

Editorial

Integrating UAV Photogrammetry and Thermal Infrared Entropy in Evaluating Rock Mass Characteristics

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0 INTRODUCTION

Rock masses are inherently discontinuous, with fractures and joints governing their mechanical behavior and stability (Liu et al., 2024; Shang et al., 2018; Lisjak and Grasselli, 2014; Scholtès and Donzé, 2012; Jiang et al., 2009; Pine et al., 2006; Aydan et al., 1989). These discontinuities, evaluated through parameters like fracture spacing, orientation, and density (Zhang Z F et al., 2024; Chen et al., 2023; Wang et al., 2022; Xia et al., 2016), pose great challenges in large-scale slope assessments due to complex geological conditions. Moreover, the relationship between discontinuity development and thermal infrared (TIR) behavior remains unclear (Franzosi et al., 2023; Mineo et al., 2022). Current methods often lack the resolution to detect small-scale discontinuities and their impact on rock mass heterogeneity (Zhang et al., 2022), highlighting the need for more precise and integrated in slope stability assessment.

Recent studies have extensively examined rock mass structures and their impact on slope stability (Chen et al., 2025; Li et al., 2025; Pantelidis, 2009). Traditional field mapping and remote sensing techniques are commonly used to identify structural features and quantify rock mass parameters (Li C et al., 2024; Zhou et al., 2024; Hasan et al., 2023), while analytical models and numerical simulations aid in understanding fractured rock behavior under varying loads (Long et al., 2024; Wang J C et al., 2024; Yang et al., 2014; Ma and An, 2008). However, many methods depend on favorable geological conditions. Field mapping and ground-based surveys require assessable slopes with stable terrain for equipment deployment (Gallay et al., 2013). On high-steep slopes, challenging topography limits the effectiveness of traditional approaches (Li et al., 2022; Lai et al., 2015), as steep and uneven terrain surfaces hinder surveys and instrument placement (Chen et al., 2025; Zhou et al., 2020; Šašak et al., 2019). These constraints reduce data accu-

racy and pose safety risks to researchers.

UAV-based remote sensing has emerged as a powerful tool for studying steep and inaccessible terrains (Filice et al., 2022; Sestras et al., 2022; Šledž et al., 2021; Rodriguez et al., 2020). High resolution cameras and photogrammetry enable detailed 3D slope modeling and data collection on fracture distribution and material properties (Tian et al., 2024; Ye et al., 2024; Congress et al., 2021; Liu et al., 2019). These methods enhance hazard mapping, slope monitoring, and structural analysis with improved safety and efficiency. However, UAV models often struggle to resolve small-scale discontinuities such as closely spaced fractures (Zhang W et al., 2024), limiting the precise assessment of rock mass integrity and mechanical behavior.

TIR technique is increasingly valuable in geotechnical studies, providing unique insights into the thermal behavior of rock masses and slopes (Li X et al., 2024; Wang et al., 2023; Loche et al., 2022; Loperte et al., 2016). By capturing surface temperature variations, it aids in monitoring heat flux, detecting moisture, and identifying weathering or instability zones (Cheng et al., 2022; Carlomagno, 2007). This non-invasive technique is particularly useful for inaccessible or hazardous areas. Beyond traditional applications, TIR enables thermal heterogeneity analysis across spatial scales, linking thermal properties with structural parameters to enhance slope stability assessments and rock mass characterization.

Entropy, a measure of disorder from information theory, has been applied in geology to assess structural complexity, material heterogeneity, and spatial variability in rock masses (Hirsh et al., 2012; Anand and Bianconi, 2009). By quantifying geological feature distribution, entropy provides a novel approach to evaluating rock mass integrity (Xie et al., 2022). However, the integration TIR technology with entropy analysis for rock mass study remains largely unexplored, despite its potential to enhance the understanding of structural development.

This study utilizes UAV equipped with high-resolution cameras and multi-angle nap-of-the-object photogrammetry methods to construct 3D slope models and acquire TIR data of slope surface at different time intervals. The concept of information entropy from information theory is employed to analyze the distinct thermodynamic behaviors exhibited by different materials. By integrat-

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ing discontinuity parameter calculations achieved through detailed discontinuity identification, the relationship between the development degree of different discontinuities and entropy values is analyzed, and a linear correlation between the two is established. This analysis offers a novel approach for quickly assessing different regions of the slope and their corresponding potential failure modes, while also enabling the rapid determination of rock mass integrity using thermodynamic parameters.

1 METHODOLOGY

1.1 Thermal Infrared Entropy and Rock Mass Characteristics

This section will explore the relationship between thermal infrared data and rock masses characteristics, emphasizing how these interactions can be used to assess rock mass quality. By understanding the thermal properties of rock surfaces and the entropy of thermal infrared data, we develop a comprehensive methodology to evaluate rock mass quality.

1.1.1 Thermal infrared characteristics of rock masses

Thermal infrared (TIR) characteristics describe the ability of surfaces to emit infrared radiation, which is determined by their thermal conductivity, emissivity, and specific heat capacity. TIR imaging detects surface temperature variations, making it an effective tool for studying rock masses (Grechi et al., 2021). Intact rocks generally exhibit isotropic thermal behavior due to their homogeneity, meaning temperature distribution across their surfaces remains relatively uniform under consistent environmental conditions. This uniform results from efficient heat conduction and consistent material properties across the rock surface (Zhang et al., 2025).

In contrast, thermal anisotropy arises when heat transfer properties vary with direction due to material heterogeneity, such as fractures, compositional differences, or varying moisture content. Fractures, in particular, introduce localized thermal resistance, leading to uneven heat dissipation and retention. As a result, fractured zones tend to experience greater temperature fluctuations compared to intact regions, generating detectable thermal contrasts (Figure 1a). The degree of thermal anisotropy is influenced by factors such as fracture density, orientation, and aperture size, which collectively impact the spatial and temporal distribution of surface temperatures.

At the microscale, individual fractures alter local thermal properties (Figure 1b), while at the macroscale, networks of fractures contribute to significant temperature variation patterns across a rock mass (Figure 1c). These patterns are critical indicators of rock mass conditions and stability. Identifying and interpreting these thermal variations help in locating potential zones of weakness. Fracture networks detected through TIR imaging correlate strongly with areas of reduced mechanical integrity, enabling targeted assessments of stability risks.

1.1.2 Rock mass TIR complexity and entropy analysis

Entropy, a concept originally introduced in thermodynamics by Rudolf Clausius, describes the degree of disorder or randomness within a system (Cropper, 1986). In information theory, Claude Shannon extended the concept to measure the uncertainty or information content of a dataset (Abou Jaoude, 2017). Mathematically, entropy is expressed as.

$$H(x) = - \sum_{i=1}^n p(x_i) \log(p(x_i)) \quad (1)$$

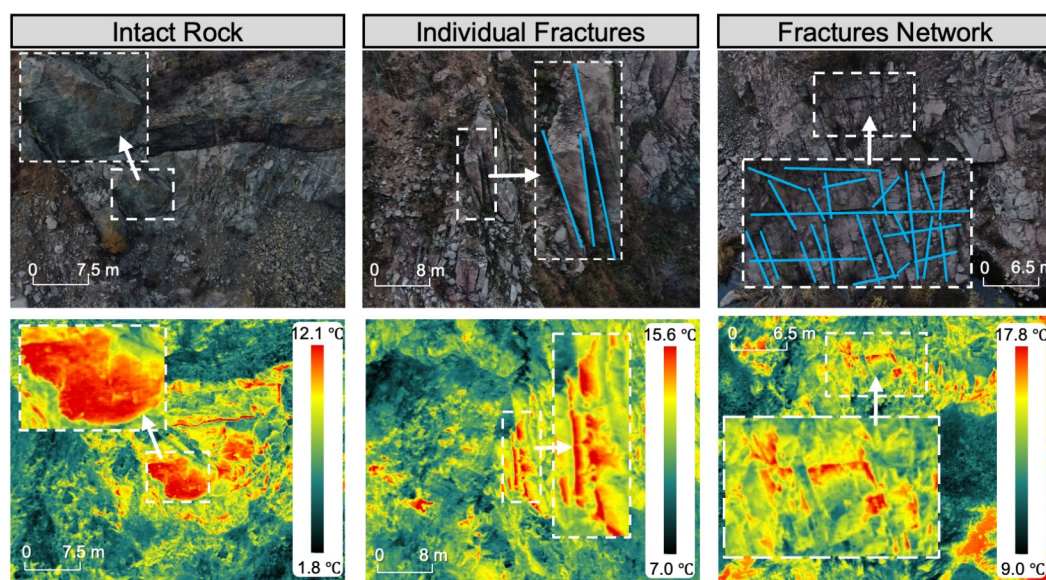


Figure 1. Different thermal infrared characteristics of rock masses. (a) Intact rock features; (b) individual rock features; (c) fractures network features.

where $p(x_i)$ is the probability of occurrence of the i th state in the system. This formula quantifies the spread or unpredictability of a system's states.

In the context of TIR analysis, entropy quantifies the variability in temperature distributions across a surface. Higher entropy values indicate greater thermal heterogeneity, often reflecting complex structural conditions such as dense fracture networks, mixed material zones, or varying surface compositions. Fracture networks disrupt the uniform heat transfer properties of intact rock, leading to spatial temperature fluctuations that manifest as increased entropy. Additionally, mixed material zones—such as debris accumulations or weathered surfaces—comprise heterogeneous thermal properties, resulting in variable heat retention and dissipation, further elevating entropy values.

Building upon the understanding that fractures alter the TIR characteristics of intact rock, entropy provides a quantitative means to evaluate these changes. For example, areas dominated by highly fractured or weathered rock surfaces typically exhibit greater thermal heterogeneity. This is due to differential heat retention and dissipation caused by variations in material properties such as thermal conductivity and emissivity. Conversely, intact and homogeneous rock masses display more uniform thermal behavior.

By calculating entropy from TIR data, researchers can assess the complexity of thermal responses and relate them to the structural integrity of rock masses. This approach enables the identification of zones with potential stability issues, linking observable temperature variations to underlying geological conditions.

Furthermore, the relationship between entropy values and rock mass quality indicators, such as fracture density, offers an avenue for integrated analysis. Investigating whether regions of high entropy correspond to lower rock quality can help validate TIR-based assessments as a reliable proxy for traditional geotechnical evaluation methods. This correlation bridges the gap between thermal complexity and physical rock mass conditions, supporting a more holistic approach to slope stability assessment.

1.1.3 TIR entropy calculation from 3D point clouds

To calculate TIR entropy, thermal infrared data will be collected from 3D point cloud models generated using UAV photogrammetry (Section 1.2). The workflow involves the following steps:

(1) Point Cloud Processing: High-resolution 3D point clouds are generated to reconstruct the geometry of the slope surface. The models ensure accurate alignment of thermal data with spatial coordinates.

(2) Temperature Mapping: Creating a georeferenced thermal model. Each point is assigned a corresponding temperature value, capturing the spatial temperature distribution across the surface.

(3) Data Segmentation: The slope surface is divided into smaller segments or grids based on materials and

discontinuity development to facilitate localized analysis. This ensures that entropy calculations reflect the variability within manageable sections of the dataset.

(4) Entropy Calculation: For each segment, the temperature values are analyzed to compute entropy using Shannon's formula (Eq. (1)). This involves determining the probability distribution of temperature occurrences and quantifying the variability.

(5) Entropy Analysis: The calculated entropy values highlight areas with high thermal complexity. These regions are further analyzed to correlate entropy with structural features, such as fracture density.

This methodology leverages the synergy between TIR data and rock mass quality to provide detailed insights into the thermal behavior of rock masses. It establishes a robust framework for assessing rock mass quality through entropy metrics, offering a quantitative approach to complement traditional geotechnical evaluations.

1.2 UAV-Based Slope Investigation and Data Acquisition

In this section, we present the methodology for reconstructing slope surface and TIR models for rock mass evaluation. The first part (Section 1.2.1) focuses on the use of UAV nap-of-the-object photogrammetry to capture high-resolution images (including visible and thermal infrared images) of the slope surface, which is then processed to generate accurate 3D models. These models serve as the foundation for the subsequent analysis of rock mass features and thermal behavior. The second part (Section 1.2.2) details the manual interpretation of discontinuities on the model. We calculate critical rock mass features, including fracture density and spacing that are essential for assessing rock mass quality. These parameters are then used to analyze the relationship between rock mass characteristics and entropy values derived from the TIR data.

1.2.1 Slope and TIR model reconstruction

This subsection introduces the concept of nap-of-the-object photogrammetry, which is a photogrammetric technique performed at short distances to capture detailed surface features (Wang S N et al., 2024; Zhao et al., 2023). Using UAVs, this method achieves high precision and efficiency in generating three-dimensional models of slopes.

The operational principle involves capturing overlapping images from multiple angles, enabling software algorithms to reconstruct the slope geometry accurately. Specific procedures include:

(a) Applying traditional UAV photogrammetry techniques to construct a rough slope model.

(b) Dividing the study area into subregions based on slope aspect and angle, and fitted as planes (Figure 2a).

(c) Planning flight routes for each subregion and setting specific routes for dominant discontinuities (Figure 2b).

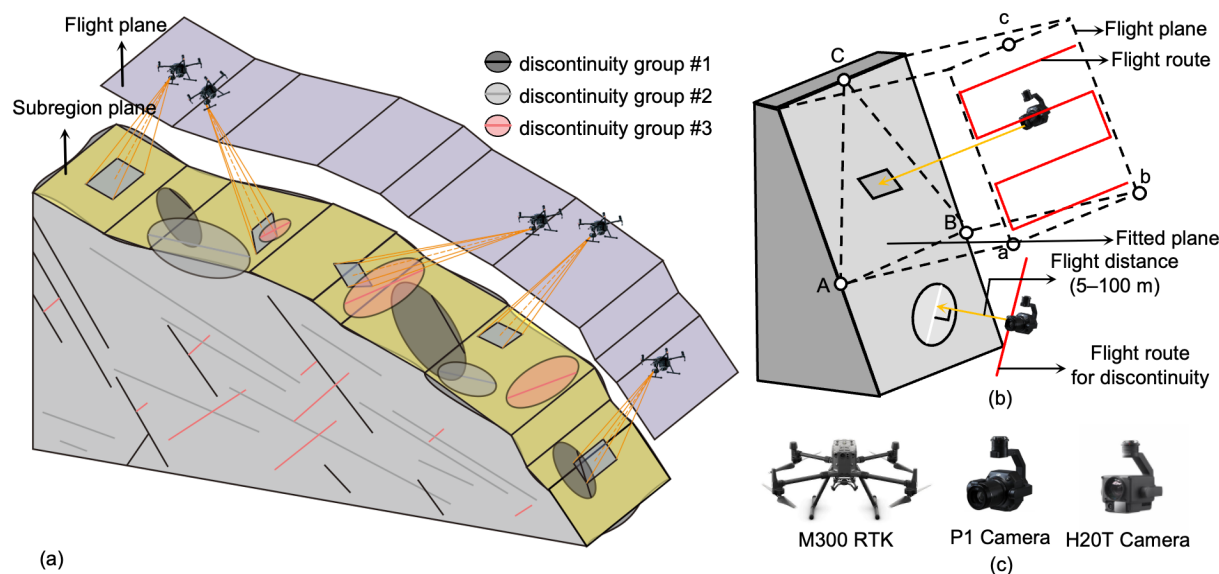


Figure 2. UAV nap-of-the-object photogrammetry. (a) Dividing subregions and fitting planes; (b) flight routes for slope and discontinuity; (c) UAV and cameras.

Table 1 Specifications for UAV platform and on-board camera

UAV platform specification		
Dimensions	810 × 670 × 430 mm	
Weight	3.77 kg (without battery)/6.47 kg (with two batteries)	
Maximum flight weight	9 kg	
Maximum speed	6 m/s (ascent)/5 m/s (descent)	
Flight duration	55 min	
On-board camera specifications		
Name	Zenmuse P1 (visible)	Zenmuse H20T (thermal)
Dimensions	198 × 166 × 129 mm	167 × 135 × 161 mm
Weight	800 g	828 g
Sensor	35.9 × 24 mm with 45 MP effective pixels	Uncooled vox microbolometer
Lens	DJI DL 24 mm F2.8 LS ASPH, FOV 84°	13.5 mm focal length with DFOV 40.6°
Image resolution	8 192 × 5 460	640 × 512

(d) Conducting automatic image collection during flight.

(e) Importing image data into DJI Terra to produce geological 3D products, including surface models and point clouds.

It is worth mentioning that the UAV used for this study is the DJI M300 RTK, equipped with a DJI Zenmuse P1 camera for visible images collection, and a DJI Zenmuse H20T for TIR data collection (Figure 2c). The specifications for UAV and camera are shown in Table 1. This method captures images of the ground surface and discontinuity at an extremely close range, enabling the acquisition of high-resolution images. Consequently, it ensures that the generated 3D model maintains high accuracy. This combination provides significant advantages in terms of data accuracy, operational efficiency, and flexibility, making it a vital tool for capturing high-resolution images and generating detailed slope models.

1.2.2 Rock mass data acquisition

In this section, we describe the specific methodology used to manually identify and interpret discontinuities on the reconstructed slope surface model and calculate critical rock mass characteristics parameters, including fracture density and spacing. These parameters are important for analyzing the relationship between rock mass and entropy values derived from TIR data.

The first step in rock mass data acquisition is to identify and map the discontinuities on the 3D slope surface model. Using the high-resolution model generated by UAV-based photogrammetry, discontinuities are manually identified and categorized based on their exposure characteristics, which exhibit three types, including planar, linear, and hybrid.

Planar discontinuities are exposed as smooth, continuous, and relatively flat surfaces, with well-defined edges (Zhao et al., 2024). These are typically fractures with uniform exposure, and feature points are placed evenly

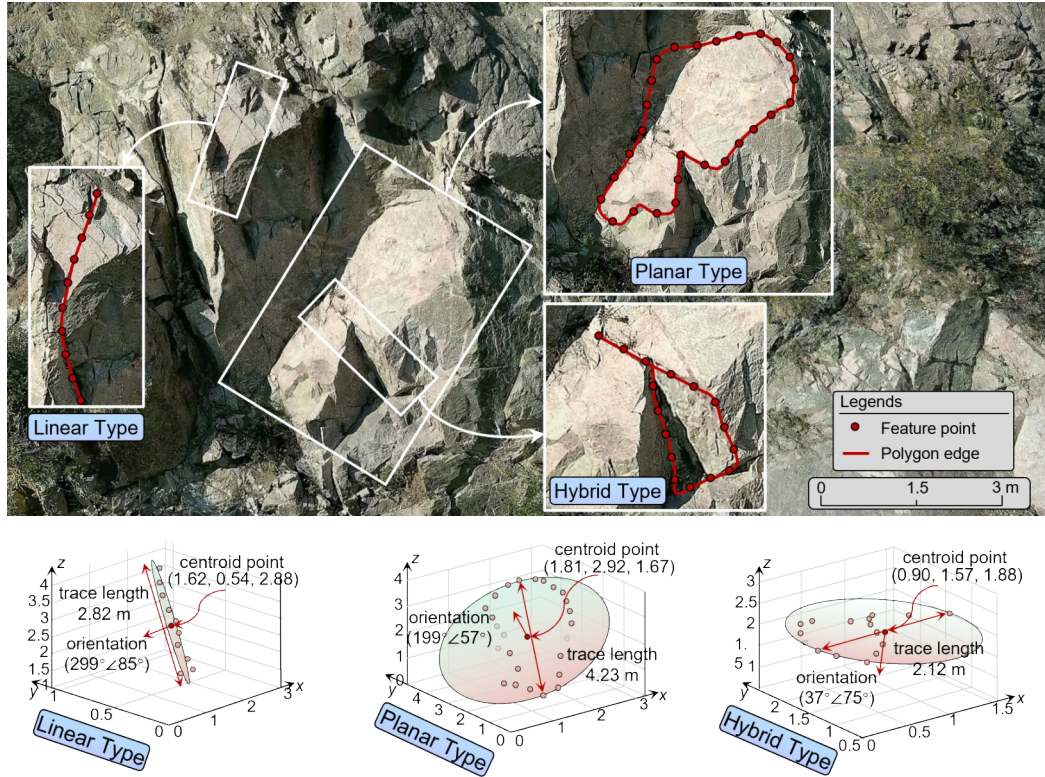


Figure 3. Interpretation of different types of discontinuities.

along the exposed edges. Linear discontinuities, on the other hand, appear as linear fracture traces that extend along a distinct direction. These fractures are identifiable by their continuous, linear pattern, and feature points are placed along the trace, starting from the initial visible fracture point. Hybrid discontinuities combine characteristics of both planar and linear types, with exposed areas that are continuous but also include linear fracture traces. For these surfaces, feature points are placed along the exposed edges and along the traces to fully capture the structure.

To calculate the orientation of each discontinuity, all feature points associated with a given surface are used to fit a disc with finite dimensions using random sample consensus algorithm. This disc represents the discontinuity and its spatial parameters, including the position, trace length, dip directions and dip angles, which are derived from the coordinates of the feature points. This method allows for an accurate determination of the discontinuities' orientation and location (Figure 3). It is worth noting that manual interpretation was chosen over automatic recognition in this study because existing algorithms primarily focus on planar type fractures, making it difficult to simultaneously identify different types of discontinuities.

Equivalent fracture spacing (d_{eq}) is a key parameter related to the frequency of discontinuity within a rock mass. It is calculated using the formula.

$$\begin{cases} d_{eq} = 1/\lambda \\ \lambda = \lambda_1 + \lambda_2 + \dots + \lambda_n \end{cases} \quad (2)$$

where d_{eq} represents the equivalent fracture spacing, λ is the total discontinuity frequency, λ_n is the discontinuity frequency of i th group of discontinuities.

This parameter provides a quantitative measure of discontinuity development, with smaller values indicating higher frequencies of discontinuities and more fractured of rock mass, which may reflect reduced rock mass quality.

2 STUDY AREA

The study area is located in a quarry near Siping City, Jilin Province, China, which features a typical rock slope of mining excavation zones (Figure 4a). Based on the slope position and orientation, the study area is divided into three sections: the left, the middle, and the right section. Each section presents distinct geological characteristics, which are crucial for analyzing the relationship between slope materials, discontinuity development, and TIR characteristics.

The left section is characterized by a "V"-shaped rock slope, with orientations of 123° on one side and 30° on the other. The maximum height difference in this section is approximately 45 m (Figure 4b). The area primarily consists of exposed bedrock, without vegetation covered. Discontinuities are highly developed in this area, and unstable rock blocks are visibly present (Figure 4c). Below the steep cliff on the right side, small-scale deposits are scattered (Figure 4d).

The middle section is the most prominent and exhibits its unique geological features. This slope has a general orientation of 154°, a height of 65 m, and a width of

around 200 m (Figure 4e). It strongly reflects the characteristics of a quarry excavation zone, with numerous areas experiencing artificial rock extraction. The upper portion is dominated by a cover layer and exposed bedrock, while the middle portion primarily consists of scattered rock deposits. The lower portion features steep bedrock exposures, with the steepest parts being nearly vertical. Additionally, scattered rubble deposits fill the gaps around the bases of the slope.

The right section is a broad excavated slope, with a width of up to 340 m and a maximum height difference of 55 m (Figure 4f). This area exhibits strong evidence of artificial excavation, leading to highly disordered slope structures (Figure 4g). The rock outcrops and deposits are distributed in a chaotic manner, with developed discontinuities and signs of intense weathering (Figures 4h, 4i).

The lithology of the strata is relatively uniform, primarily consisting of granite and granodiorite, overlain by a thin cover layer. A notable feature of the slope is a basaltic dike intruding through the middle section, introducing localized structural variations (Figure 4i). Despite the structural complexity introduced by fractures and joints, no large-scale faults are present in the vicinity.

During the data collection period in winter, the area experienced an average temperature ranging from -4 to -16 °C, with a cumulative snowfall of 10 mm, resulting in visible snow accumulation across the slope. These environmental conditions influence the thermal infrared characteristics of the slope surface and provide an important context for understanding the interaction between slope features and temperature variations.

3 SLOPE MODELS EVALUATION AND SUB-AREAS DIVISION

3.1 Slope and Discontinuity Analysis

This section presents the process of acquiring the slope surface model and TIR point cloud model using UAV-based photogrammetry and imaging. The data collections were conducted in September, October, and November, during winter conditions, with temperature ranging from 10 to -13 °C and noticeable snow cover.

For the photogrammetry, a DJI M300 RTK drone equipped with a DJI Zenmuse P1 camera was utilized. This system allowed for high-resolution imaging, essential for detailed surface reconstruction (Figure 5a). A total of 6246 images were captured over the study area, covering all three slope sections. The flight altitude was maintained at 30 m, and overlapping rates of 80% frontal

and 70% side were ensured to optimize the quality of the 3D surface model. The reconstructed slope surface model exhibits exceptional accuracy, meeting the requirements for interpreting small-scale fractures (Figure 5b), even fractures with millimeter-scale aperture can be identified (Figure 5c).

In addition, TIR data was collected using a DJI H20T camera mounted on the same UAV platform. This allowed the acquisition of both visual and thermal datasets. To better understand the diurnal thermal behavior of the slope features, TIR data was collected at five specific time intervals: 15:00 (Sep. 28), 18:00 (Oct. 18), 21:00 (Oct. 18), 24:00 (Oct. 18), and 03:00 (Nov. 28). This multi-temporal approach provided a comprehensive dataset to evaluate temperature variation.

The acquired datasets were processed using DJI Terra software, which generated detailed TIR point cloud models. The processing time for each TIR point cloud dataset does not exceed two hours. Fitting the entire point cloud into a convex hull enables the calculation of its surface point cloud density. The results indicate that the TIR point cloud data is highly dense, with point cloud densities exceeding 290 points per square meter across all five time intervals. Notably, the density reaches up to 365 points per square meter at 15:00. Table 2 provides a summary of the key characteristics of the TIR point cloud data collected at different time intervals.

3.2 Division of Slope Sub-Areas

To investigate the relationship between slope materials, the development degree of discontinuities, and TIR entropy, the slope can be classified into three categories based on field investigation and model observation, including rock masses with developed discontinuities, debris accumulation zones, and soil accumulation zones.

I. Rock masses with developed discontinuities: These areas are characterized by well-defined discontinuities and exposed rock surfaces, which significantly influence the thermal properties.

II. Debris accumulation zones: These zones are covered by variably sized fragments of rock, forming loose deposits that exhibits distinct thermal responses due to their heterogeneous composition.

III. Soil accumulation zones: These regions consist of soil or heavily weathered rock with a thin debris cover, where thermal behavior is influenced by fine-grained materials and partial rock exposure.

The division method involved field investigation combined with straightforward observations of the models to

Table 2 Specifications of TIR point cloud data

Time Interval	Number of images	Point clouds number	Point clouds density (m ²)	Ambient temperature (°C)
15:00 (Sep. 28)	558	24 133 545	365	7
18:00 (Oct. 18)	682	25 742 301	324	5
21:00 (Oct. 18)	637	30 898 926	350	-3
24:00 (Oct. 18)	658	29 598 915	319	-10
03:00 (Nov. 28)	771	29 453 493	294	-13

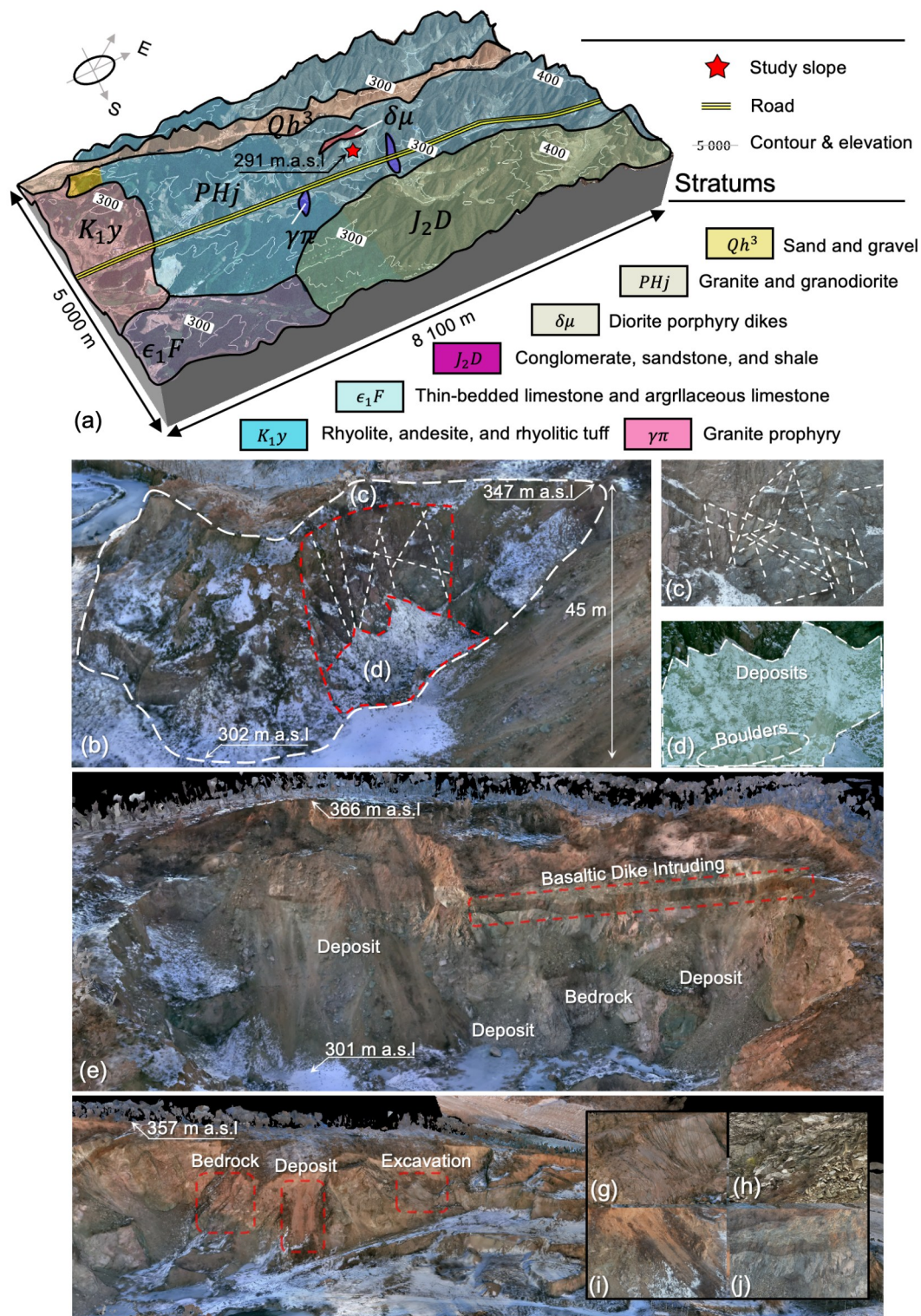


Figure 4. Geological settings of the study area. (a) Geological model of the study area; (b) the left section; (c) developed fractures and blocks; (d) small-scale deposits; (e) the middle section; (f) the right section; (g) artificial excavation; (h) rock outcrops; (i) deposit; (j) basaltic dike intruding.

distinguish different slope materials. The entire slope is divided into 11 sub-areas, with SA_1 , SA_3 , SA_5 , SA_6 , SA_8 , and SA_{10} classified as category I, SA_4 classified as category II, and SA_2 , SA_7 , SA_9 , and SA_{11} classified as category III. Specific division results are shown in Figure 6.

To further explore the relationship between discontinuity development and TIR entropy values, the I category was further subdivided into multiple sub-areas based on the degree of discontinuity development. The discontinuity equivalent spacing (joint spacing) is used as an indica-

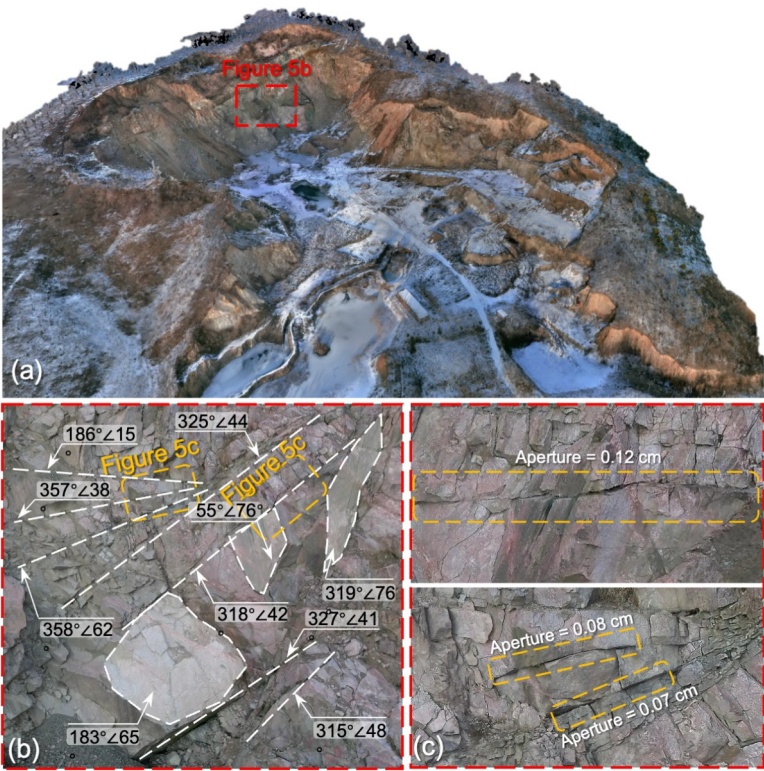


Figure 5. 3D slope surface model and discontinuity. (a) 3D high-resolution slope surface model; (b) identified discontinuities with orientations; (c) discontinuities with millimeter-level aperture.

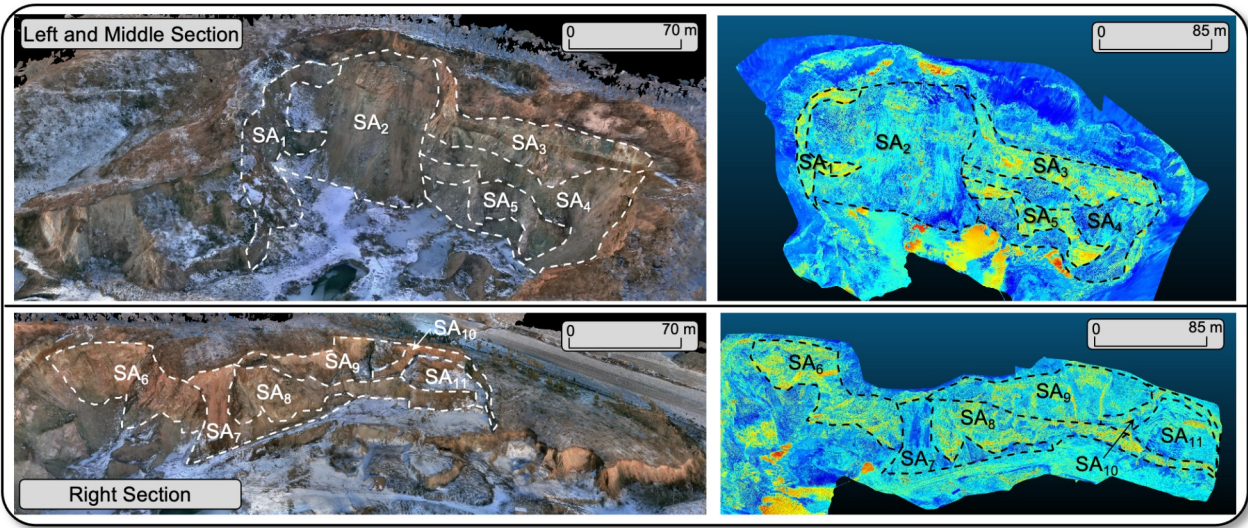


Figure 6. Slope sub-areas division based on materials.

tor to quantify the development degree in each sub-area. The specific division results are shown in Figure 7, and the corresponding fracture parameters are presented in Table 3.

4 TIR ENTROPY CHARACTERISTICS ANALYSIS

4.1 TIR Entropy Analysis for Material-Based Sub-Areas

Based on the entropy calculation formula introduced in the methodology section, the TIR entropy values were

computed for each sub-area of the slope, with a focus on material-based divisions. The results are shown in Figure 8 and indicated distinct entropy trends across different material types.

Category I. Rock masses with developed discontinuities: These areas exhibited the lowest entropy values, reflecting a relatively smooth and homogeneous surface with minimal thermal heterogeneity. For example, at 15:00, the average entropy value for this category was 6.724 6, indicating relatively stable temperature condi-

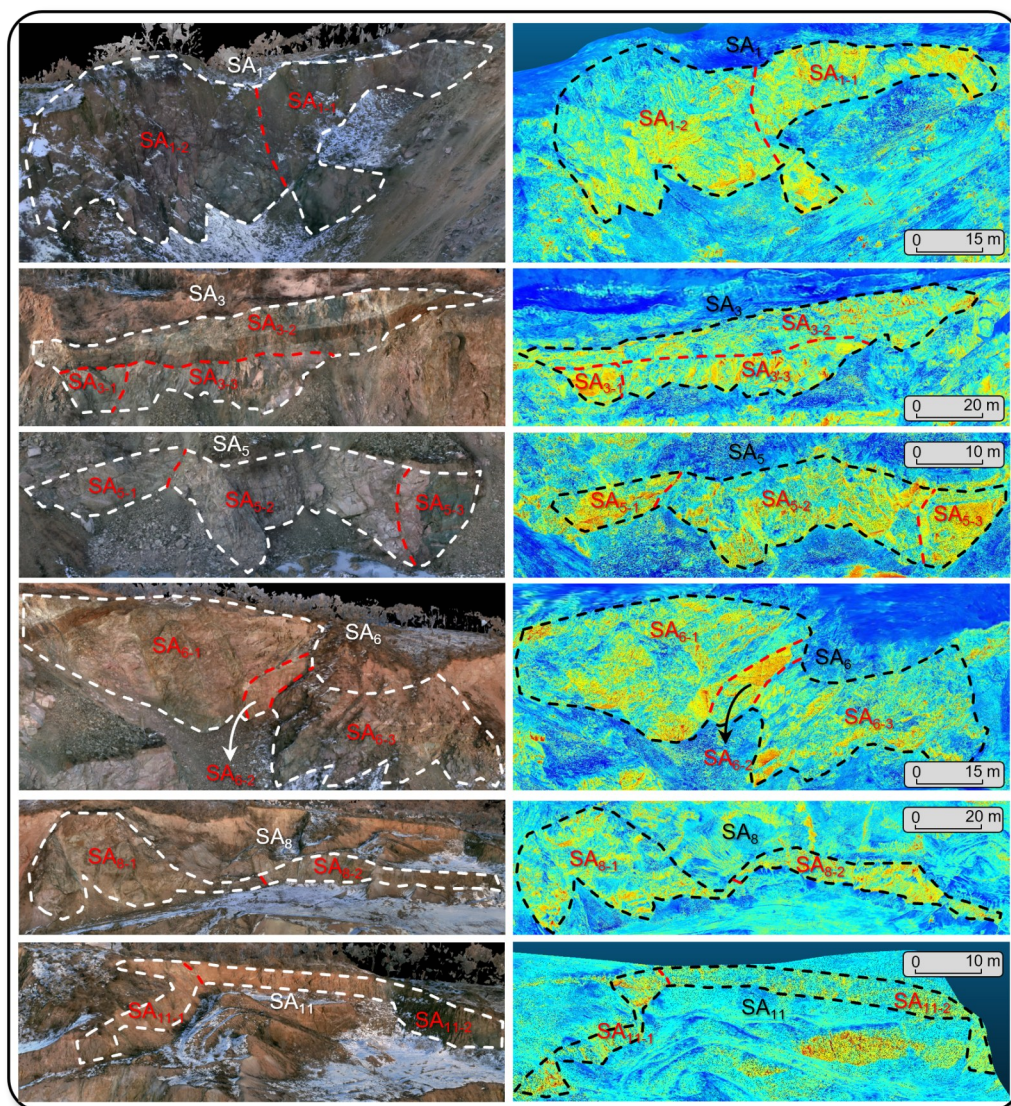


Figure 7. Specific sub-areas division based on fracture development.

tions across the rock mass.

Category II. Debris accumulation zones: These areas showed intermediate entropy values, averaging 7.237 8 at 15:00, as a result of the irregular distribution of debris and moderate thermal heterogeneity. The mixed nature of debris caused variations in temperature, leading to higher entropy compared to the rock mass areas.

Category III. Soil accumulation zones: This area exhibited the highest entropy value, with a value of 7.572 6 at 15:00, due to the complex thermal variation arising from loose soil and fine-grained materials. The significant temperature fluctuation in this area resulted in the highest entropy values, reflecting the dynamic nature of the material's thermal properties.

The results of TIR entropy calculation based on material-based sub-areas provide valuable insights into the relationship between slope materials and thermal heterogeneity. By distinguishing between rock masses, debris accumulations, and soil-like deposits, the study highlights how different materials and their thermal properties can

influence the thermal behavior of the slope. Specifically, regions with higher entropy values, such as soil-like deposits and debris accumulations, may indicate areas of greater thermal variability and potential instability. Conversely, areas with lower entropy values, such as rock masses with developed discontinuities, may suggest more stable regions with less thermal fluctuation.

4.2 Correlation Between TIR Entropy and Fracture Parameters

This section analyzes the relationship between TIR entropy values and the degree of discontinuity development, using fracture equivalent spacing as the key parameter to differentiate sub-areas. Based on the fracture equivalent spacing values acquired for each sub-area, TIR entropy values are compared and analyzed to identify trends and correlations.

Table 4 lists the TIR entropy values and fracture equivalent spacing for each sub-area. The relationship between these parameters is visually illustrated in Figure

Table 3 Fracture parameters of each sub-area

Sub-areas	Discontinuity groups	Equivalent joint spacings (m)
SA ₁	SA ₁₋₁	J ₁ 62°∠75°
		J ₂ 320°∠84°
		J ₃ 27°∠70°
		J ₄ 190°∠41°
SA ₁	SA ₁₋₂	J ₁ 62°∠58°
		J ₂ 236°∠84°
		J ₃ 103°∠86°
		J ₄ 327°∠14°
SA ₃	SA ₃₋₁	J ₁ 279°∠22°
		J ₂ 58°∠36°
		J ₃ 151°∠84°
	SA ₃₋₂	J ₁ 157°∠75°
		J ₂ 287°∠88°
		J ₃ 5°∠33°
		J ₄ 324°∠80°
	SA ₃₋₃	J ₁ 146°∠40°
		J ₂ 16°∠74°
		J ₃ 107°∠87°
SA ₅	SA ₅₋₁	J ₁ 317°∠85°
		J ₂ 39°∠74°
		J ₃ 159°∠40°
	SA ₅₋₂	J ₁ 131°∠51°
		J ₂ 111°∠84°
		J ₃ 317°∠22°
		J ₄ 44°∠76°
	SA ₅₋₃	J ₁ 139°∠75°
		J ₂ 24°∠84°
		J ₃ 322°∠30°
SA ₆	SA ₆₋₁	J ₁ 325°∠64°
		J ₂ 62°∠82°
		J ₃ 38°∠70°
		J ₄ 147°∠76°
	SA ₆₋₂	J ₁ 252°∠79°
		J ₂ 132°∠82°
		J ₃ 85°∠24°
	SA ₆₋₃	J ₁ 85°∠20°
		J ₂ 247°∠78°
		J ₃ 102°∠47°
		J ₄ 156°∠64°
SA ₈	SA ₈₋₁	J ₁ 323°∠78°
		J ₂ 228°∠86°
		J ₃ 95°∠79°
		J ₄ 349°∠46°
	SA ₈₋₂	J ₁ 89°∠88°
		J ₂ 201°∠45°
		J ₃ 32°∠73°
SA ₁₁	SA ₁₁₋₁	J ₁ 239°∠20°
		J ₂ 34°∠81°
		J ₃ 302°∠76°
	SA ₁₁₋₂	J ₁ 253°∠29°
		J ₂ 234°∠75°
		J ₃ 141°∠89°

9, where a clear linear correlation can be observed. Using the least squares method, the data is fitted with a linear polynomial model, and both the confidence interval and prediction interval of the fit are estimated. The result-

ing linear equation relating TIR entropy values (EV) to fracture equivalent spacing (F_{ES}) is as follows.

$$F_{ES} = -1.4178EV + 9.9527 \quad (3)$$

The identified linear relationship highlights the potential for using TIR entropy as a quantitative indicator for assessing fracture development in rock masses. This approach provides a robust, non-destructive method to analyze and predict the structural integrity of slope materials.

5 DISCUSSION

5.1 Materials-Based Sub-Areas and Thermal Behavior

This study provides a systematic analysis of the TIR entropy characteristics across different slope material sub-areas, including rock masses, debris accumulation, and soil accumulations. The findings demonstrate that TIR entropy effectively reflects the heterogeneity of different materials: rock masses exhibit the lowest entropy, debris accumulations display moderate entropy, and soil accumulations have the highest entropy. These differences are closely linked to the physical properties and thermal conductivity of the materials.

For rock masses areas, the low entropy values reflect the uniformity of their thermal infrared signals, attributed to consistent thermal conductivity and relatively smooth surfaces. For debris accumulations, the moderate values are influenced by the variability in particle sizes and packing density, which introduce greater temperature heterogeneity. For soil accumulations, high entropy values indicate significant heterogeneity and complex thermal radiation characteristics, especially in heavily weathered or moisture-rich conditions.

The observed patterns may provide a scientific basis for slope stability zoning by identifying stable and high-risk areas. Low entropy values in rock masses help pinpoint relatively stable zones, while entropy variations in debris accumulations and soil accumulations can indicate potential risks of sliding and debris flow initiation. These findings offer valuable tools for early warning systems and guiding engineering measures to mitigate geological hazards.

5.2 Fracture Influence on TIR Entropy Patterns

The relationship between fracture parameters and TIR entropy introduces a fresh perspective in understanding rock mass heterogeneity through thermal behavior. By integrating fracture equivalent spacing data with entropy results, the study identifies a clear linear relationship: increased fracture equivalent spacing corresponds to lower TIR entropy values.

The sub-areas with densely spaced fractures exhibit elevated TIR entropy, reflecting their highly fragmented and thermally heterogeneous surfaces. Conversely, regions with wider fracture spacing demonstrate reduced entropy values, indicating more uniform thermal responses. These findings bridge rock mass structure with thermal analysis, providing a quantitative understanding of

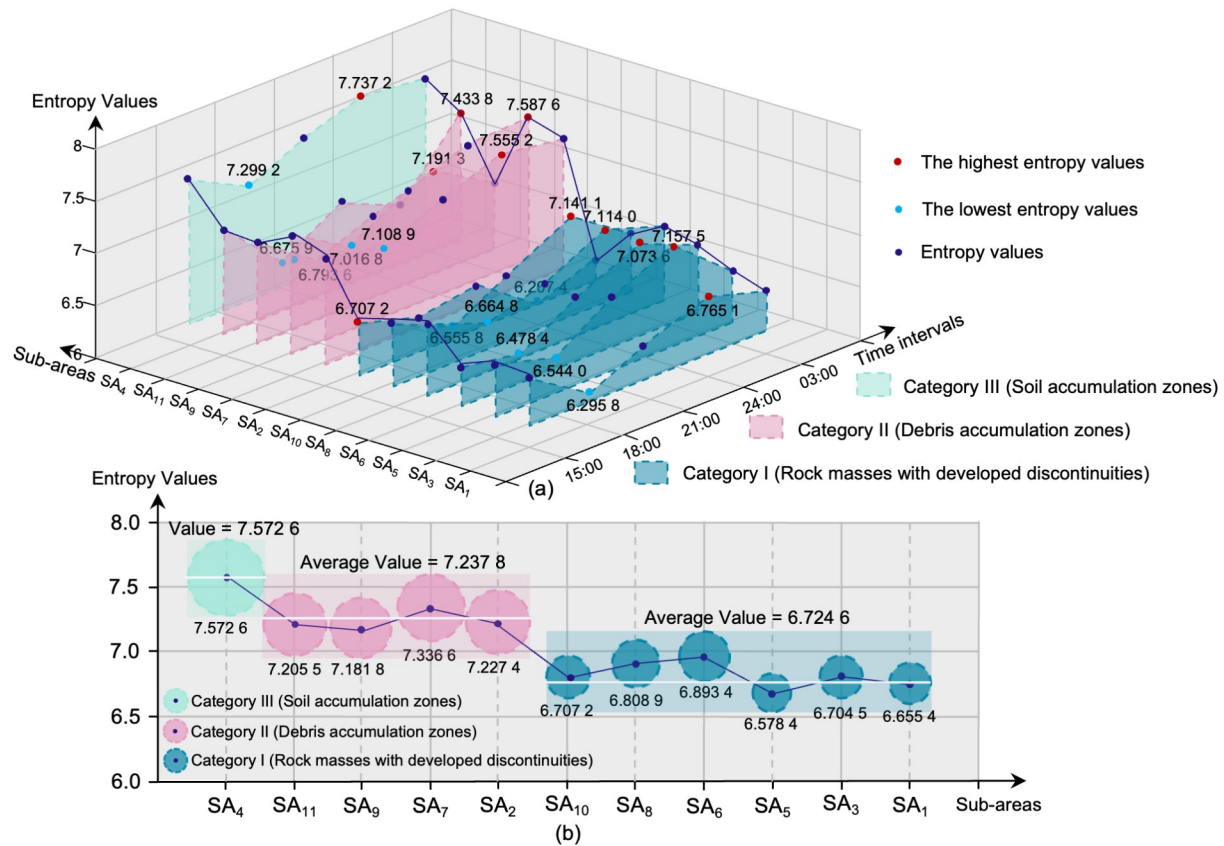


Figure 8. Entropy value results of material-based sub-areas.

Table 4 Entropy values and fracture equivalent spacing of each sub-area

Sub-areas	Entropy value (EV)	Fracture equivalent spacing (F_{ES})
SA ₁	SA ₁₋₁ 6.400 6	0.880 4
	SA ₁₋₂ 6.723 6	0.502 6
SA ₃	SA ₃₋₁ 6.580 0	0.697 1
	SA ₃₋₂ 6.936 0	0.123 7
	SA ₃₋₃ 6.837 6	0.280 8
SA ₅	SA ₅₋₁ 6.706 6	0.569 4
	SA ₅₋₂ 6.768 5	0.320 5
	SA ₅₋₃ 6.361 6	0.915 6
SA ₆	SA ₆₋₁ 6.874 8	0.308 9
	SA ₆₋₂ 6.676 4	0.572 4
	SA ₆₋₃ 6.827 3	0.206 6
SA ₈	SA ₈₋₁ 6.786 3	0.248 4
	SA ₈₋₂ 6.667 2	0.414 1
SA ₁₁	SA ₁₁₋₁ 6.774 9	0.256 7
	SA ₁₁₋₂ 6.677 9	0.367 6

the interplay between fracture development and thermal behavior.

By leveraging TIR entropy as a proxy for fracture characteristics, experts can rapidly identify zones of structural instability and thermal heterogeneity. This approach supports applications in slope stability assess-

ments, hazard detection, and geotechnical planning, offering a novel tool for managing fractured rock environments.

6 CONCLUSIONS

This study systematically investigated the TIR entropy characteristics of slope materials, combining high-resolution UAV-based photogrammetry and TIR data to analyze the relationship between slope material properties, fracture development, and thermal behavior. By integrating innovative methodologies and quantitative analyses, this research provides new insights into the application of TIR entropy in slope stability assessments and geotechnical engineering.

(1) Integration of UAV-based photogrammetry and TIR data acquisition. High-resolution 3D slope surface models and dense TIR point cloud datasets are successfully generated using UAV multi-angle nap-of-the-object photogrammetry. These models facilitated the identification of small-scale fractures and accurate TIR entropy calculations, enabling comprehensive analyses of slope thermal and structural characteristics.

(2) TIR entropy differentiation among slope materials. Significant differences in TIR entropy are observed among rock masses, debris accumulations, and soil accumulations. Rock masses exhibit the lowest entropy due to their homogeneity and uniform thermal properties, debris accumulations demonstrate moderate entropy val-

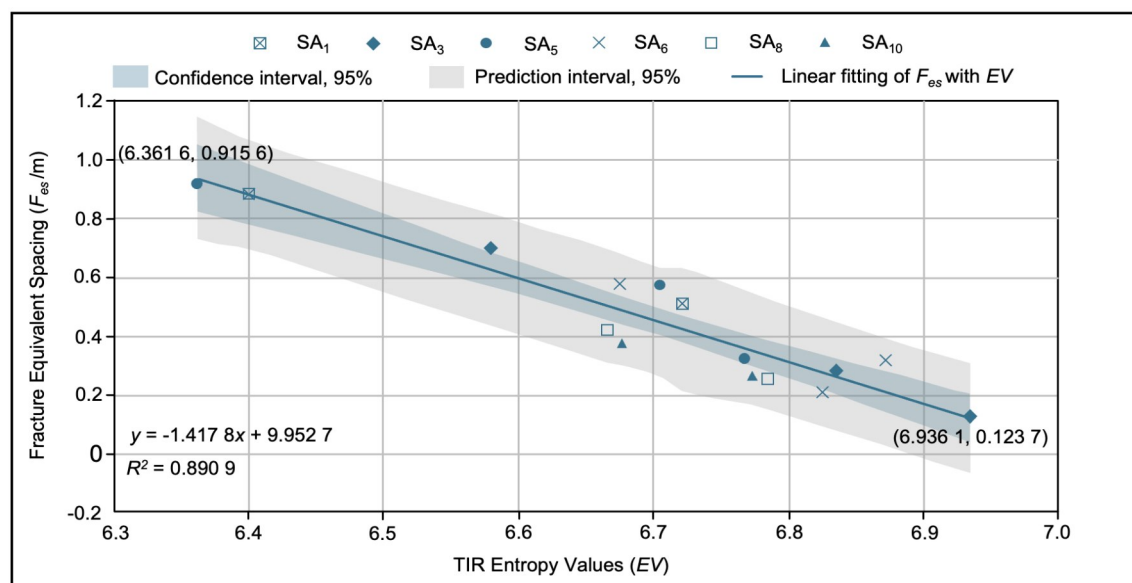


Figure 9. The linear relationship between TIR entropy values and fracture equivalent spacings.

ues due to particle variability, and soil accumulations display the highest entropy, reflecting their complex thermal behavior. These findings provide a new perspective on the thermal and structural behavior of different slope materials, contributing to refined hazard identification and stability assessments.

(3) Linear relationship between fracture development and TIR entropy. A strong linear correlation between fracture equivalent spacing and TIR entropy is established, with densely fractured zones exhibiting high entropy values. This relationship underscores the ability of TIR entropy to quantify fracture development and rock mass heterogeneity, offering a novel metric for assessing structural integrity and potential instability in slopes.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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