Review

Not peer-reviewed version

Dynamic Evaluation Model for Stability State of Slope Unstable Rock Masses and Its Engineering Application

Guang Lu , Mowen Xie * , Yan Du

Posted Date: 30 April 2026

doi: 10.20944/preprints202604.2164.v1

Keywords: slope unstable rock mass; dynamic evaluation; natural frequency; structural plane damage; stability model; monitoring and early warning; laser Doppler vibrometry

Review

Dynamic Evaluation Model for Stability State of Slope Unstable Rock Masses and Its Engineering Application

Guang Lu [1], Mowen Xie [2,*] and Yan Du [1]

[1] School of Future Cities, University of Science and Technology Beijing, Beijing 100083, China
[2] School of Resources and Safety Engineering, University of Science and Technology Beijing, Beijing 100083, China
* Correspondence: mowenxie@126.com

Abstract

Rockfall from slope unstable rock masses, a typical geological hazard induced by brittle failure, is characterized by abrupt occurrence, negligible macroscopic deformation prior to failure, and extremely short lead time for early warning, posing a severe threat to the safety of mountainous transportation systems, water conservancy and hydropower projects, and urban settlements. Conventional static analysis methods have significant limitations in real-time acquisition of damage evolution of structural planes and dynamic assessment of stability changes, which can hardly meet the practical requirements of early warning for unstable rock masses. The dynamic evaluation method for the stability state of unstable rock masses, based on the principles of structural dynamics, establishes a correlation model between dynamic parameters (natural frequency, damping ratio, mode shape, etc.) and the damage degree of structural planes, providing a new paradigm for dynamic identification and quantitative evaluation of the stability of unstable rock masses. This paper systematically reviews the dynamic behavior mechanism and theoretical evaluation framework of slope unstable rock masses, and elaborates on the damage evolution of structural planes, the disturbance effect of environmental dynamic loads, and the key dynamic parameter system. The single-degree-of-freedom dynamic models and their theoretical derivation for three typical types of unstable rock masses (sliding-type, toppling-type, and falling-type) are thoroughly analyzed, and the cutting-edge advances such as multi-block chain collapse model and data-physics dual-driven surrogate model are reviewed. Meanwhile, the contact and non-contact monitoring methods based on Micro-Electro-Mechanical System (MEMS) and Laser Doppler Vibrometer (LDV) techniques, as well as the development status of cloud-edge collaborative intelligent early warning architecture, are systematically summarized. On this basis, the core challenges are pointed out, including the long-term evolution under multi-field coupling, high-fidelity inversion calculation for large-scale rock masses, and the scientific correlation between early warning thresholds and failure probability. The full-life-cycle dynamic simulation based on digital twin is also prospected. The research results provide a systematic reference for the improvement of the theoretical system of dynamic evaluation of slope unstable rock masses and the engineering practice of disaster prevention and mitigation.

Keywords: slope unstable rock mass; dynamic evaluation; natural frequency; structural plane damage; stability model; monitoring and early warning; laser Doppler vibrometry

---

1. Introduction

1.1. Research Background and Engineering Significance

Slope unstable rock masses refer to rock masses located on steep slopes or cliffs, cut by multiple groups of rock structural planes, gradually separated from the parent rock under the actions of

doi:10.20944/preprints202604.2164.v1

gravity, weathering, and water seepage pressure, and with poor stability. Rockfall disasters induced by the instability of unstable rock masses are a global mountainous geological hazard, characterized by sudden occurrence, high movement velocity, and strong disaster-causing capacity, which seriously threaten the lives and property of residents, urban construction, mine operations, and transportation safety in mountainous areas of China [1–4]. According to statistics, mountainous and hilly areas account for approximately 65% of China's land area, with complex geological conditions and frequent tectonic activities. By the end of 2024, there were 284,000 geological hazard hidden sites nationwide, among which rockfall hazards accounted for about 30% of the total geological hazards. In the past five years, more than 6,000 rockfall disasters have occurred in China, causing huge casualties and economic losses (2024 China Natural Resources Bulletin).

With the advancement of national hydropower and transportation construction into southwest China, high and steep slopes are widely distributed along newly built lines. Coupled with the in-depth implementation of the Belt and Road Initiative, the construction of transportation infrastructure is facing widespread threats from unstable rock masses on high and steep slopes. Especially along the national major strategic projects such as the cascade hydropower stations in the lower reaches of the Yarlung Zangbo River and the Sichuan-Tibet Railway, the significant differences in topography and geomorphology, complex geological environment, and disastrous climatic conditions lead to a marked increase in the occurrence frequency and hazard degree of rockfall disasters[5–8]. Therefore, research on the rapid identification, scientific evaluation, and effective monitoring and early warning of the stability state of unstable rock masses has important engineering significance and practical urgency for ensuring the safety of people's lives and property and the sustainable operation of major infrastructure.

1.2. Limitations of Conventional Limit Equilibrium and Static Analysis Methods

For a long time, the stability evaluation of unstable rock masses has mainly relied on static analysis methods represented by the limit equilibrium method. Essentially based on Newton's first law, this method evaluates the stability of unstable rock masses by defining the factor of safety (FOS) as the ratio of anti-sliding force (anti-sliding moment) to sliding force (sliding moment) [9–11]. Through research on the instability mechanism and failure modes of unstable rock masses, scholars have roughly classified unstable rock masses into three categories: sliding-type, toppling-type, and falling-type, as well as composite unstable rock masses based on the combination of the above three forms[8,12–14]. Corresponding stability calculation methods have been established based on the limit equilibrium theory and rock mass structure theory[1,2,9,15,16]. Overall, the limit equilibrium method has the advantages of clear physical meaning and simple calculation, and has been widely used in engineering practice.

However, the limit equilibrium method has obvious limitations in the dynamic stability evaluation of unstable rock masses. Firstly, the stability of an unstable rock mass is critically determined by the bonding area and bonding strength of the main controlling structural plane, while these key parameters are difficult to obtain accurately in the field and usually rely on manual measurement or empirical estimation [17]. Secondly, under the actions of natural or anthropogenic factors such as rainfall, earthquake, blasting, and freezing, the structural planes of unstable rock masses suffer continuous damage, and the bonding area and bonding strength are in a dynamic change process. Static methods cannot reflect this damage evolution in real time, which may lead to the failure of the original safety evaluation indicators. Thirdly, rockfall of unstable rock masses mostly presents as sudden failure without obvious displacement characteristics, and conventional displacement monitoring methods are difficult to achieve effective early warning. Therefore, conventional static analysis is trapped in the dilemma of "the monitored sites do not fail, while the failed sites were not monitored" in the real-time stability evaluation and monitoring and early warning of unstable rock masses.

1.3. Proposal and Advantages of the Dynamic Evaluation Method

To address the limitations of conventional methods, the stability evaluation method for unstable rock masses based on structural dynamics theory has emerged. The theoretical basis of this method is that an unstable rock mass can be regarded as a mechanical system composed of physical parameters such as stiffness, mass, and damping. Once damage occurs to the structural plane, it will inevitably cause changes in the physical properties of the system, thereby leading to corresponding changes in dynamic parameters such as natural vibration frequency [18]. Therefore, by monitoring the changes in the dynamic parameters of the unstable rock mass, the damage state of the structural plane can be inverted, and then the dynamic evaluation of the stability of the unstable rock mass can be realized. Compared with conventional displacement and stress-strain monitoring, the monitoring method based on dynamic parameters has the following significant advantages:

(1) Timeliness advantage: Dynamic parameters show measurable changes when minor damage occurs to the structural plane, while displacement monitoring usually presents an obvious response only at the precursory stage of failure. The optimal early warning period based on dynamic indicators such as natural frequency is usually tens of seconds or even longer than that of displacement early warning [19].

(2) Scientificity and reliability: There is a clear quantitative relationship between dynamic parameters and the mechanical parameters of the structural plane of the unstable rock mass, which can realize dynamic identification and quantitative judgment of structural plane damage [20].

(3) Non-contact measurement: With the help of technologies such as laser Doppler vibrometry, remote non-contact rapid identification and safety evaluation of unstable rock masses can be realized, which greatly improves the safety and efficiency of investigation of unstable rock masses on high and steep slopes [12].

(4) Universality: Corresponding dynamic evaluation models can be established for unstable rock masses with different failure modes (sliding-type, falling-type, and toppling-type).

In recent years, domestic and foreign scholars have carried out extensive research in the field of dynamic evaluation of unstable rock masses. Okuzono et al. [21] and Fujisawa et al. [22] from Japan were the first to apply vibration measurement technology to the identification of unstable rock blocks, and found that the amplitude, particle trajectory, and spectral characteristics of unstable rock blocks are significantly different from those of stable rock masses. Ogata et al. [23] proposed a method for judging the risk of rockfall using three vibration characteristics: RMS velocity amplitude ratio, predominant frequency, and damping ratio. Uehan et al. [24] developed a remote non-contact vibration measurement system based on a laser Doppler vibrometer, and established a quantitative relationship model between natural frequency and mechanical stability. In China, Du, Xie, Jia et al. systematically carried out research on the stability evaluation model of unstable rock blocks based on natural vibration frequency, established a quantitative relationship model between natural frequency and factor of safety for sliding-type and falling-type unstable rock blocks, and successfully applied it in engineering sites such as Baihebao Reservoir[20,25]. Liu and Zhang [26,27]further established a stability evaluation model and theoretical analytical algorithm based on the first-order natural frequency for falling-type slope unstable rock masses. From the perspective of energy release during rock mass failure, Chen et al. established a calculation method of elastic-impact dynamic parameters for compression-shear type unstable rock failure, and revealed the rapid energy release mechanism of rockfall [28].

1.4. Research Scope and Structural Arrangement

This paper takes the dynamic evaluation model for the stability state of slope unstable rock masses as the core theme, and systematically reviews the theoretical system, technical methods, and engineering application progress in this field. The research scope covers: (1) The dynamic behavior mechanism and theoretical evaluation framework of unstable rock masses, including the damage evolution mechanism of structural planes, the disturbance effect of environmental dynamic loads, and the key dynamic parameter system; (2) Theoretical dynamic evaluation models of typical unstable rock masses, including three types of single-block models (sliding-type, toppling-type, falling-type) and multi-block chain collapse model; (3) Dynamic response monitoring technology and early warning system integration, including contact and non-contact monitoring technologies and cloud-edge collaborative architecture; (4) Existing problems and cutting-edge development trends.

With the logical thread of "mechanism-parameter-model-monitoring-application-prospect" (Figure 1), this paper aims to construct a systematic and complete knowledge system for dynamic evaluation of slope unstable rock masses, and provide a reference for theoretical research and engineering practice in this field.

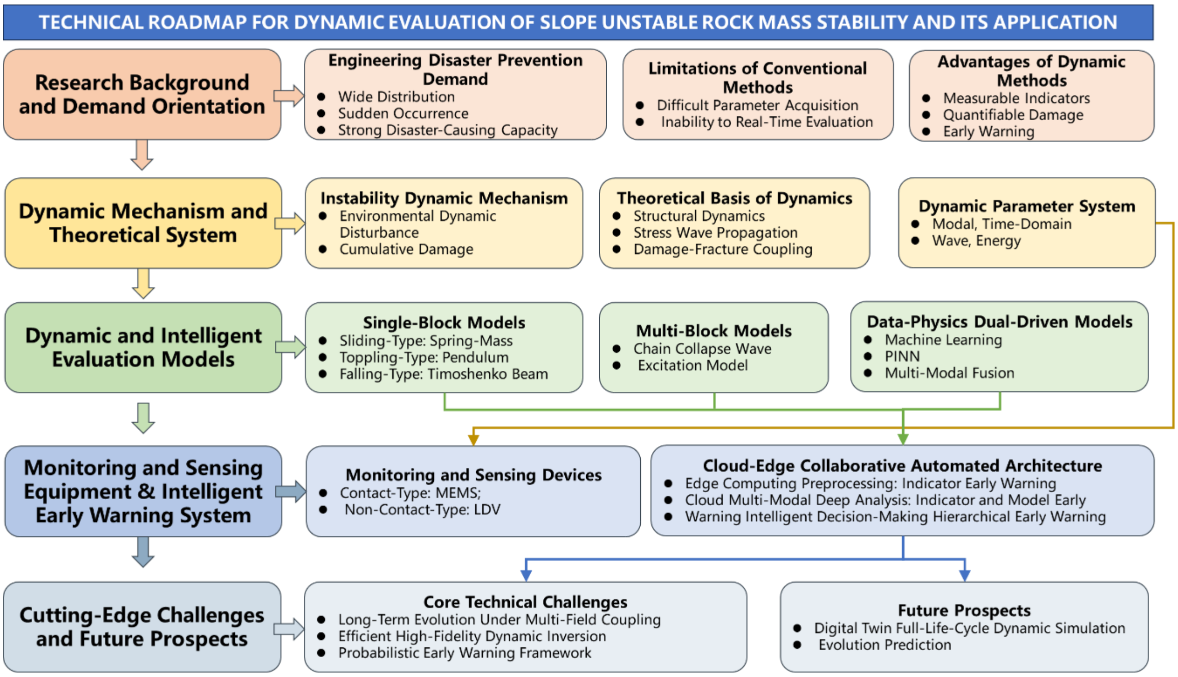

Figure 1. Technical Roadmap.

2. Dynamic Behavior Mechanism and Theoretical Evaluation Framework of Unstable Rock Masses

2.1. Dynamic Mechanism of Instability of Unstable Rock Masses

2.1.1. Mechanism of Structural Plane Damage Evolution and Time-Dependent Strength Deterioration

The instability and failure of slope unstable rock masses are essentially the result of damage evolution and fracture propagation of the main controlling structural plane. The deterioration of the mechanical properties of structural planes is affected by the coupling of various internal and external factors, presenting a complex time-dependent process. Based on damage mechanics and fracture mechanics, Chen et al. conducted an in-depth study on the damage characteristics at the tip of the main controlling structural plane of unstable rocks, found that the formation and propagation of the main controlling structural plane are the key to the failure of unstable rocks, and established a calculation method for the elastic modulus and Poisson's ratio of the damage zone at the tip of the main controlling structural plane using damage mechanics [29]. The failure and instability process of unstable rock masses can be divided into three typical stages: strong stability stage, weak stability stage, and failure stage [19]. In the strong stability stage, the unstable rock mass is effectively bonded to the bedrock, the anti-sliding force is completely provided by the bonding force in the potential sliding surface, and the friction force is zero. In the weak stability stage, with the decrease of bonding strength, the bonding layer is insufficient to resist the sliding force, the friction force begins to play a role and increases gradually, and the natural vibration frequency decreases accordingly. In the failure stage, after the maximum static friction force is reached, the unstable rock mass undergoes large displacement and failure.

From the perspective of fracture mechanics, the crack type of the main controlling structural plane of an unstable rock mass determines its failure mode. Toppling-type unstable rock corresponds to Mode I opening crack (tension-shear failure), sliding-type unstable rock corresponds to Mode II sliding crack (compression-shear failure), and falling-type unstable rock corresponds to Mode III tearing crack (shear failure) [30]. For tension-shear composite cracks, the stress field at the crack tip can be characterized by the stress intensity factors K_I and K_{II}. The maximum circumferential stress criterion is usually adopted as the crack propagation criterion, and the calculation expression of the equivalent combined stress intensity factor K_e is as follows [31]:

$$K_e = \frac{1}{2}\cos\frac{\theta_0}{2}[K_{\mathrm{I}}(1+\cos\theta_0) - 3K_{\mathrm{II}}\sin\theta_0] \tag{1}$$

where θ_0 is the crack propagation angle. When $K_e \geq K_{IC}$ (fracture toughness), unstable propagation of the main controlling structural plane occurs, followed by the failure of the unstable rock mass.

In terms of time dependence, the structural planes of unstable rock masses undergo progressive strength deterioration under the long-term actions of gravity, weathering, rainfall, and other factors. For falling-type unstable rock masses, the depth of the trailing edge crack h is a key parameter controlling the stability of the rock mass. Based on the theory of mechanics of materials, the maximum tensile stress σ_{max} and shear stress τ on the section of the trailing edge crack can be expressed as [32]:

$$\sigma_{\max} = \frac{3\gamma L^2}{H(1-\lambda)^2}, \quad \tau = \frac{\gamma L}{1-\lambda} \tag{2}$$

where γ is the unit weight of the unstable rock mass, L is the length of the unstable rock mass, H is the height of the unstable rock mass, and $\lambda = h/H$ is the relative depth of the crack. With the increase of crack depth, the maximum tensile stress and shear stress increase gradually, and the factor of safety of the unstable rock mass decreases accordingly.

2.1.2. Triggering and Cumulative Damage Effects Under Environmental Dynamic Disturbance

Environmental dynamic disturbance is an important factor triggering and aggravating the instability of unstable rock masses, mainly including earthquakes, engineering blasting, traffic vibration, etc. The influence of dynamic disturbance on the stability of unstable rock masses is reflected in three aspects:

(1) The stress wave generated by the vibration load causes reflection and oscillation at the structural plane, damages the structure of the structural plane, reduces the bonding area, and leads to the decrease of bonding strength.

(2) The inertial force generated by the vibration load acts on the unstable rock mass, increases the sliding force or sliding moment, and directly triggers instability.

(3) Cumulative damage effect caused by dynamic disturbance: repeated dynamic loads such as frequent blasting will continuously deteriorate the mechanical properties of the main controlling structural plane, the cohesion of the rock bridge section decreases with the accumulation of damage, and the factor of safety of the unstable rock mass shows a decreasing trend [33].

Studies have shown that the stability of unstable rock masses under blasting disturbance is closely related to the blasting intensity and the propagation distance of the explosion stress wave. Frequent blasting disturbance will continuously deteriorate the mechanical properties of the main controlling plane, and the stability of the unstable rock mass decreases with the increase of blasting intensity and the decrease of the propagation distance of the explosion stress wave. Moreover, the load generated by the explosion is more sensitive to the stability of the unstable rock mass than the deterioration of the mechanical properties of the rock mass [33]. Dynamic stability analysis considering blasting action needs to break through the limitations of the conventional pseudo-static method, and fully consider the influences of factors such as the shape and geometric size of the unstable rock mass, the frequency of the blasting seismic wave, and the initial incident phase [34].

The dynamic response of unstable rock masses under earthquake action has obvious elevation amplification effect and near-surface effect. Shaking table test studies have shown that limestone slopes present significant dynamic response amplification characteristics during failure, and the amplification effect is more significant at positions closer to the slope top [35]. Under strong earthquake conditions, unstable rock masses may experience toppling, sliding, and mixed failure modes of the two. The change of the loading direction of seismic waves will affect the failure mode: horizontal loading mainly causes toppling failure, while combined horizontal and vertical loading is more likely to lead to mixed sliding and toppling failure [36].

2.2. Core Theoretical Basis of Dynamic Evaluation

2.2.1. Application Principle of Structural Dynamics and Mode Shape Analysis in Unstable Rock Identification

An unstable rock mass can be regarded as a mechanical system composed of stiffness, mass and damping, whose free vibration characteristics are uniquely determined by the physical parameters of the system. For a single-degree-of-freedom system, the undamped free vibration equation is [12]:

$$m\ddot{x} + kx = 0 \tag{3}$$

The natural frequency of the system is:

$$f = \frac{1}{2\pi}\sqrt{\frac{k}{m}} \tag{4}$$

where m is the equivalent mass, and k is the equivalent stiffness. When damage occurs to the structural plane of the unstable rock mass, the equivalent stiffness k decreases, leading to a reduction in the natural frequency f. Therefore, the damage degree of the structural plane can be inverted by monitoring the change of natural frequency.

For example, a toppling-type unstable rock mass can be simplified as a simple pendulum model swinging around the pivot point (see Section 3.1.2 for details). According to the principle of structural dynamics, its differential equation of motion is [25]:

$$ML^2\ddot{\theta} + \frac{\mu AB^2}{2}\theta = 0 \tag{5}$$

where M is the mass of the unstable rock mass, L is the distance from the center of gravity to the pivot point, μ is the bonding coefficient, A and B are the width and length of the bonding surface respectively, and θ is the rotation angle. The corresponding natural frequency expression is:

$$f = \frac{1}{2\pi}\sqrt{\frac{ES^2}{2ML^2A}} \tag{6}$$

where E is the elastic modulus, and S is the bonding area. This equation shows that the natural frequency of a toppling-type unstable rock mass is proportional to the bonding area and inversely proportional to the square root of the mass of the rock mass and the length of the moment arm.

In terms of mode shape analysis, different vibration modes have different sensitivities to the damage of unstable rock masses. The study by Zhang showed that the first two modes of vibration of a falling-type unstable rock mass are the first-order transverse bending vibration in the XZ plane (vertical plane) and XY plane (horizontal plane), respectively. Among them, the natural frequency of the rock mass vibrating in the vertical plane has higher accuracy for evaluating its stability [32]. The natural frequencies of bending vibration of cantilever-type unstable rock masses in the vertical and horizontal planes have different sensitivities to the change of rock bridge length, among which the

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

natural frequency of bending vibration in the vertical plane performs better in stability evaluation [37]. Through experiments, Liu et al. found that after eliminating the calculation error of the relative depth of the critical crack, the average relative error between the calculated constraint stability coefficient of the unstable rock mass based on the natural frequency of bending vibration in the vertical plane and the measured value was only 2.97%, which proved the important influence of mode shape selection on the evaluation accuracy [38].

2.2.2. Stress Wave Propagation Theory and Elastic Wave Impedance Inversion

The propagation characteristics of stress waves in rock masses are closely related to the state of internal structural planes, which constitutes the theoretical basis of elastic wave impedance inversion. When elastic waves propagate in a rock mass with structural planes, the propagation velocity, amplitude and spectral characteristics of the waves will change due to the existence of structural planes. The increase of rock mass damage degree (e.g., crack propagation, porosity increase) will lead to the decrease of elastic wave velocity and wave impedance [39].

Coda Wave Interferometry is a method for monitoring tiny changes in media using the high sensitivity of multiple scattered coda waves [40]. Studies have shown that the monitoring of relative velocity changes based on coda wave interferometry can detect changes caused by tiny damage inside the rock mass, which has broad application prospects in the stability monitoring of rock slopes [41,42]. The theoretical basis of this technology is the cumulative amplification effect of the phase change of multiple scattered waves on the velocity disturbance of the medium. Even if an extremely small change occurs in a local area of the medium, the accumulated phase difference after multiple scattering will increase significantly, thus greatly improving the monitoring sensitivity.

Microseismic and acoustic emission (AE) monitoring technologies are based on the elastic wave signals released during rock fracture. The development process of internal cracks in the rock mass can be inferred by analyzing the temporal and spatial distribution of microseismic events, energy release characteristics and spectral evolution law [43]. Studies have shown that the main frequency of microseismic events before rock mass collapse presents a trend of migration to low frequency, and the b-value decreases significantly before imminent collapse, which can be used as an effective precursor criterion for instability [44]. In acoustic emission monitoring, the evolution of the AF/RA value can distinguish tensile fracture and shear fracture. The proportion of shear fracture increases significantly near failure, and a sudden increase occurs within 1 second before failure [45].

2.2.3. Damage-Fracture Coupled Dynamics and Constitutive Model

The instability and failure of unstable rock masses is a dynamic process coupled with damage accumulation and fracture propagation. From the perspective of energy, rockfall is sudden and belongs to a dynamic process of rapid energy release. For compression-shear type unstable rocks, Chen et al. established the constitutive equation of tangential resistance and shear displacement of the locked section of the main controlling structural plane, found that the pre-sliding accumulated energy of the system will be released and converted into the kinetic energy of rockfall at the moment of dynamic instability of the unstable rock, and derived the calculation formula of the energy consumption required for fracture propagation of the locked section of the main controlling structural plane [28]. This work revealed the dynamic instability mechanism of rockfall from the perspective of energy.

In terms of damage constitutive modeling, considering the statistical distribution characteristics of internal micro-defects (micro-cracks, pores, etc.) in the rock mass, statistical damage theory can be used to establish a constitutive model reflecting the whole process of rock deformation [46]. By abstracting rock as a composite of voids and aggregates, the damage constitutive model established by introducing statistical damage theory can well simulate the five stages of the whole process of rock deformation and failure under load. Considering the action of repeated dynamic loads such as blasting, the cumulative damage evolution model of rock mass can be constructed by inverse

 doi:10.20944/preprints202604.2164.v1

transformation of the Logistic function to reflect the damage accumulation law under the combined action of static load and cyclic impact load [47].

For unstable rock masses with a main controlling structural plane, a damage-fracture coupling model based on fracture mechanics can be adopted. This model regards the damage zone at the tip of the structural plane as the degradation area of material stiffness and strength, and defines the damage variable D to characterize the damage degree. The relationship between the effective elastic modulus E' and the original elastic modulus E is $E' = E(1-D)$ [48]. With the increase of the damage variable, the equivalent stiffness of the unstable rock mass decreases, which in turn leads to the decrease of natural frequency. By monitoring the change of natural frequency, the current value of the damage variable can be inversely calculated, and the dynamic identification of the damage state of the structural plane can be realized.

2.3. Key Dynamic Parameter System and Characterization Method

The dynamic parameter system is the core support for the dynamic evaluation of unstable rock masses. According to the type and source of parameters, the key dynamic parameters can be divided into five categories: modal parameters, time-domain parameters, wave parameters, energy parameters, and environmental sensitivity factors.

2.3.1. Modal Parameters

Modal parameters are the most basic parameters describing the natural vibration characteristics of a structure, including natural frequency, damping ratio and mode shape. Among them, natural frequency has become the core index parameter in the dynamic evaluation of unstable rock masses due to its advantages of easy measurement, high test accuracy, and independence from the measurement position.

Natural frequency: The first-order natural frequency of an unstable rock mass is the most easily excited and observed mode. The study by Zhang showed that the effective mass of the first-order mode of the unstable rock mass accounts for more than 60% of the total mass, and monitoring the first-order natural frequency can effectively reflect the damage degree of the structural plane of the unstable rock mass [32]. For falling-type unstable rock masses, there is a quantitative relationship between the relative depth of the trailing edge crack λ and the first-order natural frequency f: the natural frequency decreases monotonically with the increase of the trailing edge crack depth, showing a one-to-one correspondence between the two. Based on the natural frequency measured under ambient vibration conditions, a correlation model between the factor of safety and the first-order natural frequency can be established [38]:

$$SF = F_{\lambda}(f) \tag{7}$$

where SF is the factor of safety of the unstable rock mass, f is the measured first-order natural frequency, and F_{λ} is the prior fitting function.

For sliding-type and falling-type unstable rock blocks, assuming that the rock block is homogeneous and isotropic, the main controlling structural plane is a single plane, the system damping ratio is less than 1, and the deformation within the amplitude range is linear elastic deformation, the vibration model of the unstable rock block can be simplified as a spring-mass model, and its natural vibration frequency expression is [25]:

$$f = \frac{1}{2\pi}\sqrt{\frac{ES}{MH}} \tag{8}$$

where E is the elastic modulus, S is the bonding area, M is the mass of the unstable rock block, and H is the thickness of the bonding surface. This equation shows that the square of the natural frequency is proportional to the bonding area and inversely proportional to the mass of the unstable rock mass.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

Damping ratio: The damping ratio reflects the energy dissipation characteristics of the vibration system. The damping of unstable rock masses mainly comes from three parts: structural plane friction, material internal friction, and radiation damping. Studies have shown that as the contact stability between the unstable rock mass and the bedrock deteriorates (i.e., the degree of separation increases), the damping ratio of the unstable rock mass shows a decreasing trend, while the RMS acceleration amplitude ratio between the unstable rock mass and the bedrock increases [49]. The change of damping ratio can be used as an auxiliary index to evaluate the damage of structural planes. The relationship between the damped natural frequency f_d and the undamped natural frequency f of a weakly damped system is:

$$f_{\mathrm{d}} = f\sqrt{1-\xi^2} \tag{9}$$

where ξ is the damping ratio. When $\xi \ll 1$, the influence of damping on the natural frequency can be neglected, and the measured damped frequency is usually directly used to approximate the undamped frequency in practical engineering applications.

Mode shape: Different vibration modes have different sensitivities to structural plane damage. Studies have shown that the natural frequency of bending vibration of unstable rock masses in the vertical plane is more sensitive to the change of the depth of the trailing edge crack, and the stability evaluation of the unstable rock mass with the natural frequency in this direction can achieve higher accuracy [27]. Under ambient vibration conditions, the first-order natural frequency of the unstable rock mass is most susceptible to resonance under external excitation, so the first-order natural frequency is usually used as the main reference index in actual monitoring [50].

2.3.2. Time-Domain Parameters

Time-domain dynamic parameters are directly extracted from the vibration acceleration time history curve, which can reflect the statistical characteristics and instantaneous characteristics of the vibration signal. Through laboratory experiments, Jia et al. systematically analyzed the relationship between six time-domain indexes (coefficient of variation, skewness, kurtosis, crest factor, impulse factor, and waveform factor) of the rock block model and the depth of the trailing edge crack [49]. The results showed that the measured values of coefficient of variation, skewness, kurtosis and crest factor vary greatly under different excitations, and are significantly affected by environmental noise and excitation force characteristics, which do not have good measurability. In contrast, the measured values of impulse factor and waveform factor are similar under different excitations, showing certain measurability, among which the waveform factor has a relatively good correlation with the crack depth.

The main advantages of time-domain parameters are simple calculation and strong real-time performance, but their limitation is that they are highly dependent on the excitation characteristics, and it is difficult to maintain consistent sensitivity under different working conditions. Therefore, in engineering practice, time-domain parameters are usually used as auxiliary discrimination indexes, combined with frequency-domain parameters for comprehensive analysis.

Among the time-domain parameters, particle trajectory is an important visual index. Studies have shown that there is a significant difference in particle trajectory between unstable rock blocks and stable rock masses, and the activity range of particle trajectory of stable rock masses is much smaller than that of unstable rock masses [51]. Under the same excitation condition, the maximum particle trajectory of the experimental block decreases exponentially with the increase of the bonding area, so the change of the bonding area of the slope unstable rock mass can be qualitatively analyzed through the change of the maximum particle trajectory [52].

2.3.3. Wave Parameters

Wave parameters are used to invert the internal structure state by analyzing the propagation characteristics of elastic waves in unstable rock masses. The main parameters include wave velocity, amplitude attenuation coefficient, filtering function, and velocity change rate from coda wave interferometry.

Wave velocity attenuation: When elastic waves pass through an unstable rock mass with cracks, the existence of cracks will lead to the decrease of wave velocity and amplitude attenuation. The change of wave velocity is related to crack density, crack aperture and the properties of filling materials. Studies have shown that with the increase of the damage degree of the structural plane, the wave velocity shows a downward trend, and the wave velocity change rate can reach 10% to 30% [53].

Filtering effect: The structural plane has an obvious filtering effect on the propagation of elastic waves. High-frequency components attenuate rapidly, while low-frequency components have strong penetration ability. Therefore, the relative energy proportion of high-frequency components in the vibration spectrum of the unstable rock mass can reflect the damage degree of the structural plane. The more serious the damage is, the more obvious the attenuation of high-frequency energy is, and the spectrum shifts to low frequency [54].

Coda wave interferometry: This technology uses the high sensitivity of multiple scattered coda waves to monitor tiny changes in rock masses. The sensitivity of coda waves to the change of medium velocity is much higher than that of direct waves; under the same medium change condition, the relative travel time change of coda waves can be several times or even dozens of times that of direct waves [55]. This technology has important application potential in early damage identification and long-term evolution monitoring of unstable rock masses.

2.3.4. Energy Parameters

Energy parameters extract information reflecting the structural state of unstable rock masses from the perspective of energy distribution and dissipation characteristics of vibration signals. Hilbert-Huang Transform (HHT) is an adaptive time-frequency analysis method suitable for non-stationary and nonlinear signals. The signal is decomposed into several intrinsic mode functions through empirical mode decomposition, and then the instantaneous frequency and instantaneous energy are obtained through Hilbert transform.

The Hilbert marginal spectrum represents the distribution of signal energy on the frequency axis, and its calculation formula is:

$$E(f) = \int_0^T H^2(f,t)\,dt \tag{10}$$

where $H(f,t)$ is the Hilbert spectrum of the signal. The distribution characteristics of marginal spectrum energy are different under different damage states of unstable rock masses: with the aggravation of damage, the marginal spectrum energy is concentrated in the low-frequency region, and the proportion of high-frequency energy decreases.

The information entropy of the Hilbert marginal spectrum can reflect the concentration degree of signal energy distribution, which is defined as:

$$H_E = -\sum_{i=1}^{N} p_i \log p_i, \quad p_i = \frac{E(f_i)}{\sum_{j=1}^{N} E(f_j)} \tag{11}$$

When the structure of the unstable rock mass is complete and the stiffness is high, the marginal entropy is small (energy is concentrated); when the structural plane is damaged and the stiffness is reduced, the marginal entropy increases (energy is dispersed). The change of marginal entropy can be used as a quantitative index to evaluate the damage degree of unstable rock masses [58].

The energy dissipation during the vibration of unstable rock masses mainly comes from structural plane friction and material internal friction. In the weak stability stage, friction force plays a dominant role in the anti-sliding force, and the damping dissipated energy of the system can be calculated by analyzing the attenuation characteristics of the vibration signal. The change trend of

 doi:10.20944/preprints202604.2164.v1

dissipated energy can reflect the change of friction state of the structural plane. When the friction force is close to the maximum static friction force, the dissipated energy increases significantly, which can be used as an early warning criterion before failure [53].

2.3.5. Environmental Sensitivity Factors

Unstable rock masses occur in a complex natural environment, and environmental factors such as temperature change, rainfall seepage and stress state have a significant impact on dynamic parameters. Therefore, when using dynamic parameters for stability evaluation, the effect of environmental sensitivity factors must be considered, and the corresponding time-varying correction model must be established.

Temperature effect: MEMS tilt sensors are susceptible to ambient temperature during application, resulting in temperature drift of monitoring data. Through high and low temperature tests, He et al. found that the tilt angle and the sensor temperature present an overall "piecewise linear relationship", the temperature drift is about ±0.2° in the range of 5 °C to 45 °C, and the tilt angle will produce a larger drift with the rise and fall of temperature [59]. After temperature correction of the tilt angle using the "piecewise linear compensation" method, the temperature drift is greatly reduced to ±0.02°. Other studies have shown that the natural frequency is also affected by temperature changes: the increase of temperature leads to the decrease of the stiffness of the structural plane and the reduction of the natural frequency [60]. In long-term monitoring, the reversible changes caused by temperature must be eliminated to accurately identify the irreversible stability degradation of unstable rock masses.

Rainfall-seepage effect: Rainfall infiltration leads to the increase of water content in the structural plane. On the one hand, it reduces the effective bonding force of the structural plane; on the other hand, it increases the pore water pressure and thus the sliding force. Experiments have shown that after rainfall, the natural frequency of the unstable rock mass decreases significantly, the damping ratio increases, and the activity range of the particle trajectory expands, which qualitatively reflects a certain degree of damage to the structural plane [25].

Stress state change: The change of stress state caused by reservoir water level fluctuation, excavation unloading and other factors will also affect the dynamic parameters of unstable rock masses. With the decrease of effective stress, the normal stiffness of the structural plane decreases, and the natural frequency drops [63]. Establishing a time-varying law model of dynamic parameters considering multi-factor coupling is one of the key scientific issues to realize the accurate evaluation of the stability of unstable rock masses.

3. Theoretical Dynamic Evaluation Models and Analysis Methods for Typical Unstable Rock Masses

3.1. Dynamic Models for Single-Block Single-Degree-of-Freedom Systems

According to the previous investigation, unstable rock masses can be classified into three basic types based on their failure modes and mechanical characteristics: sliding-type, toppling-type, and falling-type. A single rock block can be simplified as a single-degree-of-freedom (SDOF) vibration system, and corresponding theoretical dynamic evaluation models can be established.

3.1.1. Sliding-Type Unstable Rock Mass

A sliding-type unstable rock mass has a dominant structural plane parallel to the slope strike, with a free face in the shear-out direction of the structural plane, and generally fails by sliding along the dominant structural plane. In terms of vibration characteristics, a sliding-type unstable rock mass can be regarded as a spring-mass-damper vibration system: the rock block is treated as a mass point, the structural plane is idealized as a parallel spring-damper element, and the base transmits dynamic loads to the rock block through the structural plane, causing the block to vibrate along the structural

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

plane. The mechanical characteristics and simplified dynamic model of this type of unstable rock mass are shown in Figure 2.

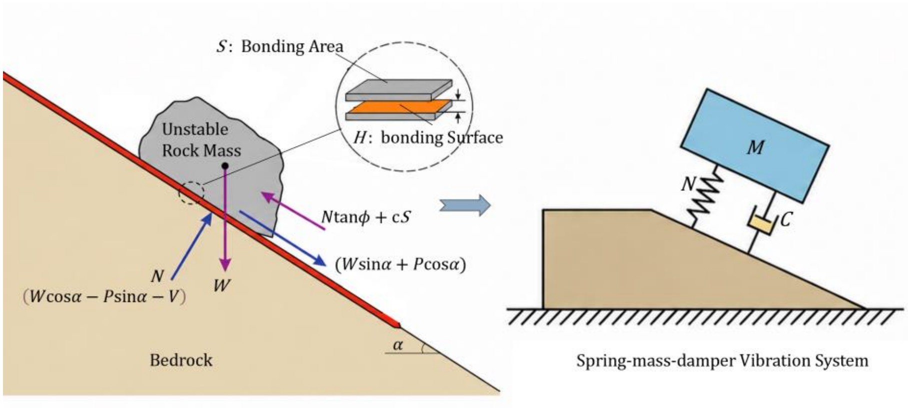

Figure 2. Simplified Dynamic Model of Sliding-Type Unstable Rock Mass.

Based on the principles of structural dynamics, when the effect of damping is neglected, the natural frequency of the spring-mass vibration system is expressed as [49]:

$$f = \frac{1}{2\pi}\sqrt{\frac{K}{M}} \tag{12}$$

where K is the equivalent stiffness and M is the mass of the rock block. Substituting the stiffness expression $K = ES/H$ (where S is the bonding area, H is the thickness of the bonding surface, and E is the elastic modulus) yields:

$$f = \frac{1}{2\pi}\sqrt{\frac{ES}{MH}} \tag{13}$$

For damped systems, the damped natural frequency is:

$$f_{\mathrm{d}} = \frac{\sqrt{1-\xi^2}}{2\pi}\sqrt{\frac{ES}{MH}} \tag{14}$$

It can be seen that when the mass, bonding surface thickness, and elastic modulus are fixed, the bonding area S is proportional to the square of the natural frequency:

$$S = \frac{4\pi^2 f_{\mathrm{d}}^2 MH}{E(1-\xi^2)} \tag{15}$$

Combined with limit equilibrium theory, the factor of safety (FOS) of a sliding-type rock mass is expressed as [64]:

$$K_{\mathrm{s}} = \frac{(W\cos\alpha - P\sin\alpha - V)\tan\phi + cS}{W\sin\alpha + P\cos\alpha} \tag{16}$$

where W is the weight of the rock mass, P is the seismic force, V is the fissure water pressure, α is the dip angle of the sliding surface, c is the cohesion, and ϕ is the internal friction angle. Substituting the bonding area S establishes a quantitative model between natural frequency and FOS:

$$K_{\mathrm{s}} = \frac{(W\cos\alpha - P\sin\alpha - V)\tan\phi}{W\sin\alpha + P\cos\alpha} + \frac{4c\pi^2 f_{\mathrm{d}}^2 MH}{E(W\sin\alpha + P\cos\alpha)} \tag{17}$$

This model reveals that the FOS of a sliding-type rock mass is linearly positively correlated with the square of the natural frequency. As the structural plane is damaged and the bonding area decreases, the natural frequency drops and the FOS decreases accordingly. Based on this relationship, real-time monitoring of natural frequency enables dynamic stability evaluation of unstable rock masses.

3.1.2. Toppling-Type Unstable Rock Mass

A toppling-type unstable rock mass has a steep dominant structural plane at the trailing edge. A depression formed by differential weathering exists at the bottom, whose edge acts as the pivot. Under internal and external loads, an outward overturning moment and an inward resisting moment are generated. When the overturning moment exceeds the resisting moment, toppling failure occurs. The structural characteristics of this type of unstable rock mass are shown in Figure 3(a).

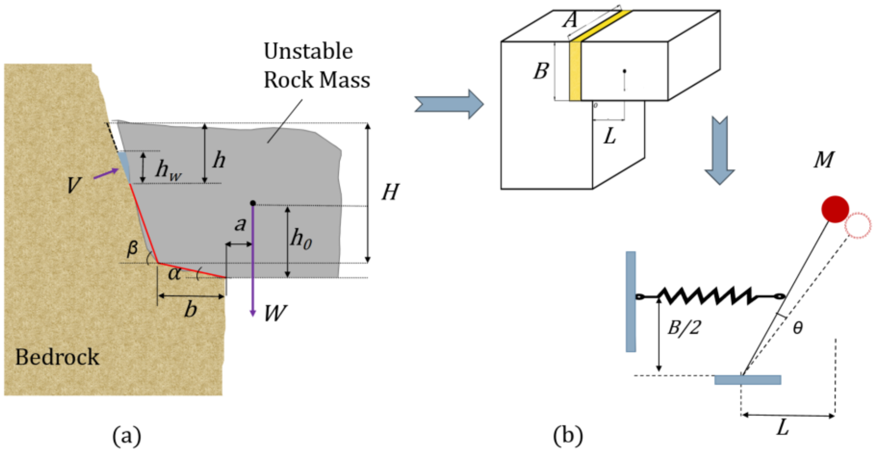

Figure 3. Structural Characteristics and Simplified Dynamic Model of Toppling-Type Unstable Rock Mass.

In terms of vibration, a toppling-type rock mass can be simplified as a pendulum model rotating around the pivot（图 3（b））. Its differential equation of motion is [53]:

$$ML^2\ddot{\theta} + \frac{\mu AB^2}{2}\theta = 0 \tag{18}$$

The corresponding natural frequency is:

$$f = \frac{1}{2\pi}\sqrt{\frac{ES^2}{2ML^2A}} \tag{19}$$

With damping, the damped natural frequency becomes:

$$f_{\mathrm{d}} = \frac{\sqrt{1-\xi^2}}{2\pi}\sqrt{\frac{ES^2}{2ML^2A}} \tag{20}$$

It shows that the bonding area S is linearly proportional to the natural frequency:

$$S = f_{\mathrm{d}}\frac{2\pi}{\sqrt{1-\xi^2}}\sqrt{\frac{2ML^2A}{E}} \tag{21}$$

The FOS of a toppling-type rock mass is the ratio of the anti-toppling moment to the overturning moment. For a center of gravity outside the pivot [64]:

$$K_{\mathrm{t}} = \frac{f_{\mathrm{tk}} \dfrac{S(H-h)}{\sin\beta}}{Wa + Ph_0 + V\left(\dfrac{h_{\mathrm{w}}}{3\sin\beta} + \dfrac{H-h}{\sin\beta}\right)} \tag{22}$$

Substituting the bonding area S gives the quantitative relation between FOS and natural frequency:

$$K_{\mathrm{t}} = \frac{2\pi f_{\mathrm{d}} f_{\mathrm{tk}}(H-h)}{\sqrt{1-\xi^2}\sin\beta} \sqrt{\frac{2ML^2A}{E}} \cdot \frac{1}{Wa + Ph_0 + V\left(\dfrac{h_{\mathrm{w}}}{3\sin\beta} + \dfrac{H-h}{\sin\beta}\right)} \tag{23}$$

Studies show that the FOS of a toppling-type rock mass is proportional to the **4/3 power** of the natural frequency [53]. This theoretical derivation confirms that simplifying a toppling rock mass as a spring-pendulum model allows derivation of a quantitative link between natural frequency and limit-equilibrium FOS, providing a theoretical basis for MEMS-based toppling rockfall monitoring.

3.1.3. Falling-Type Unstable Rock Mass

A falling-type unstable rock mass usually has a steep dominant structural plane along the slope strike, with a free face below that leaves the block overhanging. Under external loads, it fails by falling along the structural plane. Vibration-wise, it can also be simplified as a spring-mass system. According to failure patterns, falling-type rock masses are further divided into tensile failure and shear failure (Figure 4). Tensile failure blocks are wider than they are tall, failing in tension; shear failure blocks are taller than they are wide, failing in shear. Among the above two failure modes, the mechanical mode of shear failure-type unstable rock masses is relatively simple. A quantitative relationship model between the bonding area of the trailing edge and the natural frequency can be established using the single-degree-of-freedom (SDOF) spring-mass model. Furthermore, by calculating the ratio of the shear resistance of the constrained section to the gravity, a correlation model between the natural frequency and the factor of safety (FOS) is finally established.

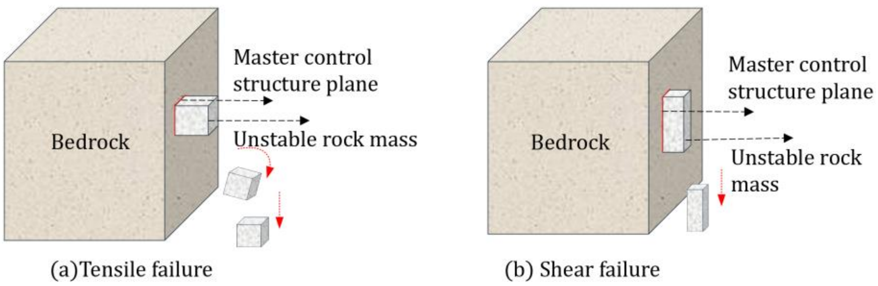

Figure 4. Two Failure Modes of Falling-Type Unstable Rock Masses.

For falling-type unstable rock masses with tensile failure mode, they can be idealized as a cantilever beam model (Figure 5). Based on the modified Timoshenko beam theory, the dynamic equation of the rock beam can be established [32]:

$$EI\frac{\partial^4 y}{\partial x^4} + \rho S\frac{\partial^2 y}{\partial x^2} - \rho I\frac{\partial^4 y}{\partial x^2\,\partial t^2} + \frac{\rho SEI}{SG\mu}\frac{\partial^4 y}{\partial x^2\,\partial t^2} = 0 \tag{24}$$

 doi:10.20944/preprints202604.2164.v1

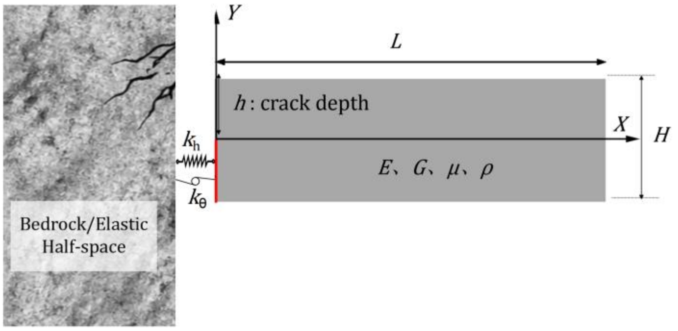

Figure 5. Timoshenko Beam and Elastic Half-space Foundation Model.

Combined with dynamic half-space theory and the equivalent continuous stiffness model of cracks, the constrained boundary conditions and analytical solution of the first-order natural frequency can be derived. The first-order natural frequency decreases monotonically with the relative crack depth λ, with an average relative error of only 1.93% and a minimum of 0.44% between theoretical and simulated values [27].

The FOS of a falling-type rock mass is taken as the smaller value between tensile and shear failure modes. The constrained FOS based on natural frequency is defined as [38]:

$$SF_{\omega} = \frac{\omega - \omega_c}{\omega_0 - \omega_c} \tag{25}$$

where ω is the measured natural frequency, ω_0 is the initial natural frequency (crack depth = 0), and ω_c is the critical natural frequency (at failure). This formula evaluates stability by comparing the current constraint margin with the maximum: intact rock mass $SF\omega = 1$, failed rock mass $SF\omega = 0$.

Through failure tests of scaled rock models with different sizes, Liu et al. found that using the natural frequency of vertical bending vibration as the stability index yields an average error of 3.85% for natural frequency and only 2.97% for constrained FOS, fully validating the model [26,38].

3.2. Chain Collapse Dynamic Models for Multi-Block Multi-Degree-of-Freedom Systems

In practice, unstable rock masses usually exist not as isolated blocks but as clusters. Failure of any single block triggers vibration excitation, degrades the stability of adjacent blocks, and may cause chain collapse of the whole cluster (Figure 6). Therefore, establishing chain-collapse dynamic models for multi-block MDOF systems is of great engineering significance.

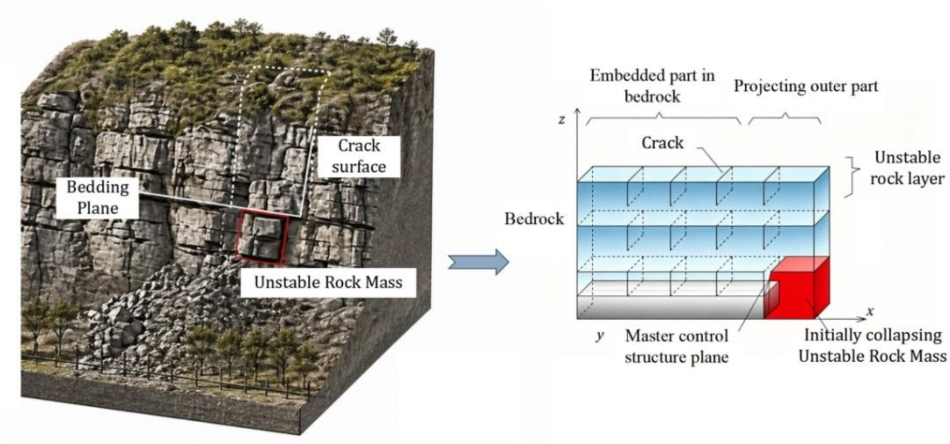

Figure 6. Schematic Diagram of Chain Collapse Model for Unstable Rock Clusters.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

Chen et al. focused on the chain-collapse behavior of rock clusters triggered by vibration. They idealized the unpenetrated part of vertical fissures as a prismatic body and derived a dynamic vibration model for rock clusters under excitation waves from rock failure using wave theory [65]. The characteristic method was used to obtain the vibration, displacement, stress, and velocity equations of the rock cluster. The particle vibration equation is:

$$u(x,t) = \sum_{n=1}^{\infty} (-1)^n \frac{2\epsilon}{\beta_n^2} \cos C_0 \beta_n t \cdot \sin \beta_n x + \epsilon x \tag{26}$$

where $C_0^2 = E/\rho$ is the elastic longitudinal wave velocity, $\epsilon = F(t)/EA$ is the strain at the free end of the prism, and $\beta n = (2n-1)\pi/(2l)$. The corresponding stress equation is:

$$\sigma(x,t) = E \sum_{n=1}^{\infty} (-1)^n \frac{2\epsilon}{\beta_n^2} \cos C_0 \beta_n t \cdot \cos \beta_n x + E\epsilon \tag{27}$$

The vibration velocity equation is:

$$v_i(x,t) = -\sum_{n=1}^{\infty} (-1)^n \frac{2\epsilon C_0}{\beta_n} \sin C_0 \beta_n t \cdot \sin \beta_n x \tag{28}$$

Laboratory model tests verified that the error between theoretical solutions and test data is only 6.12%, proving the reliability of the excitation model [65].

For the triggering mechanism of chain collapse, Chen et al. analyzed the energy release process using catastrophe theory. When the elastic strain energy of the dominant structural plane reaches a critical value, the system undergoes catastrophic instability. The released energy propagates to adjacent blocks as vibration waves, inducing vibration and possibly degrading stability [28]. The excitation signal from rock failure shows obvious frequency-domain characteristics: local information is periodic, and the spectrum is mainly concentrated in the low-frequency band [66].

For dynamic modeling of multi-block systems, the discrete element method (DEM) can simulate the progressive failure of rock clusters under excitation. With the propagation of excitation waves, cracks initiate from the tip of the dominant fissure and propagate approximately horizontally to the boundary, causing instability. The angle between secondary and main fissures significantly affects the failure mode: small angles ($\alpha \leq 60°$) lead to sliding failure, while large angles ($\alpha > 60°$) lead to toppling failure [67].

3.3. Data-Physics Dual-Driven Dynamic Surrogate Models and Intelligent Evaluation

With the rapid development of artificial intelligence, data-physics dual-driven surrogate models show great potential in dynamic evaluation of unstable rock masses. Such models deeply integrate physical mechanisms and data-driven methods, retaining interpretability while enabling strong nonlinear mapping. They overcome the low accuracy of pure physical models under complex conditions and the poor generalization of pure data-driven models. By integrating rock mass monitoring data, physical parameters, historical working conditions and other information, incorporating the data-physics dual-driven surrogate model, and combining the multi-modal adaptive fusion algorithm, the intelligent evaluation of stability state and collapse prediction of unstable rock masses can be finally realized. Figure 7 shows the technical flow architecture diagram of this method.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

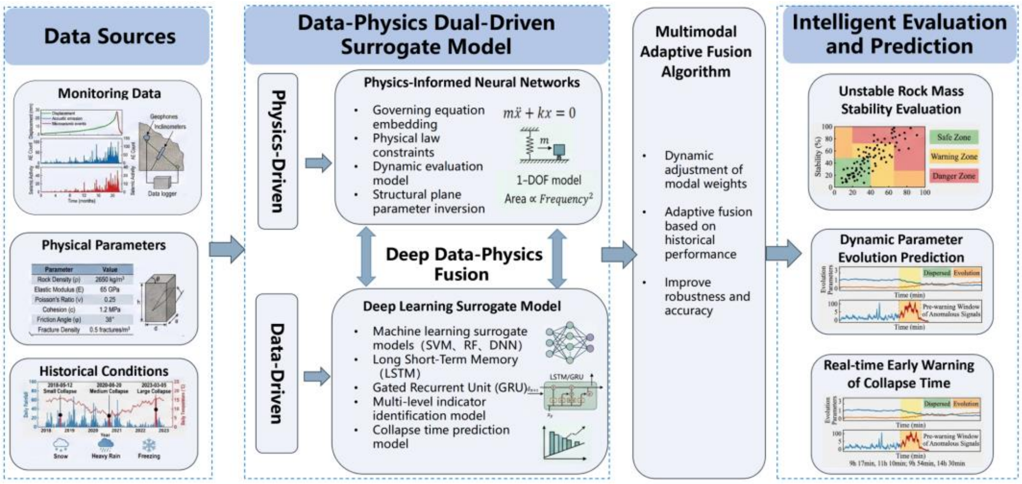

Figure 7. Data-physics dual-driven Dynamic Surrogate Model and Intelligent Evaluation.

Machine learning surrogate models: Typical methods including support vector machine (SVM), random forest (RF), and deep neural network (DNN) have been widely used in stability evaluation and dynamic parameter prediction of unstable rock masses[68,69]. Huo et al. used the PSO-SVM algorithm to establish a multi-level dynamic index-based rock mass identification model, integrating six time-domain, frequency-domain, and energy indicators [70]. The model achieved the best prediction performance, with MSE = 0.004772 and R2 = 0.984865. The sensitivity ranking of dynamic indicators was: mean square frequency > margin index > first band relative energy > centroid frequency > impact energy > pulse index.

Physics-informed neural networks (PINNs): PINNs embed governing differential equations (e.g., dynamic equations, wave equations) as constraints into the neural network loss function, making the model fit observations while satisfying physical laws[71,72]. For rock mass dynamic evaluation, SDOF vibration equations or Timoshenko beam equations can be used as physical constraints. The network is trained using measured natural frequency, damping ratio, etc., to intelligently invert structural plane parameters. PINNs offer three distinct advantages: (1) They impose less stringent requirements on the volume and quality of training data; (2) Their predictions are physically consistent with fundamental governing laws, thus exhibiting superior interpretability; (3) They are capable of extrapolating to unseen working conditions outside the scope of the training dataset..

Deep learning time-series prediction models: Time-series models such as long short-term memory (LSTM) and gated recurrent unit (GRU) perform excellently in predicting the evolution of dynamic parameters of unstable rock masses[73,74]. He et al. established a collapse time prediction model called the inverse tilt rate method based on MEMS tilt sensing features. By revealing the exponential relationship between cumulative tilt deformation and tilt rate during the accelerated stage before collapse, real-time prediction of collapse time was achieved. In two field cases, the model predicted collapse 9 h 17 min and 11 h 10 min in advance, at 9 h 54 min and 14 h 30 min before failure, providing sufficient early warning for emergency evacuation.

Multi-model adaptive fusion: To address the varying applicability of single models under different conditions, an adaptive multi-model fusion algorithm dynamically adjusts weights based on real-time monitoring and historical predictions[75–77]. For example, weighted fusion of predictions from limit equilibrium, dynamic theoretical, and machine learning models—with weights adaptively adjusted according to historical performance—significantly improves the robustness and accuracy of evaluation.

3.4. Applicability and Limitations of Existing Theoretical Models

 doi:10.20944/preprints202604.2164.v1

A comprehensive comparative review of the aforementioned dynamic theoretical evaluation models is presented from the dimensions of applicable conditions, accuracy, computational efficiency, and engineering practicality.

(1) Single-Degree-of-Freedom (SDOF) Spring-Mass Model

The SDOF spring-mass model is the most fundamental model for dynamic evaluation of unstable rock masses, applicable to sliding-type and falling-type rock masses. Its advantages include concise theoretical derivation, clear physical meaning of parameters, and ease of engineering application. Jia et al. established a quantitative relationship between natural frequency and bonding area based on this model, and verified its feasibility through field application at Baihebao Reservoir [49]. However, this model simplifies the unstable rock mass as a particle, neglecting its inherent elastic deformation and rotational inertia, leading to non-negligible calculation errors for stocky rock masses with small slenderness ratios. In addition, the model assumes a single dominant structural plane, thus exhibiting poor applicability to complex rock masses cut by multiple structural planes.

(2) Pendulum Vibration Model

The pendulum vibration model applies to toppling-type unstable rock masses and well characterizes their rotational dynamic characteristics around the pivot. Chen et al. derived the 4/3-power proportional relationship between natural frequency and factor of safety based on this model, and verified it through MEMS sensing experiments [53]. The advantage of this model lies in its full consideration of the geometric features of the rock mass (center of gravity position, moment arm length, etc.), enabling a more accurate description of the toppling failure mechanism. Its limitations are as follows: the model assumes a fixed pivot position, but in practice, the pivot may shift as the rock cavity weathers and expands; moreover, the friction and collision effects between the unstable rock mass and the trailing edge rock mass are not considered.

(3) Modified Timoshenko Beam Model

The modified Timoshenko beam model is mainly suitable for falling-type unstable rock masses, especially cantilever-type rock masses with large slenderness ratios. This model considers both shear deformation and bending rotational inertia, overcoming the limitation of Euler-Bernoulli beam theory which is only applicable to slender beams. Zhang et al. derived analytical solutions for the first-order natural frequency of tensile failure and shear failure type unstable rock masses based on this model, with average relative errors of 1.93% and 2.95% between theoretical calculations and numerical simulations, respectively [27,32]. The advantages of this model include high calculation accuracy, consideration of the cross-sectional size effect of the rock mass, and applicability to rock masses with various slenderness ratios. Its limitation lies in the relatively complex derivation, which requires numerical iteration for solution, posing certain inconvenience for rapid on-site engineering application.

(4) Multi-Block MDOF Chain Excitation Model

The multi-block excitation model is suitable for chain collapse analysis of unstable rock clusters, and can characterize the propagation effect of excitation waves among multiple rock blocks. Based on wave theory, this model has a clear physical mechanism. Its limitations are twofold: first, it strongly depends on the characteristics of the excitation source (e.g., excitation force magnitude, duration), which are difficult to measure accurately in practical engineering; second, the high computational complexity limits its application to theoretical research and laboratory test verification at present, and further simplification and development are required for large-scale engineering deployment.

(5) Applicability and Limitations of Data-Physics Dual-Driven Models

Data-physics dual-driven models represent the future development direction of dynamic evaluation for unstable rock masses, combining physical interpretability and data-driven flexibility. Their advantages include high-precision state estimation and trend prediction with limited monitoring data, as well as strong adaptability to complex working conditions and uncertain factors. Their limitations are as follows: model training requires high-quality monitoring data, while the accumulation of unstable rock mass failure cases is still insufficient; the generalization ability and

 doi:10.20944/preprints202604.2164.v1

robustness of the models need to be verified by more engineering cases; and the high demand for computational resources poses certain challenges to real-time on-site application.

4. Dynamic Response Monitoring Technology and Early Warning System Integration

4.1. Dynamic Response Monitoring and Sensing Technologies for Unstable Rock Masses

Dynamic monitoring technology is the hardware foundation for the dynamic evaluation of unstable rock masses. According to the contact mode between the sensor and the rock mass, it can be divided into two categories: contact monitoring and non-contact monitoring.

4.1.1. Contact Monitoring: Micro-Electro-Mechanical System (MEMS) and High-Sensitivity Vibration Sensing Equipment

Contact monitoring involves installing sensors directly on the surface of an unstable rock mass to obtain dynamic parameters by sensing physical quantities such as vibration acceleration, velocity, and displacement of the rock mass. Among them, vibration sensing equipment based on Micro-Electro-Mechanical System (MEMS) technology has been widely used in bridge, building, and unstable rock mass monitoring in recent years due to its advantages of small size, low power consumption, and low cost[53,78–80].

MEMS accelerometers, based on silicon micromachining technology, convert the inertial force generated by the vibration of the unstable rock mass into electrical signals. The core principle is that when the rock mass vibrates, the mass block inside the MEMS sensor undergoes inertial motion, and outputs triaxial acceleration signals by detecting changes in capacitance or piezoresistance. The triaxial acceleration $\bar{a}(t)$ of the MEMS sensor includes two parts: gravitational acceleration $\bar{G}$ and vibration impact acceleration $\bar{F}(t)/m$

$$\bar{a}(t) = \frac{\bar{F}(t) + \bar{G}}{m} \tag{29}$$

Under ambient vibration conditions, the vibration response of an unstable rock mass can be regarded as an underdamped single-degree-of-freedom forced vibration. Based on the synchronously monitored vibration signals of the bedrock and the unstable rock mass by MEMS sensors, the frequency response function $H(f)$ can be calculated, and then modal parameters such as natural frequency and damping ratio of the rock mass can be extracted [53].

Jia et al. developed a real-time online monitoring system for unstable rock blocks based on wireless vibration sensors. Adopting Microcore wireless vibration sensors with a maximum sampling frequency of 800 Hz, the system can transmit monitoring data to the cloud platform in real time via wireless communication [49]. The system was successfully applied to the monitoring of unstable rock blocks on the slopes on both sides of Baihebao Reservoir, realizing real-time calculation of the factor of safety and dynamic assessment of the safety state of the rock blocks.

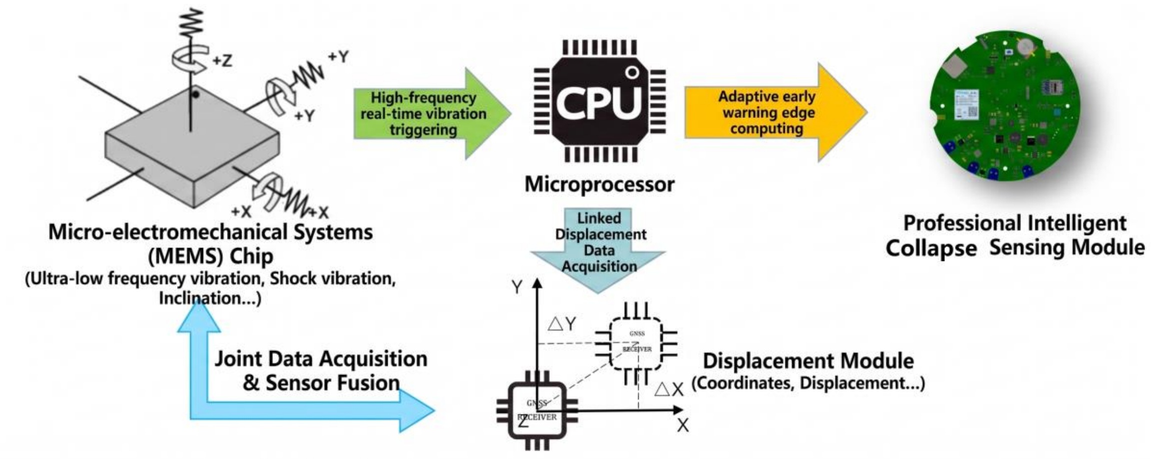

Figure 8. Sensing Mechanism of MEMS-based Geological Hazard Monitoring.

Xie et al. developed the “micro-core pile” geological hazard monitoring sensor based on MEMS technology. It integrates a MEMS acceleration acquisition module, edge computing module, wireless transmission module, and power supply module, realizing the “acquisition-calculation-transmission” mechanism for micro-tilt angle and strong vibration acceleration of unstable rock masses [59]. The sensor has the following characteristics: (1) An acquisition and transmission mode combining active high-frequency acquisition with timing and threshold-triggered wake-up transmission, which not only ensures real-time acquisition of monitoring data but also effectively reduces power consumption; (2) A tilt angle calculation method based on the spatial vector included angle, where the cumulative change of tilt angle directly reflects the deformation degree in the main tilt direction of the rock mass; (3) A built-in multi-threshold judgment mechanism at the edge end, enabling local second-level early warning and long-term trend analysis on the cloud; (4) A solar self-powered design to ensure long-term stable operation of the sensor in harsh field environments.Through field measurements at tensile-type unstable rock collapse sites in Shiyan, Hubei Province, the micro-core pile sensors successfully captured the micro-tilt deformation trend before rock collapse. In the two cases, the cumulative tilt angle changes of the rock masses were only 2.318° and 1.957°, with the maximum tilt angle change rates of 0.198°/h and 0.093°/h, respectively, and the sensors successfully issued early warning signals before the collapse [59].

4.1.2. Non-Contact Monitoring: Laser Doppler Vibrometry Technology

A Laser Doppler Vibrometer (LDV) is a non-contact vibration measurement device based on the principle of optical interference. It can remotely measure the vibration velocity of the surface of an unstable rock mass, with the advantages of high accuracy, high spatial resolution, and no need for sensor installation. It is especially suitable for monitoring unstable rock masses on high and steep slopes that are inaccessible to personnel [81,82].

LDV is based on the Doppler effect. When a laser beam irradiates the surface of a moving object, there is a frequency shift Δf_D between the frequency of the reflected light and the incident light, which is proportional to the vibration velocity v of the object [82]:

$$\Delta f_{\mathrm{D}} = \frac{2vf}{c}\cos\theta = \frac{2v}{\lambda}\cos\theta \tag{30}$$

where f is the laser frequency, c is the speed of light, λ is the laser wavelength, and θ is the angle between the laser incident direction and the motion direction of the object. The vibration velocity of the object can be calculated by detecting the frequency shift.

Uehan et al. developed the “U-Doppler” remote non-contact vibration measurement system suitable for field use. The core feature of the system is the built-in compensation sensor, as LDV measures the relative velocity between the equipment and the target, and the measurement accuracy

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

will be affected when the equipment itself is subjected to ground vibration or wind load. In addition to the optical sensor, U-Doppler integrates a contact vibrometer with the same sensitivity and phase characteristics, eliminating the influence of the equipment's own vibration through differential processing of time history data [83]. Furthermore, Uehan et al. developed a three-dimensional remote vibration measurement system, which uses three sets of U-Doppler equipment for synchronous measurement from different angles, and combines principal component analysis to estimate the three-dimensional vibration velocity and main vibration direction of the unstable rock mass [84]. The system can realize synchronous control via wireless local area network, with a measuring distance of more than 100 meters, and its effectiveness has been verified in laboratory three-dimensional shaking table tests and field unstable rock mass measurements.

Ma et al. carried out model experiments on concrete test blocks with different bonding conditions to the base using LDV, and found that there is an approximately linear positive correlation between the bonding length and the predominant frequency, which is affected by the size of the test block and the physical properties of the bonding material [85]. Based on this, a conceptual quantitative evaluation method of "factor of safety-predominant frequency nomogram" was proposed. By remotely measuring the predominant frequency of the unstable rock mass and combining the physical properties of rock samples, the overturning safety rate of the rock mass can be estimated.

Nassif et al. compared the dynamic load test results of LDV and contact sensors, and found that the displacement and velocity measured by LDV are highly consistent with the results of traditional sensors, but LDV does not require sensor installation, which greatly saves measurement time and reduces personnel safety risks [86]. Siringoringo et al. carried out modal analysis using ambient vibration and a dual laser vibrometer system, successfully identified the modal parameters of bridges, and confirmed that damage identification can be characterized by quantified stiffness and damping coefficients [87]. Studies have shown that LDV is equivalent to traditional accelerometers in measurement accuracy, but has significant advantages in operability, safety, and flexibility of measuring point arrangement.

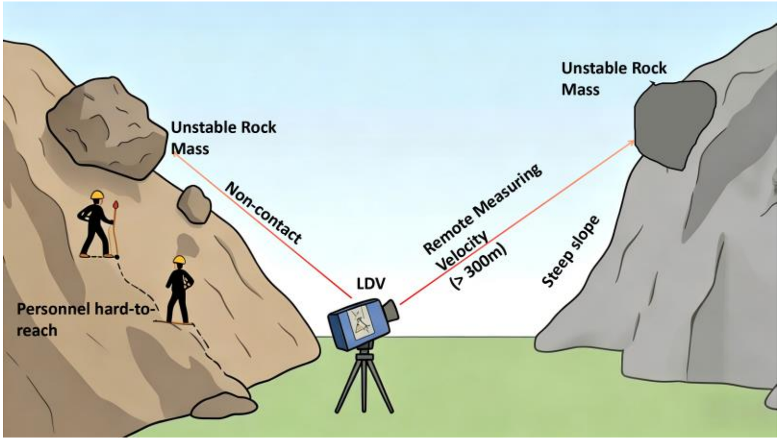

Figure 9. Ultra-long-range Dynamic Detection of High and Steep Slopes Using LDV.

With the advancement of technology, the maximum field measurement distance of the new-generation LDV can exceed 300 meters, with further improvements in measurement velocity, acceleration, and frequency domain coverage. For unstable rock masses on slopes in alpine canyon regions, which are inaccessible to personnel for close-range investigation and contact monitoring, it is more convenient to use ultra-long-range LDV to acquire rock mass dynamic parameters for stability evaluation, which has promising engineering application prospects.

4.2. Cloud-Edge Collaborative Automated Monitoring and Early Warning Architecture

 doi:10.20944/preprints202604.2164.v1

With the integrated development of MEMS sensing technology, Internet of Things (IoT) communication technology, and cloud computing technology, the cloud-edge collaborative automated monitoring and early warning architecture for unstable rock masses has gradually matured, providing technical support for large-scale, wide-area, and real-time dynamic monitoring of unstable rock masses [88]. The architecture consists of an edge computing layer, a cloud platform layer, and a communication layer. This architecture consists of an edge computing layer, a cloud platform layer, and a communication layer. Figure 10 illustrates in detail the structural composition and functional applications of this architecture.

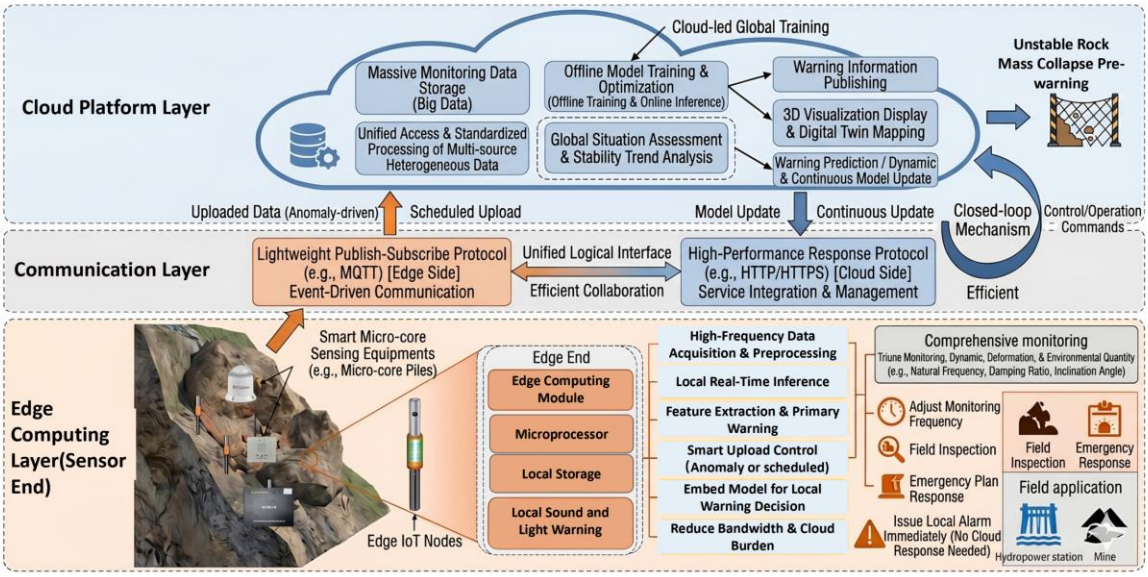

Figure 10. Schematic Diagram of Cloud-Edge Collaborative Autonomous Monitoring and Early Warning Architecture for Unstable Rock Masses.

The edge computing layer embeds edge computing modules in the sensor end or field acquisition terminal to realize local preprocessing, feature extraction, and primary early warning judgment of monitoring data.The main functions of edge computing include: (1) High-frequency data acquisition and real-time filtering and denoising; (2) Threshold early warning based on dynamic parameters (such as natural frequency, damping ratio, tilt angle); (3) Data compression and intelligent upload control, which only sends data to the cloud when abnormal changes are detected or the scheduled upload condition is met, effectively reducing communication power consumption and cloud computing burden; (4) Local sound and light warning, which immediately issues a local alarm when an emergency danger is detected, without waiting for cloud response.Edge computing devices can preprocess data on site, including cleaning, filtering, and preliminary analysis, to reduce data transmission bandwidth requirements and cloud computing burden. The dynamic stability evaluation model of unstable rock masses is embedded in edge devices, and response mechanisms for different early warning levels are established, such as adjusting monitoring frequency, carrying out field inspections, and activating emergency plans[59,89].

The cloud platform layer is responsible for the storage, in-depth analysis, and global situation judgment of massive monitoring data [90]. Its main functions include: (1) Unified access and standardized processing of multi-source heterogeneous data; (2) Stability trend analysis and instability condition prediction based on big data; (3) Offline training and online inference of complex models; (4) Multi-model fusion decision-making and early warning information release; (5) 3D visual display and digital twin mapping.Relying on the powerful computing capacity of the cloud, big data analysis and machine learning training can be carried out to optimize the early warning model. With the core monitoring data automatically uploaded by edge devices, the cloud early warning and

 doi:10.20944/preprints202604.2164.v1

prediction model can realize dynamic and continuous update, thus continuously improving the accuracy and timeliness of early warning[53,90].

The communication layer adopts a layered communication protocol architecture. The edge end is constrained by resources and uses a lightweight publish-subscribe protocol (such as MQTT) to realize event-driven communication; the cloud focuses on high-performance response protocols (such as HTTP/HTTPS) to support service integration and management. The two realize efficient collaboration through a unified logical interface [89].

Building on the aforementioned cloud-edge collaborative architecture, research teams worldwide have developed a suite of integrated platforms for geotechnical hazard monitoring and early warning, which have been deployed in demonstration applications across slope monitoring sectors including hydropower, highways, and open-pit mines [91–94]. However, the monitoring indicator systems of these conventional platforms are predominantly based on "static-deformation-environmental" parameters, and are fundamentally rooted in force-displacement variation trends for safety warning and risk prediction. While they perform reliably in plastic failure scenarios (e.g., landslides), they can only capture post-failure collapse or rockfall events for brittle failure modes, rather than providing effective precursor warning prior to catastrophic failure.

In contrast, Xie et al. deeply integrated structural dynamics theory with edge computing, developed edge IoT nodes centered on *Micro-core Intelligent Sensing Equipment* (e.g., Micro-core Piles), and constructed a three-in-one dynamic monitoring and early warning system for rockfall hazards integrating "dynamics-deformation-environmental" parameters. This system has been implemented in large-scale demonstration applications for monitoring unstable rock masses on high and steep slopes in the reservoir areas of major hydropower stations (Baihetan and Wudongde) and large open-pit coal mines [4,53,59]. This closed-loop mechanism of *"cloud-led global training, edge-led real-time inference"* significantly enhances the robustness of geological hazard early warning systems across diverse geographical regions and complex working conditions.

5. Existing Challenges and Cutting-Edge Development Trends

5.1. Challenges of Long-Term Dynamic Performance Evolution Under Multi-Field Coupling

Unstable rock masses occur in complex natural geological environments, and the long-term evolution of their dynamic performance is subjected to the multi-field coupling of stress field, seepage field, temperature field, and chemical field. Most existing studies focus on the influence of a single factor on the dynamic parameters of unstable rock masses, lacking a systematic understanding of multi-field coupling effects.

Diurnal temperature variation and seasonal temperature changes cause thermal expansion and contraction of unstable rock masses and their structural planes, leading to changes in stress state and periodic variation of structural plane aperture, which further affect dynamic parameters such as natural frequency. Studies have shown that the tilt monitoring data of MEMS sensors has obvious diurnal fluctuation and seasonal drift, which mainly originates from the dual influence of temperature change on sensor elements and the rock mass itself [59]. Although the "piecewise linear compensation" method can correct temperature drift to a certain extent, there is still a lack of effective methods to separate and quantify the stiffness change of the rock mass itself caused by temperature variation.

Rainfall infiltration increases the water content of the structural plane. On the one hand, it reduces the effective bonding force of the structural plane; on the other hand, it increases the pore water pressure and thus the sliding force. Field monitoring data show that the natural frequency of unstable rock masses generally decreases and the damping ratio increases after rainfall, but some parameters are reversible while others are irreversible after rainfall stops. How to distinguish reversible and irreversible changes to accurately identify the real damage state of unstable rock masses is an urgent scientific problem to be solved [25].

In alpine regions, freeze-thaw cycles are a key factor leading to damage and deterioration of structural planes of unstable rock masses. The frost heave force generated by the water-ice phase transition during freeze-thaw cycles propagates cracks in the structural plane, reduces the bonding area, and continuously degrades the rock mass strength. Studies have shown that the fracture toughness of the structural plane decreases exponentially with the number of freeze-thaw cycles, and the cohesion and internal friction angle of the dominant structural plane are significantly deteriorated [95]. Establishing a long-term dynamic performance evolution model of unstable rock masses considering freeze-thaw effects is of great significance for stability evaluation in alpine regions.

Chemical dissolution in karst areas gradually expands the aperture of structural planes, reduces the strength of structural planes, and changes the geometric boundary conditions of unstable rock masses. Although the rate of this process is slow, it cannot be ignored on a geological time scale of decades or even centuries. There is a complex interaction between chemical erosion, seepage field and temperature field, and the long-term influence mechanism on the dynamic performance of unstable rock masses remains to be further studied[96,97].

5.2. Computational Bottleneck of High-Fidelity Dynamic Inversion for Large-Scale Heterogeneous Rock Masses

In practical engineering, unstable rock masses are often of large scale (tens to hundreds of meters), and there are a large number of heterogeneous structures such as joints, cracks, and weak interlayers inside the rock mass, which pose severe computational challenges for high-fidelity dynamic inversion.

(1) Contradiction between Model Complexity and Computational Efficiency

High-fidelity dynamic inversion requires a refined 3D numerical model, including the geometric shape of the unstable rock mass, internal fracture network, and material heterogeneity. However, the computational cost of a large-scale refined model is extremely high: a single forward analysis may take hours or even days, while the inversion process usually requires hundreds or thousands of forward calculations, which is almost infeasible in engineering practice.

(2) Application of Surrogate and Reduced-Order Models

To address the computational efficiency problem, scholars have begun to explore inversion methods based on surrogate models and reduced-order models. Surrogate models (e.g., Kriging model [98], neural network model [99]) approximate the original model by learning a small number of high-fidelity forward results, which can reduce the single inversion calculation time from hours to seconds [100]. Physics-informed neural networks (PINNs), which embed governing equations into network training, greatly improve computational efficiency while ensuring physical consistency, and are an important technical direction for future dynamic inversion[101,102].

(3) Multi-Scale Modeling Strategy

For large-scale heterogeneous rock masses, a multi-scale modeling strategy can be adopted: an equivalent continuum model is used at the macro scale, and a refined discrete fracture network model is used in key areas (e.g., near the dominant structural plane). Information transfer between models of different scales is realized through computational homogenization or concurrent multi-scale methods. This strategy can control the overall computational cost while ensuring the simulation accuracy of key areas [103].

5.3. Scientific Correlation Between Dynamic Early Warning Thresholds and Failure Probability

At present, dynamic early warning of unstable rock masses generally adopts a fixed threshold method based on experience or statistical laws, lacking a scientific correlation with the failure probability of rock masses. How to construct a failure probability model based on dynamic monitoring indicators to realize the leap from deterministic early warning to probabilistic early warning is a key problem to be urgently solved in this field.

Current early warning thresholds are mainly derived from laboratory model tests and empirical judgment. For example, the natural frequency corresponding to a factor of safety of 1.0 is taken as the

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 April 2026 doi:10.20944/preprints202604.2164.v1

red early warning threshold, and the natural frequency corresponding to the prevention and control safety factor is taken as the yellow early warning threshold [25]. However, this deterministic threshold setting method does not consider the discreteness of rock mass materials, the measurement error of monitoring data, and the randomness of environmental factors, which is prone to missing or false alarms.

By introducing the structural reliability theory, the natural frequency, structural plane strength parameters, geometric dimensions and other parameters of the unstable rock mass are regarded as random variables, and the limit state equation is established to calculate the failure probability of the rock mass under different working conditions[104,105]. Zhou Fuchuan et al. introduced the first-order second-moment checking point method into the frequency response stability and reliability evaluation of tower-column unstable rock masses. The calculated failure probabilities were 80.3% and 96.27% under natural and saturated conditions, respectively, which were consistent with the conclusions of frequency response stability analysis [105]. This study provides a theoretical basis for the development of early warning indicators based on dynamic monitoring.

With the continuous accumulation of monitoring data, the Bayesian method can be used to update the reliability of unstable rock masses in real time [106]. The preliminary survey and laboratory test results are taken as prior information, and the field monitoring data are taken as observation information, and the posterior failure probability is calculated through the Bayesian formula[107,108]. Dynamically adjusting the early warning threshold based on the posterior failure probability can realize adaptive early warning: the threshold is appropriately increased to reduce the false alarm rate when the rock mass is in good condition, and the threshold is lowered to improve the early warning sensitivity when an abnormal trend is detected.

5.4. Prospect of Full-Life-Cycle Dynamic Simulation of Unstable Rock Masses Based on Digital Twin

Digital twin technology provides a brand-new technical framework for dynamic evaluation and early warning of unstable rock masses by constructing a high-fidelity digital mapping of physical entities to realize virtual-real interaction and full-life-cycle management[109–111]. The construction of a digital twin for unstable rock masses includes four levels: (1) Geometry level: a high-precision geometric model of the unstable rock mass and slope obtained by UAV tilt photography and 3D laser scanning; (2) Physics level: physico-mechanical parameters of the rock mass and structural planes obtained through laboratory tests and field measurements; (3) Behavior level: response laws of the unstable rock mass under different working conditions established based on dynamic theoretical models and data-driven models; (4) Rule level: a rule base for stability evaluation and early warning decision-making integrated with geological criteria, engineering experience, and code standards.

The core of digital twin is to maintain real-time synchronization between the digital model and the physical entity. Multi-source means such as LDV remote vibration measurement, MEMS sensor network, InSAR deformation monitoring and GNSS displacement monitoring are used to continuously obtain the dynamic parameters and deformation information of the unstable rock mass. Data assimilation technology (e.g., ensemble Kalman filter) is used to integrate the observation data into the digital model to realize dynamic correction of model parameters and states [112,113].

Under the digital twin framework, dynamic simulation deduction of the full life cycle of the unstable rock mass from the current state to future evolution can be carried out, including: (1) Normal evolution simulation: simulating the progressive damage process of the structural plane under long-term actions such as gravity and weathering; (2) Extreme working condition simulation: simulating the dynamic response and failure process of the unstable rock mass under extreme working conditions such as earthquake, heavy rainfall, and blasting; (3) Reinforcement effect evaluation: simulating the improvement effect of dynamic performance of the unstable rock mass after the implementation of different reinforcement schemes (anchoring, supporting, drainage, etc.).

The simulation deduction results based on digital twin can provide scientific decision support for the prevention and control of unstable rock masses. First, risk classification: the risk level of the unstable rock mass is divided according to the failure probability under different time scales obtained

 doi:10.20944/preprints202604.2164.v1

by simulation. Second, optimization of prevention and control timing: the optimal reinforcement timing is determined to balance the prevention cost and failure risk. Third, emergency plan formulation: targeted emergency plans are developed according to the failure mode, influence scope and early warning lead time.

6. Conclusions and Recommendations

This paper systematically reviews the domestic and international research progress on dynamic evaluation models for the stability state of slope unstable rock masses and their engineering applications, covering the dynamic behavior mechanism, key parameter system, theoretical evaluation models, monitoring and early warning technologies, and cutting-edge development trends. The main conclusions are as follows:

(1) The essence of unstable rock mass instability is the result of damage evolution and fracture propagation of the dominant structural plane, which can be divided into three stages: strong stability stage, weak stability stage, and failure stage. Environmental dynamic disturbances (earthquakes, blasting, traffic vibration) affect the stability of unstable rock masses through two mechanisms: direct triggering and cumulative damage. Structural dynamics, stress wave propagation theory, and damage-fracture coupled dynamics constitute the core theoretical basis for the dynamic evaluation of unstable rock masses.

(2) A multi-level dynamic parameter system has been formed, including modal parameters represented by natural frequency, damping ratio and mode shape, time-domain parameters represented by coefficient of variation, skewness and kurtosis, wave parameters represented by wave velocity attenuation and coda wave interferometry, energy parameters represented by Hilbert marginal spectrum energy and marginal entropy, and environmental sensitivity factors under temperature-stress-seepage coupling. Among them, natural frequency has become the core evaluation index due to its advantages of easy measurement, high sensitivity, and clear quantitative relationship with stability.

(3) For the three typical types of unstable rock masses (sliding-type, toppling-type, and falling-type), the single-degree-of-freedom spring-mass model, pendulum vibration model, and modified Timoshenko beam model are established respectively, revealing the quantitative relationship between natural frequency and factor of safety: a linear positive correlation with the square of natural frequency for sliding-type rock masses, a proportional relationship with the 4/3 power of natural frequency for toppling-type rock masses, and evaluation via the constrained stability coefficient model for falling-type rock masses. The multi-block excitation model and data-physics dual-driven surrogate model further expand the application scope and intelligent level of dynamic evaluation.

(4) Contact monitoring based on MEMS technology and non-contact monitoring based on LDV constitute the two technical pillars for dynamic response monitoring of unstable rock masses. MEMS sensors have the advantages of small size, low power consumption, and networkability, suitable for long-term online monitoring; LDV has the advantages of non-contact, high precision, and remote measurement, suitable for rapid identification and regular inspection of unstable rock masses. The cloud-edge collaborative automated monitoring and early warning architecture is driving a paradigm shift in unstable rock mass monitoring from “point-type” to “area-type” and from “passive” to “active”.

(5) The long-term dynamic performance evolution mechanism under multi-field coupling, the computational bottleneck of high-fidelity dynamic inversion for large-scale heterogeneous rock masses, and the establishment of a scientific correlation between dynamic early warning thresholds and failure probability are the three core challenges currently faced in this field. Full-life-cycle dynamic simulation based on digital twin represents the future development direction of dynamic evaluation for unstable rock masses.

In view of the above research status and existing problems, the following recommendations are proposed:

(1) Strengthen research on the long-term evolution mechanism under multi-field coupling: Carry out laboratory and field tests on the long-term dynamic performance evolution of unstable rock masses considering temperature-seepage-stress-chemical coupling, reveal the time-varying law of structural plane damage evolution under the action of multiple factors, and establish a dynamic evaluation model with time-varying parameters.

(2) Develop efficient and high-fidelity dynamic inversion methods: Promote the application of physics-informed deep learning methods (such as PINN) and multi-scale modeling strategies in the dynamic inversion of unstable rock masses, break through the computational bottleneck of large-scale heterogeneous rock masses, and realize rapid and accurate inversion of dynamic parameters.

(3) Construct a probabilistic early warning framework: Introduce structural reliability theory and Bayesian updating method, establish a failure probability model based on dynamic monitoring indicators, and realize the upgrade from deterministic threshold early warning to probabilistic risk early warning.

(4) Build a digital twin platform: Integrate multi-source monitoring data, dynamic theoretical models and artificial intelligence algorithms to construct a digital twin platform for unstable rock masses, realizing state assessment, evolution prediction and intelligent decision support for the whole life cycle of unstable rock masses.

(5) Promote standardization and normalization: On the basis of systematic summary of existing research results, formulate technical standards and engineering specifications for dynamic evaluation of unstable rock masses, and promote the standardized application and large-scale promotion of this technology in practical engineering.

Author Contributions: Conceptualization, G.L. and M.X.; methodology, G.L. and Y.D.; software, G.L.; validation, L.Z., M.X. and Y.D.; formal analysis, G.L.; investigation, G.L.; resources, G.L.; data curation, G.L.; writing—original draft preparation, G.L.; writing—review and editing, G.L., L.Z. and Y.D.; visualization, G.L.; funding acquisition, M.X. and Y.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by National Natural Science Foundation of China, grant number 42477167 and National Key Research and Development Program of China, grant number 2023YFC3081400.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data generated or analyzed during this study are included in this published article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors gratefully acknowledge the financial support from the National Natural Science Foundation of China (42477167), the National Key R&D Program of China (2023YFC3081400).

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

AE	Acoustic Emission
DEM	Discrete Element Method
FOS	Factor of Safety
HHT	Hilbert-Huang Transform
MDOF	Multi-Degree of Freedom
RMS	Root Mean Square
SDOF	Single Degree of Freedom
GNSS	Global Navigation Satellite System
InSAR	Interferometric Synthetic Aperture Radar
LDV	Laser Doppler Vibrometer

 doi:10.20944/preprints202604.2164.v1

MEMS	Micro-Electro-Mechanical System
DNN	Deep Neural Network
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory
PINN	Physics-Informed Neural Network
PSO	Particle Swarm Optimization
RF	Random Forest
SVM	Support Vector Machine

References

1. Yang, H.; Xing, B.; He, J.; Jiang, H.; Cheng, Q. The formation mechanism and failure mode of a talus slope induced by rockfalls in Nayong County, Southwest China. *Frontiers in Earth Science* **2022**, 10. doi:10.3389/feart.2022.973528.
2. Chen, L.; Yu, X.; Luo, R.; Zeng, L.; Cao, H. High steep rock slope instability mechanism induced by the pillar deterioration in the mountain mining area. *Mathematics* **2023**, 11. doi:10.3390/math11081889.
3. Wei, T.; Chen, G.; Zhu, Z.; Tang, P.; Yan, M. Slope instability mechanism with differential rock mass structure along a fault: a mine landslide from Southwest China. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources* **2024**, 10. doi:10.1007/s40948-024-00795-5.
4. Du, Y.; Zhang, H.D.; Xie, M.W.; Jiang, Y.J.; Li, S.Q.; Liu, J.N. Review of early monitoring and early warning technologies for large-scale unstable rock mass collapse disasters. *Journal of Engineering Science and Technology* **2024**, 56, 10–23.
5. Guo, J.; Cui, Y.; Xu, W.; Shen, W.; Li, T.; Yi, S. A novel friction weakening-based dynamic model for landslide runout assessment along the Sichuan-Tibet Railway. *Engineering Geology* **2022**, 306. doi:10.1016/j.enggeo.2022.106721.
6. Ming, Z.; Fan, R.; Fan, J.; Tang, Y.; Zeng, W.; Tian, F.; Luo, Y.; Zou, B. Factors controlling the formation of collapse disasters and its hazards to power transmission projects in Erlang Mountain - Zheduo Mountain, China. *Polish Journal of Environmental Studies* **2024**, 33, 5221–5228. doi:10.15244/pjoes/182898.
7. Zhang, Q.; Ma, W.; Gao, Y.; Zhang, T.; Ma, X.; Li, L.; Zhou, Q.; Liu, F. Zoning of the disaster-inducing environment and driving factors for landslides, collapses, and debris flows on the Qinghai-Tibet Plateau. *Applied Sciences-Basel* **2025**, 15. doi:10.3390/app15126569.
8. Zhang, Y.; Yin, Y.; Li, B.; Tie, Y.; Li, C.; Gao, Y.; Wang, M.; Wang, L. Geostructural characteristics and failure mechanism of the Benduo mountain slope in the Yigong Zangbo River, Qinghai-Tibet Plateau, China. *Landslides* **2025**, 22, 2005–2020. doi:10.1007/s10346-025-02472-4.
9. Azarafza, M.; Akgün, H.; Ghazifard, A.; Asghari-Kaljahi, E.; Rahnamarad, J.; Derakhshani, R. Discontinuous rock slope stability analysis by limit equilibrium approaches - a review. *International Journal of Digital Earth* **2021**, 14, 1918–1941. doi:10.1080/17538947.2021.1988163.
10. Melentijevic, S.; Berisavljevic, Z.; Berisavljevic, D.; Marañón, C. Rock slope stability analysis under Hoek-Brown failure criterion with different flow rules. *Bulletin of Engineering Geology and the Environment* **2024**, 83. doi:10.1007/s10064-024-03667-0.
11. Zhang, X.; Jiang, Y.; Du, Y.; Wang, K.; Cai, Y.; Wang, X.; Su, H.; Golsanami, N.; Liu, B. Influence of joint spacing and rock characteristics on the toppling stability of cut rock slope through a simplified limit equilibrium method. *Journal of Central South University* **2024**, 31, 2694–2702. doi:10.1007/s11771-024-5717-1.
12. Lu, G.; Xie, M.; Chen, C.; Du, Y. Evolution of time-frequency dynamic parameters during the instability of falling-type unstable rock masses: an experimental study. *Applied Sciences-Basel* **2026**, 16. doi:10.3390/app16031402.
13. Mao, Y.; Azarafza, M.; Bonab, M.; Pusatli, T.; Nanehkaran, Y. Innovative stability analysis of complex secondary toppling failures in rock slopes using the block theory. *Landslides* **2025**, 22, 2037–2054. doi:10.1007/s10346-025-02464-4.
14. Chen, T.; Zhang, G.; Xiang, X. Deformation calculation and stability analysis of unstable rock slopes based on the cantilever beam model. *Rock Mechanics and Rock Engineering* **2025**, 58, 6575–6598. doi:10.1007/s00603-025-04398-8.

 doi:10.20944/preprints202604.2164.v1

15. Gong, Y.; Yao, A.; Li, Y.; Li, Y.; Li, Y.; Sun, Y. Model test study on sliding-toppling composite deformation evolution of anti-dip layered rock slope. *Bulletin of Engineering Geology and the Environment* **2023**, 82. doi:10.1007/s10064-023-03213-4.
16. Ding, B.; Han, Z.; Zhang, G.; Beng, X.; Yang, Y. Flexural toppling mechanism and stability analysis of an anti-dip rock slope. *Rock Mechanics and Rock Engineering* **2021**, 54, 3721–3735. doi:10.1007/s00603-021-02435-w.
17. Li, Q.B.; Wang, H.F.; Xie, M.W.; Liu, W.N. Calculation method of bonding section of joint surface of dangerous rock mass based on amplitude ratio. *Shock and Vibration* **2020**, 2020. doi:10.1155/2020/8820639.
18. Du, Y.; Xie, M.W.; Jiang, Y.J.; Liu, W.N.; Liu, R.C.; Liu, Q.Q. Research progress on early warning of collapse based on dynamic monitoring indicators. *Chinese Journal of Engineering* **2019**, 41, 427–435. doi:10.13374/j.issn2095-9389.2019.04.002.
19. Du, Y.; Xie, M.W.; Lü, F.X.; Wang, Z.F.; Wang, G.J.; Liu, Q.Q. A new method for dynamic stability analysis of slopes based on variation of modal parameters. *Chinese Journal of Geotechnical Engineering* **2015**, 37, 1334–1339. doi:10.11779/CJGE201507022.
20. Du, Y.; Xie, M.W.; Jiang, Y.J.; Li, B.; Gao, Y. Determination method of monitoring and early warning indicators based on natural vibration frequency. *Rock and Soil Mechanics* **2015**, 36, 2284–2290. doi:10.16285/j.rsm.2015.08.020.
21. Okuzono, S.; Iwatake, K.; Ikeda, K.; Sakai, K. The method to evaluate the danger of rock-collapse at the slope by vibration measurement. *Journal of the Japan Society of Engineering Geology* **1980**.
22. Tanaka, H.; Fujisawa, K.; Asai, K. Identifying unstable rock blocks by measuring micro-tremors and vibration on cliffs. *Advances in Geosciences* **2008**, 14.
23. Ogata, K.; Matsuyama, H.; Amano, K. Evaluation of the rockfall potential utilizing the characteristics of vibration. *Doboku Gakkai Ronbunshu* **2003**.
24. Uehan, F.; Murata, O.; Saito, H. Fundamental study on the remote vibration measuring system for evaluating rock slope stability. *RTRI Report* **2010**, 24, 5–10.
25. Jia, Y.C.; Xie, M.W.; Chang, S.X.; Lü, F.X. Stability evaluation models for sliding and falling unstable rock blocks based on natural vibration frequency. *Rock and Soil Mechanics* **2017**, 38, 2149–2156. doi:10.16285/j.rsm.2017.07.039.
26. Liu, W.N. Research on dynamic evaluation model for stability of falling-type unstable rock masses on slopes. Ph.D. Thesis, University of Science and Technology Beijing, Beijing, China, **2022**.
27. Zhang, X.Y. Research on stability evaluation model of falling-type unstable rock masses on slopes based on natural frequency. Ph.D. Thesis, University of Science and Technology Beijing, Beijing, China, **2023**.
28. Chen, H.K.; Zhang, R.G.; Tang, H.M. Study on elastic-impulse dynamic parameters of compression-shear type unstable rock failure. *Journal of Vibration and Shock* **2012**, 31, 30–33.
29. Chen, H.-k.; Tang, H.-m. Method to calculate fatigue fracture life of control fissure in perilous rock. *Applied Mathematics and Mechanics* **2007**, 28, 643–649. doi:10.1007/s10483-007-0509-1.
30. Wang, L.F. Damage and fracture failure mechanism of complex rock slopes. Ph.D. Thesis, Chongqing Jiaotong University, Chongqing, China, **2012**.
31. Wu, L.Z.; Shao, G.Q.; Huang, R.Q.; He, Q. Overhanging rock: theoretical, physical and numerical modeling. *Rock Mechanics and Rock Engineering* **2018**, 51, 3585–3597. doi:10.1007/s00603-018-1543-9.
32. Zhang, X.Y.; Xie, M.W.; Zhang, L.; Du, Y.; Liu, W.N.; Gao, S.C. Study on calculation model of stability coefficient for falling unstable rock masses based on natural frequency. *Chinese Journal of Rock Mechanics and Engineering* **2023**, 42, 585–593. doi:10.13722/j.cnki.jrme.2022.0361.
33. Wei, J.H.; Deng, Z.D.; Liu, H.; Liu, S.Y. Analysis of stability deterioration of sliding-type unstable rock masses induced by blasting disturbance. *Journal of Vibration and Shock* **2025**, 44, 11, 70-79. doi:10.13465/j.cnki.jvs.2025.11.008.
34. Qu, X.Y.; Li, H.T.; Yao, Q.; Li, C.; Feng, S.M. Dynamic stability study of toppling-type unstable rock masses under blasting vibration considering size effect. *Blasting* **2023**, 40, 154–159.
35. Wu, M.L.; Luo, G.; Mei, X.F.; Zhou, P. Study on dynamic mechanism of collapse of base-damaged unstable rock masses. *Journal of China Three Gorges University (Natural Sciences)* **2024**, 46.

36. Huang, J.W.; Su, G.S. Study on dynamic response characteristics and mechanism of high and steep unstable rock masses under earthquake action. *Hydrogeology & Engineering Geology* 2026, 53, 1–16.
37. Gao, S.C.; Xie, M.W.; Zhang, X.Y.; Huang, Z.J.; Fan, S.S. Study on vibration characteristics of cantilever-type unstable rock masses. *Mining Research and Development* **2023**, 43, 147–153.
38. Liu, W.N.; Song, H.K. Study on stability evaluation model of cantilever-type unstable rock masses based on natural frequency. *Journal of Chongqing Jiaotong University (Natural Science)* **2025**, 44, 68–74.
39. He, Z.; Xie, M.W.; Zhao, C.; Li, S.Q.; Wu, Z.X.; Lu, X.Y.; Chen, X.H. Collapse prediction equation and experimental study of tensile failure-type unstable rock masses based on time-varying characteristics of resonant frequency. *Engineering Mechanics* **2026**, 1-13.
40. Chen, H.K.; Xian, X.F.; Tang, H.M. Fracture mechanics calculation method for unstable rock stability. *Journal of Chongqing University (Natural Science Edition)* **2009**, 32, 5.
41. He, S.M.; Wu, Y.; Li, X.P. Mechanical mechanism of earthquake-induced rock mass collapse. *Chinese Journal of Rock Mechanics and Engineering* **2010**, 29, 3359–3363.
42. Yin, Y.P.; Wang, W.P.; Zhang, N.; Yan, J.K.; Wei, Y.J.; Yang, L.W. Study on remote disaster characteristics of high-level landslides in strong earthquake areas: a case study of Xinmo landslide in Maoxian County, Sichuan Province. *Geology in China* **2017**, 44, 15.
43. Chen, B.R.; Feng, X.T.; Zeng, X.H.; Xiao, Y.X.; Zhang, Z.T.; Ming, H.J.; Feng, G.L. Real-time microseismic monitoring and characteristic analysis of TBM excavation in deep-buried tunnels. *Chinese Journal of Rock Mechanics and Engineering* **2011**, 30, 275–283.
44. Su, G.S.; Xiong, X.L.; Ren, Y.K.; Huang, L.; Liu, X.M.; Zhang, Y. In-situ microseismic test study on toppling-type unstable rock collapse process. *Earth Science* **2026**, 1-12.
45. Wang, Z.; Su, Z.; Niu, Y.; Tao, Z.; Wang, H.; Gan, F. Analysis of deformation–fracture evolution and instability precursor characteristics of rock-like models with a single pre-existing flaw. *Rock Mechanics and Rock Engineering* **2026**. doi:10.1007/s00603-026-05343-z.
46. Li, X.; Cao, W.-G.; Su, Y.-H. A statistical damage constitutive model for softening behavior of rocks. *Engineering Geology* **2012**, 143-144, 1–17. doi:10.1016/j.enggeo.2012.05.005.
47. Wang, R.; Wang, G.; Zhang, L.; Sun, F.; Cao, T.; Li, B.; Xu, H. Coupled macro–meso damage constitutive model for fractured rocks based on logistic growth theory. *Engineering Fracture Mechanics* **2023**, 281, 109132. doi:10.1016/j.engfracmech.2023.109132.
48. Alves, M.l.; Yu, J.; Jones, N. On the elastic modulus degradation in continuum damage mechanics. *Computers & Structures* **2000**, 76, 703–712. doi:10.1016/S0045-7949(99)00187-X.
49. Jia, Y.C. Research on stability model of slope unstable rock blocks based on dynamic characteristic parameters. Ph.D. Thesis, University of Science and Technology Beijing, Beijing, China, **2018**.
50. Wu, Z.X.; Xie, M.W.; Zhang, X.Y.; Zhang, L.; Wang, J.H.; Chen, X. Damage identification experiment of unstable rock mass with single structural plane based on ambient vibration. *Chinese Journal of Engineering* **2024**, 46, 589–599. doi:10.13374/j.issn2095-9389.2023.03.12.002.
51. Tanaka, H.; Fujisawa, K.; Asai, K. Identifying unstable rock blocks by measuring micro-tremors and vibration on cliffs. *Advances in Geosciences* 2008, 14, 165–171. doi:10.5194/adgeo-14-165-**2008**.
52. Zhao, C.; Xie, M.W.; Liu, W.N.; Lu, G. Study on damage identification of unstable rock masses based on particle trajectory. *Metal Mine* **2022**, 6.
53. Chen, C.; Xie, M.W.; Du, Y.; Zhang, X.Y. Monitoring method for toppling-type unstable rock collapse based on MEMS sensing technology. *Chinese Journal of Rock Mechanics and Engineering* **2025**, 44, 32–42.
54. Zhao, Y.; Dong, J.; Liu, H.; Wang, C. Seismic response and damage model analysis of rocky slopes with weak interlayers. *Open Geosciences* **2025**, 17. doi:10.1515/geo-2022-0621.
55. Peng, Z.; Shukui, L.; Jun, Z.; Lei, C.; Luyun, D. Study on early damage monitoring and inversion of tunnel bolt support system based on coda wave interferometry. *Journal of Basic Science and Engineering* **2025**, 33, 1408–1420. doi:10.16058/j.issn.1005-0930.2025.05.016.
56. Li, Z.; Li, L.; Huang, K.; Xue, L.; Jiang, T.; Dong, J.; Wang, C.; Ding, H. The seismic dynamic response characteristics of the steep bedding rock slope are investigated using the Hilbert–Huang transform and marginal spectrum theory. *Applied Sciences* **2025**, 15, 3078.

 doi:10.20944/preprints202604.2164.v1

57. Song, D.; Liu, X.; Huang, J.; Zhang, J. Energy-based analysis of seismic failure mechanism of a rock slope with discontinuities using Hilbert-Huang transform and marginal spectrum in the time-frequency domain. *Landslides* **2021**, 18, 105–123. doi:10.1007/s10346-020-01491-7.
58. Zhao, C.; Xie, M.W.; Du, Y.; Huang, Z.J.; He, Z.; Lu, G. Spatial vibration characteristics and damage identification of toppling-type unstable rock masses. *Journal of Engineering Science and Technology* **2024**, 56, 48–59.
59. He, Z.; Xie, M.W.; Wu, Z.X.; Zhao, C.; Sun, G.C.; Xu, L. Field measurement study on pre-collapse tilt deformation characteristics of tensile failure-type slope unstable rock masses using micro-core pile sensors. *Rock and Soil Mechanics* **2024**, 45, 3399–3415. doi:10.16285/j.rsm.2024.0146.
60. Bottelin, P.; Jongmans, D.; Baillet, L.; Lebourg, T.; Hantz, D.; Levy, C.; Roux, O.; Cadet, H.; Lorier, L.; Rouiller, J.-D.; et al. Spectral analysis of prone-to-fall rock compartments using ambient vibrations. *Journal of Environmental & Engineering Geophysics* **2013**, 18, 205–217. doi:10.2113/JEEG18.4.205.
61. Shi, W.; Zhang, J.; Song, D.; Liu, X.; Wang, E.; Zhang, J. Dynamic responses of steep bedding slope-tunnel system under coupled rainfall-seismicity: shaking table test. *Journal of Rock Mechanics and Geotechnical Engineering* **2025**, 17, 2072–2090. doi:10.1016/j.jrmge.2024.09.011.
62. Liu, X.; Lang, Q.; Zhang, J.; Zhang, Y.; Yu, C.; Jin, Q.; Liu, Y.; Wan, Z.; Liu, P.; et al. Dynamic failure mechanisms and hazard evaluation of rock collapse induced by extreme rainfall in Changbai County highways. *Scientific Reports* **2025**, 15, 9794. doi:10.1038/s41598-025-94756-x.
63. Wu, Z.X. Research on evolution law of static and dynamic deformation indicators and early warning model of reservoir bank retrogressive landslides. Ph.D. Thesis, University of Science and Technology Beijing, Beijing, China, 2024.
64. Chen, H.K.; Tang, H.M.; Wang, R. Calculation method and application of unstable rock stability in Three Gorges Reservoir area. *Chinese Journal of Rock Mechanics and Engineering* **2004**, 23, 614–619.
65. Chen, H.K.; Tang, H.M.; Wang, Z.; He, X.Y. Study on vibration equation of unstable rock aggregate failure. *Journal of Vibration and Shock* **2018**, 37, 60–66. doi:10.13465/j.cnki.jvs.2018.12.010.
66. Chen, H.K.; Tang, H.M.; Wang, Z.; He, X.Y. Study on frequency domain characteristics of excitation signals from unstable rock failure. *Journal of Vibration and Shock* **2014**, 33, 64–68. doi:10.13465/j.cnki.jvs.2014.19.011.
67. Huang, J.W.; Su, G.S. Study on dynamic response characteristics and mechanism of high and steep unstable rock masses under earthquake action. *Hydrogeology & Engineering Geology* **2025**, 1-16.
68. Arif, A.; Zhang, C.; Sajib, M.H.; Uddin, M.N.; Habibullah, M.; Feng, R.; Feng, M.; Rahman, M.S.; Zhang, Y. Rock slope stability prediction: a review of machine learning techniques. *Geotechnical and Geological Engineering* **2025**, 43, 124. doi:10.1007/s10706-025-03091-5.
69. Nanehkaran, Y.A.; Licai, Z.; Chengyong, J.; Chen, J.; Anwar, S.; Azarafza, M.; Derakhshani, R. Comparative analysis for slope stability by using machine learning methods. *Applied Sciences* **2023**, 13, 1555. doi:10.3390/app13031555.
70. Huo, L.C.; Du, Y.; Xie, M.W.; Liu, W.N.; Zhang, X.Y.; Jia, B.N.; Cong, X.M. Identification method of unstable rock masses based on multi-level dynamic indicators. *Chinese Journal of Rock Mechanics and Engineering* **2022**, 41, 3124–3131. doi:10.13722/j.cnki.jrme.2021.1058.
71. Raissi, M.; Perdikaris, P.; Karniadakis, G.E. Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics* **2019**, 378, 686–707. doi:10.1016/j.jcp.2018.10.045.
72. Liu, X.; Zhang, X.; Zhong, Y.; Yan, Z.; Hong, Y. Two-scale physics-informed neural networks for structural dynamics parameter inversion: numerical and experimental validation on T-shaped tower health monitoring. *Buildings* **2025**, 15, 1876. doi:10.3390/buildings15111876.
73. Huang, C.; Xie, X.; Deng, Y.; Liu, M. Landslide displacement prediction based on time series and GRU-ATTENTION neural network. In Proceedings of the IET International Radar Conference (IRC 2023), 3–5 Dec **2023**; pp. 1004–1011.
74. Zhang, Y.; Tang, J.; Cheng, Y.; Huang, L.; Guo, F.; Yin, X.; Li, N. Prediction of landslide displacement with dynamic features using intelligent approaches. *International Journal of Mining Science and Technology* **2022**, 32, 539–549. doi:10.1016/j.ijmst.2022.02.004.

75. Liu, Y.Y.; Ju, L.; Li, R.X.; Tian, T. Trend prediction of structural health state based on multi-model integration. *Transactions of Beijing Institute of Technology* **2023**, 43, 602–608. doi:10.15918/j.tbit1001-0645.2022.119.
76. Zhao, X.; Fen, W.; Dai, Z.; Jiao, W.; Geng, J.; Xiong, Q.; Zhang, N. Dynamic rockfall risk assessment using multi-source data fusion and 3D simulation: a case study of Jiaohua rock. *Sci Rep* **2026**, 16, 5903. doi:10.1038/s41598-026-36769-8.
77. Guo, H.; Gil-González, A.B.; Martínez-Graña, A.M. Liquid neural networks and multimodal remote sensing fusion applied to dynamic landslide susceptibility assessment. *Remote Sensing* **2026**, 18, 1035. doi:10.3390/rs18071035.
78. Hasani, H.; Freddi, F.; Piazza, R.; Ceruffi, F. A wireless data acquisition system based on MEMS accelerometers for operational modal analysis of bridges. *Sensors* **2024**, 24, 2121. doi:10.3390/s24072121.
79. Ragam, P.; Nimaje, D. Application of MEMS-based accelerometer wireless sensor systems for monitoring of blast-induced ground vibration and structural health: a review. *IET Wireless Sensor Systems* **2019**, 9, 103–109. doi:10.1049/iet-wss.2018.5099.
80. Gara, F.; Corneli, A.; D'Aparo, R.D.; Spegni, F.; Ranzi, G. Dynamic characterization of civil engineering structures with wireless MEMS accelerometers. *Buildings* **2025**, 15, 3896.
81. Saito, H.; Tsuji, M.; Ohtsuka, Y.; Uehan, F.; Murata, O.; Ma, G.; Sawada, K.; Yashima, A.; Fukata, T. A study on evaluating rock slope stability by remotely-positioned laser Doppler vibrometers. **2011**.
82. Rothberg, S.J.; Allen, M.S.; Castellini, P.; Di Maio, D.; Dirckx, J.J.J.; Ewins, D.J.; Halkon, B.J.; Muyshondt, P.; Paone, N.; Ryan, T.; et al. An international review of laser Doppler vibrometry: making light work of vibration measurement. *Optics and Lasers in Engineering* **2017**, 99, 11–22. doi:10.1016/j.optlaseng.2016.10.023.
83. Uehan, F. Development of the U-Doppler non-contact vibration measuring system for diagnosis of railway structures. *Quarterly Report of RTRI* **2008**, 49, 178–183. doi:10.2219/rtriqr.49.178.
84. Uehan, F. Fundamental study on the remote vibration measuring system for evaluating rock slope stability. **2012**.
85. Ma, G. Study on evaluating rock block stability by using a remotely positioned laser Doppler vibrometer. *International Journal of Geomate* 2012. doi:10.21660/2012.4.3j.
86. Nassif, H.H.; Gindy, M.; Davis, J. Comparison of laser Doppler vibrometer with contact sensors for monitoring bridge deflection and vibration. *NDT & E International* **2005**, 38, 213–218. doi:10.1016/j.ndteint.2004.06.012.
87. Siringoringo, D.M.; Fujino, Y. Noncontact operational modal analysis of structural members by laser Doppler vibrometer. *Computer-Aided Civil and Infrastructure Engineering* **2009**, 24, 249–265. doi:10.1111/j.1467-8667.2008.00585.x.
88. Aggarwal, K.; Kaladeep, P.; Patel, B.; Sasireka, C.S.; Kumar, J.A.; Venu, N. Incorporating edge-AI in IoT-cloud framework for landslide surveillance and forecasting; **2024**; pp. 1–6.
89. Zhang, H.; Zhang, R.; Sun, J. Developing real-time IoT-based public safety alert and emergency response systems. *Sci Rep* **2025**, 15, 29056. doi:10.1038/s41598-025-13465-7.
90. Dong, X.; Li, S.; Ma, R.; Tian, W.; Zhao, K.; Xiang, H.; Zhu, J.; Qiu, Y. Cloud-based slope risk monitoring and early warning system for open-pit coal mines: a case study of Zhonglian Runshi. *Sci Rep* **2025**, 15, 44396. doi:10.1038/s41598-025-28190-4.
91. Abaker, M.; Dafaalla, H.; Eisa, T.; Abdelgader, H.; Mohammed, A.; Burhanur, M.; Hasabelrsoul, A.; Alfakey, M.; Morsi, M. Deep learning- and IoT-based framework for rock-fall early warning. *Applied Sciences-Basel* **2023**, 13. doi:10.3390/app13179978.
92. Joshi, A.; Agarwal, S.; Kanungo, D.; Panigrahi, R. Integration of edge-AI into IoT-cloud architecture for landslide monitoring and prediction. *IEEE Transactions on Industrial Informatics* **2024**, 20, 4246–4258. doi:10.1109/tii.2023.3319671.
93. Song, Y.; Zou, Y.; Li, Y.; He, Y.; Wu, W.; Niu, R.; Xu, S. Enhancing landslide detection with SBConv-optimized U-Net architecture based on multisource remote sensing data. *Land* **2024**, 13. doi:10.3390/land13060835.
94. Kumar, S.; Ramesh, M. A case study on digital twin-enabled IoT communication architecture for landslide monitoring. *Information and Software Technology* 2026, 195. doi:10.1016/j.infsof.2026.108131.

95. Deng, Z.D.; Zhan, X.X.; Shu, J.J.; Yang, S.K.; Cao, M.S. Stability deterioration mechanism and sensitive parameter analysis of unstable rock masses under freeze-thaw cycles. *Journal of Engineering Science and Technology* **2022**, 54, 150–161. doi:10.15961/j.jsuese.202100086.
96. Loew, S.; Gschwind, S.; Gischig, V.; Keller-Signer, A.; Valenti, G. Monitoring and early warning of the 2012 Preonzo catastrophic rockslope failure. *Landslides* **2017**, 14, 141–154. doi:10.1007/s10346-016-0701-y.
97. Carlà, T.; Intrieri, E.; Di Traglia, F.; Nolesini, T.; Gigli, G.; Casagli, N. Guidelines on the use of inverse velocity method as a tool for setting alarm thresholds and forecasting landslides and structure collapses. *Landslides* **2017**, 14, 517–534. doi:10.1007/s10346-016-0731-5.
98. Ren, Z.H. Surrogate model-assisted optimization algorithm based on Q-learning. *Information Systems Engineering* **2025**, 79–82.
99. Fu, W.; Liu, P.; Zhang, K.; Zhang, J.; Chen, X.; Zhang, L.; Yan, X. Use deep transfer learning for efficient time-series updating of subsurface flow surrogate model. *Engineering Applications of Artificial Intelligence* **2025**, 153, 110873. doi:10.1016/j.engappai.2025.110873.
100. Dai, Y.; Dai, W.; Chen, C.; Ao, M.; Li, J.; Huang, Q. Landslide displacement intelligent dynamic inversion: technical framework and engineering application. *Remote Sensing* **2025**, 17, 2820. doi:10.3390/rs17162820.
101. Misaka, T.; Mizuno, Y.; Nakasumi, S.; Furukawa, Y. Data assimilation with physics-informed neural network surrogates constructed against prediction uncertainty. *Journal of Computational Physics* **2026**, 548, 114587. doi:10.1016/j.jcp.2025.114587.
102. Degen, D.; Cacace, M.; Wellmann, F. 3D multi-physics uncertainty quantification using physics-based machine learning. *Sci Rep* **2022**, 12, 17491. doi:10.1038/s41598-022-21739-7.
103. Adinolfi, G.M.; Umili, G.; Comina, C.; Vinciguerra, S.C. Inversion of short-period seismic signals as a tool to understand small-volume rockslide mechanics: the case study of the 26 January 2023, Lorgino (Crevoladossola, NW Italy) rockslide. *Earth and Space Science* **2026**, 13, e2025EA004635. doi:10.1029/2025EA004635.
104. Zhao, L.; Yu, C.; Cheng, X.; Zuo, S.; Jiao, K. A method for seismic stability analysis of jointed rock slopes using Barton-Bandis failure criterion. *International Journal of Rock Mechanics and Mining Sciences* **2020**, 136, 104487. doi:10.1016/j.ijrmms.2020.104487.
105. Zhou, F.; Liu, X.; Tang, H.; Miao, M.; Xu, B.; Guo, X. Analysis of the frequency–response stability and reliability of a tower-column unstable rock mass on a high and steep slope. *Scientific Reports* **2024**, 14, 20308. doi:10.1038/s41598-024-70941-5.
106. Wang, S.; Zeng, P.; Li, T.; Sun, X.; Xia, C.; Xu, B. 3D probabilistic assessment of potentially unstable rock slope failure via sequential Bayesian updating. *Landslides* **2025**, 22, 2293–2310. doi:10.1007/s10346-025-02504-z.
107. Tian, H.; Li, D.Q. Collaborative reliability updating of soil slopes with spatially varying soil properties considering different site investigation data. *Chinese Journal of Geotechnical Engineering* **2024**, 46, 1613–1621. doi:10.11779/CJGE20221579.
108. Zhao, C.; Lin, C.; Wang, F.; Qi, H.; Li, Z.; Li, T.; He, Y. Time-variant deformation prediction and reliability assessment of slopes based on dynamic Bayesian model averaging. *Engineering Geology* **2026**, 365, 108647. doi:10.1016/j.enggeo.2026.108647.
109. Zhu, J.; Ren, Y.; Guo, Y.; Lu, J.; Wu, J.; Guo, Z.; Gu, H.; Zhao, H. A digital twin-driven enhanced visualization method for high-steep slope scene. *International Journal of Digital Earth* **2025**, 18, 2509082. doi:10.1080/17538947.2025.2509082.
110. Xu, J.; Zhang, Y. AI-powered digital twin technology for highway system slope stability risk monitoring. *Geotechnics* **2025**, 5, 19. doi:10.3390/geotechnics5010019.
111. Li, L.; Tang, B.; Cai, F.; Wei, L.; Zhu, X.; Fan, D. Digital twin modeling for landslide risk scenarios in mountainous regions. *Sensors (Basel)* **2026**, 26. doi:10.3390/s26020421.

 doi:10.20944/preprints202604.2164.v1

112. Bar, N. Digital twin concept for the safe and economic design and management of rock slopes; **2024**.
113. Chen, G.; Deng, W.; Lin, M.; Lv, J. Slope stability analysis based on convolutional neural network and digital twin. *Natural Hazards* **2023**, 118, 1427–1443. doi:10.1007/s11069-023-06055-1.