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Debris Flow Susceptibility in the Jinsha River Basin, China: A Bayesian Assessment Framework Based on Geomorphodynamic Parameters

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Abstract. Accurately identifying the spatial and temporal locations of debris flow occurrences is a significant challenge in assessing mountain hazard susceptibility and is essential for developing effective disaster mitigation and ecological restoration strategies. The Jinsha River basin, a typical region in China characterized by alpine gorges, frequently experiences debris flow disasters. Due to its vast area and the complex mechanisms underlying debris flow formation, using slope-based indicators alone to assess susceptibility, without considering the "source-sink" process of debris flow formation, results in low accuracy in susceptibility evaluations. To address this issue, we carefully selected a set of geomorphodynamic parameters, designed corresponding quantitative characterization methods, and developed a Bayesian model-based framework to more accurately identify debris flow-prone areas. This framework provides a comprehensive understanding of the spatial distribution and intensity of debris flow events, thereby improving the accuracy and robustness of susceptibility assessments. The model's evaluation results indicate debris flow susceptibility in the Jinsha River basin for small, medium, and large-scale events, with an average accuracy of 63%. Furthermore, through an empirical analysis of the catastrophic mountain flood and debris flow event ("8.21") in Jinyang County, Sichuan Province, we found that the model's predictions closely matched the actual disaster locations, further validating the model's effectiveness. Our study reveals that the importance of factors contributing to debris flow susceptibility in the Jinsha River basin decreases in the following order: surface material erodibility > connectivity > stream power > frequency and intensity of extreme precipitation. Debris flow-prone valleys are primarily concentrated within a 30 km stretch along the middle and lower reaches of the Jinsha and Yalong Rivers, with approximately 32,000 risk-prone river valleys longer than 200 meters, most of which are small to medium-sized gullies. The distribution of these valleys follows a power function relationship with the distance from the main stream. In areas where debris flow events occur infrequently but with high probability, when such events do occur, they tend to be larger and more destructive. Given that many existing and planned large reservoirs in the Jinsha River basin are in regions densely populated with debris flow-prone valleys, and considering the projected increase in extreme precipitation events, preventing and mitigating debris flow susceptibility remains a significant challenge. The datasets generated in this study,

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including river power, surface connectivity, and debris flow occurrence probability, provide valuable insights for major construction projects, such as large reservoirs, bridges, and residential developments, helping to improve infrastructure siting and disaster mitigation planning.

1 Instroduction

Debris flows in mountainous regions are characterized by active runoff erosion, significant topographic relief, and the interplay of tectonic uplift and river incision (Qiu et al., 2021; Ciccarese et al., 2020; Ye et al., 2023). These flows are triggered by various processes, including shallow landslides, runoff infiltration, channel mobilization, dam failure, and rapid snowmelt (Qiu et al., 2021; Ciccarese et al., 2020; Ye et al., 2023). Due to their high kinetic energy, debris flows pose significant risks to infrastructure, including roads, bridges, and buildings. Globally, debris flow-prone areas are concentrated in the Pacific Rim fold belt, the Alpine-Himalayan fold belt, and mountainous regions in Eurasia(Ye et al., 2023). In China, regions such as the Gongga Mountains, the western Loess Plateau, and the Jinsha River Basin are particularly vulnerable, with the latter contributing significantly to debris flow disasters in the country (Hu et al., 2020).

In recent decades, the ongoing global and regional climate warming has exacerbated the risks associated with debris flows by increasing the frequency of extreme weather events (Lu et al., 2021; Zhao et al., 2021). This highlights the urgent need for research on debris flows. Such research has informed the development of quantitative models, including the power-law relationship between mean intensity and rainfall duration (Coe et al., 2008; Badoux et al., 2009; Oorthuis et al., 2021; Hürlimann et al., 2019; Nikolopoulos et al., 2014), and the linear relationship between surge front velocities and flow depth (Mccoy et al., 2011). These advancements aim to enhance the working principles of monitoring and early warning stations to achieve more accurate debris flow forecasting. However, despite these efforts, debris flow disasters continue to occur, and the role of monitoring stations in regional safety remains limited. From 1999 to 2019, debris flows in China resulted in 4,742 deaths, with an average of 226 deaths per year. In 2010 alone, 2,073 people lost their lives. Notably, on August 7, 2010, a large debris flow in Zhouqu, Gansu, destroyed over 390 buildings (Zhang et al., 2018b); on June 28, 2012, debris flows occurred in ten gullies upstream of the Baihetan hydropower station, including the Aizi gully, resulting in the death or disappearance of 41 people (Hu et al., 2017); and on August 17, 2020, a debris flow occurred in Dayi, Sichuan, blocking a river and causing flooding (An et al., 2022). The uncertainty in the spatiotemporal distribution of extreme precipitation events, combined with insufficient understanding of regional debris flow risk assessment and patterns, has led to the absence of monitoring stations or improper site selection in some high-risk areas, thus limiting the effectiveness of early warning systems (Li et al., 2024).

Currently, numerical simulations based on momentum conservation, mass conservation, and rheological equations are commonly used to model the kinematic characteristics of material flow in debris-flow-prone gullies. These simulations provide key parameters, such as flow velocity and transport volume. However, accurately identifying potential debris flow locations in large-scale areas remains a significant challenge. In the past, there has been a heavy reliance on the direct interpretation of remote sensing images (Yi and Qu, 2018; Lyu et al., 2022; Hu et al., 2017), using abnormal reflectance from surface damage areas after debris flows, such as vegetation, bare soil, and gravel, as indicators. More recently, the accuracy and efficiency of debris flow susceptibility assessments have significantly improved with the development and application of machine learning models. These models are trained using quantitative surface characteristics of debris flow-prone areas, including slope, aspect, topographic relief and roughness, lithology, and NDVI (Li et al., 2024). However, the development of debris-flow channels is an intense "source-sink" process, where debris and surface water flow along specific slopes, with the valley bottom being the most destructive area. The current assessment systems based on indicators such as slope, lithology, and NDVI mainly reflect the characteristics of the valley slopes on both sides, which do not fully correspond to the dynamic nature of the valley bottom. Therefore, it is necessary to reconstruct the indicator framework and establish a parameter system that better aligns with the physical characteristics of the valley bottom to improve the accuracy of debris flow susceptibility assessments. To address these challenges, we propose an assessment framework based on a Naïve Bayesian model to improve the identification of debris flow locations, timing, and likelihood. Focusing on the Jinsha River Basin, this framework incorporates parameters such as stream power, surface erosion susceptibility, sediment transport connectivity, and the frequency and intensity of extreme precipitation events. The dataset generated by this approach describes the dynamic quantitative characteristics of debris flow gullies and the probability of occurrence, helping us identify many potential debris flow locations previously overlooked. This framework provides practical reference points for site selection in major infrastructure projects and disaster prevention engineering.

2 Study Area

The Jinsha River, a crucial tributary of the Yangtze River, originates in the Tanggula Mountains of China. It traverses several distinct natural regions, including the eastern Qinghai-Tibet Plateau, the northwestern Yunnan-Guizhou Plateau, and the southwestern Sichuan Basin (Fig. 1). The river spans approximately 2,316 km, with an average gradient of 1.48%, and an annual average discharge of 4,750 m^3/s, draining a catchment area of about 5×10^5 km^2 (Li et al., 2018). In its upper reaches, the terrain is relatively flat, underlain by continental crust that was formed and recycled during the Paleozoic era. The landscape is characterized by desert meadows, and the valley is wide and shallow, resulting in slow river flow. As the river progresses into the middle reaches, it enters the Indosinian fold belt, where the continental crust formed during the Meso-Cenozoic era. The lower basement consists of ancient Precambrian continental crust (Ma, 2002). The entire river basin lies within a seismically active zone due to ongoing neotectonic activity, characterized by numerous faults and generally fractured rock masses. Precipitation in the region is concentrated between May and October, driven by both southwest and southeast monsoons, with extreme rainfall typically occurring from June to August. The annual average precipitation is 632 mm, increasing gradually from northwest to southeast. However, in areas above 4,000 m, the average annual rainfall drops to just 344 mm, making it the driest region in the Yangtze River basin (Cao et al., 2011). Over the past six decades, river discharge has increased, driven by global warming and the accelerated melting of ice and snow (Liu et al., 2016). The rapid

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tectonic uplift and river erosion in the region have shaped deep canyon-type landforms, with valley depths exceeding 1,000 m. The dynamic interaction between internal tectonic forces and external erosional processes has contributed to the development of a highly active river system, prone to frequent landslides and debris flows (Liu et al., 2018).

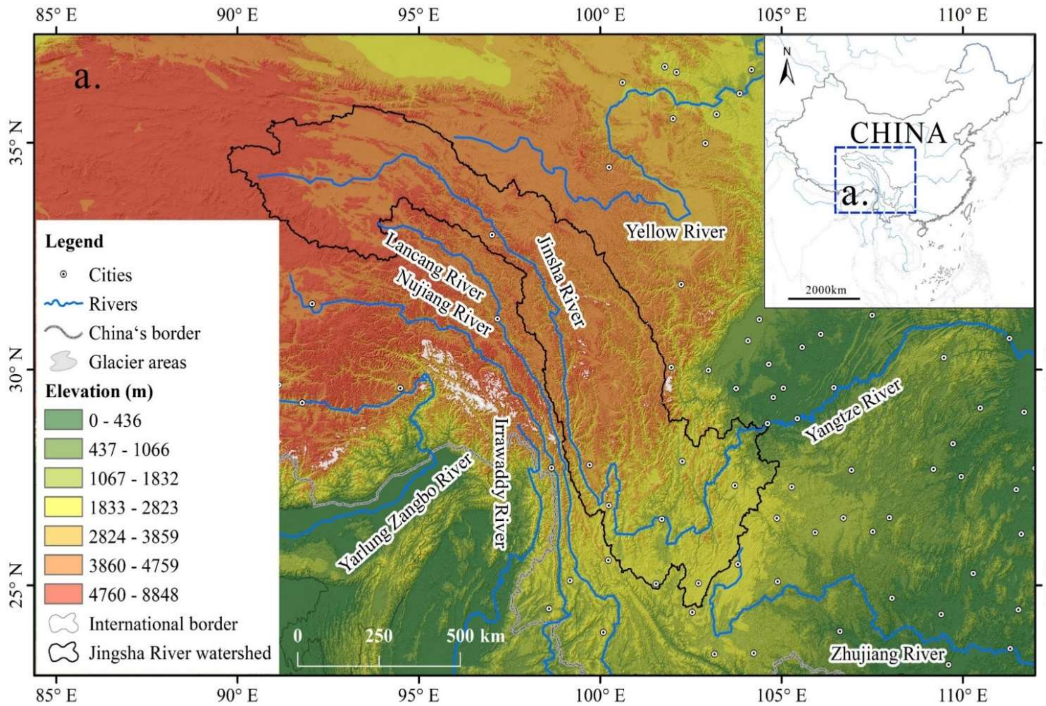

Figure 1: The Jinsha River Basin and Its Adjacent River Systems.

3 Methodology

3.1 Data and Preprocessing

This study utilizes a comprehensive set of data sourced from various repositories, including debris-flow surveys, stream discharge records, precipitation data, topographic information, and soil characteristics. The key datasets and preprocessing steps are outlined below: 1)Stream Discharge, Discharge data from hydrological stations are crucial for estimating stream power; 2) Rainfall, the Standardized Precipitation Index (SPI) is computed at daily, monthly, and annual scales using high-resolution, long-term daily grid precipitation data from the ECMWF ERA5 product, which is derived from radar and satellite-based weather observations (https://cds.climate.copernicus.eu); 3) Topography, elevation and catchment areas along

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the longitudinal profile are extracted from SRTM 1" DEM data, which offers a spatial resolution of approximately 30 meters; 4) Debris Flow Incident Sites, the distribution of debris flow events in China is mapped at a scale of 1:5,000,000. This map, based on field investigations and depositional markers, provides locations and magnitudes of historical debris flows (Yi and Qu, 2018); 5) Soil Characteristics, the China Soil Map-based Harmonized World Soil Database (HWSD v1.2) is used to estimate soil erodibility (K), with a spatial resolution of 250 meters (Wieder et al., 2014). To reduce potential errors, data from flat surfaces are excluded.

Debris flows are categorized into three classes based on the volume of the accumulation body: small ($< 1 \times 10^4$ m^3), medium (1×10^4–1×10^5 m^3), and large ($> 1 \times 10^5$–1×10^6 m^3). Volume estimates account for factors such as debris-flow bulk density, solid particle bulk density, debris-flow duration, and peak discharge (Yu and Tang, 2016). The surface regolith data at a reference depth of 1 meter provide detailed information on the percentage contents of gravel, sand, clay, and organic matter, along with related parameters (Meng and Wang, 2018). This methodological framework ensures an accurate assessment of debris-flow susceptibility by integrating critical environmental and geological factors.

3.2 Modeling Approach

Debris flows are influenced by surface erosion and sediment supply, requiring a thorough consideration and quantification of related factors. Before designing the assessment framework, we identified key indicators with significant physical relevance to Earth's surface processes and made necessary adjustments to produce a three-dimensional visual representation of the numerical values. During the research, we used parameter sequences from debris-flow survey sites as training and testing samples. These parameters include dynamic characteristics of surface rock erosion, sediment connectivity, stream power, and the frequency and severity of extreme precipitation events in highly sensitive debris-flow valleys within the Jinsha River basin. A Naïve Bayes model was then applied to assess debris-flow probability across daily, monthly, and annual timescales (Fig. 2).

This model calculates the posterior probability of each feature using Bayesian inference based on its prior probability, assigning it to the category with the highest posterior probability. Specifically, if there are m classes (e.g., non-occurring, small, medium, and large debris flows) denoted as $C_1, C_2, ..., C_m$, and spatiotemporal variables denoted as $x_1, x_2, ..., x_n$ (e.g., stream power, erodibility, connectivity, and the severity and frequency of extreme precipitation), the model predicts the class of an unknown sample S by selecting the class Ci that maximizes the posterior probability, such that $P(C_i|S) > P(C_j|S)$ for all $1 \leq j \leq m$ and $j \neq i$. The probability of class Ci, given sample S, is calculated as follows:

$$P(C_i|S) = \frac{P(x_1|C_2)P(x_2|C_2),\cdots P(x_n|C_i)\frac{L_i}{L}}{\sum_{i=1}^{m} P(C_i)P(S|C_i)} \qquad (1)$$

where $P(C_i)$ is the probability of C_i; $P(S|C_i)$ is the probability of S under C_i; $P(xn|C_i)$ is the probability of variable xn under C_i; Li is the number of C_i in the total training sample dataset; and L is the total number of training samples. The attribute value for a point within the basin is computed as the average value of the upstream confluence interval, using the following formula:

$$\bar{F}_j=\frac{\sum_{i=1}^{n} E_{i,j}}{N_{i,j}} \tag{2}$$

In the formula, $E_{i,j}$ is the attribute value of the j^{th} parameter at point i, and N is the number of corresponding grids. Due to the algorithm's resilience, this model is not susceptible to missing data, and the discriminant effect is steady (Mu et al., 2021; Soomro et al., 2022). Following this scheme, the probability of debris flow at various sizes and durations can be determined to produce a more realistic and understandable illustration of debris-flow susceptibility.

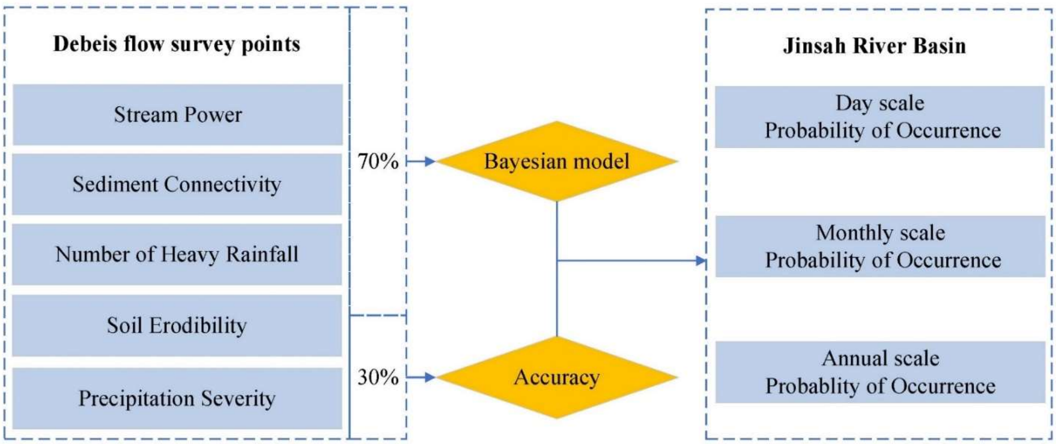

Figure 2: Study Implementation Framework.

3.3 Quantitative parameters

3.3.1 Stream power and its gradient

Stream power (W/m) is the rate at which runoff's gravitational potential energy is transformed into kinetic energy (Pérez-Peña et al., 2009). Its ratio (ω, W/m²) to river width may be used to quantify runoff erosivity to river channels (Bagnold, 1960). When stream power increases throughout the channel, the value is more significant than 0, and runoff erodes; when stream power is reduced downstream, the value is less than 0, indicating an energy-dissipating stretch and sediment deposition occur. Erosion and deposition are balanced at 0 (Lea and Legleiter, 2016). Stream power is mainly affected by river width and discharge in plain areas since the riverbed gradient varies significantly less. This study employed a formula to characterize the valley erosion spatial variation:

$$\omega = \Omega/L \tag{3}$$

L is the reach length (m), and Ω is the stream power (W/m). Since stream power is a function of discharge (Q, m³/s) and gradient (S, %) and discharge can be expressed as a power function of catchment area (A, m²), then

$$\omega=\frac{\gamma a A^{b} S}{L} \tag{4}$$

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where γ=9800 N/m³in the water flow condition; The density of stream debris-flow is between 1000-2400 kg/m³, and a slightly larger coefficient than γ=9800 N/m³ is needed to calculate the power of debris-flow; Since our primary purpose was to understand the fundamental erosion of the channel in the region, the value γ=1.6×104 N/m³ has been used; a and b are constants and can be estimated by function fitting with known flow and catchment area values.

Stream power computation involves depression-filling, slope aspect, catchment area, channel numbering, and elevation extraction. Using a threshold of 1 km², we extracted the longitudinal profile of the valley and its catchment areas (m²), and

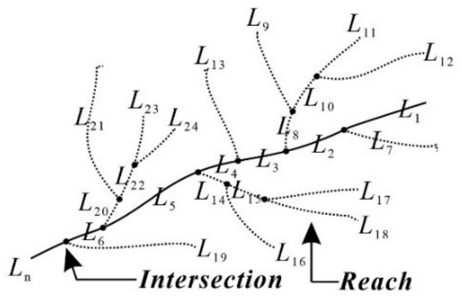

Figure 3: Diagram of numbering reaches. Note: The reach between the two gully junctions is considered a gradient cell.

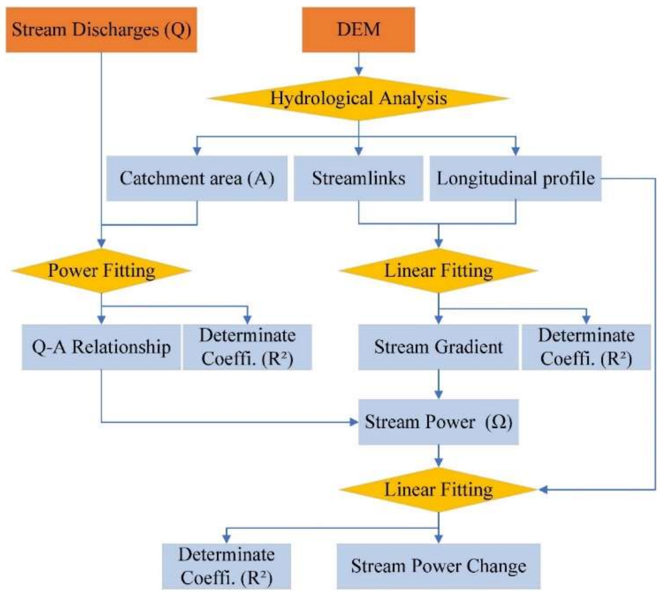

Figure: 4 The calculation process of stream power and its gradient.

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the channel gradients were computed using the first-order fitting function (Fig. 3):

$$\begin{cases} h_{1,i} = k_1 L_{1,i} + c_{1,i}, & R_1^2 \\ h_{2,j} = k_2 L_{2,j} + c_{2,j}, & R_2^2 \\ \quad \dots & \\ h_{n,m} = k_n L_{n,m} + c_{n,m}, & R_n^2 \end{cases} \tag{5}$$

where n is the number of reaches; $h_{\mathrm{n,m}}$ denotes the elevation of point m; C is the corresponding constant; k_{n} is the ratio of the calculation; R_{n}^2 is the linear fitting coefficient of the reach; $L_{\mathrm{n,m}}$ is the length (m) between the mth point of a certain reach and its gully head; and i, j..., m has the same meaning as m but represents river segments with different lengths, that is, the distance between the intersection of two confluence points (Fig. 3). The calculation process is shown in Fig. 4.

3.3.2 Index of connectivity (IC)

Connectivity reflects the topographic resistance of detrital material on a mountain as it is transported. The transport mechanism of detrital materials will change due to the tight relationship between the upslope component (Dup) and the downslope component (Ddn) with topographic variations. The following equation is as follows:

$$\mathrm{IC} = \mathrm{Log}_{10}\left(\frac{\mathrm{D_{up}}}{\mathrm{D_{dn}}}\right) \tag{6}$$

where IC is defined in the range of [-∞, +∞], with greater IC values indicating higher connectivity. The upslope component (Dup) describes the potential for the downward routing of sediment produced upslope and is estimated as follows:

$$D_{up} = \overline{W}\,\overline{S}\sqrt{A} \tag{7}$$

where $\overline{W}$ is the average weighting factor for the upslope contributing area, $\overline{S}$ is the mean slope (%), and A is the size (m²). The downslope component (Ddn) considers particles' flow path lengths to reach the nearest target or sink. It is expressed as follows:

$$D_{dn} = \sum_i \frac{d_i}{W_i S_i} \tag{8}$$

where di is the length of the flow path along the ith cell according to the steepest downslope direction (m), and Wi and Si are the weighting factor and slope of the ith cell, respectively (Jing et al., 2022).Determining weighting factors within a watershed uses the standardized roughness index (SRI) or land use classification data (Zanandrea et al., 2020). The determination of weights in this paper is based on the standardized roughness index (RI), which is calculated as the standard deviation of the difference between the nonsmoothed and smoothed DTM and can represent vegetated regions(Zanandrea et al., 2020). The RI values provide valuable surface roughness information computed in an n×n cell moving window over the residual topography grid. The RI is defined as follows:

$$RI = \sqrt{\frac{\sum_{i=1}^{25}(x_i - x_m)^2}{25}} \tag{9}$$

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where xi is the value of each cell of the residual topography within the moving window, and xm is the mean of the n×n cell values. Here, we used nine as the number of processing cells within the 3×3 cell moving window. The W value is typically calculated from the RI according to the methodology defined by the following:

$$W_{RI} = 1 - \left(\frac{RI}{RI_{Max}}\right) \quad (10)$$

where RIMax is the maximum RI value in the study area.

3.3.3 Extreme precipitation identification

Extreme precipitation (or wetting) events are identified using the run theory (Huang et al., 2021; Yevjevich, 1969). We used McKee's standardized precipitation index (SPI) from 1993 to characterize the precipitation probabilities and observed extreme precipitation events at three scales: daily, monthly, and annual. In the SPI, a two-parameter gamma probability density function is used to explain the frequency distribution of precipitation:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} \quad (11)$$

where x is the precipitation accumulation, and Γ(α) is the gamma function. The gamma distribution's shape and scale parameters, α and β, may be calculated using the most excellent likelihood method (Edwards, 1997). Under certain conditions, the cumulative probability G(x) can be reduced to the so-called incomplete cumulative gamma distribution function, $t=\frac{x}{\beta}$:

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha-1} e^{-t} dt \quad (12)$$

Since Eq. (12) is invalid for zero precipitation (x=0), the cumulative probability distribution, including zeros, may be stated as H(x)=q+(1-q) G(x), where q and 1-q are the probabilities of zero (x=0) and nonzero (x≠0) precipitations, respectively. The SPI is computed by changing H(x) to a zero-mean, one-variance normal distribution. Positive SPI levels imply moist periods, whereas negative values suggest dry periods (Farahmand and Aghakouchak, 2015). The severity of precipitation can be described as the total of the SPI across the length of numerous single severe rainfalls.

$$S_{ij} = \left(\frac{1}{m}\sum_{i=1}^{m}|SPI_i|\right)_j \quad (13)$$

where m is the number of extreme wetting events, indicating wetting occurrences dominated by precipitation.

Table 1 Category of standardized precipitation index (SPI) based on range values (Dutta et al., 2015; Mckee et al., 1993)

SPI Range	Category
+2 to more	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry

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-1.5 to -1.99	Severely dry
-2 to less	Extremely dry

3.3.4 Erodibility (K)

Erodibility (K) is a surface erosion factor related to the concentration of organic materials, sand, mud, and gravel in weathered accumulations. A higher number suggests a more easily degraded surface nature. It is commonly represented as the number of soil particles lost due to precipitation erosivity per unit of time in a standard area. The models used to calculate K include Nomograph (Wischmeier et al., 1971), EPIC(Sharpley and Williams, 1990), Torri (Torri et al., 1997), Shirazi(Shirazi et al., 1988), and Wang (Wang et al., 2013). As it is more widespread in hilly places, the EPIC model (Erosion/Productivity Impact Calculator) was utilized to estimate erosion in this study. The model can be expressed as follows:

$$K_{EPIC} = \left[0.2 + 0.3e^{-0.0256\varphi_{sa}\left(1-\frac{\varphi_{si}}{100}\right)}\right] \times \left(\frac{\varphi_{si}}{\varphi_{cl} + \varphi_{si}}\right)^{0.3}$$

$$\times \left(1-\frac{0.25\varphi_{oc}}{\varphi_{oc}+e^{3.72-2.95\varphi_{oc}}}\right) \times \left[1-\frac{0.7(\varphi_{cl}+\varphi_{si})}{\varphi_{cl}+\varphi_{si}+e^{-5.51+22.9(\varphi_{cl}+\varphi_{si})}}\right] \quad (14)$$

where φ_{sa}, φ_{si}, φ_{oc} and φ_{cl}(%) are the sand, silt, organic carbon and clay contents, respectively (Sharpley and Williams, 1990).

4 Results

4.1 Mapping of High-Energy Valleys and Erosion Dynamics

Stream power is a critical parameter in erosion processes, as it reflects the rate at which gravitational potential energy is converted into kinetic energy, closely linking it to the channel gradient. In the Jinsha River basin, most areas have a channel slope of less than 5.63%, with regions of steeper gradients predominantly concentrated in the middle and lower reaches of the Jinsha and Yalong Rivers, within approximately 30 kilometers of the riverbanks (Fig. 5a and 6).Typically, the morphological evolution of river valleys follows a continuous erosional pattern, progressing through various stages such as linear, exponential, logarithmic, and power function curves (Ohmori and Saito, 1993; Ohmori, 1991; Rădoane et al., 2003). In contrast, the longitudinal profiles of most valleys in the basin display distinct linear characteristics, with an average linear fitting coefficient (R^2) exceeding 0.94 (Fig. 5b). This suggests that the majority of valleys in the basin are still in the early stages of erosional evolution. To quantify stream power, we estimated the flow parameters and gradients at each grid location, converting them into stream power values (Fig. 5d). In Fig. 5c, we categorized river segments by different stream power intervals. Figures 5e, h, and k show the geographical locations of erosion and deposition along the downstream river sections. Our analysis revealed that effective erosion in the Jinsha River basin is primarily concentrated in the middle and lower reaches, with tributaries on both sides exhibiting stronger erosional activity (Fig. 5a). By using an average stream power gradient threshold of 1×10^{-4} W/m², we identified high-energy valleys and validated this threshold using debris flow

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240 fans as geomorphic markers (Fig. 5f-1 and 5f-2). We then quantified the number of high-energy valleys at various buffer distances along the Jinsha and Yalong Rivers, which revealed a significant power-function relationship (Fig. 6). The total number of valleys longer than 200 meters is approximately 32,000. These valleys, requiring substantial driving forces for debris flows, are likely to pose significant disaster risks.

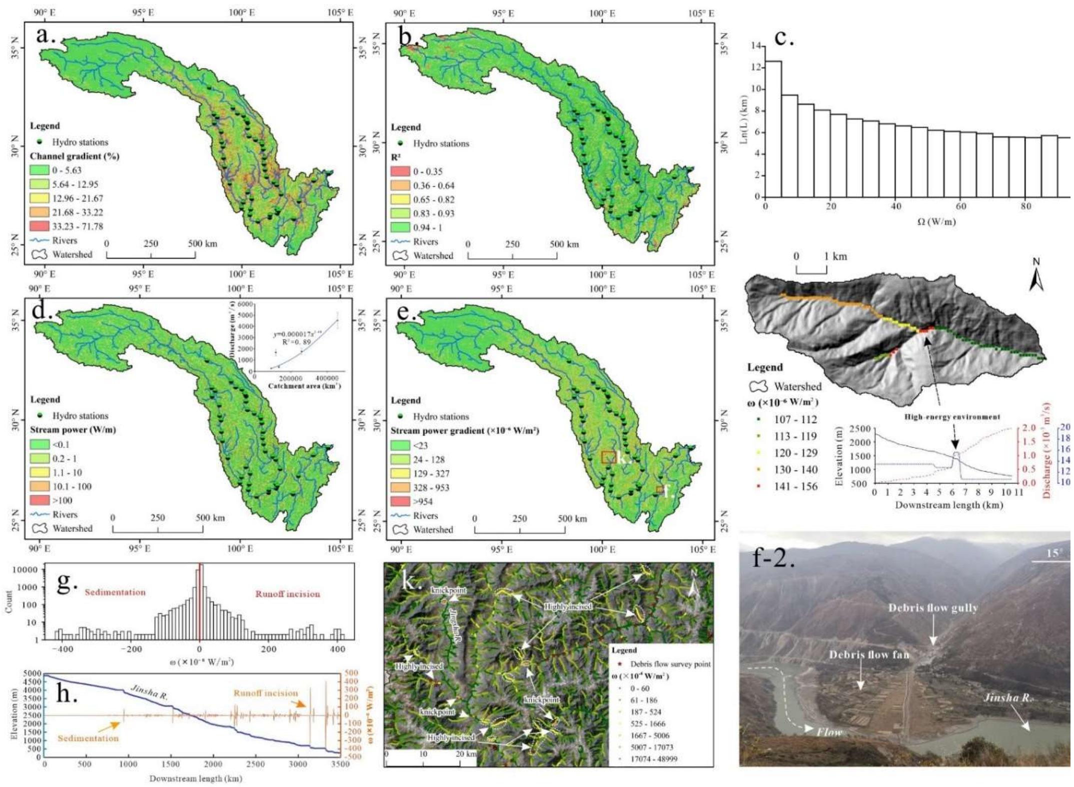

Figure 5: Spatial Distribution Characteristics of Runoff Erosion Activity: (a) Channel gradient; (b) Linear fit coefficients of the longitudinal profile; (c) Length of river segments across different stream power intervals; (d) Stream power distribution; (e) Stream power gradient; (f) A typical debris-flow valley (f-1) and its geomorphic landscape (f-2); (g) Number of erosion and deposition grids in the mainstream of the Jinsha River; (h) Longitudinal profile of the Jinsha River and stream power gradient along the river; (k) A typical high-energy watershed environment. Note: In this study, we calculated the gradient values, stream power, and power gradients for all river reaches. Due to the extensive spatial data involved, we applied interpolation techniques to simplify the results for easier interpretation by readers, as shown in (a), (b), (d), and (e). The photo was taken by the author in January 2021.

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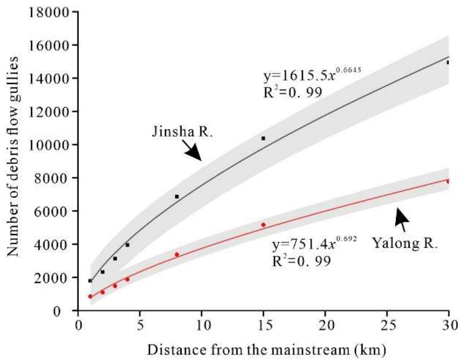

Figure 6: Variation in the Number of High-Energy Reaches with Channel Buffer Distance. Note: High-energy valleys are defined here as those with a stream power gradient greater than 1.3×10^{-3}W/m². This chart displays the count of high-energy valleys within a 200m buffer along the Jinsha River and Yalong River, across a range of buffer widths, specifically including those with a stream power gradient exceeding 1.3×10^{-3} W/m².

4.2 Variations in Surface Erodibility and Connectivity

The formation and transportation of debris flow source material are significantly influenced by surface erodibility and terrain connectivity. During the short period of debris flow formation, an equilibrium is often established between the supply of eroded material to the river and the river's capacity to transport and deposit these materials. The source material typically originates from loose debris triggered by earthquakes, landslides, or shallow landslides, which evolve into unconfined debris (mud) flows. In flatter regions, stable accumulation occurs, disrupting surface connectivity.

As shown in Fig. 7, areas with high erodibility in the Jinsha River basin are primarily concentrated in the downstream regions, where the erodibility factor (K) typically exceeds 0.245 t·ha·h·(ha·MJ·mm)$^{-1}$. These regions are characterized by high clay content and low organic matter. The connectivity of these areas follows a distinct pattern, with lower values in the source regions and higher values in the middle and lower reaches. The Index of Connectivity (IC) values range from -2.47 to 1.17, with high-connectivity zones mainly found in the middle sections of the Jinsha River and along both sides of the Yalong River. In these high-connectivity zones, IC values generally exceed 2.68, which corresponds to the spatial distribution of high-energy or high-gradient valleys. The transition in connectivity between valley slopes and valley bottoms shows a clear decline in values, from high at the slopes to low at the valley bottoms. Deeply incised valleys typically exhibit low connectivity, with the valley bottom often having lower connectivity than the adjacent valley branches. These low-connectivity regions are highly prone to sediment accumulation, which can lead to the formation of barrier dams.

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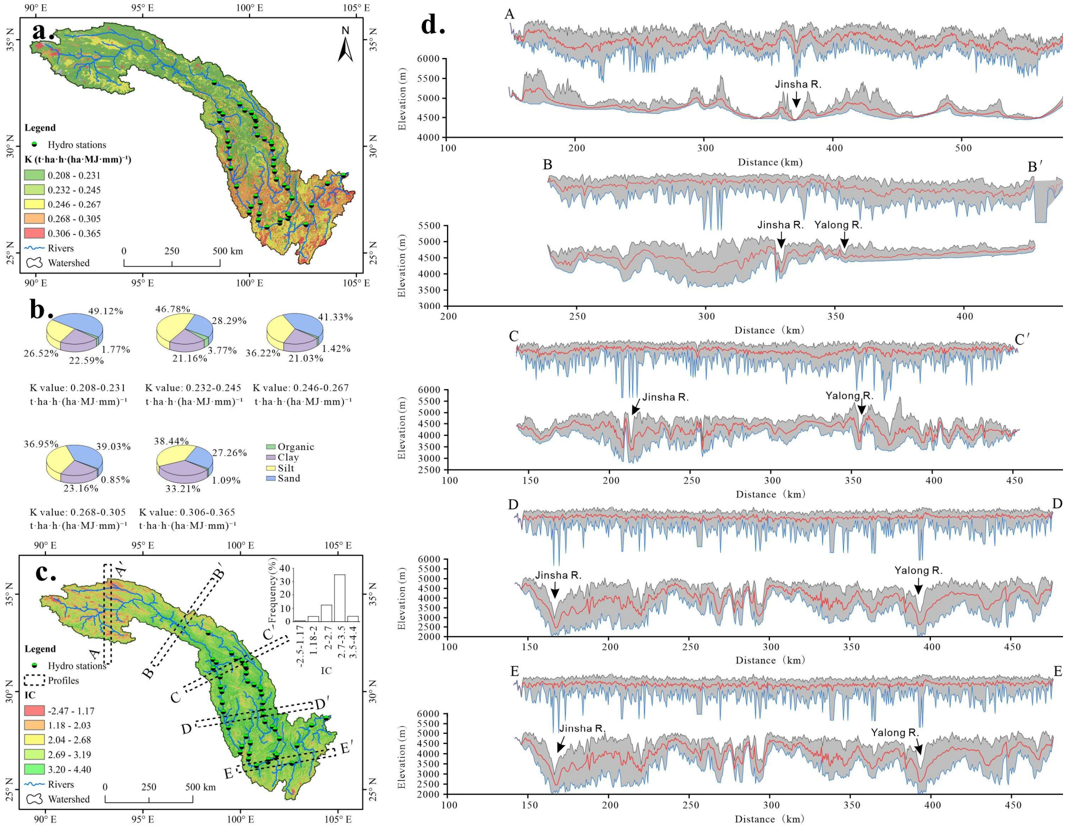

Figure 7: Spatial Variation Characteristics of Surface Erodibility and Connectivity: (a) Spatial distribution of erodibility; (b) Composition of materials within different erodibility ranges; (c) Surface connectivity of the Jinsha River basin; (d) Combined profile of connectivity and elevation (red: mean; black: maximum; blue: minimum).

4.3 Variations in Extreme Precipitation Events and Implications for Debris Flow Risk

We identified extreme precipitation events in the Jinsha River basin over the past decade (2010-2020) using the Standardized Precipitation Index (SPI) on daily, monthly, and yearly time scales, as well as the Run Theory. Figure 8 illustrates that the frequency of extreme precipitation events in any given area is generally fewer than 22 occurrences. The middle and lower reaches of the Jinsha River are identified as high-frequency zones for extreme rainfall events. However, as the observation

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time scale increases, a noticeable shift of these high-frequency areas towards the upstream regions occurs. This spatial shift suggests that the pattern of extreme precipitation events is not stable over time. Figures 8b, e, and h display the severity of precipitation events under daily, monthly, and yearly observation scales. The severity of these events is negatively correlated with the frequency of extreme precipitation events (Figs. 8c, f, and i). Consequently, in regions with fewer occurrences of extreme precipitation, when debris flows do occur, they may be more destructive in terms of scale and intensity than in areas with higher frequencies of extreme precipitation events. Time-series statistical analysis reveals that 2014 experienced a

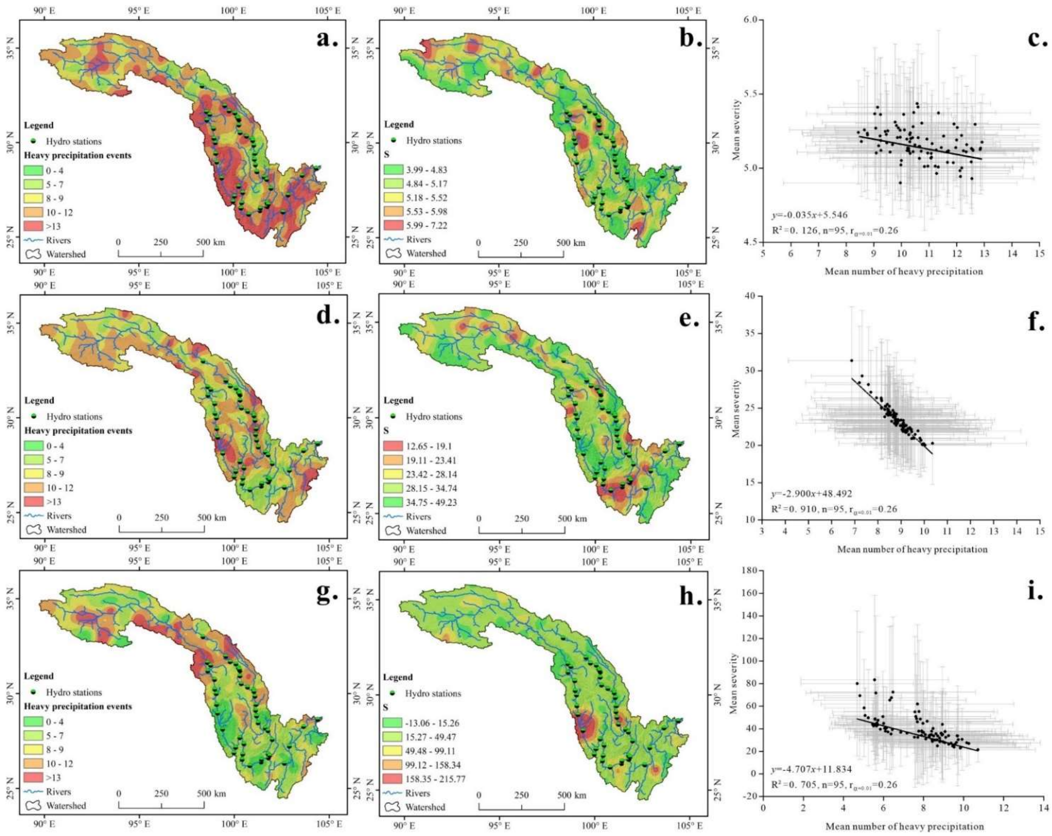

Figure 8: Frequency, Severity, and Correlation of Extreme Precipitation in the Jinsha River Basin (2010–2020). Note: Panels (a), (d), and (g) illustrate the number of extreme precipitation events from 2010 to 2020 at daily, monthly, and yearly observation scales, respectively. Panels (c), (f), and (i) depict the severity of extreme precipitation under the corresponding conditions.

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higher number of extreme precipitation events, with a decrease in frequency observed starting from 2015 (Fig. 9a). This trend indicates a declining risk of debris flows in the Jinsha River basin in recent years. Extreme precipitation events most frequently occur in July, accounting for approximately 30% of the total annual occurrences (Fig. 9b). The severity of major precipitation events shows minimal interannual variation (Fig. 9c).

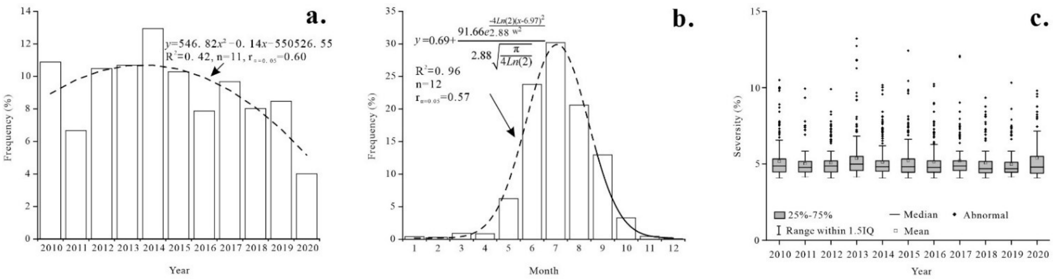

Fig. 9 Temporal Characteristics of Extreme Precipitation Frequency and Severity in the Jinsha River Basin: (a) Interannual variation in the frequency of extreme precipitation from 2010 to 2020; (b) Monthly variations in the frequency of extreme precipitation; (c) Severity of extreme precipitation events.

4.4 Probability of Debris Flow Occurrence at Different Observation Scales

The occurrence probabilities of small, medium, and large debris flow events under daily, monthly, and yearly observation scales are presented in Figure 10. The corresponding test results indicate that the average accuracy of the predictions is 63% (Fig. 11a). The estimation results show that medium- and small-sized debris flows are more prevalent in the basin. During the disaster formation process, the relative importance of various factors contributing to debris flow risk decreases in the following order: surface material erodibility > connectivity > stream power > extreme precipitation frequency and severity (Fig. 11b).

To explore the variability in disaster risk, we constructed a Taylor diagram to evaluate the differences in risk across different time scales. This diagram provides a visual comparison of risk deviations at the monthly and yearly scales relative to the daily scale, characterized by standard deviation, root mean square error (RMSE), and correlation coefficient (Fig. 11c). We found that the standard deviation and RMSE for large debris flows at the yearly scale are significantly smaller compared to the other two categories, suggesting that the risk of large debris flows exhibits relatively stable spatial and temporal patterns. Based on these findings, we can conclude that the temporal and spatial stability of debris flow occurrence probabilities in the Jinsha River basin follows this order: large debris flows > small debris flows > medium debris flows.

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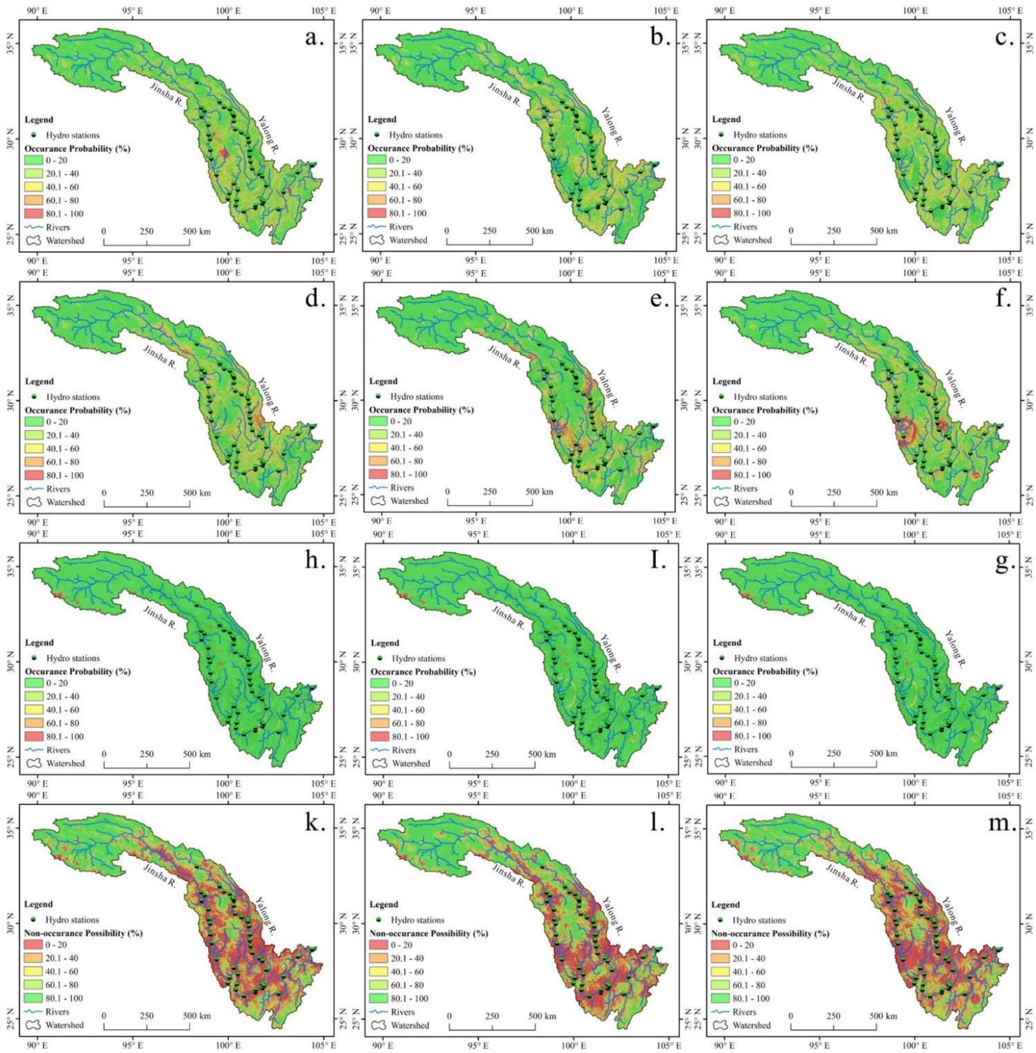

Figure 10: Probability of Debris Flow Occurrence in the Jinsha River Basin. Note: Panels (a), (b), and (c) represent the probabilities of small debris flows occurring at daily, monthly, and yearly scales, respectively; Panels (d), (e), and (f) depict the probabilities of medium-sized debris flows under the same three time scales; Panels (g), (h), and (i) illustrate the probabilities of large debris flows occurring at daily, monthly, and yearly scales; Panels (k), (l), and (m) show the probabilities of no debris flow occurrence under these three time scales.

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4.5 Verification of Disaster Probability Maps with Actual Cases

To validate the accuracy of the disaster probability maps, we reviewed news reports of recent debris flow events in the Jinsha River basin and compared them with our evaluation results. One such event occurred in the early morning of August 21, when a flash flood and debris flow impacted the Yanjiang Expressway JN1 project section in Lugao Town, Jinyang County, Liangshan Prefecture. The site, managed by Shudao Group, is located in the lower reaches of the Jinsha River. According to reports, heavy rainfall persisted for nearly 10 hours prior to the disaster, with accumulated precipitation reaching 160 mm (Fig. 12). Lugao Town (Fig. 13) was the hardest hit, with four confirmed fatalities and 48 missing individuals at the time of reporting. Tragically, in the months following the event, all the missing persons were confirmed dead, raising the total death toll to 52.

When compared with the probability map we created, the likelihood of a medium-scale debris flow occurring at this location was found to exceed 80%, significantly higher than the surrounding areas (Fig. 13b and f). This supports the accuracy of our model, as it predicted the occurrence of debris flow in a high-risk zone. In the aftermath of the disaster, the local geomorphic landscape was significantly altered (Fig. 13d and e), likely due to a combination of accumulated loose sediment, heavy precipitation, and the presence of a high-energy valley. While the probability of small, large, and super-large scale debris flows in this area was relatively low (Fig. 13a and c), it is important to note that this does not imply safety in all areas outside the event zone. Our model also identified other high-risk zones in Jinyang County and its surroundings, highlighting the need for enhanced disaster risk preparedness in the future (Fig. 13b).

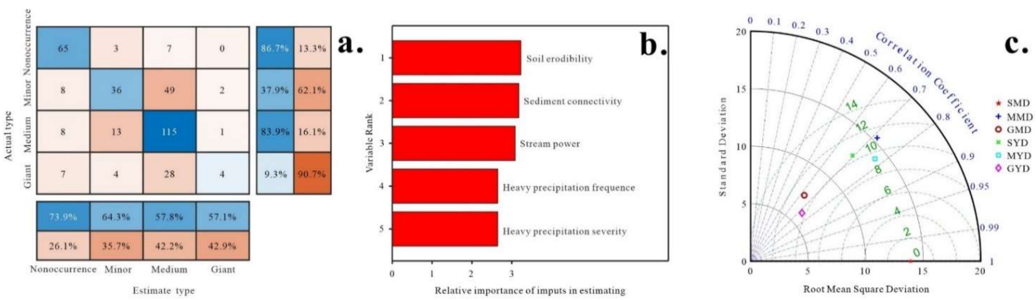

Figure 11: Characteristics of the Probabilistic Model for Debris Flow Occurrence: (a) Confusion matrix; (b) Ranking of covariate importance; (c) Comparisons between daily, monthly, and annual observational scales. Note: SMD, MMD, and GMD represent the deviations of small, medium, and large debris flow occurrence probabilities at the monthly scale relative to the daily scale, respectively; SYD, MYD, and GYD represent the deviations of small, medium, and large debris flow occurrence probabilities at the annual scale relative to the daily scale, respectively.

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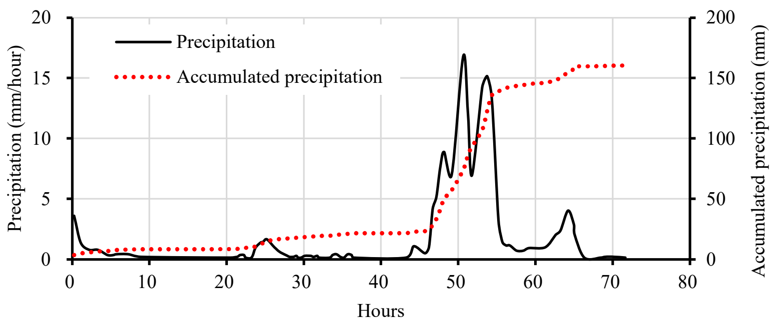

Figure 12: Precipitation Changes in Jinyang County, Sichuan Province, China, Since 00:00 on August 20, 2003.

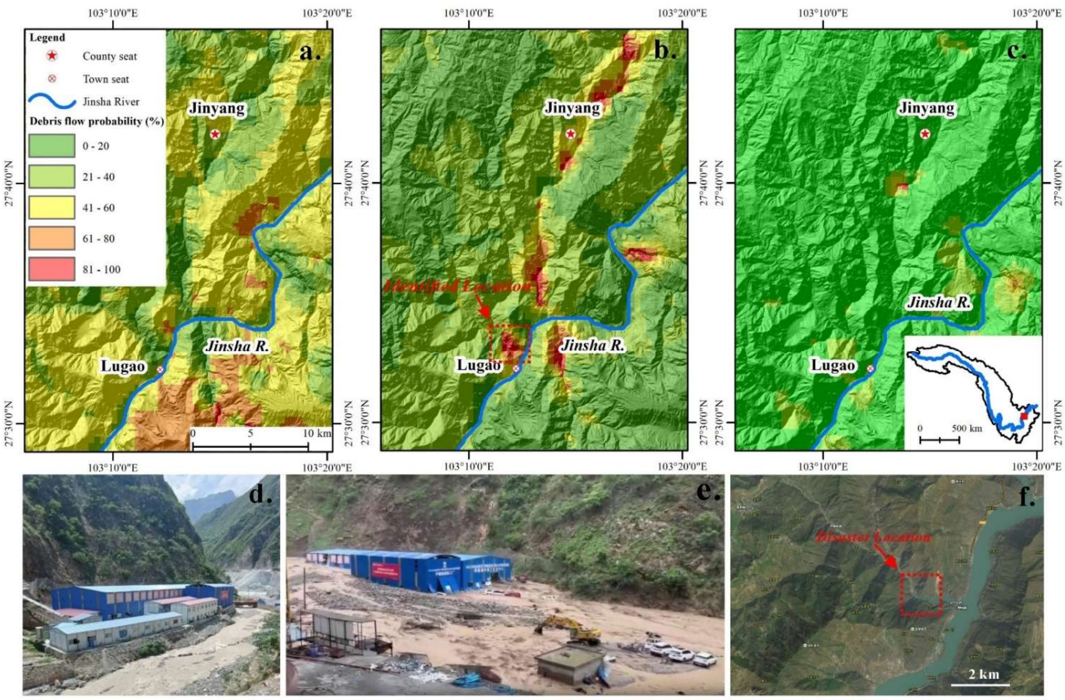

Figure 13: Analysis of the "8·21" Debris Flow in Jinyang County Based on Daily Scale Probability of Occurrence: (a) Probability of small debris flow; (b) Probability of medium-sized debris flow; (c) Probability of large debris flow; (d) Photos of the site before the disaster; (e) Photos of the site after the disaster; (f) Location of the disaster on a satellite image. The photo was taken by the author in August 2023.

5 Discussion

5.1 Impact of Temporal Observation Scale Changes on the Assessment

Precipitation characteristics are among the most dynamic and least predictable factors influencing debris flow formation. There are substantial differences in precipitation characteristics across different temporal observation scales. These differences significantly affect our understanding of debris flow susceptibility, suggesting that both the spatial extent and precipitation variables influencing debris flow risk may vary depending on the time scale of observation. We observed an inverse relationship between the frequency and severity of extreme precipitation events, along with notable spatial inconsistencies in the Jinsha River basin at daily, monthly, and annual time scales. Specifically, as the observation scale increased, the number of extreme precipitation events and the extent of high-incidence areas both decreased and shifted (Fig. 9). These findings suggest a pattern in which extreme precipitation events are more frequent, shorter in duration, and more localized on shorter observation scales. In contrast, on longer time scales, these events are less frequent but tend to cover broader spatial and temporal extents. This pattern aligns with broader changes in climate elements such as temperature, wind, and atmospheric pressure (Mckitrick and Christy, 2019), reflecting the complex dynamics of the surface environmental system. Daily precipitation variations are heavily influenced by factors such as diurnal temperature fluctuations, local topography, wind patterns, vegetation cover, and human activities, leading to high variability and low regularity in regional climate change. In contrast, monthly variations are more strongly influenced by seasonal changes driven by Earth's orbital fluctuations, exhibiting clear periodicity and recurrence patterns. For effective disaster preparedness, it is crucial to focus on areas where debris flow susceptibility remains consistent across different time scales. These regions indicate relatively stable spatial and temporal risk, with more predictable probability values. Furthermore, before a debris flow can form, rainfall must undergo processes such as interception, infiltration, and convergence with the vegetation and soil layers to generate sufficient erosive force—processes that inherently require time. Therefore, assessing debris flow susceptibility under different temporal observation scales can help mitigate bias from response time differences, leading to more accurate risk assessments.

5.2 Changes in Debris Flow Susceptibility Influenced by Climate Change

The rapid uplift of the Tibetan Plateau within the Jinsha River basin has caused widespread stratigraphic fracturing, destabilizing rock masses and creating favorable conditions for accelerated weathering and gravitational erosion (Zhu et al., 2021; Li et al., 2020). This process has contributed to the accumulation of debris and the formation of highly undulating terrain, creating a high-energy environment conducive to debris flow development. These geomorphological features also play a key role in controlling the spatial distribution of debris flow-prone areas. Between 2000 and 2015, China experienced 10,927 debris flow disasters, accounting for 36.14% of fatalities from geological hazards (Wei et al., 2021; Zhang et al., 2018a). However, given the vast geographical span of the Jinsha River basin, which covers multiple natural zones with

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significant spatial and temporal climatic variations, the locations and frequency of such disasters may shift under the influence of global warming (Wei et al., 2021).

The IPCC's 5th Assessment Report indicates a global average surface temperature increase of approximately 0.85°C between 1880 and 2012, with the warming more pronounced in the Northern Hemisphere. The past 30 years have likely experienced the highest temperatures in the last 1,400 years. According to the Clausius-Clapeyron relation, for every 1°C rise in global temperature, the intensity of extreme precipitation increases by 7%, by 15% in high-altitude areas, and precipitation variability rises by 5% (Zhang and Zhou, 2020; Ombadi et al., 2023). This suggests a more uneven temporal distribution of precipitation, with greater fluctuations between wet and dry periods, and an expanded range of precipitation intensities. Two primary theories explain the increase in extreme precipitation events. First, climate warming leads to higher atmospheric moisture content and a slowdown in atmospheric circulation, causing low-pressure systems to remain stationary. Second, weakened summer atmospheric circulation causes it to become slower and more erratic, resulting in prolonged heatwaves and droughts (associated with high-pressure systems) and extended periods of heavy rainfall (associated with low-pressure systems). In China, the intensity and frequency of extreme precipitation events, particularly in the southern regions and the Yangtze River basin, have significantly increased from 1970 to 2018 (Li et al., 2022). These changes have altered the hydrological cycle, leading to shifts in the spatial and temporal distribution of water resources, as well as changes in the overall quantity of available water resources (Wu et al., 2020). As a result, the susceptibility of disaster-prone environments has increased. The Jinsha River basin, in line with general climate trends, has seen increases in temperature, precipitation, and runoff between 1972 and 2017, primarily driven by ice melt and precipitation (Wu et al., 2020). This has caused a significant rise in streamflow from May to June, peaking in July (Fig. 10b). Consequently, this period is critical for debris flow preparedness. Previous studies indicate that precipitation in the Jinsha River basin follows a distinct wet and dry cycle with minimal interannual variability (Song et al., 2012). Future projections for extreme precipitation indices in China suggest a consistent upward trend, with a slight decrease in the number of consecutive dry days (CDD). The growth rate of these indices is expected to accelerate over the coming decades, extending into the middle of this century. Changes in thermal (temperature) and dynamic (circulation) factors are likely contributors to the increased intensity and frequency of future precipitation events (Guo et al., 2018). Recent precipitation simulations for the Yalong River basin under future warming scenarios suggest that the region may experience more frequent and intense precipitation events, which would increase the likelihood of debris flows. While heavy precipitation typically results in flooding in plains, it can have catastrophic consequences in high mountain valleys, such as those found in the Jinsha River basin. Therefore, the susceptibility areas identified in Figure 10 should be prioritized for disaster prevention efforts.

5.3 Interaction Between Reservoir Operations and Debris Flow Activity

The Jinsha River basin is rich in hydropower resources, with an exploitable capacity of approximately 1.1×10^8 kilowatts, making it one of China's strategically significant hydropower bases. Several large hydropower plants have already been constructed, including Wudongde (dam height: 270 m), Baihetan (289 m), Xiluodu (285.5 m), and Xiangjiaba (88.2 m), with a total installed generation capacity exceeding 4.2 × 10^6 kilowatts. Additionally, numerous smaller hydropower plants are either operational or in the planning stages along the main streams of the Jinsha and Yalong Rivers (Fig. 4).

The development of hydropower has significantly altered the river valley landscape, transforming it from one primarily shaped by runoff and erosion into a series of reservoirs extending hundreds of kilometers. Debris flows bring substantial sediment into these reservoir areas, leading to complex interactions between reservoir water levels and debris flow activity. The presence of dams raises the water level, elevating the base level of erosion, which reduces the erosive and incisional forces acting on the valleys along the reservoir areas of the Jinsha River. However, the sediment carried by debris flows contributes to soil and water conservation within the reservoirs, effectively reducing sediment flux and intercepting 71.4% of the sediment in the Yangtze River, surpassing the impacts of land reclamation and landslides caused by agricultural activities. For example, the average annual sediment load at the Panzhihua station increased by 42.4% from 1966–1984 to 1985–2010, primarily due to mineral extraction and deforestation. However, this was followed by a 75.9% decrease from 2011–2015, attributed to the operation of cascade reservoirs in the middle Jinsha River basin since 2010 (Li et al., 2018). Such fluctuations in sediment load can significantly impact the lifespan of the reservoirs.

The long-term interplay between regional geology, geomorphology, and hydrology will be shaped by this reciprocal feedback. Notably, nearly all completed and planned reservoirs along the Jinsha and Yalong main streams are situated in areas highly susceptible to debris flows, as identified in this study (Fig. 8a). The number of debris-flow channels exhibits a multiplicative power function relationship with their distance from the mainstream channel, with a distinct trend change occurring within a 5 km radius of the reservoir area (Fig. 6). The relatively dense distribution of debris-flow channels in this zone highlights the significant interaction between reservoir operations and debris flow activity.

5.4 Response to Debris Flow Hazards

The distribution of debris flow gullies in the middle and lower reaches of the Jinsha River is notably dense (Fig. 8a), and the challenges associated with responding to debris flow disasters are exacerbated by global climate change and the development of engineering infrastructure. The occurrence of debris flows has disrupted river ecosystems, making the scientific management of these hazards a pressing societal concern. Effective responses to debris flow disasters must consider the principles of geomorphological evolution and human safety, utilizing the specific spatial and energy characteristics of the affected areas. Currently, a combination of check dams, ecological engineering, and management practices is widely adopted to mitigate the impacts of debris flows on critical infrastructure and residential areas. These measures include constructing check dams and dredging channels at the mouths of debris flow gullies, creating terraces, afforesting catchment areas, and installing monitoring and early warning systems (Xiong et al., 2016). Globally, building check dams in potential debris flow gullies is recognized as one of the most effective disaster prevention methods (Gao et al., 2022; Chong et al., 2021). This intervention modifies the micro-environment of river valleys in hydrological, geomorphological, and ecological dimensions. In the initial stages, check dams serve multiple functions: storing water, reducing runoff peaks, slowing flow velocity, promoting seepage, and recharging groundwater. Additionally, the dams trap organic matter and sediment, contributing to carbon sequestration and sediment retention. As silt accumulates, the topography upstream of the check dam gradually flattens, creating favorable conditions for vegetation growth and fostering ecological restoration in the local environment (Xiong et al., 2016). Over time, this process can transform debris flow gullies into ecological corridors, directly reflected in reduced surface connectivity and adjustments in river power. A critical challenge in debris flow control is identifying optimal locations and determining the appropriate scale for check dam construction. During dam construction, structures must be designed to accommodate peak flow from potential debris flows. However, for many debris flow gullies, the necessary engineering parameters are often derived from industry-standard formulas, which may be limited by regional variations and insufficient observational data.

The findings of this study provide valuable insights into the spatial locations and occurrence probabilities of debris flow-prone valleys in the Jinsha River basin. Beyond merely identifying areas with high debris flow density, this research offers data on stream power, gradient values, surface connectivity, and the probability of debris flow events in specific channels. This enables the precise identification of high-energy valleys and the targeted monitoring and management of these areas. In the context of global climate change, although controlling the frequency and intensity of extreme precipitation events may be challenging, disaster risk areas can be more effectively identified using the debris flow probability maps generated in this study (Fig. 10). High-risk zones of river power and connectivity can be pinpointed from Figures 5d and 7c, allowing for the accurate determination of locations for constructing silt dams. The scale of dam construction can then be optimized based on the relationship between soil erodibility, sediment connectivity, river power, and the observed effects of existing check dams of varying sizes.

6 Conclusions

Accurately defining the spatial and temporal intervals of debris flow occurrences is a significant challenge in assessing mountain disaster susceptibility. This task is also crucial for developing effective disaster mitigation and ecological restoration strategies. The Jinsha River basin, a typical region in China characterized by densely distributed high mountain valleys, experiences frequent debris flows. Due to the basin's vast area and the complex mechanisms behind debris flow formation, relying solely on simple indicators fails to capture the underlying physical processes, resulting in low spatial accuracy when assessing debris flow susceptibility.

To address this challenge, we focused on the fundamental "source-sink" process underlying debris flow formation. A carefully selected set of geomorphodynamic parameters was identified, and their quantitative characteristics were systematically analyzed. Based on these parameters, we developed a Bayesian model-based assessment framework that aims to capture more precise and reliable debris flow susceptibility patterns. This approach enables a more comprehensive understanding of the spatial distribution and intensity of debris flow events, improving the accuracy and robustness of susceptibility assessments in complex terrains. The model's estimation results indicate the debris flow susceptibility in the Jinsha River basin for small, medium, and large events, with an average accuracy of 63%. Furthermore, through an empirical

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analysis of the catastrophic mountain flood and debris flow event ("8.21") in Jin-yang County, Sichuan Province, China, we found that the evaluation based on this model closely matched the actual disaster locations, validating the accuracy of the assessment. Our study concluded that, during the disaster formation process, the relative importance of the various factors contributing to debris flow risk decreases in the following order: surface material erodibility > connectivity > stream power > extreme precipitation frequency and severity. Debris flow-prone valleys are densely distributed within a 30 km stretch along the middle and lower reaches of the Jinsha and Yalong Rivers, with approximately 32,000 risk-prone river valleys longer than 200 meters. The majority of these valleys are small to medium-sized gullies. The distribution of these valleys follows a power function relationship with the distance from the main river.

In areas with high probability but infrequent debris flow occurrences, when such events do occur, they tend to be of a larger scale and greater destructiveness. Given that many existing and planned large reservoirs in the Jinsha River basin are located in regions densely populated with debris flow-prone valleys, and considering that the likelihood of extreme precipitation events is projected to increase in the future, addressing debris flow susceptibility remains a significant and ongoing challenge.The datasets generated in this study, including river power, surface connectivity, and debris flow occurrence probability, provide valuable insights into the dynamics and susceptibility of debris flow gullies. These datasets offer practical reference value for major construction projects, such as large reservoirs, bridges, and residential developments.

Data availability

Our study provides a dataset consisting of the following: (1) "River Power and River Power Gradient Spatial Data for the Jinsha River Basin," (2) "Surface Connectivity Spatial Data for the Jinsha River Basin," and (3) "Debris Flow Occurrence Probability Maps for Small, Medium, and Large-Scale Events in the Jinsha River Basin." The data has a spatial resolution of approximately 90 meters. Interested readers may request access to the dataset free of charge from the corresponding author.

Author contributions

Zhenkui Gu plannet the campaign; Zhenkui Gu and Xin Yao performed the measurements; Xuchao Zhu provided some key data.

Competing interests

The authors declare that they have no conflict of interest.

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