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Accounting for Climate Uncertainty in Landslide Hazard Assessment: A Quantitative Weighting Framework for Meizhou City, South China

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ABSTRACT

Climate change is intensifying landslide risks in mountainous regions, yet existing susceptibility models rarely offer a quantitative framework that explicitly accounts for the uncertainties of multiple climate-driven hazard factors. To address this gap, this study develops an adaptive Fuzzy Analytic Hierarchy Process (FAHP) protocol to determine weighting coefficients for climate-related landslide triggers, using Meizhou City, Guangdong Province, South China, as a case study. A three-tier hierarchy—linking hazard factors, landslide types, and slope components—is constructed. Based on fuzzy pairwise comparisons from 12 interdisciplinary experts and validated against meteorological records (2020–2025), weights are computed via Chang's Fuzzy Synthetic Extent (FSE) method. Results identify rainfall as the dominant factor (weight 0.46), followed by typhoon-induced heavy rainfall (0.28), temperature fluctuations (0.15), and freeze-thaw cycles (0.11). Sensitivity analyses reveal distinct patterns: shallow soil landslides respond most strongly to rainfall (0.48), rockfalls to typhoon-induced rain (0.35), and deep rock landslides to the combined effect of both (0.42 and 0.32, respectively). At the slope-component level, the overburden layer under rainfall receives the highest weight (0.52), prioritizing it for reinforcement. The proposed framework offers a reproducible, uncertainty-aware tool that generates quantitative inputs for early warning thresholds, engineering prioritization, and resource allocation in Meizhou—and is readily transferable to other mountainous regions of South China with comparable climatic and geological settings.

Keywords: Landslide susceptibility; Climate hazard factors; Fuzzy Analytic Hierarchy Process (FAHP); Multi-criteria decision making; Slope stability

1. Introduction

Landslides constitute a major natural hazard, posing significant threats to human safety, critical infrastructure, and natural ecosystems worldwide. The risk is particularly elevated in mountainous and hilly terrains, where steep slopes, complex geological conditions, and intensive human activities converge. South China, characterized by its humid subtropical climate and weathered granite landscapes, is one such region with historically high landslide susceptibility [1–3]. Meizhou City, located in northeastern Guangdong Province, epitomizes this vulnerability: mountains and hills cover approximately 80% of its territory, and its complex geological fabric has rendered it a historical hotspot for geological disasters. In recent years, this inherent susceptibility has been critically amplified by intensifying climate extremes. Since the 2024 flood season, average precipitation in Meizhou reached 1,033.8 mm—86% above the long-term average—while the 2025–2026 winter recorded a mean temperature of 15.4°C, 1.7°C above normal and the highest since 1951. These climatic anomalies have significantly escalated landslide risk, underscoring an urgent need for more adaptive and quantitative hazard assessment tools.

Climate change is fundamentally altering precipitation regimes, typhoon dynamics, and freeze-thaw cycles worldwide [4–6]. However, current landslide assessment and early warning systems remain largely anchored to historical climate benchmarks. They predominantly emphasize static geological factors and qualitative risk classifications, while lacking robust quantitative frameworks capable of: (i) integrating multiple climate-driven hazard factors; (ii) capturing the synergies among these factors; and

(iii) explicitly accounting for the inherent uncertainties in both climate projections and expert knowledge [7–9]. The Guangdong Provincial Department of Natural Resources recently highlighted a growing spatiotemporal convergence between geological hazards and heavy rainfall events, explicitly calling for the incorporation of climate forecasts into quantitative landslide risk assessments [10]. Despite these pressing needs, existing studies have primarily offered qualitative rankings of climate-related landslide triggers (Table 1) [1, 4, 11, 12], consistently identifying rainfall as the primary driver, yet failing to provide a unified quantitative scale that can be directly operationalized in early warning systems or engineering design. While this global consensus provides a useful starting point, it remains qualitative in nature and does not reflect the distinct climatic conditions of subtropical South China, where snowmelt is absent and typhoon-induced rainfall plays a critical role. Furthermore, these rankings lack quantitative weights at the slope, landslide-type, and component scales—information that is essential for targeted engineering interventions and early warning threshold calibration. These limitations motivate the present study.

Table 1

Consensus global ranking of climate-related landslide triggers from existing literature [1–6].

Rank	Causative Factor	Core Mechanism
1	Extreme rainfall	Increases pore pressure, reduces effective stress
2	Snowmelt/glacial melt	Alters hydrological conditions, reduces suction
3	Freeze-thaw cycles	Ice wedging widens cracks, reduces strength
4	Temperature changes	Accelerates weathering, alters hydrology

The Fuzzy Analytic Hierarchy Process (FAHP) has emerged as a robust multi-criteria decision-making (MCDM) tool that systematically encodes expert uncertainty through triangular fuzzy numbers [13, 14]. It has found successful applications in flood risk mapping [15], infrastructure vulnerability assessment [16], and multi-hazard susceptibility modeling [17]. Nevertheless, its application to systematically quantify the weights of climate factors for different landslide types and slope components—particularly at a regional scale with localized climate characteristics—remains scarce. Meizhou City presents a unique and compelling case for such a study: it experiences concentrated rainfall from April to September, receives 3–4 typhoons annually, and exhibits significant diurnal temperature variation without sustained freezing periods. These distinct conditions necessitate a tailored, multi-level assessment that goes beyond generic global rankings.

To address these gaps, this study develops an adaptive FAHP protocol to determine the Climate Hazard Importance Factors (CHIF) for representative natural slopes in Meizhou. A three-tier hierarchical model (hazard factors → landslide types → slope components) is constructed, drawing on fuzzy pairwise comparisons from 12 interdisciplinary experts and validated against meteorological data from 2020–2025. The study specifically focuses on four climate-related hazard factors: rainfall, typhoon-induced heavy rainfall, temperature fluctuations, and freeze-thaw cycles.

The main contributions of this work are threefold:

- It provides a reproducible, uncertainty-quantifiable framework for regional multi-hazard landslide weighting, addressing a critical gap in current practice.
- It generates quantitative CHIF values at slope, landslide-type, and component scales, offering

directly actionable inputs for early warning systems in Meizhou and analogous mountainous regions of South China.

- It delivers decision support for prioritizing slope stabilization measures and optimizing disaster-prevention resource allocation under climate uncertainty.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature; Section 3 presents the methodological framework; Section 4 reports the results; Section 5 discusses the findings and their implications; Section 6 concludes the study; and Section 7 outlines the practical applications and policy recommendations.

2. Literature Review

This section reviews three bodies of literature that underpin the methodological framework of this study: (1) climate change projections and their regional manifestations in South China; (2) the limitations of existing multi-factor landslide assessment frameworks; and (3) the application of Fuzzy Analytic Hierarchy Process (FAHP) and multi-expert aggregation methods in hazard weighting. By synthesizing these strands, we identify a critical gap—the absence of a quantitative, uncertainty-aware framework for weighting climate-driven hazard factors at multiple slope-relevant scales—that the present study aims to fill.

2.1 Climate Change Projections and Regional Characteristics

The Intergovernmental Panel on Climate Change (IPCC) has developed Representative Concentration Pathways (RCP2.6–8.5) and Shared Socioeconomic Pathways (SSPs) to project future climate trajectories [1, 2]. These scenarios consistently indicate that global warming will intensify the frequency and magnitude of extreme precipitation, tropical cyclones, and temperature extremes in many regions, with profound implications for landslide activity [4, 7]. In South China, these projections are already materializing: the 2025 Guangdong Climate Bulletin reported an annual precipitation of 1,839.6 mm (8% above normal), with 15 tropical cyclones affecting the province—tying the 1961 record [9]. Nationally, 2024 witnessed 41 regional torrential rain events and 13 typhoon landfalls [10].

Meizhou City exemplifies these trends at the local scale. The 2024 average temperature in Meijiang District reached 22.4°C (0.6°C above normal), with 49 high-temperature days ($\geq 35^{\circ}\text{C}$) [12]. The 2025–2026 winter was exceptionally warm, averaging 15.4°C (1.7°C above normal, the highest since 1951), yet punctuated by 11 cold-air episodes, four of which brought widespread temperatures $\leq 5^{\circ}\text{C}$ [11]. Meizhou receives approximately three typhoons annually, and observational data suggest a characteristic landslide trigger sequence: “prolonged rainfall $\rightarrow$ slope saturation $\rightarrow$ extreme triggering event.” In this sequence, conventional rainfall acts as a preparatory factor, typhoon-induced rain serves as the direct trigger, while freeze-thaw cycles and temperature fluctuations exert cumulative effects on long-term slope stability. Although the present study primarily draws on field data (2020–2025), the proposed FAHP framework is designed to accommodate future RCP/SSP projections, enabling dynamic CHIF updates as climate scenarios evolve.

2.2 Challenges in Multi-Factor Landslide Assessment

Landslides are rarely monocausal; compound events—involving simultaneous or sequential triggers—can substantially exacerbate disaster severity [13–17]. Despite growing recognition of this complexity, most existing assessment frameworks remain qualitative or semi-quantitative. The PIEVC protocol [27] offers only ordinal ratings without numerical weights; ISO 14091:2021 [24] provides general adaptation guidelines but lacks specific weighting methodologies; Guangdong Province's local standard [25] still relies predominantly on a single rainfall threshold; and the provincial three-year action plan [26] does not quantitatively differentiate among typhoon-induced rain, freeze-thaw cycles, and temperature fluctuations. These limitations are not merely academic: they translate into operational deficiencies in early warning systems (which cannot set differentiated thresholds), engineering design (which cannot prioritize interventions across slope components), and resource allocation (which cannot optimize budget

distribution across hazard types).

2.3 FAHP and Multi-Expert Aggregation

The Analytic Hierarchy Process (AHP) [18, 21] decomposes complex decisions into hierarchical structures for pairwise comparisons. Its fuzzy extension (FAHP) incorporates fuzzy set theory to encode uncertainty in expert judgments [22, 23]. Among FAHP variants, Chang's Fuzzy Synthetic Extent (FSE) method [23] is well-suited for interdependent and uncertain criteria, computing fuzzy weights directly from comparison matrices [24, 20].

In landslide research, AHP/FAHP has been extensively applied to susceptibility mapping, but predominantly for static factors (slope, lithology, land use), with limited attention to dynamic climatic factors [5, 6]. This gap is notable given that climate variables are inherently more uncertain than static site conditions—precisely the uncertainty FAHP handles. This study addresses this gap by applying FAHP to climate-related hazard factors.

A critical consideration is the aggregation of individual expert judgments. Forman and Peniwati [19] distinguished Aggregation of Individual Judgments (AIJ) from Aggregation of Individual Priorities (AIP). Aczél and Alsina [25] proved the geometric mean (GM) is the only operator satisfying associativity and scale invariance, making it the theoretically preferred choice. Empirically, Altamimi et al. [5] validated AIJ-GM with group consistency ratios below 0.088. Following this precedent, this study adopts AIJ-GM aggregation, supplemented by dual sensitivity analyses (arithmetic mean re-aggregation and expert consensus filtering) to assess robustness [20].

In summary, climate change is intensifying landslide hazards, existing frameworks remain qualitatively limited, and FAHP offers an underexploited tool for quantitative hazard weighting. This study operationalizes FAHP at three hierarchical levels (slope, landslide-type, component scales) within Meizhou's context, producing actionable CHIF values.

2.3 FAHP and Multi-Expert Aggregation

The Analytic Hierarchy Process (AHP), introduced by Saaty [18, 21], decomposes complex decision problems into hierarchical structures, enabling systematic pairwise comparisons of criteria. Its fuzzy extension (FAHP) incorporates fuzzy set theory to encode the uncertainty inherent in expert judgments [22, 23]. Among various FAHP implementations, Chang's Fuzzy Synthetic Extent (FSE) method [23] is particularly well-suited for problems with interdependent and uncertain criteria, as it computes fuzzy weights directly from pairwise comparison matrices without requiring additional optimization procedures [24, 20].

In landslide research, AHP and FAHP have been extensively applied to susceptibility mapping, but predominantly for static topographic and geological factors (e.g., slope angle, lithology, land use), with comparatively limited attention to dynamic climatic factors [5, 6]. This gap is especially notable given that climate variables are inherently more uncertain and variable than static site conditions—precisely the type of uncertainty that FAHP is designed to handle. The present study addresses this gap by applying FAHP specifically to climate-related hazard factors.

A critical methodological consideration in FAHP is the aggregation of individual expert judgments. Forman and Peniwati [19] distinguished between two aggregation paradigms: Aggregation of Individual Judgments (AIJ) and Aggregation of Individual Priorities (AIP). Aczél and Alsina [25] demonstrated that the geometric mean (GM) is the only aggregation operator that satisfies fundamental properties of associativity and invariance under scale transformations, making it the theoretically preferred choice. Empirically, Altamimi et al. [5] validated the AIJ-GM approach in a bridge infrastructure study, reporting group consistency ratios (CR) below 0.088. Following this precedent, the present study adopts AIJ-GM aggregation, supplemented by dual sensitivity analyses (arithmetic mean re-aggregation and expert consensus filtering) to assess robustness [20].

In summary, the literature reveals a clear trajectory: climate change is intensifying landslide hazards,

existing multi-factor frameworks are qualitatively limited, and FAHP offers a promising but underexploited tool for quantitative hazard weighting. The present study contributes by operationalizing FAHP at three hierarchical levels (slope, landslide-type, and component scales) within the specific climatic and geological context of Meizhou City, thereby producing directly actionable CHIF values.

3. Methods

This study establishes a structured methodological framework aimed at quantifying, based on expert judgment, the relative importance of climate-related hazard factors affecting slope stability in Meizhou City. The framework employs the Adaptive Fuzzy Hierarchical Analysis Method (FAHP) to address the assessment of multiple hazard factors and integrates uncertainty management mechanisms through fuzzy set theory. Figure 1 illustrates the hierarchical structure for assessing the impact of four climate-related hazard factors—rainfall (R), temperature variation (T), typhoon-induced heavy rainfall (S), and freeze-thaw cycles (F)—on representative natural slopes in Meizhou City. This hierarchical structure comprises three levels:

- First Layer (Disaster-Causing Factors): Rainfall, temperature fluctuations, typhoon-induced heavy rainfall, freeze-thaw cycles;
- Second Layer (Landslide Types): Shallow soil landslides, deep rock landslides, rockfalls;
- Third Layer (Slope Component Layer): For each landslide type listed in the second layer, assess the corresponding key slope components. Specifically, for shallow soil landslides, assess the overburden, bedrock interface, and tensile fracture zones; for deep rock landslides, similarly assess the overburden, bedrock interface, and tensile fracture zones; and for rockfalls, also assess the overburden, bedrock interface, and tensile fracture zones.

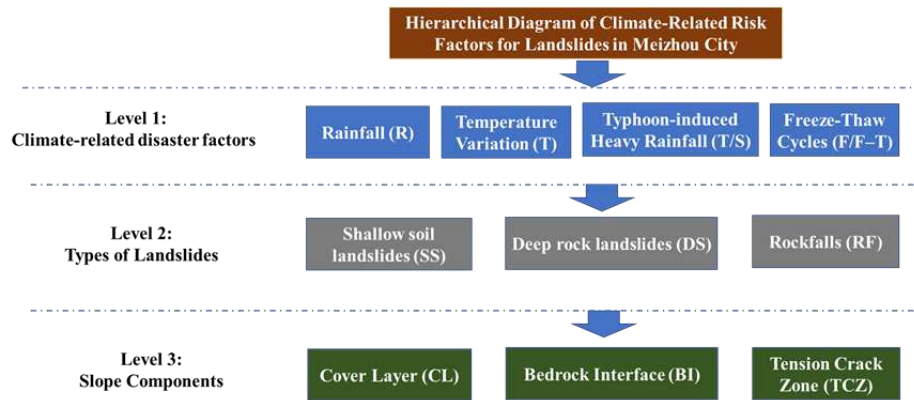


Fig.1.A Hierarchical Framework for Assessing the Impact of Climate-Related Disaster Factors on Landslide Disasters

3.1 Climatic Hazard Importance Factor (CHIF) for Landslides

Table 2 and Figure 2 illustrate the FAHP framework adopted in this study. Figure 2 depicts a three-tiered hierarchical structure composed of climate-induced disaster factors, landslide types, and slope components, while Table 2 outlines the fuzzy pairwise comparison and aggregation processes. Let w_i denote the climate hazard factor importance coefficient (CHIF) for hazard factor i . At each level, w_i represents the relative importance of a specific hazard factor compared to other hazard factors. As shown in Table 2, the CHIF is determined at every level of the hierarchy, thereby generating a complete set of weights, with the sum of the weights at each level equal to 1:

Level 1 (Disaster-Causing Factors):

$$w_R + w_T + w_S + w_F = 1$$

Second layer (landslide type layer, given the causative factor):

$$w_{SS} + w_{DS} + w_{RF} = 1$$

Third layer (slope component stratification, given combinations of disaster-causing factors and landslide types):

$$w_{CL} + w_{BI} + w_{TCZ} = 1$$

- First layer: w_X represents the CHIF of hazard factor $X \in \{R, T, S, F\}$ at the overall slope scale;
- Second layer: $w_{(X,Y)}$ represents the CHIF of landslide type $Y \in \{SS, DS, RF\}$ under the influence of disaster-causing factor X ;
- Third layer: $w_{(X,Y,Z)}$ represent the CHIF of slope component $Z \in \{CL, BI, TCZ\}$ under disaster-causing factor X and landslide type Y .

Complete CHIF sets at each level are computed through subsequent fuzzy pairwise comparison and aggregation processes.

The subscripts $\{R, T, S, F\}$ correspond to rainfall, temperature variations, typhoon-induced heavy rainfall, and freeze-thaw cycles in the first layer (hazard factors), respectively. Similarly, CHIF evaluates climate-related hazard factors in the second layer (landslide types) and the third layer (slope components). This generates a set of weights covering all combinations of hazard factors and layers. For example, in Figure 2: w_X corresponds to the CHIF for rainfall at the overall slope surface scale (first layer); $w_{(X,Y)}$ corresponds to the CHIF for the impact of rainfall on shallow soil landslides (second layer); and $w_{(X,Y,Z)}$ corresponds to the CHIF for the impact of rainfall on the overburden (third layer). Generally speaking: for the first level, w_i represents the CHIF of hazard factor i at the overall slope scale; for the second level, w_{ig} represents the CHIF of hazard factor i acting on landslide type g ; for the third level, w_{igh} represents the CHIF of hazard factor i acting on slope component h within landslide type g (as shown in Table 2 and Figure 2).

At each level of the hierarchy (disaster-causing factors, landslide types, and slope components), CHIF values are assigned and calculated based on expert judgment using an adaptive FAHP protocol.

Table 2

A Three-Level Fuzzy Analytic Hierarchy Process (AHP) Framework for Determining Climate Hazard Importance Factors (CHIF) in Landslides

Level	Category	Element	Symbol	Description
1	Climate-related disaster factors	Rainfall	R	Conventional heavy rainfall, increasing pore water pressure
		Temperature fluctuations	T	Extreme heat/temperature variations, accelerating weathering
		Typhoon-induced downpours	S	Short-term, extreme heavy rainfall brought by typhoons
		Freeze-thaw cycles	F	Ice spalling widens cracks, causing strength degradation
2	Types of Landslides	Shallow soil landslides	SS	Weathered residual soil on granite, slip surface 2–5 m
		Deep rock landslides	DS	Tectonic fractures/groundwater, large-scale
		Rockfalls	RF	Road cuts, slope-cut construction, high and steep overhanging faces
3	Slope components	Overburden	CL	Weathered residual soil that softens when wet

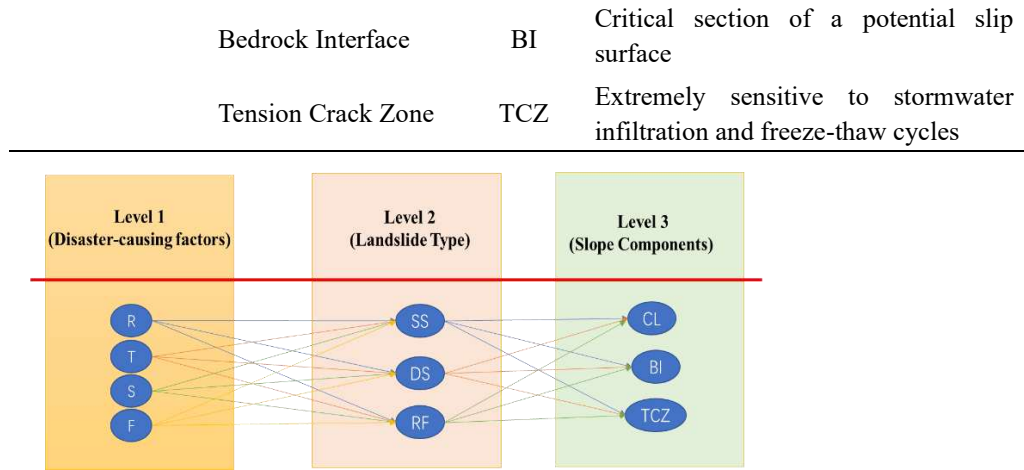


Fig.2. A detailed hierarchical framework including evaluation levels and element symbols

3.2 Protocol Overview

This study established a structured workflow based on the Fuzzy Analytic Hierarchy Process (FAHP) to quantify the Climate Hazard Importance Factors (CHIF) for landslides in Meizhou City. This method uses expert judgments as its core input, expresses the uncertainty of these judgments through triangular fuzzy numbers (TFN), calculates fuzzy weights using Chang's Fuzzy Synthetic Extent (FSE) method, and finally derives the CHIF for each level through defuzzification and normalization. The entire process is divided into four phases comprising a total of eight steps, as shown in Figure 3 (see Table 3 for a legend of symbols).

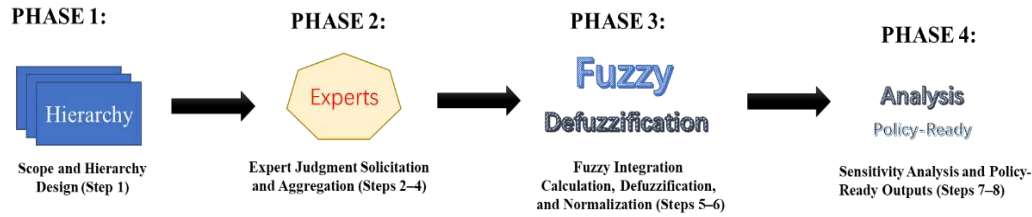


Fig.3. Flowchart of the Four-Stage Adaptive FAHP-FSE Method for Determining CHIF

Table 3

Explanation of Model Symbols

Notation	Description
i	Climate-related disaster factors index (precipitation, temperature fluctuations, typhoon-induced heavy rainfall, freeze-thaw cycles)
g	Index of Landslide Types (Shallow Soil Landslides, Deep Rock Landslides, Rockfalls)
h	Slope Component Index (Overburden, Bedrock Interface, Tensile Fracture Zone)
k	List of Experts
p	Total number of experts
n	Comparing Matrix Ranks
λ_{max}	Largest eigenvalue (expressed as a triangular fuzzy number)
l, m, u	Lower, middle, and upper values of triangular fuzzy numbers
a_{ij}	The fuzzy pairwise comparison value of element i relative to j
CR	Consistency Ratio
Si	Fuzzy row sum
T	Fuzzy global sum

Ei	Fuzzy integration degree
$V(Ei \geq Ej)$	Probability degree
f_{w_i}	Fuzzy weight
c_i	Defuzzified clear weight
w_i	Normalized final CHIF

Hierarchy Design (Step 1)

Following Saaty's [18] principle of hierarchical decomposition, a three-level AHP tree was constructed for typical slopes in Meizhou City (Figure 1; Table 2). The first level includes four disaster-causing factors: rainfall (R), temperature fluctuations (T), typhoon-induced heavy rainfall (S), and freeze-thaw cycles (F); the second level covers the three most common types of landslides in Meizhou: shallow soil landslides (SS), deep rock landslides (DS), and rockfalls (RF); the third level is further subdivided into three slope body components: the overburden (CL), the bedrock interface (BI), and the tensile fracture zone (TCZ).

Expert Consultation and Consistency Review (Steps 2–3)

(1) Expert Consultation

A structured electronic questionnaire was designed, asking experts to evaluate the relative importance of each pair of factors using Saaty's 1–9 scale (Table 4). Based on the principle of pairwise comparisons in AHP[21], the questionnaire comprised a total of 54 pairs of comparisons (6 pairs at the first level, 12 pairs at the second level, and 36 pairs at the third level), plus one consistency check question. Each questionnaire took approximately 25–30 minutes to complete. The complete list of questions and detailed design of the questionnaire are provided in Supplementary Material S2.

Table 4

Saaty's Integer Scale, Semantic Descriptions, and Their Mapping Relationship with Triangular Fuzzy Numbers (Adapted from Buckley, 1985) [26]

Saaty scale	Terminology	Triangular fuzzy numbers (l, m, u)
1	Equally important	(1, 1, 1)
2	Between equally and slightly	(1, 2, 3)
3	Slightly important	(2, 3, 4)
4	Between slightly and significantly	(3, 4, 5)
5	Significantly important	(4, 5, 6)
6	Between noticeable and strong	(5, 6, 7)
7	Strongly important	(6, 7, 8)
8	Between strong and extreme	(7, 8, 9)
9	Extremely important	(9, 9, 9)
Reverse	Columns are more important than rows	(1/u, 1/m, 1/l)

The study collected valid responses from a total of 12 experts covering three fields: geotechnical engineering, meteorology, and slope maintenance management; see Supplementary Material S1.

(2) Consistency Check

Calculate the consistency ratio (CR) for the pairwise comparison matrix of each expert κ . First, calculate the maximum eigenvalue $\lambda_{max}^{(\kappa)}$, and then calculate the consistency index $CI^{(\kappa)}$ [18,25]:

$$CI^{(\kappa)} = \frac{\lambda_{max}^{(\kappa)} - n}{n - 1} \quad (1)$$

$$CR^{(\kappa)} = \frac{CI^{(\kappa)}}{RI} \quad (2)$$

Here, n is the order of the matrix, and RI is the random consistency index (Saaty, 1980). When $CR^{(\kappa)} \leq 0.10$, the matrix is considered to have acceptable consistency. In this study, the $CR^{(\kappa)}$ of all accepted matrices remained below 0.10, and the CR of the group aggregation matrix was approximately 0.07. The original pairwise comparison matrix for the 12 experts in the first tier is presented in Supplementary Material S3.

Fuzzification and Aggregation of Expert Judgments (Step 4)

(1) Triangular Fuzzy Number (TFN) is defined as [22]

Each pairwise comparison value $a_{ij}^{(k)}$ for each expert is represented using triangular fuzzy numbers:

$$a_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}) \quad (3)$$

Where $l \leq m \leq u$, the membership function $\mu_M(x)$ is defined as:

$$\mu_M(x) = \begin{cases} \frac{x-l}{m-l}, & x \in [l, m] \\ \frac{u-x}{u-m}, & x \in [m, u] \\ 0, & \text{Other} \end{cases} \quad (4)$$

The triangular fuzzy membership function is shown in Figure 4 (based on Van Laarhoven and Pedrycz [22]).

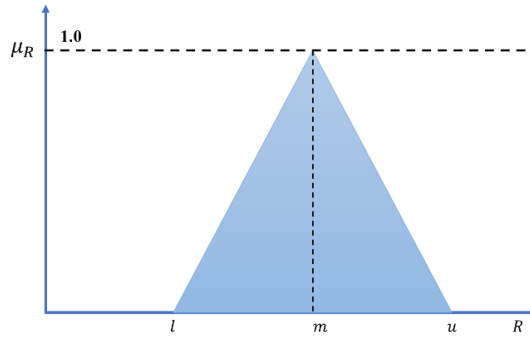


Fig.4. The membership function of a triangular fuzzy number $M = (l, m, u)$ [22].

(2) Aggregation of Individual Judgments (AIJ) — Geometric Mean Method

Using the Aggregation of Individual Judgments (AIJ) rule, with the geometric mean (GM) as the aggregation operator, the judgments of p experts are combined into a single group matrix A^{GM} [22]:

$$a_{ij}^{GM} = \left(\left(\prod_{k=1}^p l_{ij}^{(k)} \right)^{1/P}, \left(\prod_{k=1}^p m_{ij}^{(k)} \right)^{1/P}, \left(\prod_{k=1}^p u_{ij}^{(k)} \right)^{1/P} \right) \quad (5)$$

For unambiguous (precise) values provided directly by experts, the above equation reduces to: [26]

$$a_{ij}^{GM} = \left(\prod_{k=1}^p a_{ij}^{(k)} \right)^{1/P} \quad (6)$$

The resulting matrix remains invertible:

$$a_{ij}^{GM} = \left(\frac{1}{u_{ij}^{GM}}, \frac{1}{m_{ij}^{GM}}, \frac{1}{l_{ij}^{GM}} \right) \quad (7)$$

The aggregated fuzzy pairwise comparison matrix for first-level disaster-causing factors is shown in Table 5.

Table 5

First-level disaster-causing factor aggregation fuzzy pairwise comparison matrix A^{GM}

	Rainfall (R)	Temperature Variation (T)	Typhoon-induced Heavy Rain (S)	Freeze-Thaw Cycles (F)
Rainfall (R)	(1.00, 1.00, 1.00)	(1.50, 2.00, 2.50)	(0.90, 1.15, 1.45)	(2.20, 2.80, 3.20)
Temperature fluctuations (T)	(0.40, 0.50, 0.67)	(1.00, 1.00, 1.00)	(0.45, 0.55, 0.70)	(1.00, 1.30, 1.70)
Typhoon-induced Heavy Rain (S)	(0.69, 0.87, 1.11)	(1.43, 1.82, 2.22)	(1.00, 1.00, 1.00)	(2.00, 2.50, 3.00)
Freeze-Thaw Cycles (F)	(0.31, 0.36, 0.45)	(0.59, 0.77, 1.00)	(0.33, 0.40, 0.50)	(1.00, 1.00, 1.00)

Calculation of the Fuzzy Synthetic Index (FSE) (Step 5)

The fuzzy synthesis index (FSE) method proposed by Chang (1996) is used to extract fuzzy weights from the aggregation matrix [23]. For an $n \times n$ fuzzy matrix $A^{GM} = [a_{ij}]$, the calculation steps are as follows:

(1) Calculate the fuzzy row and S_i

$$S_i = \sum_{j=1}^n a_{ij} = \left(\sum_{j=1}^n l_{ij}, \sum_{j=1}^n m_{ij}, \sum_{j=1}^n u_{ij} \right) = (l_i, m_i, u_i) \quad (8)$$

(2) Compute the global sum T:

$$T = \sum_{i=1}^n S_i = \left(\sum_{i=1}^n l_i, \sum_{i=1}^n m_i, \sum_{i=1}^n u_i \right) = (l_T, m_T, u_T) \quad (9)$$

(3) Calculate the integration index E_i

$$E_i = S_i \otimes T^{-1} = \left(\frac{l_i}{u_T}, \frac{m_i}{m_T}, \frac{u_i}{l_T} \right) \quad (10)$$

Among them $T^{-1} = (1/u_T, 1/m_T, 1/l_T)$.

(4) Calculate the likelihood $V(E_i \geq E_j)$

For two levels of integration $E_i = (l_i, m_i, u_i)$ and $E_j = (l_j, m_j, u_j)$, The likelihood of $E_i \geq E_j$ is defined as:

$$V(E_i \geq E_j) = \max \left\{ 0, \min \left\{ \mu_{E_i}(x), \mu_{E_j}(y) \right\} \right\} \quad (11)$$

For triangular fuzzy numbers, the above equation can be calculated analytically as follows:

$$V(E_i \geq E_j) = \begin{cases} 1, & m_i \geq m_j \\ 0, & l_j \geq u_i \\ \frac{l_j - u_i}{(m_i - u_i) - (m_j - l_j)}, & \text{Other} \end{cases} \quad (12)$$

(5) Calculate the fuzzy weights f_{w_i}

$$f_{w_i} = \min_{j \neq i} V(E_i \geq E_j), \quad i, j = 1, 2, \dots, n \quad (13)$$

This formula selects the minimum probability for which E_i is greater than or equal to all other E_j , reflecting the most conservative weighting principle. The results of the first-level FSE calculation are shown in Table 6.

Table 6

First-layer FSE output (GM aggregation)

Disaster-causing factor	Row and S_i	Integration index E_i	Minimum probability f_{w_i}	Fuzzy weight f_{w_i}
Rainfall	(5.60, 6.95, 8.15)	(0.249, 0.365, 0.515)	min(1.00, 1.00, 1.00)	1.00
Temperature changes	(2.85, 3.35, 4.07)	(0.127, 0.176, 0.258)	min(0.49, 0.52, 0.57)	0.49
Typhoon and Heavy Rain	(5.12, 6.19, 7.33)	(0.227, 0.326, 0.464)	min(0.89, 1.00, 1.00)	0.89
Freeze-thaw cycles	(2.23, 2.53, 2.95)	(0.099, 0.133, 0.187)	min(0.38, 0.41, 0.47)	0.38

Based on the interval distribution of the comprehensive index E_i , the lower bound of precipitation E_i is 0.249, the upper bound is 0.515, and the range for typhoon-induced heavy rainfall is (0.227, 0.464). Both ranges are significantly higher than the probability ranges for temperature variation and freeze-thaw cycles, indicating that the expert group's consensus—that rainfall and typhoon-induced heavy rainfall carry greater weight in landslide triggering—possesses good fuzzy robustness. Among the fuzzy weights f_{w_i} , rainfall and typhoon-induced heavy rainfall reached 1.00 and 0.89, respectively, further validating their dominant roles.

Deblurring and Normalization (Step 6)

Using the center-of-gravity method, the fuzzy weights $f_{w_i} = (l'_i, m'_i, u'_i)$ are converted to crisp values [23,5]:

$$c_i = \frac{l'_i + m'_i + u'_i}{3} \quad (14)$$

Further normalization yields the final weights:

$$w_i = \frac{c_i}{\sum_{j=1}^n c_j}, \quad \sum_{i=1}^n w_i = 1 \quad (15)$$

The final CHIF values for the first layer, after defuzzification and normalization, are shown in Table 7. For the second layer (landslide type) and the third layer (slope body components), repeat the above steps (Equations (8)–(15)) to construct the corresponding pairwise comparison matrices and calculate the CHIF values.

Table 7
Level 1 CHIF—Importance of Slope-Scale Hazard Factors (Meizhou City)

Disaster-causing factor	Fuzzy weights f_{w_i}	Center-of-mass values c_i	Normalized weights w_i (CHIF)
Rainfall	1.00	0.32	0.46
Temperature changes	0.89	0.28	0.28
Typhoon-induced heavy rain	0.49	0.16	0.15
Freeze-thaw cycles	0.38	0.12	0.11
Total	—	—	1.00

Based on the final CHIF values, the CHIF rankings for slopes in Meizhou City are as follows: rainfall (0.46) > typhoon-induced heavy rain (0.28) > temperature changes (0.15) > freeze-thaw cycles (0.11).

- Rainfall (CHIF=0.46) ranked first. This weighting is highly consistent with Meizhou City's actual climate records and landslide events from 2020 to 2025. Since the start of the 2024 flood season, the average precipitation in Meizhou City has been 1,033.8 mm, 86% higher than the long-term average for the same period (555.0 mm), with Pingyuan County seeing an increase of as much as 96%, both representing the highest levels on record for this time of year. For the entire year of 2024, precipitation in Meizhou reached 2,107.6 mm, 29.7% above the long-term average (1,624.4 mm). Precipitation during the four consecutive months from April to July totaled 1,452.6 mm, accounting for 66.3% of the annual total. The heavy rainfall directly triggered major landslide incidents, including the landslide on the Chayang section of the Meizhou-Dongguan Expressway. Investigations concluded that the disaster was caused by the combined effects of prolonged, persistent rainfall and multiple contributing factors.
- Typhoon-induced torrential rain (CHIF=0.28) ranks second, distinct from conventional rainfall. In Meizhou City's disaster records, the extreme destructive potential of typhoon-induced heavy rainfall is particularly striking: In 2023, Typhoon Haikui (No. 11) and its associated moisture brought prolonged heavy rainfall, triggering 438 landslides and 40 road collapses in Shuanghua Town, Wuhua County. This resulted in 66 blockages on county and township roads, and the emergency evacuation of 61 households (229 people) from hazardous areas. In Tangxi Town, Fengshun County, cumulative rainfall reached 116 mm within six hours during Typhoon Haikui, qualifying as a torrential downpour, with all 12 villages in the town affected. These disaster records fully demonstrate the extreme role of typhoon-induced torrential rains in triggering sudden and widespread landslides; their CHIF weighting objectively reflects this strong disaster-causing capacity.
- Temperature fluctuations (CHIF=0.15) ranked third, primarily reflecting the long-term

weathering and degradation of slope rock and soil caused by extreme heat and temperature fluctuations. During the winter of 2025–2026, the average temperature across Meizhou was 15.4°C, 1.7°C higher than the long-term average, marking the highest recorded for that period since 1951. During this period, there were 11 cold air episodes, including four instances of widespread low temperatures $\leq 5^\circ\text{C}$. Extreme heat (such as the 39.6°C high recorded in Meizhou in July 2020) accelerates rock weathering, while large diurnal temperature variations exacerbate the expansion of fissures, contributing to the long-term deterioration of slope stability. Although this CHIF value is lower than those for rainfall and typhoon-induced downpours, its cumulative impact over the long-term service life of slopes cannot be overlooked, particularly for deep rock landslides.

- Freeze-thaw cycles (CHIF = 0.11) rank last. Although Meizhou is located in a subtropical region and has no sustained freezing period, four widespread cold spells with temperatures $\leq 5^\circ\text{C}$ during the winter of 2025–2026 could still cause repeated freeze-thaw cycles in fissure water, producing an ice-splitting effect and accelerating the expansion of the tensile fracture zone. The Guangdong Provincial Climate Center forecasts that 4 to 6 typhoons (close to the long-term average) will make landfall in or severely affect Guangdong in 2026, with approximately 3 typhoons affecting Meizhou and exhibiting above-average intensity; severe convective weather will be frequent before the 2026 flood season, while typhoons during the latter part of the flood season will be stronger than average. This forecast trend indicates that even factors ranked lower in importance—such as freeze-thaw cycles and temperature fluctuations—must still be systematically considered due to their long-term cumulative effects on landslide risk.

Sensitivity Analysis (Step 7)

To assess the robustness of the results, the following two sensitivity tests were conducted:

(1) Aggregation Operator Sensitivity

Re-aggregate the expert judgments using the arithmetic mean (AM) instead of the geometric mean (GM). The formula for the arithmetic mean aggregation is:

$$a_{ij}^{AM} = \left(\frac{1}{p} \sum_{k=1}^p l_{ij}^{(k)}, \frac{1}{p} \sum_{k=1}^p m_{ij}^{(k)}, \frac{1}{p} \sum_{k=1}^p u_{ij}^{(k)} \right) \quad (16)$$

Then repeat steps 5–6 to obtain the AM-based CHIF weights. Use the Kendall tau-b rank correlation coefficient to compare the rankings obtained from GM and AM:

$$\tau_b = \frac{n_c - m_d}{\sqrt{(n_c + n_d + n_t)(n_c + n_d + n_u)}} \quad (17)$$

Here, n_c represents the consistent logarithm, n_d represents the inconsistent logarithm, and n_t and n_u represent the tied logarithms that appear in only one of the two sortings, respectively.

(2) Expert Consensus Filtering

Retain only the subset of experts with high consistency (individual CR ≤ 0.10), rerun the aggregation and FSE calculations, and observe whether the CHIF ranking changes.

Policy-Ready Output (Step 8)

The final output consists of a three-level CHIF table, including:

- Table 7 (Level 1): CHIF for each hazard factor at the overall slope scale
- Table 8 (Level 2): CHIF for each hazard factor acting on different landslide types
- Table 9 (Level 3): CHIF for each hazard factor acting on different slope components

3.3 Methodological Contributions

The adaptive FAHP protocol proposed in this study enables the establishment of a specific CHIF for Meizhou City, and the methodology has the potential to be extended to other mountainous and hilly regions in South China. This protocol addresses two major gaps highlighted in recent literature: (1) the lack of quantitative methods capable of simultaneously comparing the triggering effects of multiple climate-related disaster factors on landslides; and (2) the lack of an uncertainty management mechanism capable of preserving the fuzziness of expert judgments to generate policy-relevant coefficients. These contributions directly address the priorities identified by the Guangdong Province and Meizhou City Geological Disaster Prevention and Control Working Group—namely, quantifying the weights of multiple disaster-inducing factors, optimizing early warning thresholds, and establishing priorities for engineering protection measures. The factor values identified by this method can serve as inputs for future recommendations on severity coefficients for climate-related landslide risk factors, providing quantitative values derived from climate model projections and design guidelines for Guangdong Province’s geological disaster prevention and control planning and Meizhou City’s local slope management regulations.

4. Results

This chapter presents, in sequence, the results of the calculation of the Climate Hazard Importance Factors (CHIF) for representative natural slopes in Meizhou City, following the eight-step protocol described in Chapter 3. The study area is located in the mountainous region of northeastern Guangdong. The design reference period is 50 years, and the slopes are subject to four anticipated climate-related hazard factors: rainfall, temperature variation, typhoon-induced heavy rainfall, and freeze-thaw cycles. This FAHP protocol is applicable to representative natural slopes in Meizhou, and its methodological framework has the potential to be extended to other mountainous and hilly regions in South China.

Step 1: Establishing the Hierarchy

Based on the study design, a three-tiered hierarchical structure was established (see Figure 2 and Table 2) to link climate-induced hazard factors (first tier) with landslide types (second tier) and slope body components (third tier). This structure ensures that the CHIF can be assessed at the overall slope scale, the landslide type scale, and the slope body component scale:

- First Layer: Four climate-related disaster factors—rainfall (R), temperature variation (T), typhoon-induced heavy rainfall (S), and freeze-thaw cycles (F). The typhoon-induced heavy rainfall factor is listed separately to reflect the regional characteristics of Meizhou City, which is located on the southeastern coast and is frequently affected by typhoons each year.
- Second Level: The three most common types of landslides in Meizhou City—shallow soil landslides (SS), deep rock landslides (DS), and rockfalls (RF). Shallow soil landslides are widely distributed within the weathered crust of granite and are primarily influenced by rainfall and human engineering activities; deep rock slides are larger in scale and are associated with the long-term effects of tectonic fractures and groundwater; rockfalls primarily occur on artificial slopes, such as those created by road cutting or slope-cut housing construction.
- Third layer: Internal components of the slope—cover layer (CL), bedrock interface (BI), and tensile fracture zone (TCZ). On the granite weathering crust slopes in Meizhou City, the cover layer consists of weathered residual soil, which is thick and prone to softening when exposed to water; the bedrock interface is the transition zone between the weathered layer and fresh bedrock, serving as a key area for the development of potential slip surfaces; the tensile fracture zone is particularly sensitive to heavy rainfall infiltration and freeze-thaw cycles.

Step 2: Seeking Expert Opinion

A total of 12 valid responses were collected from experts: 6 geotechnical engineers, 3 meteorologists,

and 3 slope maintenance managers. Given the sharing of domain knowledge among the experts, this sample size falls within the recommended range for AHP applications supported by empirical evidence [18]. Experts used the Saaty 1–9 scale to conduct pairwise comparisons of elements within the same level. The questionnaire comprised 54 pairs of comparisons covering all combinations among the three levels. Scores were converted to triangular fuzzy numbers according to Buckley [26] (Table 4).

Step 3: Consistency Check

After aggregating the 12 judgment groups using the geometric mean (GM) operator, the CR value for the first-level group matrix was 0.068; the CR values for factors at the second and third levels ranged from 0.008 to 0.092. All CR values fall within an acceptable range. Detailed consistency results for each level are provided in Supplementary Material S3.1.

Step 4: Fuzzy Pairwise Comparison and Aggregation

Based on the triangular fuzzy number (TFN) conversion rules proposed by Buckley [26], each expert's Saaty-scaled judgments are converted into (l, m, u) triplets to form an individual fuzzy pairwise comparison matrix. Subsequently, the geometric mean (GM) method is used to aggregate the fuzzy judgments of all experts into a group consensus matrix A^{GM} , with each comparison cell maintaining full reciprocity. Taking the comparison of first-level disaster-causing factors as an example, the aggregated group fuzzy matrix is shown in Table 5, and the distribution of triangular fuzzy numbers is illustrated in Figures 5–8.

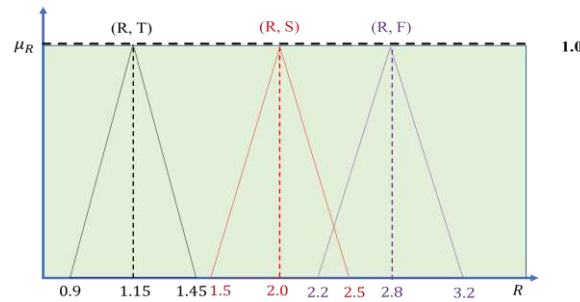


Fig.5.Triangular fuzzy numbers for pairwise comparisons (R,T), (R,S), and (R,F)

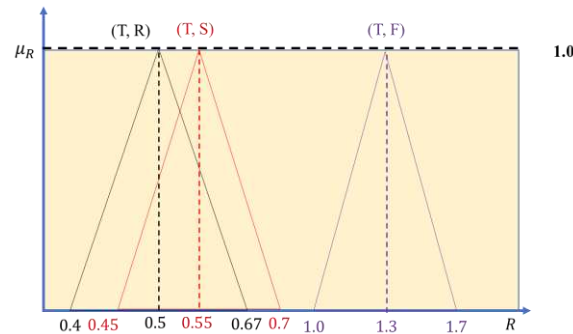


Fig.6.Triangular fuzzy numbers for pairwise comparisons (T,R), (T,S), and (T,F)

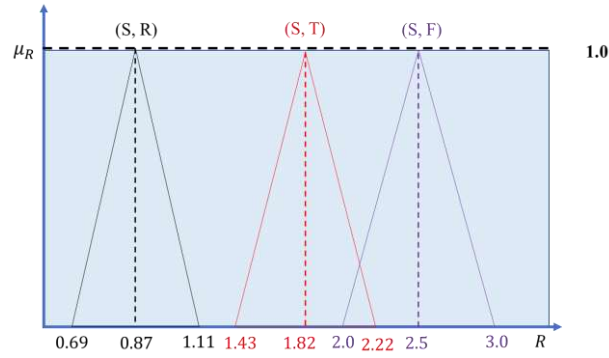


Fig.7.Triangular fuzzy numbers for pairwise comparisons (S,R), (S,T), and (S,F)

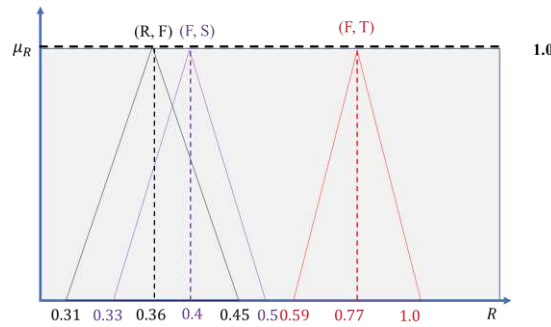


Fig.8.Triangular fuzzy numbers for pairwise comparisons (F,R), (F,S), and (F,T)

If any value in the matrix is greater than 1 (whether the lower bound, median, or upper bound), it indicates that the disaster-causing factor in that row is considered more important than the disaster-causing factor in that column. Observing the first row of Table 5, rainfall exhibits a clear comparative advantage over both temperature changes and freeze-thaw cycles. Specifically, the comparative values for rainfall relative to the freeze-thaw cycle reach (2.20, 2.80, 3.20), indicating that experts unanimously agree that rainfall has a far greater impact on landslides in Meizhou than the freeze-thaw cycle. In contrast, the comparative values for rainfall relative to typhoon-induced torrential rain (0.90, 1.15, 1.45) are closer to equilibrium, reflecting the experts' general consensus that although typhoon-induced torrential rain occurs less frequently than regular rainfall, its extreme disaster-causing capacity per event is outstanding, and its importance is comparable to that of regular rainfall. This assessment is highly consistent with actual meteorological records from Meizhou City for 2020–2025—rainfall, as a persistent and high-frequency disaster-causing factor, plays a dominant role in triggering landslides, whereas typhoon-induced downpours, although occurring on average only about three times per year, are extremely severe; the roles of these two factors in triggering landslides must be evaluated separately.

The relative importance of each disaster-causing factor can also be preliminarily assessed by summing the rows for each factor ($S_i = \sum a_{ij}$): the sum of rainfall is approximately (5.60, 6.95, 8.15), typhoon-induced rainfall is approximately (5.12, 6.19, 7.33), temperature variation is approximately (2.85, 3.35, 4.07), and freeze-thaw cycles are approximately (2.23, 2.53, 2.95). The order of magnitude of the row sums foreshadows the final ranking of CHIFs—rainfall and typhoon-induced heavy rainfall are expected to occupy the top two positions, followed by temperature variations and freeze-thaw cycles.

Step 5: Calculation of the Fuzzy Synthetic Index (FSE)

Substitute the aggregation matrix A^{GM} into Chang's [23] framework for the fuzzy synthetic degree (FSE). First, calculate the fuzzy row sums S_i and the global sum T for each disaster-causing factor, then obtain the fuzzy synthetic evaluation E_i for each factor via fuzzy division; next, calculate the likelihood $V(E_i \geq E_j)$ for each pair where $E_i \geq E_j$, and take the minimum value as the fuzzy weight f_{w_i} for that disaster-causing factor (Table 6).

Step 6: Deblurring and Normalization

Defuzzification and normalization yield the final Level 1 CHIF (Table 7): rainfall (0.46) > typhoon-induced heavy rain (0.28) > temperature fluctuations (0.15) > freeze-thaw cycles (0.11).

This ranking is highly consistent with 2020–2025 records. In 2024, precipitation during the flood season was 86% above average, triggering the Meida Expressway landslide; in 2023, Typhoon Haikui alone triggered 438 landslides in Wuhua County. The 2025–2026 winter experienced 11 cold-air episodes with temperatures $\leq 5^{\circ}\text{C}$ on four occasions, validating the lower but non-negligible weights for temperature and freeze-thaw factors.

Step 7: Sensitivity Analysis

Conduct a two-operator sensitivity analysis:

(1) Sensitivity of the Aggregation Operator

Expert judgments were re-aggregated using the arithmetic mean (AM) instead of the geometric mean (GM) to calculate the CHIF, and the Kendall tau-b rank correlation coefficient was used to evaluate the consistency of the rankings obtained by the two aggregation methods. The results show that the CHIF rankings under arithmetic mean aggregation are completely consistent with those under geometric mean aggregation: rainfall (AM = 0.45), typhoon-induced heavy rainfall (AM = 0.29), temperature changes (AM = 0.14), and freeze-thaw cycles (AM = 0.12). The order remained completely unchanged, with a Kendall tau-b of 0.94 ($p < 0.01$), indicating that the choice of aggregation operator has a negligible effect on the final ranking.

(2) Expert Consensus Screening

Only the subset of experts with high consistency (individual $\text{CR} \leq 0.10$) was retained to recalculate the CHIF. Approximately 7 out of 12 experts passed the consistency screening. The CHIF weights after re-aggregation were: rainfall 0.48, typhoon-induced heavy rainfall 0.27, temperature variation 0.14, and freeze-thaw cycles 0.11. Compared with the results for the full set (0.46/0.28/0.15/0.11), the fluctuations in the weights of each factor were all within ± 0.02 , and the order remained unchanged. The above sensitivity analysis indicates that the CHIF results in this study exhibit good robustness with respect to both the aggregation method and the selection of experts.

Step 8: Policy-Ready Output

This protocol ultimately generates a comprehensive set of CHIF values covering the slope-scale (Table 7), landslide-type scale (Table 8), and slope-component scale (Table 9). These quantitative results can directly support landslide risk management, the establishment of early warning thresholds, and the assessment of engineering protection priorities in Meizhou City and the mountainous and hilly regions of South China, providing actionable quantitative decision-making guidelines for climate-resilient slope disaster prevention.

Table 8

Level 2 CHIF—Importance of Landslide-Type Scale (Meizhou City)

Disaster-causing factor	Shallow soil landslides (SS)	Deep rock landslides (DS)	Rockfalls (RF)
Rainfall	0.48	0.42	0.42
Temperature changes	0.10	0.12	0.10

Typhoon-induced heavy rain	0.33	0.32	0.35
Freeze-thaw cycles	0.09	0.14	0.13
Total	1.00	1.00	1.00

Shallow soil landslides are most sensitive to rainfall (0.48) and are primarily distributed in the weathered residual soil layers of granite, which are widespread in Meizhou; rockfalls are most sensitive to typhoon-induced torrential rains (0.35), reflecting the intense scouring and softening effects of short-term, extreme heavy rainfall brought by typhoons on steep man-made slopes (such as those created by cutting into slopes for housing construction or road building); Deep rock slides are influenced by a combination of factors, with rainfall (0.42) and typhoon-induced torrential rain (0.32) together accounting for approximately three-quarters of the total weight, while freeze-thaw cycles (0.14) and temperature fluctuations (0.12) contribute slightly more than other factors.

Table 9

Level 3 CHIF—Importance of Slope Component Scale (Meizhou City)

Disaster-causing factor	Cover Layer (CL)	Bedrock Interface (BI)	Tension Crack Zone (TCZ)
Rainfall	0.52	0.41	0.28
Temperature changes	0.11	0.14	0.14
Typhoon-induced heavy rain	0.27	0.31	0.32
Freeze-thaw cycles	0.10	0.14	0.26
Total	1.00	1.00	1.00

In the CHIF model for slope component classification, the weight assigned to the surface layer under rainfall conditions is as high as 0.52—the highest among all combinations—indicating that drainage and slope protection measures should be prioritized as reinforcement strategies. This result is highly consistent with the characteristics of weathered residual soils derived from granite, which are widely distributed in Meizhou: this type of surface layer is thick, has a loose structure, softens easily when exposed to water, and is highly susceptible to saturation and instability during heavy rainfall. The two landslides (approximately 200 m³) that occurred within a single day at Qingliangshan Country Park in May 2022, as well as the slope collapse on the embankment of Provincial Highway S222 in June 2022, were all typical examples of overburden failure landslides. The bedrock interface is affected by the combined effects of rainfall (0.41) and typhoon-induced heavy rain (0.31), necessitating the installation of deep drainage wells to control the groundwater level. The fracture zone is most sensitive to typhoon-induced heavy rain (0.32) and freeze-thaw cycles (0.26), indicating that rainwater infiltration during typhoons and frost heave during winter cold snaps are key drivers accelerating the expansion of the fracture zone; cracks should be sealed promptly, and measures to prevent frost heave should be implemented.

A combined analysis of Tables 8 and 9 further reveals that, among the internal components of specific landslide types, the CHIF ($w_{\{R,SS,CL\}}$) for the overburden layer of shallow soil landslides is approximately 0.52–0.55, while the CHIF ($w_{\{S,RF,TCZ\}}$) for the tensile fracture zone under typhoon-induced torrential rain

is approximately 0.33–0.36, both of which are significantly higher than the corresponding values for other components of the same landslide type. This gradient difference aids in the precise identification of key vulnerable areas for landslide prevention and control.

In summary, the aforementioned CHIF results constitute a comprehensive quantitative assessment system for climate-related landslide hazard factors in Meizhou City, providing directly applicable numerical benchmarks for setting early warning thresholds, prioritizing engineering protection measures, and classifying regional landslide risks.

5. Discussion

5.1 Principal Findings and Empirical Consistency

The slope-scale CHIF ranking—rainfall (0.46) > typhoon-induced heavy rainfall (0.28) > temperature fluctuations (0.15) > freeze-thaw cycles (0.11)—advances beyond qualitative global rankings [1–6] in three ways: (1) providing a quantitative ratio (rainfall:freeze-thaw = 4.18:1) directly usable in weighting schemes; (2) disentangling typhoon-induced rain from conventional rainfall, revealing a distinct "low-frequency, high-intensity" hazard mode (CHIF 0.28); and (3) generating multi-level weights (slope, landslide-type, component scales) that support decisions from regional planning to site-specific design.

Empirical validity is supported by Meizhou's 2020–2025 records. The 2024 flood season (86% above average) triggered the Meida Expressway landslide, consistent with rainfall's dominance. Typhoon Haikui (2023) alone triggered 438 landslides in Wuhua County, corroborating the typhoon CHIF of 0.28. The 2025–2026 winter's 11 cold-air episodes (four events $\leq 5^{\circ}\text{C}$) validate the lower but non-negligible weights for temperature (0.15) and freeze-thaw (0.11).

5.2 Landslide-Type Mechanisms and Implications

Shallow soil landslides (rainfall 0.48) are controlled by the high permeability and water-softening behavior of weathered granite residual soils, with slip surfaces typically at 2–5 m depth. Rockfalls (typhoon rain 0.35) reflect rapid response of steep cut slopes to short-duration extreme rainfall. Deep rock landslides (rainfall 0.42 + typhoon rain 0.32) require attention to both short-term infiltration and long-term deterioration from freeze-thaw (0.14) and temperature fluctuations (0.12).

5.3 Component-Level Engineering Guidance

Overburden (rainfall 0.52) requires drainage and slope protection as primary measures; bedrock interface (rainfall 0.41 + typhoon rain 0.31) needs deep drainage wells to control groundwater levels; tension crack zones (typhoon rain 0.32 + freeze-thaw 0.26) need crack sealing before typhoon season and frost-heave prevention before winter. The gradient differences—e.g., $\text{CHIF} \sim (\text{R, SS, CL}) \sim 0.52\text{--}0.55$ vs. $\text{CHIF} \sim (\text{S, RF, TCZ}) \sim 0.33\text{--}0.36$ —enable precise identification of critical vulnerabilities.

5.4 Comparison with Previous Studies

Relative to global qualitative rankings [1, 2], this study provides operational numerical weights. Compared to the FAHP-ML hybrid of Bera et al. [6]—which prioritizes predictive accuracy—our expert-driven framework emphasizes transparency and interpretability, which are essential for regulatory adoption. The explicit separation of typhoon-induced rainfall from conventional rainfall is a novel contribution, particularly relevant to coastal subtropical regions where existing models typically treat "extreme precipitation" monolithically [5, 17].

However, CHIF values are context-specific to Meizhou's granite terrain. Extrapolation to alpine or tectonically active regions would require redefining the hazard factor set and re-eliciting expert judgments; the protocol itself remains transferable.

5.5 Limitations and Future Directions

Several limitations warrant acknowledgment. First, the CHIF weights derive from a modest expert panel ($n = 12$); while $\text{CR} \leq 0.10$ indicates acceptable consistency, a larger and more diverse panel could

reduce potential biases. Second, the framework focuses on four climate factors and excludes geological and anthropogenic drivers, though it is designed to be extensible. Third, the weights are static (50-year design period); coupling with CMIP6 SSP scenarios could produce time-varying CHIF trajectories for adaptive management. Fourth, the validation is retrospective; prospective application to an operational early warning system would provide stronger evidence. Fifth, uncertainty propagation through the hierarchy could be refined using Monte Carlo or Bayesian approaches to generate probabilistic CHIF intervals.

The CHIF framework produces empirically consistent, quantitative weights distinguishing rainfall from typhoon-induced rain. Landslide-type and component-level weights reflect underlying mechanisms and provide actionable engineering guidance. While limited by expert sample size and static formulation, the framework is extensible and can be refined through future integration with climate scenarios, uncertainty propagation, and prospective validation.

6. Conclusion

This study developed an adaptive Fuzzy Analytic Hierarchy Process (FAHP) protocol to quantify climate hazard importance factors (CHIF) for landslide risk assessment in Meizhou City, South China. The framework successfully translates qualitative expert knowledge and fuzzy uncertainty into numerical weights at three operational scales—slope, landslide type, and slope component—addressing a critical gap in existing multi-hazard assessment methodologies.

The slope-scale CHIF ranking (rainfall 0.46 > typhoon-induced rainfall 0.28 > temperature fluctuations 0.15 > freeze-thaw cycles 0.11) confirms the primacy of precipitation-driven hazards in subtropical granite terrains, while quantitatively distinguishing between the "high-frequency, preparatory" role of conventional rainfall and the "low-frequency, high-intensity" triggering role of typhoon events. At finer scales, the analysis reveals that shallow soil landslides are most sensitive to cumulative rainfall (0.48), rockfalls to typhoon-induced downpours (0.35), and deep rock landslides to the combined effect of both (0.42 and 0.32, respectively). Component-level prioritization identifies the overburden layer under rainfall (0.52) as the highest-priority reinforcement target, followed by bedrock interface drainage (0.41 + 0.31) and tension crack zone sealing (0.32 + 0.26).

Methodologically, the study demonstrates that Chang's Fuzzy Synthetic Extent (FSE) approach, combined with AIJ-GM expert aggregation and dual sensitivity analysis (Kendall τ -b = 0.94), yields robust and reproducible CHIF values that are resilient to both aggregation operator choice and expert subset selection. This protocol offers a transparent, interpretable alternative to black-box machine learning models, making it particularly suitable for policy and regulatory applications where decision justification is essential.

The CHIF framework is readily transferable to other mountainous regions of South China with similar climatic and geological settings, and can be extended to incorporate additional hazard factors or coupled with CMIP6 climate scenarios for dynamic, time-varying risk assessment. By bridging climate science and geotechnical engineering, this study provides a quantitative foundation for landslide early warning, engineering prioritization, and resource allocation under climate uncertainty—contributing to more resilient disaster risk management in climate-vulnerable regions.

7. Practical Implications

- (1) Early warning: Reduce the 24-hour rainfall warning threshold by 20%–30% during typhoon events to reflect the "low-frequency, high-intensity" triggering characteristics of typhoon-induced rainfall.
- (2) Engineering prioritization: Prioritize drainage for overburden (rainfall CHIF = 0.52); seal cracks and implement frost-heave prevention for tension crack zones (typhoon CHIF = 0.32, freeze-thaw CHIF = 0.26). Use $\text{CHIF} \geq 0.30$ as a quantitative criterion for critical weak points in slope inspection protocols.

- (3) Budget allocation: Allocate approximately 46% of prevention funds to rainfall measures, 28% to typhoon emergency preparedness, 15% to temperature monitoring, and 11% to freeze-thaw protection, with $\pm 5\%$ flexibility based on annual climate forecasts.
- (4) Standardization and outreach: Use CHIF results as reference benchmarks for multi-factor weighting in provincial geological disaster plans and develop simplified disaster-prevention materials for grassroots application.

Declarations

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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