributaries of JJG, accounting for 64.7% of the entire drainage area. The upstream areas of the two main tributaries are the initiation zones of the debris flows, and the channels of the upstream tributaries are narrow and V-shaped (Zhang et al., 2020).

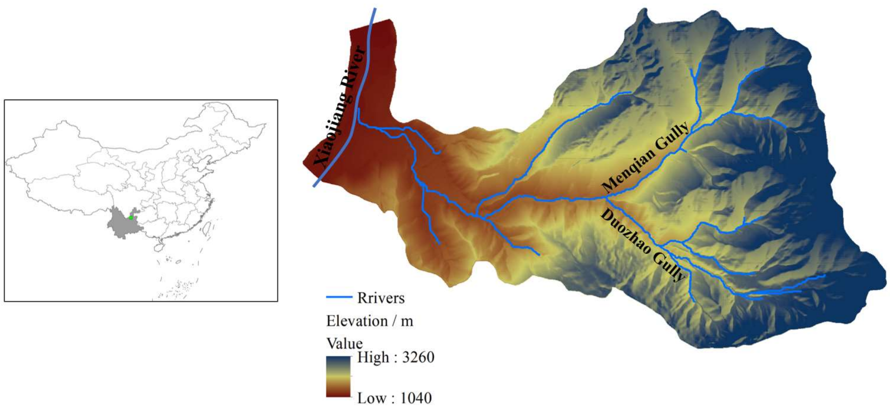

Fig.1 Location of JJG

Steep terrain provides a beneficial potential energy condition for transporting a large amount of loose solid materials from JJG to Xiaojiang River. Consequently, debris flows in JJG can be easily triggered by rainfall. Based on the collected rainfall data, high-intensity rainstorm or long-duration rainfall processes can cause debris flow occurrence (Zhang et al., 2020). The solid material necessary for a debris flow in a gully may be sourced from shallow landslides (Iverson et al., 1997; Gabet and Mudd, 2006; Zhang et al., 2020; Long et al., 2020) or runoff-induced bed erosions (Berti and Simoni, 2005; Coe et al., 2008; Tang et al., 2020; Bernard and Gregoretti, 2021). In JJG, the solid material is sourced primarily from shallow landslides (Zhang et al., 2014; Liu et al., 2016; Yang et al., 2022), which is consistent with the assumptions of Dens-ID (Zhang et al., 2020). Thus, JJG is used as the study zone for deriving the function that describes the relationship between AEP and P_{df}.

The JJG datasets for Dens-ID are terrain data, hydrological parameters, and soil mechanical

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

parameters. The DEM is the basal data for deriving other terrain data, including slope length, gradient, and river channels; the spatial resolution of the DEM is 0.5 m, and a DEM with a grid size of 10 m was generated using the resampling technology in ArcGIS. The hydrological parameters are related to the soil types within JJG; the five key parameters are the saturated soil water content, residual soil water content, the two parameters of soil water characteristic curve including *n* and *m*, and the infiltration rate of topsoil. The soil mechanical parameters are the soil cohesion force and internal friction angle, which were obtained through direct shear tests on the soil samples. Detailed data are available in Zhang et al. (2020) and Long et al. (2020).

Rainfall data for the rainy seasons between 2006 and 2020 were collected from the JJG observation station, and it was necessary to identify each rainfall process from the long-term rainfall sequences. Inter-event time (IET) was defined as the minimum time interval between two consecutive rainfall pulses (Adams et al., 1986). IET has a strong influence on the rainfall event starting and ending times (Bel et al., 2017), and Peres et al. (2018) identified that IET depends on whether the mean daily potential evapotranspiration (MDPE) is larger than precipitation within the IET. The long observation of evaporation within JJG showed that MDPE is about 4 mm; precipitation during IET >0.5 mm is considered the end of a rainfall process. Under this standard, 1094 rainfall events and 37 debris flow events were identified during the sampling period. Detailed rainfall data information can be found in “appendix 1-1094 rainfall and 37 debris flow data.xlsx”. The AEP listed in this appendix was considered the weighted sum of the rainfall periods before the occurrence of debris flow (Long et al., 2020) and it can be calculated using Eq. 1.

$$AEP = \sum_{i=1}^{n} K^n R_i \tag{1}$$

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
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Discussions

where AEP is the antecedent effective rainfall; K is the attenuation coefficient, which is equal to 0.78 based on the field test in JJG (Zhang et al., 2020); and n is the number of days preceding the debris flow occurrence.

Based on the observed rainfall data, the 1094 AEPs were calculated using Eq. 1 and are listed in Appendix 1. The AEP corresponding to each rainfall event varies from 0–88 mm. Taking this variation range as a reference, the variation range of the AEP input in the Dens-ID model was set between 10 and 130 mm. When the AEP was less than 90 mm, it was gradually increased by 5 mm; after the AEP was larger than 90 mm, its increment was set to 10 mm. Dens-ID presets several AEP values including 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 100, 110, 120, and 130 mm. P_{df} can be calculated under different AEP conditions. The preset AEP values exceeded the observed maximum value of 88 mm because we wanted to observe whether P_{df} tended to stabilize and determine its boundary value

3 Methods

3.1 Dens-ID

Debris flow gullies, characterized by a solid source supply from landslides, are widely distributed in southwest China (Zhang et al., 2014). For this type of debris flow gully, our previous study proposed a numerical model (denoted as Dens-ID) based on the evolution law of fluid density (Zhang et al., 2020; Long et al., 2020). Den-ID assumes the debris flow to be a water-soil mixture. Based on the digital elevation model (DEM) of a gully, Den-ID, which uses a grid cell as a basic mapping unit, can simulate the surface runoff and water diffusion in the vertical direction within the soil mass.

$$-D(\theta)\frac{\partial\theta}{\partial z}+K(\theta)=I(t) \tag{2}$$

where θ is the soil water content; $D(\theta) = K(\theta)/(d\theta/d\psi)$, which represents the soil water diffusivity; z is the soil depth, which is positive downwards along the soil depth as the topsoil is taken as the origin point; $K(\theta)$ is the hydraulic conductivity; $I(t)$ is the rainfall intensity; and ψ is the soil matrix suction. When the rainfall intensity was less than the surface infiltration capacity, Eq. 2 was used to represent this physical process. The case of precipitation intensity exceeding the infiltration capacity of topsoil means that the surface is saturated, and the excess precipitation from the topsoil is typically converted into runoff; therefore, the pressure infiltration of each grid cell is not considered. As the topsoil is saturated by rainfall, Eq. 2, which controls the infiltration border, uses $\theta = \theta_s$, where θ_s is the saturated water content of a soil type within a debris flow gully.

$$\frac{\partial\theta}{\partial t} = \frac{\partial}{\partial z}[D(\theta)\frac{\partial\theta}{\partial z}] - \frac{\partial K(\theta)}{\partial\theta} \tag{3}$$

Eq. 3 is the Richard differential infiltration equation (Richards, 1931), which is used to describe the water movement law along the vertical direction within the soil mass after precipitation infiltrates the topsoil. Dens-ID uses the finite-difference method to solve Eqs. 2 and 3 and can provide the runoff depth (denoted as $dw(i,t)$), soil water content, and soil matrix suction for each grid cell. Dens-ID then calculates the runoff volume using runoff depth $dw(i, t)$ in Eq. 4.

$$V_w(t) = \sum_{t=1}^{T}\sum_{i=1}^{n} S_g * dw(i,t) \tag{4}$$

where n represents the total number of grid cells that can generate runoff at time t and $V_w(t)$ represents the total volume of runoff within a gully at time t.

Taking hydrological parameters such as soil water content and soil matrix suction as inputs, Dens-ID uses Eqs. 5 and 6 to estimate the supply volume of rainfall-induced loose solid materials within a gully. Eq. 5 calculates safety factor F_s of each grid cell as a function of the matrix suction and soil moisture. $F_s > 1$ indicates that the grid cell is stable and cannot supply solid material to the

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

gully, whereas a grid with $F_s < 1$ can provide solid material in the form of a shallow landslide.

$$F_s = \frac{\tan\varphi}{\tan\beta} + \frac{c + \psi\, ta\ \ (\varphi^b)}{\gamma_t d_s \cos\beta \sin\beta} \tag{5}$$

where F_s represents the safety factor of each grid cell, c is the soil cohesion force, φ is the internal friction angle, φ^b is related to the matrix suction and is approximately equal to φ as the low matrix suction is small, d_s is the soil depth, and ψ is the matrix suction of the soil, a function of soil water content, and can be described by the Van Genuchten model (Van Genuchten, 1980).

Using d_s derived from Eq. 5 as input, Eq. 6 is used to estimate the total volume of solid materials provided from all the instable grid cells in the gully from the beginning to the end of the rainfall process.

$$V_s(t) = \sum_{t=1}^{T} \sum_{j=1}^{m} S_g * ds(j,t) \tag{6}$$

where m represents the number of grid cells that can provide solid material at time t and $V_s(t)$ is the total volume of solid material within a gully at time t. At time t, the density of the water-soil mixture after full coupling between runoff and solid material can be calculated using Eq. 7.

$$\rho_{mix}(t) = \frac{\rho_w V_w(t) + \rho_s V_s(t)}{V_{mix}(t)} \tag{7}$$

where $\rho_{mix}(t)$ is the density of the water-soil mixture, ρ_w is the water density, ρ_s is the density of the soil particles, and $V_{mix}(t)$ is the volume of the water-soil mixture, which is the sum of $V_w(t)$ and $V_s(t)$. $V_w(t)$ and $V_s(t)$ are the key variables that can be derived using Eqs. 4 and 6.

Dens-ID presets the density of the water-soil mixture as ρ_{mix}. By simulating many rainfall scenarios, including long durations with low-intensity rainfall and short durations with high-intensity rainfall, Dens-ID can obtain adequate combinations of [D_i, l_i]. Using each [D_i, I_i] as input, Dens-ID derives the density value via hydrology simulation and estimate the solid material and runoff volumes. When the calculated density is equal to ρ_{mix}, the [D_i, I_i] combination is saved by

Dens-ID. After Dens-ID completes the trial calculations, all combination data of [D_i, I_i] that satisfy the constraints of the preset density (ρ_{mix}) can be collected, forming a dataset. Each collected [D_i, I_i] within the dataset corresponds to ρ_{mix}; therefore, Dens-ID can map rainfall parameters (D and I) and debris flow density (Long et al., 2020). Dens-ID can derive the ID threshold curves by fitting the selected [D_i, I_i] data; each ID curve corresponds to a debris flow density value (Zhang et al., 2020). As the density of debris flow in JJG varies in a specific interval of 1.2–2.3g/cm^3 (Zhang et al., 2014; Zhuang et al., 2015; Long et al., 2020), the threshold curve that corresponds to the boundary value can form a closed area with the I- and D-axes in the ID coordinate system. The case of monitoring or forecasting rainfall falling into this closed area in the I-D coordinate system indicates that the rainfall condition may trigger debris flow. The verification results for JJG show that Dens-ID effectively describes the mechanism and process of debris flow formation using shallow landslides as a solid source supply, and its prediction accuracy is approximately 80.5%, which is 27.7% higher than that of statistical models (Zhang et al., 2020). Such a high prediction accuracy can further indicate that the closed area formed by the derived ID curves has a very reasonable location and coverage in the ID coordinate system, providing extremely reliable analytical data in this study.

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3.2 Monte Carlo method for calculating the definite integral

Because of the boundary of the debris-flow density in JJG (1.2–2.3g/cm^3), Dens-ID produces the corresponding upper and lower boundary curves under a specific AEP condition. The two boundary curves can be described using the power function

$$\begin{cases} f(D)_{up} = I_{up} = \alpha_1 D^{\beta_1} & D\epsilon[a_1, b_1] \\ f(D)_{low} = I_{low} = \alpha_2 D^{\beta_2} & D\epsilon[a_2, b_2] \end{cases} \tag{8}$$

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

These two threshold curves can form a closed warning area in the ID coordinate system, denoted as W_{ID}. The independent variable (D) and dependent variable (I) in Eq. 8 also form a closed rectangular region in the ID coordinate system, denoted as R_{ID}. In the ID coordinate system, the coverage of R_{ID} is larger than that of W_{ID}, as will be shown in detail in Section 4.1. Within R_{ID}, if certain rainfall processes are located in W_{ID}, this rainfall condition can trigger debris flow. As long as the probability of rainfall falling into the range of W_{ID} under random conditions can be determined, the occurrence probability of debris flow can be estimated for a specific AEP. Many physical phenomena are stochastic in nature and governed by stochastic partial differential equations with nondeterministic initial/boundary conditions or integral equations (Yan and Hong, 2014). Albert (1956) proposed the Monte Carlo method for solving integral equations. This method was subsequently used to estimate the peak flow and volume of debris flow (Donovan and Santi, 2017; Paola et al., 2017), entrainment of the underlying bed sediment (Han et al., 2015), and risk assessment (Calvo and Savi, 2009; Li et al., 2021). Based on the Monte Carlo principle (Peres and Cancelliere, 2014), the probability of the rainfall condition within the R_{ID} range falling into the W_{ID} range can be determined using W_{ID}/R_{ID}. The physical meaning of the Monte Carlo solving definite integral is the estimation of the area enclosed by the function curve and horizontal axis. Therefore, the area of W_{ID} can be calculated by the difference in the definite integral formula of the two equations in Eq. 7.

$$W_{ID} = S_{up} - S_{low} = \int_{a1}^{b1} f(D)_{up} dD - \int_{a2}^{b2} f(D)_{low} dD \tag{9}$$

where S_{up} and S_{low} represent the area enclosed by the two threshold curves and the horizontal axis, respectively, and a_1, b_1, a_2, and b_2 are the boundary values of D in the two curves. For the upper boundary line (or lower boundary), if the probability distribution function of D between [a1, b1] is

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
Discussions
Open Access

p(D), Eq. 9 can be derived by substituting p(D) into Eq. 8, which is used to calculate S_{up} and S_{low}.

$$\begin{cases} S_{up} = \int_{a_1}^{b_1} f(D)_{up} dD = \int_{a_1}^{b_1} \frac{f(D)_{up}}{p(D)} p(D) dD \approx \frac{1}{n}\sum_{k=1}^{n} \frac{f(D_i)_{up}}{p(D_i)} \\ S_{low} = \int_{a_2}^{b_2} f(D)_{low} dD = \int_{a_2}^{b_2} \frac{f(D)_{low}}{p(D)} p(D) dD \approx \frac{1}{n}\sum_{k=1}^{n} \frac{f(D_i)_{low}}{p(D_i)} \end{cases} \tag{10}$$

$$W_{ID} = \frac{1}{n}\sum_{k=1}^{n} \frac{f(D_i)_{up}}{p(D_i)} - \frac{1}{n}\sum_{k=1}^{n} \frac{f(D_i)_{low}}{p(D_i)} \tag{11}$$

where n represents the number of random samples drawn from the variation range of D and $p(D_i)$ is the probability density distribution function of D in the interval [a_1,b_1] or [a_2,b_2]. The key to solving Eq. 10 is sampling from $p(D)$. The following steps were used to explain how samples were taken using $p(D_i)$.

Step 1: Based on the probability density distribution function p(D), the cumulative probability distribution function can be derived by cdf(D)=$\int_{-\infty}^{b} f(D) dD$;

Step 2: Assume that $U^{(i)}$ obeys a uniform distribution within [0,1], which can be randomly collected from this interval and denoted as $U^{(i)}$~U(0,1).

Step 3: Substitute $U^{(i)}$ into the inverse function of the cumulative probability distribution cdf(D) to obtain random sample $D^{(i)}$, denoted by $D^{(i)} = cdf^{-1}(U^{(i)})$. Then, a dataset composed of n data points of $D^{(i)}$ was obtained.

Step 4: W_{ID} can be calculated by substituting n data points of $D^{(i)}$ into Eq. 10, and the P_{df} ($P_{df} = \frac{R_{ID}}{W_{ID}}$) corresponding to a specific AEP is determined. P_{df} represents the probability that the subsequent precipitation process may trigger debris flow for a certain AEP. Thus, the influence of the AEP on the occurrence probability of debris flows can be quantified.

3.3 Correlation analysis between numerical and observation results

The relationship between the AEP-P_{df} fit through the observational data was used as a reference standard, and the correlation analysis method was used to verify the function of the AEP-P_{df} derived

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

by Dens-ID. Correlation analysis was used to study the degree of linear correlation between variables, which is represented by correlation coefficient r:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{12}$$

where x represents the P_{df} derived from the observed data, y represents the P_{df} derived from Dens-ID, $\bar{x}$ and $\bar{y}$ represent the averages, r represents the correlation coefficient, and n represents the number of samples. $|r|\geq0.8$ can be regarded as a high correlation between two variables; $0.5\leq|r|<0.8$ represents a moderate correlation; $0.3\leq|r|<0.5$ represents a low correlation; and $|r|<0.3$ indicates the degree of correlation between the two variables is weak and can be regarded as uncorrelated.

4 Results and discussion

4.1 ID threshold curves and warning zone closed by the derived curves

The ID threshold curves corresponding to the different AEPs derived from Dens-ID are listed in Table 1. Each AEP corresponded to the upper and lower boundary lines of the ID threshold, and these two boundary lines corresponded to different debris flow density values. In Table 1, when AEP≤15 mm, the maximum density corresponding to the ID threshold curve cannot reach 2.2, which are equal to 1.8 and 2.0 when AEP=10 and 15 mm. This is because a lower AEP makes the supply rate of solid resources in JJG far less than the runoff rate during rainfall (Long et al., 2020). At this time, Dens-ID determines that it is easier to form a low-density water-soil mixture in JJG.

Table 1 ID threshold curve database under different AEP

AEP (mm)	ID threshold curve function for JJG	
	1.2 g/cm^3	2.2 g/cm^3
10	$I_{1.2} = 19.85D^{-0.54}$ D∈[1, 269] (R^2 = 0.991)	$I_{1.8}$=15.85$D^{-0.48}$ D∈[1, 263] (R^2=0.990)
15	$I_{1.2}$= 21.69$D^{-0.55}$ D∈[1, 236] (R^2=0.993)	$I_{2.0}$=16.10$D^{-0.50}$ D∈[1, 229] (R^2=0.995)
20	$I_{1.2}$=23.22$D^{-0.58}$ D∈[1, 203] (R^2=0.996)	$I_{2.2}$=17.20$D^{-0.53}$ D∈[1, 192] (R^2=0.995)
25	$I_{1.2}$=24.47$D^{-0.60}$ D∈[1, 171] (R^2=0.997)	$I_{2.2}$=16.92$D^{-0.53}$ D∈[1, 160] (R^2=0.998)

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

30	$I_{1.2}=26.24D^{-0.64}$ $D\in[1, 143]$ ($R^2=0.996$)	$I_{2.2}= 18.09D^{-0.57}$ $D\in[1, 132]$ ($R^2=0.995$)
35	$I_{1.2}=35.47D^{-0.65}$ $D\in[1, 123]$ ($R^2=0.958$)	$I_{2.2}= 19.55D^{-0.58}$ $D\in[1, 112]$ ($R^2=0.985$)
40	$I_{1.2}= 40.59D^{-0.78}$ $D\in[1, 103]$ ($R^2=0.966$)	$I_{2.2}= 22.15D^{-0.64}$ $D\in[1, 92]$ ($R^2=0.984$)
45	$I_{1.2}= 41.12D^{-0.78}$ $D\in[1, 83]$ ($R^2=0.932$)	$I_{2.2}= 23.19D^{-0.69}$ $D\in[1, 72]$ ($R^2=0.981$)
50	$I_{1.2}=41.26D^{-0.86}$ $D\in[1, 65]$ ($R^2=0.981$)	$I_{2.2}= 23.50D^{-0.74}$ $D\in[1, 55]$ ($R^2=0.980$)
55	$I_{1.2}=38.63D^{-0.88}$ $D\in[1, 53]$ ($R^2=0.950$)	$I_{2.2}= 23.31D^{-0.70}$ $D\in[1, 42]$ ($R^2=0.932$)
60	$I_{1.2}= 31.49D^{-0.92}$ $D\in[1, 40]$ ($R^2=0.992$)	$I_{2.2}= 20.73D^{-0.86}$ $D\in[1, 30]$ ($R^2=0.977$)
65	$I_{1.2}= 29.14D^{-0.95}$ $D\in[1, 32]$ ($R^2=0.957$)	$I_{2.2}= 18.10D^{-0.91}$ $D\in[1, 22]$ ($R^2=0.893$)
70	$I_{1.2}= 23.05D^{-0.96}$ $D\in[1, 25]$ ($R^2=0.998$)	$I_{2.2}= 13.04D^{-0.93}$ $D\in[1, 15]$ ($R^2=0.995$)
75	$I_{1.2}= 21.13D^{-0.97}$ $D\in[1, 22]$ ($R^2=0.994$)	$I_{2.2}=10.90D^{-0.95}$ $D\in[1, 12]$ ($R^2=0.995$)
80	$I_{1.2}= 18.72D^{-0.98}$ $D\in[1, 20]$ ($R^2=0.997$)	$I_{2.2}= 9.96D^{-0.95}$ $D\in[1, 11]$ ($R^2=0.999$)
85	$I_{1.2}= 18.47D^{-0.99}$ $D\in[1, 18]$ ($R^2=0.999$)	$I_{2.2}= 8.17D^{-0.95}$ $D\in[1, 9]$ ($R^2=0.999$)
90	$I_{1.2} = 16.99D^{-0.98}$ $D\in[1, 18]$ ($R^2=0.999$)	$I_{2.2}=6.81D^{-0.95}$ $D\in[1, 7]$ ($R^2=0.994$)
100	$I_{1.2} = 16.90D^{-0.98}$ $D\in[1, 18]$ ($R^2=0.999$)	$I_{2.2}=6.81D^{-0.95}$ $D\in[1, 7]$ ($R^2=0.994$)
110	$I_{1.2} = 16.87D^{-0.98}$ $D\in[1, 16]$ ($R^2=0.999$)	$I_{2.2}=6.76D^{-0.95}$ $D\in[1, 7]$ ($R^2=0.997$)
120	$I_{1.2} = 16.87D^{-0.98}$ $D\in[1, 16]$ ($R^2=0.999$)	$I_{2.2}=6.76D^{-0.95}$ $D\in[1, 7]$ ($R^2=0.997$)
130	$I_{1.2} = 16.87D^{-0.98}$ $D\in[1, 16]$ ($R^2=0.999$)	$I_{2.2}=6.76D^{-0.95}$ $D\in[1, 7]$ ($R^2=0.997$)

When AEP < 10 mm, Dens-ID cannot derive the threshold curve corresponding to even the minimum density value of 1.2 g/cm^3, which indicates that the subsequent rainfall can hardly trigger debris flow JJG. Table 1 also shows that when the AEP reaches 110 mm, α and β in the threshold curve become constant and no longer change with AEP. An AEP ranging from 10 to 110 mm can affect the debris flow formation in JJG. After the AEP in Table 1 exceeded 90 mm, the effect of AEP on the ID threshold curve was not significant.

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
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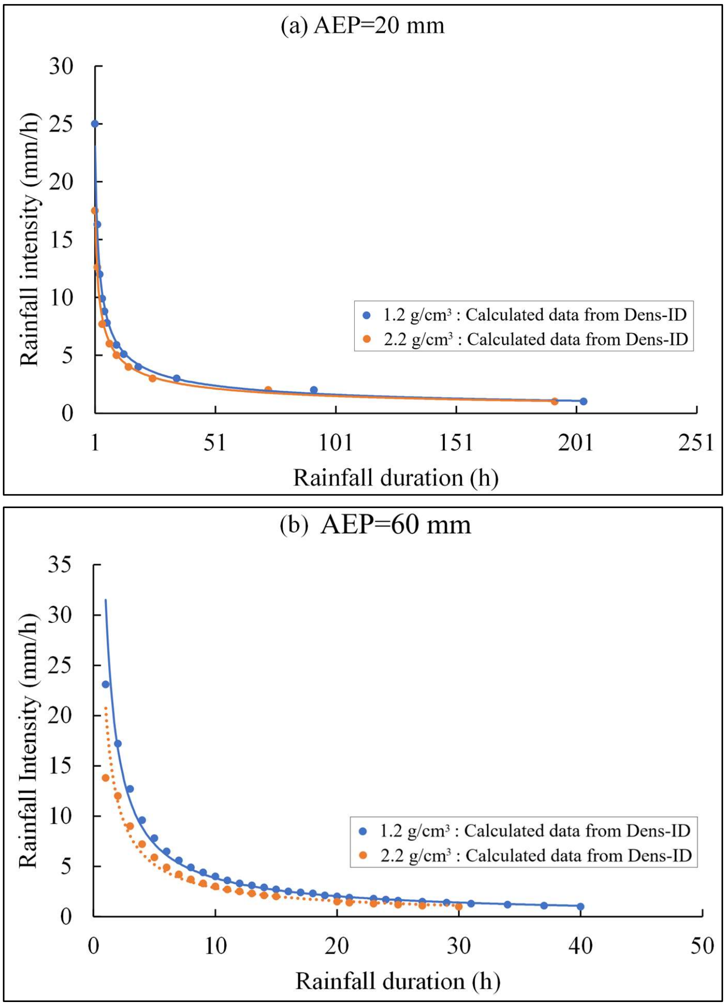
Discussions



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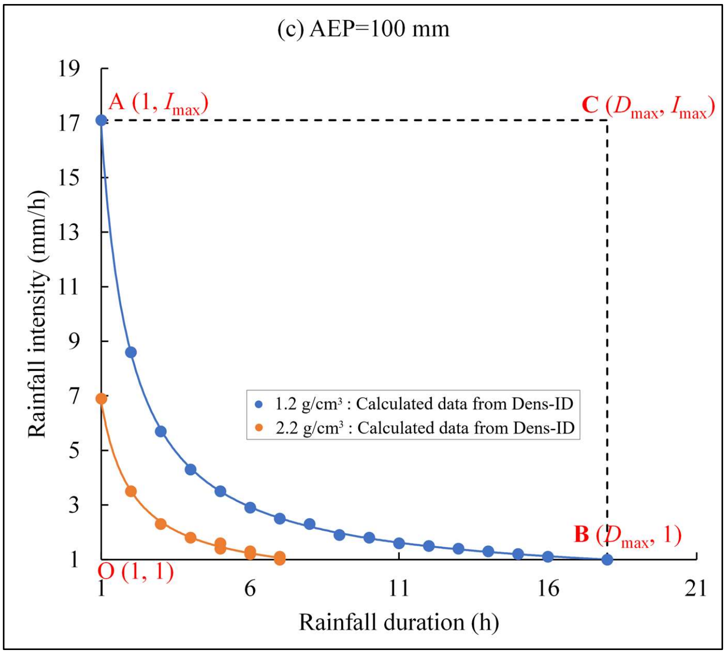

Fig.2 ID threshold curves derived by Dens-ID (the blue line corresponds to 1.2 g/cm^3, and the orange line corresponds to 2.2 g/cm^3 in the figures)

There are two ID threshold curves in each subplot of Fig. 2, which correspond to 1.2 g/cm^3 and 2.2 g/cm^3, respectively. Because the debris flow density in JJG varies within a certain range from 1.2–2.3 g/cm^3, the two ID threshold curves shown in each subplot can be regarded as the upper and lower boundary lines for determining the occurrence of debris flow (Zhang et al., 2020). As shown in Fig.2c, the two derived curves, together with the I- and D-axes, form a closed area in the ID coordinate system; this area is denoted as W_{ID}. If the monitored rainfall, represented by the combination of I and D, can enter W_{ID}, rainfall may trigger debris flows. As shown in each subplot, the threshold curve can be represented by power function $I=\alpha D^{\beta}$. The variation intervals of the independent (D) and dependent (I) variables of the power function are [1, D_{max}] and [1, I_{max}], respectively, where D_{max} represents the rainfall duration required to trigger debris flow when I= 1

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

mm/h, and I_{max} represents the rainfall intensity required for debris flow formation for D=1 h. As shown in Fig.2c, independent variable D and dependent variable I can form a larger rectangular area (AOBC) in the ID plane than W_{ID}, which is denoted as R_{ID}. The coverage area of R_{ID} is much larger than that of W_{ID}, indicating that the proportion of rainfall conditions that can trigger debris flows is low. Therefore, even for AEP=100 mm, the occurrence probability of debris flows remains low. As shown in each subplot, each AEP corresponds to a different W_{ID} and R_{ID}, which provides basic data for the quantitative evaluation of the effect of different AEPs on the occurrence probability of debris flows.

4.2 Occurrence probability of debris flow under different AEP

Based on the Monte Carlo method of calculating the definite integral, it is necessary to explore the probability density function of rainfall duration (D) to calculate the occurrence probability of debris flow under different AEP conditions. For the 1094 rainfall events listed in Appendix 1, we found that the probability distribution of rainfall duration D in JJG can be described by a power function (Fig. 3). As shown in Fig.3, the number of samples with $D<1$ accounted for 37.7%, $1<D<3$ for 23.5%, $3<D<5$ for 14.7%, and $5<D<10$ for 16.9%; the number of rainfall events with D exceeding 10 h accounted for only 6.7%.

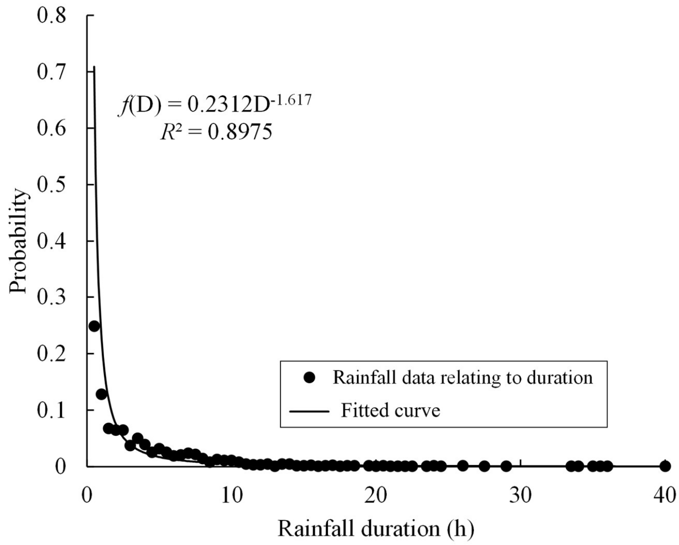

Fig. 3 Probability density function of *f*(D)

Based on the probability density distribution function *f*(D)=0.2312D$^{-1.617}$, the cumulative probability function *cdf*(D) can be obtained through integration. In *cdf*(D), denoted as Eq. 11, the integration constant *C* needs to be determined.

$$cdf(D)=\int_{-\infty}^{D} f(D)dD = -0.3747*D^{-0.617}+C \quad (11)$$

The interval of 0–40 h was evenly divided into 56 statistical intervals (the second column in Appendix 2, titled "appendix 2-f(D)and CFD(D). xlsx"), and each statistical interval was separated by 0.5 h. The proportion of the sample size in each interval among the 1094 samples can be calculated (second column in Appendix 2), and the cumulative proportion that increases with D is obtained (third column in Appendix 2). The data in the first and third columns of Appendix 2 are substituted into Eq. 11 to calculate *C*. *C* increases with D but gradually stabilizes at approximately 1.04 (the fifth column in Appendix 2), and *C* is set to 1.04.

Based on the process of calculating P_{df} under different AEP conditions in Section 3.4, the P_{df} corresponding to each AEP in Table 1 was obtained, and the function $P_{df} = f(AEP)$ for describing

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
Discussions

their relationship was fitted using the AEP and P_{df} data.

$$\begin{cases} P_{df} = 0 & 0 < AEP < 10 \\ P_{df} = 0.34e^{0.046AEP} & 10 \le AEP < 85 \\ P_{df} = 0.1AEP + 7.6 & 85 \le AEP < 110 \\ P_{df} = 18.96 & 110 \le AEP \ge 130 \end{cases} \tag{12}$$

As shown in Eq.12, $P_{df} = f(AEP)$ is a piecewise function. The evolution of P_{df} with AEP variation can be divided into four stages (Fig. 4). Two key issues must be stated before discussing these four stages in depth: (1) Based on the calculation results of the Dens-ID model, an upper limit volume of the rainfall-induced solid material supply is derived in JJG, which is the basic condition for determining the scale of debris flow in JJG (Zhang et al., 2020). (2) Based on the principle of water balance, AEP is defined as the rainfall that is preserved in the soil before the triggering rainfall process (Kohler and Linsley, 1951); field observations in JJG show that the AEP is positively correlated with the soil water content (Cui et al., 2007), and the field observations of the Liudaogou catchment in the northern Loess Plateau of China have the same result (Zhu and Shao, 2008); therefore, the AEP is typically used to estimate soil water content (Crozier, 1986; Chen et al., 2018; Zhao et al., 2019b). The water soil content before the triggering rainfall process can be characterized by AEP (Thomas et al., 2019; Schoener and Stone, 2020).

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

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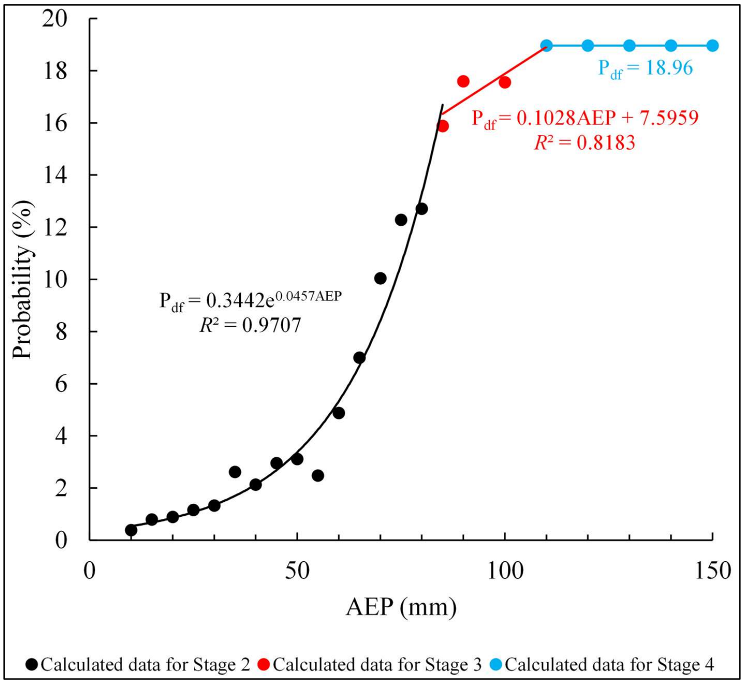

Fig.4 Relationship of P_{df} and AEP derived from Dens-ID (the black line represents the fitted curve of Stage 2, the red line represents the fitted curve of Stage 3, the blue lien represents the fitted curve of Stage 4)

Stage 1: The probability of debris flow occurrence in JJG is equal to 0 when the AEP is < 10 mm. Dens-ID estimates the solid material volume by simulating rainfall-induced shallow landslides. According to Eq. 4, the key hydrological process that triggers shallow landslides is the continuous increase in soil water content caused by rainfall infiltration. The increase in soil moisture content reduces soil matrix suction and eventually contributes to shallow landslides. The soil water content of the loose soil mass in JJG was low when the AEP was < 10 mm (Long et al., 2020), and a long duration of rainfall infiltration was needed to increase the soil water content. However, based on the infiltration border of Dens-ID (Eq. 1), limited by the infiltration capacity of the topsoil in JJG, the portion of precipitation that exceeds the infiltration capacity is be converted into runoff; therefore, when the water content of the soil layer in JJG is low, the surface runoff has already been generated. Accordingly, the runoff generation rate can be much higher than the supply rate of solid material in the Dens-ID simulation. In this hydrological scenario, Dens-ID determines that even a soil-water mixture with a density of 1.2 g/cm^3 is difficult to generate in JJG; thus, the probability of debris flow is 0.

Stage 2: The relationship between $P_{df}{\sim}AEP$ can be described by an exponential function, indicating that the probability of debris flow occurrence is enhanced by gradually increasing AEP. This trend obeys the following function: $P_{df} = 0.3442e^{0.0457AEP}$, which can be further divided into two subprocesses using AEP = 50 mm as the demarcation point, where the slope of the curve changes significantly. Stage 2-1: When 10 mm≤AEP≤50 mm, the soil water content increased significantly compared to AEP < 10 mm, but a necessary infiltration time to increase it to the critical state for triggering shallow landslides is still required. Therefore, limited by the supply rate of the solid material, the rate of increase of P_{df} was relatively low, and the maximum P_{df} was 3.11%. Stage 2-2: When 50 mm<AEP≤85 mm, the soil water content is relatively large compared to Stage 1; the solid material from shallow landslides can be immediately ready without a long rainfall infiltration duration, and a large soil water content of topsoil is beneficial to the rapid generation of runoff (Jones et al., 2017; Hirschberg et al., 2021). When there is a sufficient supply of provenance and runoff, the probability of debris flow occurrence in this subprocess is significantly enhanced by the increasing AEP.

Stage 3: After the AEP exceeded 85 mm, the rate of increase of P_{df} decreased, exhibiting a moderate linear increasing trend with AEP. Because of the very high soil water content, most of the loose soil layer in JJG is close to the saturated state (Long et al., 2020). Then, the total volume of

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

solid material reaches the maximum level, and the increased AEP can hardly contribute to the runoff generation rate. Consequently, the increasing trend of P_{df} slows compared with that in Stage 2-2.

Stage 4 (AEP≥ 110 mm): According to the ID threshold curves in Table 1, the two key parameters α and β of the threshold curve at this stage are already in a constant state, which means that there is no longer any change in R_{ID} and W_{ID} in Fig. 2c. Therefore, the P_{df} no longer changed with increasing AEP and remained unchanged at 18.96%.

4.3 Correlation analysis of the two curves derived from Dens-ID and observation data

The AEP in Appendix 1 varied from 0–87.9 mm. Limited by this range, we can only test the reasonability of the first and second stages, as shown in Fig. 4. We introduce how to use the rainfall and debris flow data recorded in Appendix 1 to calculate P_{df}: (1) The original AEP value is rounded to one decimal place, and the rounded AEP are listed in the 8th column of Appendix 1, which were sorted from largest to smallest; (2) the maximum AEP_i was set to 90 mm, and [AEP_i, AEP_i-5] was used as the search window to collect the rainfall events and debris flow events; and (3) we count the number of debris flow events N_{df} and the number of rainfall events N_{rain} in each search window and then calculate $P_{df}=N_{df}/N_{rain}$. Based on the above steps, the collected data and calculated P_{df} are listed in Table 2. As shown in Table 2, a positive correlation between the probability of debris flow occurrence and AEP in JJG was determined. When AEP < 10 mm, a total of 205 rainfall processes were recorded; however, no debris flow events were observed, and the debris flow occurrence probability was 0, which is consistent with the results of Stage 1 derived from Dens-ID.

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Table 2 Collected and calculated P_{df} in each search window

	Field observation data and calculated P_{df}										
AEP intervals	0-10	10-15	15-20	20-25	25-30	35-40	35-40	45-50	50-55	70-75	75-80
N_{df}	0	3	2	7	7	4	4	5	3	1	1
N_{rain}	205	133	111	127	124	106	106	49	31	8	5
P_{df} (%)	0	2.3	1.8	5.5	5.6	3.8	3.8	10.2	9.7	12.5	20.0

Based on P_{df} and AEP listed in Table 2, their relationship can be described by the exponential function denoted as $P_{df} = 1.5917e^{0.031AEP}$, which is similar to that of Stage 2 in Fig.4. Therefore, two P_{df}-AEP curves derived from field observation data and the Dens-ID model were obtained for further analysis, as shown in Fig.5. The two curves were nearly parallel. Eq. 12 is used to analyze the correlation of the two curves, and r is equal to 0.93, suggesting they have a very high correlation. Therefore, the function of $P_{df} = f(AEP)$ derived from Dens-ID, which is used to describe the evolution trend of debris flow occurrence probability with AEP variation, is reasonable.

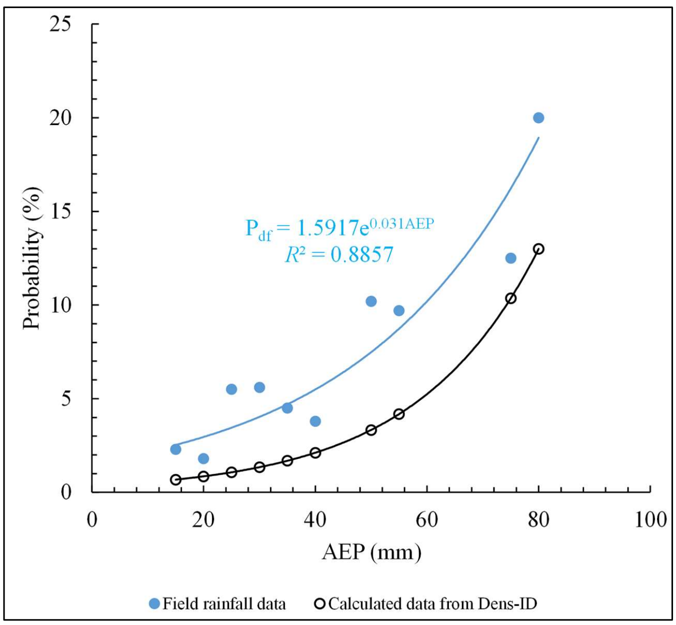

Fig.5 Relationship of AEP and P_{df} obtained from field observation data and Dens-ID model (the blue line is

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

derived from field observation data, and the black line is derived from Dens-ID)

We can also see from Fig.5 that although the variation tendencies of the two curves are consistent, there is a significant bias between them. As shown in Fig.5, the blue line fitted through the observation data is above the black line derived from Dens-ID, indicating that Dens-ID underestimated the probability of debris flow occurrence if the observation data were used as the reference. However, we cannot conclude that there is a precision problem in the calculation results of the Dens-ID. (1) Although 1094 rainfall processes and 37 debris flow events are field observation data, there are many uncertain factors in Eq. 7 for calculating AEP using these rainfall data (Kim et al., 2021), such as the subjectivity existing in K and n of Eq. 7, which render uncertainty in the calculated AEP. In this case, if the data in Appendix 1 are used as the real value for evaluating the precision of Dens-ID, the error evaluation result may be unfair to Dens-ID. In this case, it is unfair to evaluate the Dens-ID error by using the calculated AEP in Appendix 1 as the true value. However, this uncertainty can show consistent directional deviations because of the fixed values of K and n in Eq.7; therefore, the uncertainty has no effect on the correlation analysis. (2) To establish the functional relationship between P_{df}-AEP, a large number of rainfall scenarios were simulated using the Dens-ID model. Dens-ID simulated 3376, 3182, 2677, and 2677 rainfall processes with AEP = 20, 40, 45, and 50 mm, respectively. The total number of simulated rainfall processes was significantly larger than that of the 1094 observed rainfall events. The collected 1094 rainfall events still cannot fully reflect all rainfall conditions in nature; that is, the amount of the observed 1094 rainfall data is still inadequate when used as the denominator for calculating the probability of debris flow occurrence in JJG. Therefore, the P_{df} calculated using the field observation data may be generally higher than that calculated using Dens-ID. (3) Dens-ID cannot fully and accurately

https://doi.org/10.5194/hess-2022-263
Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
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Discussions

describe the formation process of the debris flow in JJG because of the simplification in theory and boundaries. Dens-ID is also affected by the accuracy of the input parameters (Zhang et al., 2020), which may eventually lead to deviations between the simulation results and field observations.

5 Conclusions

The Dens-ID model was used to derive the ID threshold curves corresponding to different AEP in the JJG. Thus, the Monte Carlo integral equation was used to construct the function of P_{df}-AEP for a probability density distribution of field observation rainfall data. The functional relationship was verified using a large amount of field observation data from JJG. The following conclusions were drawn.

The qualitative conclusion recognized by scholars that "the greater the AEP, the higher the probability of subsequent rainfall triggering debris flow" is described by a clear mathematical equation in this study. For the probability of debris flow occurrence in JJG, the effective range of AEP that can affect debris flow formation was verified as 10–110 mm. Based on the simulation results, the probability of debris flow occurrence in JJG is 0 when AEP < 10 mm, and the relationship between P_{df} and AEP can be described by an exponential function when 10 mm≤AEP≤85 mm. Limited by the total volume of provenance supply, infiltration capacity of topsoil, and soil saturation, when the AEP is greater than 85 mm, the growth rate of the probability curve slows, and the maximum P_{df} stabilizes at 18.96%. The plausibility of the first two evolution stages of the P_{df}-AEP piecewise function is effectively confirmed by the field observation data because the P_{df}-AEP relationship obtained from field observation data is highly correlated with the simulation results of Dens-ID. However, the reasonability of the last two stages of the P_{df}-AEP piecewise function cannot be tested because of the lack of field observation data, and the errors of the P_{df}-AEP piecewise

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Preprint. Discussion started: 5 September 2022

Hydrology and Earth System Sciences
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Discussions

function cannot be verified because of the uncertainty of the AEP derived from the observation rainfall data.

This study mathematically confirms that "the greater the AEP, the higher the probability of subsequent rainfall triggering debris flow" and quantifies this qualitative conclusion using piecewise functions. This can effectively reveal the essential relationship between the two natural events of rainfall and debris flow, quantitatively describe the impact of different AEPs on the probability of debris flow occurrence, and provide key technical support for the early warning of debris flows.

Data availability

No data sets were used in this article.

Author contributions

All the authors searched, collected, and process the historical rainfall and debris flow data from JJG field observation station. Shaojie Zhang and Hongjuan Yang wrote parts of the paper, Both Shaojie Zhang and Kaiheng Hu are the Supervision and Funding acquisition, Juan Ma is responsible for Formal analysis, and Dunlong Liu is responsible for data curation.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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