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Monitoring, early warning and mitigation of natural and engineered slopes, volume IV

Edited by
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Monitoring, early warning and mitigation of natural and engineered slopes, volume IV

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Editorial: Monitoring, early warning, and mitigation of natural and engineered slopes – volume IV

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Editorial on the Research Topic
Monitoring, early warning, and mitigation of natural and engineered slopes – volume IV

Introduction

Landslides and slope instabilities pose significant threats to infrastructure, human safety, and the environment, making it essential to develop effective monitoring, early warning, and mitigation strategies (Zhou et al., 2022; Wei et al., 2024; Qiu et al., 2025). The growing impacts of climate change, extreme weather conditions, and human activities have further intensified the risks of slope instability, highlighting the critical need for effective hazard assessment and risk mitigation strategies (Hürlimann et al., 2022; Pei et al., 2023; Zhu et al., 2024). Recent advancements in slope control technology, coupled with the development of interdisciplinary and multidisciplinary interaction theories, have created new opportunities for the early detection, dynamic monitoring, and risk reduction of unstable slopes (Fang et al., 2024; Liu et al., 2024; Cifaldi et al., 2025). However, achieving large-scale, long-term, and cost-effective monitoring, along with precise risk assessment, accurate early warning, and efficient disaster recovery, remains a significant challenge that requires further technological and methodological advancements (Thirugnanam et al., 2022; Wang et al., 2022). Building on the contributions of Volume III, which included 16 research papers (Qiu et al., 2024), Volume IV presents 30 new studies that reflect key advancements in landslide hazard assessment, predictive modeling, and innovative mitigation strategies. The selected articles offered an interdisciplinary perspective and incorporating approaches from geotechnical engineering, remote sensing, and artificial intelligence. By integrating real-time monitoring tools, deep learning models, and optimization techniques, these studies have greatly improved the ability to forecast, assess,

and mitigate landslide risks, contributing to the advancement of safer and more resilient infrastructures.

Slope hazard mitigation: mechanisms and technologies

Seventeen of the 30 research papers in this volume investigated advancements in landslide risk assessment methodologies, real-time monitoring technologies, and innovative mitigation strategies, with the goal of providing scientific insights and practical solutions for slope stabilization and disaster prevention. Huang et al. present a hybrid Principal Component Analysis (PCA)-Sparrow Search Algorithm (SSA)-Support Vector Machine (SVM) model to enhance the slope stability prediction accuracy. PCA reduces data dimensionality while preserving essential features, and the SSA optimizes SVM parameters, overcoming the limitations of traditional methods. Wang et al. conducted a back-analysis by using a coupled particle flow model and an elastic viscoplastic model to study the dynamic process of the Yanghuachi (YHC) landslide-triggered debris flow. Han et al. proposed an automated failure mode identification method for slope stability monitoring by integrating rainfall, surface displacement, and vertical displacement data. Using a deep convolutional autoencoder model, this approach extracts features from normal operational data and detects anomalies based on reconstruction error variations. Feng et al. systematically analyzed the spatial relationships between landslides and fault zones and established a correction coefficient value table and distribution map. An improved Newmark model incorporating fault effects was developed and compared with the traditional model under seismic conditions (10% exceedance probability over 50 years). Liu et al. developed an intelligent monitoring, early warning, and forecasting system for a transmission line tower with high and steep sandstone slope along a highway under construction in Guangxi, China. The study analyzed automatic monitoring data, assessed an emergency rescue program, and evaluated the effectiveness of slope protection measures. Zhang constructed a landslide susceptibility spatial distribution prediction model using an integrated particle swarm optimization in Lianhe Village, Sichuan Province. The study analyzed the sensitivity and weighting of influencing factors and applied a support vector machine (SVM) for prediction. By incorporating simulated annealing and mutation operations, the model effectively extracted high-weight features and improved landslide susceptibility mapping, thereby enhancing hazard prediction accuracy. Mihu-Pintilie et al. analyzed climatic, anthropogenic, geological, and geomorphological factors that contributing to a debris flow-slide event in October 2023 through field investigations and UAV-based data reconstruction. The study further explored the reactivation potential of landslides, dam stability concerns, and the future evolution of the impounded lake, providing insights into hazard assessment and mitigation strategies. He et al. proposed a rapid landslide hazard assessment method to reduce reliance on large datasets while improving efficiency and accuracy. Using the Analytic Hierarchy Process (AHP) combined with Information Value (IV), Certainty Factor (CF), and Frequency Ratio (FR) methods, this study assessed landslide risk in Yongxing Town, Sichuan Province. The results showed that AHP-IV and AHP-FR assign a moderate risk level to the region aligning well with field investigations, whereas AHP-CF produced a slightly lower hazard assessment due to the exclusion of water system factors. Cifaldi et al. developed a low-cost Arduino©-based wire extensometer for landslide monitoring, capable of measuring bi-directional displacements between fixed points. Unlike traditional extensometers, which use potentiometers with limited measurement capacity, the device integrates a capacitive rotary encoder, enabling the monitoring of infinite displacements over time. Li et al. proposed an integrated automatic recognition method for coastal slope landslide detection combining Image Clipping (IC), Image Information Enhancement (IE), Adaptive K-means Clustering Segmentation (AKS), and optimization (O). This approach can achieve the precise extraction of deformation areas in landslide images, thereby improving the accuracy and efficiency of slope stability assessment using image-based analysis. Saik et al. conducted a stress-strain state modeling study on rock mass at Vostochny Quarry in the East Saryoba field to identify vulnerable quarry slopes and develop strengthening strategies. Utilizing geodetic, geophysical, and aerospace technologies, their research enhanced the predictive accuracy of technogenic disasters. Li et al. combined image information enhancement technology with image segmentation techniques to improve landslide identification accuracy. Verified on a coastal slope landslide in Pingtan, the method achieved an average relative error of 5.20% in the X-direction and 5.14% in the Y-direction. Key advantages include the enhanced identification of blurred landslide areas, extended temporal monitoring capability, and improved boundary condition segmentation, contributing to more precise and reliable coastal slope monitoring. Wu et al. developed a numerical model incorporating elevation conditions and slope shape factors using the modified Sadovsky formula to analyze the vibration attenuation law of open-pit slopes under blasting. Taking the Yunfu area in Guangdong Province as an example, FLAC3D software was used for analysis, and the results showed that considering slope shape factors reduced the relative error from 15% to 10% compared to field data. While the peak particle velocities in the simulations were higher owing to the simplified rock mass modeling, the proposed model provided more accurate results, offering a reliable reference for slope stability assessment under blasting conditions. Liu et al. applied the minimum distance principle and quantitative theory to assess coal burst risk in isolated working faces. Taking Yangcheng Coal Mine as an example, a three-dimensional risk assessment model was established, and it was found that abutment pressure and elastic strain energy density initially increase exponentially before declining to *in situ* stress. Compared to one-dimensional and two-dimensional models, the three-dimensional model significantly improved the risk assessment accuracy and effectively identified strong coal and gas outburst risks. Zhang et al. studied stick-slip instability in deep coal-rock structures, identifying weak surface conditions and friction behavior as key factors. They found that grinding slip and soft interlayers increased the failure risk, triggering dynamic disasters. Local stick-slip in coal seams generates compression pulses that cause layer cracking and fragment ejection. Numerical simulations of a coal bump accident in the Yima coal mine confirmed this instability mechanism. Shao et al. proposed a GF-DeepAR model for slope deformation prediction, combining a Gaussian-filter (GF) denoising algorithm with the DeepAR deep learning method for point and probability analysis.

The model was validated using two slope engineering cases, showing improved accuracy over the GF-LSTM, GF-XGBoost, and GF-SVR models. The results demonstrated that the model has effective noise reduction effect, higher R^2 values, and lower prediction errors, and can reliably capture the complex deformation trends. The study highlights the GF-DeepAR model's superior performance in slope deformation prediction, offering a useful reference for early warning systems in geotechnical engineering. Zhou and Wei studied the challenges associated with earth pressure in slope retaining structures, a critical Research Topic in geotechnical engineering that remains inadequately understood. Their study categorizes research into three main approaches: theoretical calculations, model testing, and numerical simulations, summarizing existing findings, and highlighting unresolved Research Topic. They emphasized the need for further research on earth pressure distribution in complex conditions, such as stratified soils or groundwater presence, as well as the displacement behavior of retaining structures. Additionally, they pointed out the lack of experimental verification and engineering measurements for the existing calculation formulas and assumed fracture surfaces.

Natural disasters and their ecological-land use impacts across regions

Geographical and tectonic variations significantly influence the diversity of disaster risks across different regions, thereby affecting the ecological stability and spatial patterns. Consequently, these factors have become the central focus of scholarly research. Yang et al. developed a flood forecasting framework that integrates Geomorphological Instantaneous Unit Hydrograph (GIUH) with the Xinanjiang model, and optimized it using the Cooperation Search Algorithm (CSA). Applied to six Chinese catchments, CSA achieved NSE >0.9 with only 16 trials, outperforming SCE-UA algorithms. The model effectively handled data-sparse regions and accurately simulated extreme rainfall events, thereby proving its potential for global flood forecasting. Teng et al. proposed an optimized method for rapid and accurate flood inundation extraction using Sentinel-1 SAR (Synthetic Aperture Radar and Sentinel-2 MSI (Multi-spectral Image) images. By integrating the normalized difference water index (NDWI), a refined threshold method and a filtering process, the approach effectively identifies pre- and post-flood water bodies. When applied to the 2020 Tongling flood, the method achieved kappa accuracies of 98% (optical images) and 89% (SAR), demonstrating its potential for dynamic flood monitoring and emergency response. Liu et al. analyzed future precipitation variations in the Daxi River Basin using CMIP6 data and applied distributed hydrological models to simulate flash flood discharges. The study found that precipitation under the SSP5-8.5 scenario was the highest, whereas the CREST model underestimated peak floods compared to the CNFF model. The results indicate a low probability of flash floods exceeding a 10-year return period from 2026 to 2070, thereby providing insights for disaster prevention. Wei et al. investigated the impact of climate warming on permafrost landslides along the Qinghai-Tibet Engineering Corridor (QTEC). Their findings showed that rising temperatures have caused permafrost to thaw, increasing the thickness of the active layer and leading to more frequent landslides, particularly in 2016. Laboratory tests confirmed that as the soil temperature approached 0°C to −1°C, its strength decreased, making the slopes more unstable. Li et al. investigated Zhongbao landslide reactivation in Chongqing, China, on 25 July 2020. Their analysis revealed that heavy rainfall, stratigraphic lithology, and sliding surface morphology triggered failure, which progressed through four stages: initiation, shear-out, acceleration, and accumulation blockage. He et al. analyzed the "720" flood in the WZD-HGZ basin, attributing it to heavy rainfall, complex terrain, backwater obstruction, and human activity. Flood amplification occurs in three stages: runoff concentration, infrastructure collapse, and backwater formation. Weak flood awareness, unclear warnings, and poor emergency responses further worsen the disaster. The study offers insights into improving flood prevention. Ren et al. developed a remote sensing method to improve shallow landslide identification in low-resolution images under complex lighting. To reduce the misjudgment caused by spectral similarity, they applied an improved Otsu algorithm with a multi-feature threshold at the Yangjunba disaster site in Leshan City. Using the Retinex theory, image enhancements and morphological transformations were implemented to detect landslide areas. The method achieved a recognition rate of no less than 95%, demonstrating its effectiveness for accurate landslide identification.

Experimental investigation, stabilization mechanisms and mitigation of soil erosion

These six studies focused on the experimental investigation, stabilization mechanisms, and mitigation strategies of soil erosion, and examined the effects of internal and external factors on erosion processes. Zhang et al. explored the use of chemical stabilizers to enhance the erosion resistance of sandy silt soils. The study on the effects of lignosulfonate (LS), lime (LI), and lignin fiber (LF) found that LF increased the critical shear stress, while LI reduced the erosion coefficient, thereby improving soil stability. SEM analysis revealed that LF promoted agglomerate formation and enhanced resistance, whereas LS had a minimal impact. Guo et al. analyzed the time series of soil erosion deformation in the Yuanmou dry-hot valley from 2018 to 2022 using Small Baseline Subset InSAR (SBAS-InSAR) technology, revealing erosion patterns significantly influenced by altitude, rainfall, and fractional vegetation cover (FVC). The study found severe erosion area concentrated in river basins and confluence zones, with deformation rates reaching −101.68 mm/yr to 30.57 mm/yr. Erosion intensity varied with elevation, being rainfall-dominated below 1,350 m and variations in FVC become the primary factor for soil erosion in dry red soil. Yao et al. discussed the backward erosion piping mechanism in dike foundations, emphasizing the impact of the model size on hydraulic gradients and piping behavior. Numerical simulations and small-scale experiments reveal that dikes without blanket layers experience steady gradient increases, leading to failure, whereas blanket layers induce a self-healing effect that mitigates erosion. Huang et al. explored the effectiveness of check dam openings in controlling debris flow by analyzing 67 check dams in Wenxian County, Gansu Province. Experimental testing of five check dams with opening rates ranging from 2.1% to 10.4% revealed that

increasing the opening rate initially reduced the volumetric water content and pore water pressure. The findings highlight an optimal opening range of 4.2%–6.3%. Dam II (4.2%) outperformed others in reducing flow energy and trapping coarse particles,but required higher strength. Jiang et al. performed laboratory experiments on landslide dam breaching under varying inflow rates (1–4 L/s) and revealed a consistent three-stage breach process, with the peak discharge increasing as the inflow increased. Breach width and depth expand proportionally, with the width-to-depth ratio progressing toward 1. The breaching process follows a logistic function, where the shape parameter k exhibits an exponential relationship with the inflow rate, providing insights for predicting dam failure dynamics. Chu et al. studied that Loess with 10% moisture transitioned from strain softening to hardening after six cycles, while at 18% moisture, it shifted from strong to weak hardening. The strength degradation was most significant after the first cycle, and tended to stabilize after ten cycles, with the cohesion deteriorating more than the internal friction angle. SEM analysis showed increased overhead pores and particle contacts, explaining the strength loss due to freeze–thaw cycles.

Prospectives

This volume emphasizes the integration of modern technologies, data-driven approaches, and multidisciplinary techniques for monitoring, early warning, and mitigation of risks associated with natural and engineered slopes. The application of remote sensing, machine learning, and numerical simulation models has significantly enhanced the slope stability assessment. However, under the influence of extreme weather events, global climate change, and large-scale construction activities, slope failure requires renewed attention. In this context, further in-depth studies are necessary to advance disaster-mitigation strategies. This study provides a reference for damage reduction and risk management from the following key aspects: 1) Advancing AI-driven monitoring solutions for real-time landslide detection. 2) Enhancing interdisciplinary collaboration for holistic slope stability analysis. 3) Developing eco-friendly and sustainable mitigation methods to balance infrastructure safety and environmental conservation. 4) Establishing long-term monitoring frameworks to assess gradual slope deformations and predict future failures.

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Study on erosion deformation of dry-red soil in Yuanmou dry-hot valley with different elevation gradients based on SBAS-InSAR technology

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The Yuanmou dry-hot valley has been confirmed as a typical area subjected to severe soil erosion in southwestern China. The research on the soil erosion deformation exhibited by the dry-red soil that is extensively distributed in this region takes on critical significance in deepening the investigation of soil and water loss control efforts in the Yuanmou dry-hot valley. In this study, a time series of soil erosion deformation was established at different altitudinal gradients from March 2018 to October 2022 using Small Baseline Subset InSAR (SBAS-InSAR) technology to explore the deformation patterns exhibited by soil erosion in the dry-red soil of the Yuanmou dry-hot valley. Next, the time series of fractional vegetation cover (FVC) and monthly average rainfall in the identical period were analyzed comprehensively. The result of this study are presented as follows: 1) The dry-red soil regions in the Yuanmou dry-hot valley, which were observed in the line of sight (LOS) direction, attained the deformation rates ranging from −101.683 mm/yr to 30.57 mm/yr (Ascending),-79.658 mm/yr to 41.942 mm/yr (Descending). In general, areas with significant surface erosion were concentrated in the Longchuan River basin flowing through the north and south of Yuanmou County as well as in the river confluence zones. Uplifted areas have been more widely reported in the central and northern regions of Yuanmou (e.g., the Wudongde hydroelectric power station reservoir area). 2) A significant altitudinal gradient effect was exerted by soil erosion in the dry-red soil of the Yuanmou dry-hot valley. The valley-dam area and the medium and low mountain areas were subjected to the most severe soil erosion, and the maximum erosion reached over 80 mm. Erosion was mitigated in the low mountain areas around the dam and the medium and high mountain areas, and the maximum erosion reached 60 mm and 30 mm, respectively. At an altitude of 1,350 m, soil erosion in the dry-red soil was more significantly affected by rainfall. Nevertheless, at an altitude over 1,350 m, variations in FVC become the

primary factor for soil erosion in the dry-red soil. The results of this study can scientifically support soil and water loss control efforts in the Yuanmou dry-hot valley.

KEYWORDS

soil erosion, SBAS-InSAR, fractional vegetation cover, Yuanmou dry-hot valley, dry-red soil

1 Introduction

Soil has been reported as a vital natural resource. Nearly 95% of the food worldwide originates from soil. Moreover, soil conserves at least a quarter of global biodiversity, offering ecosystems and humanity a wide variety of services (Rong et al., 2019; Borrelli et al., 2021; Pei et al., 2023). Soil erosion has been posing the most significant threat to soil, which results in soil loss or degradation. Consequently, shallower, less fertile, and infertile soil layers are triggered (Chen, Yang, et al., 2023), and even non-arable desertified areas have been formed (Vanwalleghem et al., 2017; Qiu et al., 2024). As revealed by existing research, changes in soil erosion are primarily driven by variations in rainfall and FVC. Under the variations in rainfall and vegetation cover, the process of soil erosion can either be slowed down or accelerated (Alatorre et al., 2012; Zhang et al., 2022; Zhao et al., 2022). However, under different altitude gradients, there are different types of vegetation distributed, and the vegetation coverage varies greatly, and the influence of precipitation and vegetation coverage on soil erosion is different. According to previous studies (Ou, 2017), the study area was divided into four different altitude gradients. Remote sensing was used to explore the response relationship between dry red soil erosion and precipitation and vegetation coverage under different altitude gradients in the dry hot valley of Yuanmo, and to distinguish the contribution degree of precipitation and vegetation coverage to dry red soil erosion under different altitude gradients in the dry hot valley of Yuanmo. It provides scientific basis for soil and water loss control and ecological restoration in Yuanmou dry-hot river Valley.

A total of three main categories of methods are capable of for monitoring surface deformation arising from erosion. The first category comprises conventional monitoring techniques (e.g., the use of precise leveling instruments and Global Navigation Satellite Systems (GNSS)). The above-mentioned methods are straightforward and offer high precision, whereas they are commonly limited by field conditions. Besides, these methods are time-consuming and may not conform to the requirements of large-scale surface deformation monitoring research (Zheng et al., 2018; Hu et al., 2019). The second category covers monitoring methods based on optical remote sensing imagery. Optical remote sensing is capable of capturing extensive surface information, and it is combined with a wide variety of machine learning algorithms for surface deformation monitoring (Ye et al., 2019). It has been extensively employed to identify geological hazards (e.g., landslides and debris flows) (Qiu et al., 2022; W. Yang et al., 2020), such that it serves as a crucial tool for Earth observations. Compared with conventional methods, optical remote sensing has overcome a range of drawbacks (e.g., low efficiency and hazardous working environments), whereas it can still be affected by weather conditions, especially in cloud-prone high-altitude regions. The third category involves InSAR-based ground monitoring techniques. The InSAR technology is characterized by its advantages of wide coverage, all-weather capabilities, and high accuracy (Liu et al., 2022), It has achieved widespread applications in a wide range of fields (e.g., landslide identification (Wang et al., 2022), mining subsidence monitoring (Z. Yang et al., 2020), urban deformation monitoring (Z. Zhang et al., 2018), glacier displacement tracking (Reinosch et al., 2021; Liu et al., 2024), and earthquake and volcano hazard monitoring (Wang et al., 2018). The time-series InSAR technology is capable of observing the identical area over extended time periods using repeat orbit passes. It identifies stable phase observations in interferograms, while it extracts deformation information after phase unwrapping. Notably, the SBAS-InSAR technology enhances coherence by combining multiple master images to constrain interferometric baseline, such that the millimeter-level monitoring accuracy can be attained (Yu et al., 2019; Ye et al., 2024). Moreover, since the launch of the SeaSat satellite carrying synthetic aperture radar by NASA in 1978, many countries have launched SAR satellites that exhibited different frequency bands for Earth observation (Born et al., 1979; Chen, Liang, et al., 2023). The above-described satellites with more scanning modes, shorter revisit cycles, and higher resolutions continuously provide more data support for radar interferometry's theoretical and applied research. Furthermore, data sources have been enriched with the European Space Agency's Sentinel-1A/B satellite radar data from the Copernicus program and the increasing availability of "cloud + edge" SAR data processing platforms (Bonì et al., 2020). This considerable data sources and a wide variety of processing methods highlight the unique advantages and significant potential application of the InSAR technology in monitoring surface deformation arising from erosion.

The Yuanmou dry-hot valley has been confirmed as a distinctive geographical unit in China's southwestern mountainous region. It serves as a vital area for agricultural development for its high heat and ample sunlight (Duan et al., 2016). However, this region is also subjected to several challenges (e.g., extreme high temperatures, drought, uneven rainfall, low FVC, and fragile ecological environment). It is noteworthy that dry-red soil in the region, which is characterized by high clay content, poor soil structure, and weak water-holding capacity, displays a widespread distribution. As a result, the soil turns out to be highly susceptible to erosion. As a result, the Yuanmou dry-hot valley has become a typical area of severe soil and water loss in the southwestern mountainous region of China (Chen et al., 2015; Ding et al., 2017). Since 2010, local farmers in Yuanmou County have spontaneously organized the construction of flat ditches for orchard planting, integrating soil and water loss control, land development, and

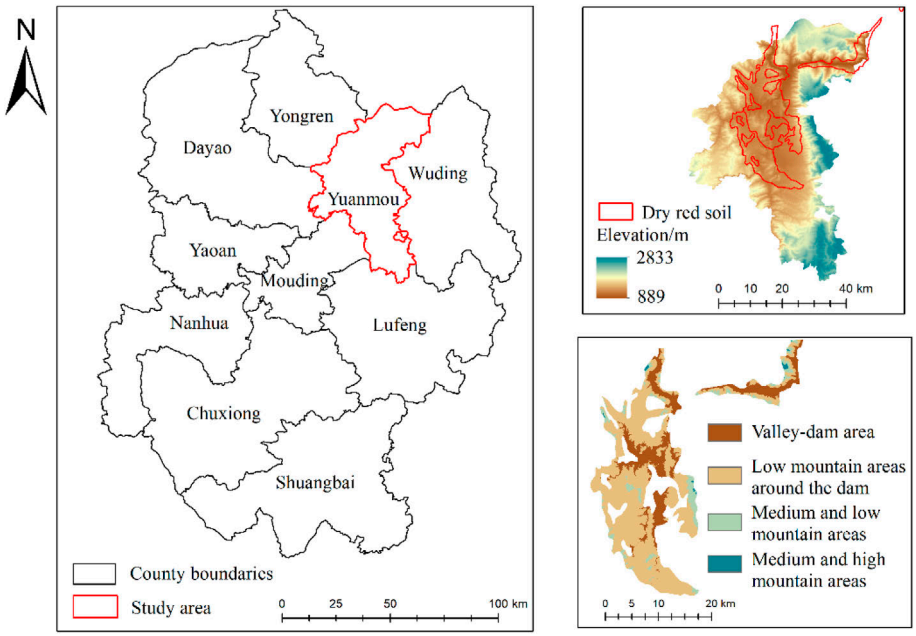

FIGURE 1
Location of the study area.

fruit garden establishment (Lin et al., 2020). The cultivated land area and land use benefits in Yuanmou County have been notably increased over the past decade. However, increasingly pronounced conflicts between human and environmental needs have been triggered with the growth of the local population, the advancement of flat ditch projects, and intensified human activities. This has led to reduced FVC, coupled with the unique climatic influences of the area, contributing to the escalating level of soil erosion in the Yuanmou dry-hot valley. In the 21st century, both national and local governments have enacted a wide variety of policies to promote soil and water loss control, consistently emphasizing its importance. Accordingly, conducting research on the correlation between soil erosion of dry-red soil at different altitudinal gradients and variations in rainfall and FVC in the Yuanmou dry-hot valley takes on critical significance in regional sustainable development and soil and water conservation efforts.

In brief, given the sophisticated relationship between soil erosion and variations in rainfall and FVC, this study primarily aimed at exploring the response relationship between soil erosion of dry-red soil and variations in rainfall and FVC at different altitudinal gradients in the Yuanmou dry-hot valley. First, the SBAS-InSAR technology was employed to develop the surface deformation information of dry-red soil at different altitudinal gradients in the Yuanmou dry-hot valley between March 2018 and October 2022. Subsequently, the time series of FVC in the identical period was determined on the Google Earth Engine (GEE) platform. Lastly, with the aim of distinguishing the contributions of rainfall and FVC to soil erosion of dry-red soil at different altitudinal gradients in the Yuanmou dry-hot valley, a comprehensive analysis was conducted by combining the dry-red soil deformation information, FVC, and rainfall data. The ultimate objective of this study was to lay a scientific basis for soil and water loss control and ecological restoration efforts in Yuanmou and even the entire dry-hot valley region.

2 Study area and data overview

2.1 Study area

2.1.1 Geographic location and topography

In this study, the focus was placed on the Yuanmou dry-hot valley as the research area (Figure 1). The Yuanmou dry-hot valley is located in the Chuxiong Yi Autonomous Prefecture of Yunnan Province, China (25°25′–26°07′N, 101°35′–102°05′E), along the lower reaches of the Longchuan River, i.e., a major tributary of the Jinsha River (Deng et al., 2015). The valley covers a total area of approximately 2021.46 km^2. The overall altitude ranges from 889 to 2,833 m, with a relative difference of 1,944 m. Due to the above-mentioned notable altitude difference, different landform types (e.g., river valleys, hills, and plateaus) have developed in the area (Ou et al., 2018). Moreover, landforms in the region displays a distinct vertical distribution, such that the entire Yuanmou dry-hot valley has been divided into four vertical zones (Table 1); (Li, 2021).

2.1.2 Rainfall and soil characteristics

The Yuanmou dry-hot valley is subjected to distinct wet and dry seasons, with an average annual temperature of 22°C and extreme temperatures reaching over 40°C. The average annual rainfall reaches 634 mm, with approximately 90% of rainfall occurring in the rainy season from May to October (B. Zhang et al., 2018). The average annual potential evapotranspiration is around 6 times the rainfall amount (Dong et al., 2013). The soils in the area have been classified into nine soil orders, 14 suborders, 25 great groups, as

TABLE 1 Vertical area division of Yuanmou dry-hot valley.

Altitude/m	H<1,100	1,100<H<1,350	1,350<H<1,600	H>1,600
Area name	Valley-dam area	Low mountain areas around the dam	Medium and low mountain areas	Medium and high mountain areas

well as 51 soil species. The most prevalent among these divisions is dry-red soil with high clay content. To be specific, dry-red soil is typically red or reddish-orange in color, characterized by poor soil structure, weak water-holding capacity, low nutrient content. Furthermore, it is highly susceptible to erosion, leading to soil and water loss (Peng et al., 2013).

2.1.3 Vegetation characteristics

The natural vegetation in the Yuanmou dry-hot valley is primarily characterized by sparse shrubs and grasses, with a few shrubs and trees, which can be broadly divided into three layers (i.e., trees, shrubs, and grasses). The above-mentioned vegetation composition has adapted to the extreme natural conditions of the dry-hot valley in the long term. The plant communities in this area exhibit several traits (e.g., small stature, thorny surfaces, as well as well-developed root systems) (Du et al., 2022). The surface of the Yuanmou dry-hot valley is highly susceptible to erosion and damage since this valley region has the unique geographical environment and soil hydrological conditions, such that it is challenging to carry out ecological restoration in this region. As a result, the Yuanmou dry-hot valley has become a relatively typical area of severe soil and water loss in the upper reaches of the Yangtze River.

2.2 Data introduction

The main data employed in this study are elucidated in the following: ① C-band Sentinel-1A radar images downloaded freely from the European Space Agency (ESA). The above-mentioned images were in Interferometric Wide (IW) mode and Single Look Complex (SLC) format. The time span covered March 2018 to October 2022, with a swath width of 250 km. The polarization was VV, and the spatial resolution reached 5 m × 20 m. The above-described images were employed to determine the time series of surface deformation information regarding land erosion in the research area. They can be accessed online at https://search.asf.alaska.edu/#/. ② Sentinel-2 data: The Sentinel-2 satellite series comprised high-resolution multispectral imaging satellites equipped with the Multispectral Imager (MSI). The above-mentioned satellites flew at an altitude of 786 km, covering 13 spectral bands with a swath width of nearly 290 km. Level-2A products were adopted in this study, especially including the red, green, blue, and near-infrared bands, to determine the FVC in the research area. The above-described data can be accessed and downloaded from https://scihub.copernicus.eu/. ③ Precise Orbit Determination (POD) ephemeris data from the Copernicus Sentinels POD Data Hub to increase the satellite orbit accuracy, https://scihub.copernicus.eu/gnss/#/home. ④ 30-m resolution Digital Elevation Model (DEM) provided by JAXA ALOS WORLD 3D (https://www.eorc.jaxa.jp/ALOS/en/aw3d30/data/index.htm) to remove terrain phase effects from Sentinel-1A data processing. ⑤ Google Earth satellite images were utilized for high-resolution imagery comparison and analysis with InSAR results. The above-mentioned images can be accessed through http://www.google.cn/intl/zh-CN/earth/. ⑥ Monthly average rainfall data for Yuanmou County, which can be obtained from the China Meteorological Data Service Center: https://data.cma.cn/. Table 2 lists the detailed data descriptions.

3 Research methods and data processing

Figure 2 illustrates the overall technical method of this study. The primary technical processes are elucidated as follows: 1) Processing Sentinel-1A data using the SBAS-InSAR technology; 2) Calculating FVC on the Google Earth Engine (GEE) platform.

3.1 Information acquisition of surface erosion deformation in Yuanmou dry-hot valley

The SBAS-InSAR technology, proposed by Berardino and Lanari based on differential InSAR, refers to a time-series InSAR method (Berardino et al., 2002; Ma et al., 2023). This technology is capable of reducing phase noise and errors by constraining multiple small baseline subsets based on time and spatial baseline thresholds, which can be adopted to retrieve surface deformation information from centimeters to millimeters. Compared with conventional D-InSAR technologies, the SBAS-InSAR technology exhibits a higher temporal sampling rate, which can be used to perform long-term time-series observations and extract non-linear ground deformation information (Chen et al., 2021). Compared with PS-InSAR technologies, the SBAS-InSAR technology is not required to consider temporal and spatial baselines or select master images, and it raises less rigorous requirements for the number of images (Osmanoğlu et al., 2016).

It is assumed that $N+1$ SAR images are acquired for the identical study area, one of these images was selected as the master image, and the others were co-registered to this master image. Under the combination conditions, a range of interferometric pairs M can be expressed as Eq. 1 (Tizzani et al., 2007):

$$\left[\frac{(N+1)}{2} \le M \le \frac{N(N+1)}{2}\right] \tag{1}$$

For the $j(j = 1, 2, \ldots, N+1)$ differential interferogram generated from the two images at time instances TA and TB ($TA<TB$), the interferometric phase of the pixel in the azimuth coordinate x and range coordinate y is written as Eq. 2

$$\Delta\varphi_j(x,y) = \Delta\varphi_{T_B}(x,y) - \Delta\varphi_{T_A}(x,y) \approx \Delta\varphi_j^{def} + \Delta\varphi_j^{topo} + \Delta\varphi_j^{atm} + \Delta\varphi_j^{noise} \tag{2}$$

TABLE 2 Data introduction.

Data name	Orbit	Time span	Incident angle/°	Scale/m	Source
Sentinel-1	Ascending	2018.03–2022.10	34.17	5 × 20	European Space Agency
Sentinel-1	Descending	2018.03–2022.10	39.62	5 × 20	European Space Agency
Sentinel-2	—	2018.03–2022.10	—	10	European Space Agency
Copernicus Sentinels POD Data Hub	—	2018.03–2022.10	—	—	European Space Agency
DEM	—	2020	—	30	JAPA
Google Satellite Imaging	—	2018.03–2022.10	—	0.2	Google Earth
Monthly average rainfall in Yuanmou County	—	2018.03–2022.10	—	—	China Meteorological Data Service Center

Where $\Delta\varphi_j^{def}$ denotes the cumulative shape variable of the radar line of sight direction; $\Delta\varphi_j^{topo}$ represents the residual terrain phase in the differential interferogram; $\Delta\varphi_j^{atm}$ expresses the atmospheric delay phase; and $\Delta\varphi_j^{noise}$ denotes the decoherent noise.

With the aim of obtaining a settlement sequence with physical significance, the product of the average phase velocity and time between two acquisition times is defined as Eq. 3

$$v_j = \frac{\varphi_j - \varphi_{j-1}}{T_j - T_{j-1}} \tag{3}$$

The phase value of the j interferogram is defined as Eq. 4

$$\sum_{p=T_{A,j+1}}^{T_{B,j}} \left(T_p - T_{p-1}\right) v_p = \Delta\varphi_j \tag{4}$$

The integral of the speed between the master and slave images in the respective time period is rewritten into an $M \times N$ as Eq. 5

$$Bv = \Delta\varphi \tag{5}$$

Matrix B will be prone to rank defects since a multi main image strategy is applied in differential interferograms of SBAS-InSAR technology. Thus, singular value decomposition (SVD) can be adopted to develop the generalized inverse matrix of matrix B. On that basis, the minimum norm solution of the velocity vector can be yielded. Lastly, the shape variables of the respective time period can be derived (Cigna et al., 2021; Su et al., 2022) by integrating the velocity in each time period.

The SBAS-InSAR technology was employed to process Sentinel-1A data for ascending and descending orbits in the study area. First, the precise orbit determination ephemeris of the Copernican Sentinel-1A satellite was adopted to correct its orbital parameters, as an attempt to reduce the effect exerted by orbital errors on the interference phase. Subsequently, the maximum percentage of critical baseline and the maximum time baseline thresholds were set to 5% and 36days, respectively. The multi aspect ratio was set to 1:4, such that speckle noise can be effectively suppressed. Minimum Cost Flow unwrapping and Goldstein filtering were applied to interference workflow processing, the interference maps were generated, and pairs with unsatisfactory interference effects were eliminated. Moreover, deformation inversion was performed using the least squares method and the singular value decomposition method. Lastly, the radar line of sight (LOS) deformation information under the ascending and descending orbits in the research area was yielded after geocoding.

Since radar side imaging exhibits the inherent characteristics, imaging was recorded following the order of ground object reflection information in the distance direction, and even small variations in altitude can trigger considerable distortion. The above-described inducing factors comprised perspective shrinkage, overlap, and shadows (Dun et al., 2021; Guo et al., 2021), (Figure 3).

To ensure the accuracy of InSAR deformation monitoring, based on the local incidence angle θ of the satellite and the incident angle α of the radar line of sight, the Layer and Shadow Map (LSM) algorithm and R-index were used to identify the geometric distortion of radar visibility in the study area, as shown in Figure 4. The correlation between the local incident angle of the satellite and the incident angle of the radar line of sight

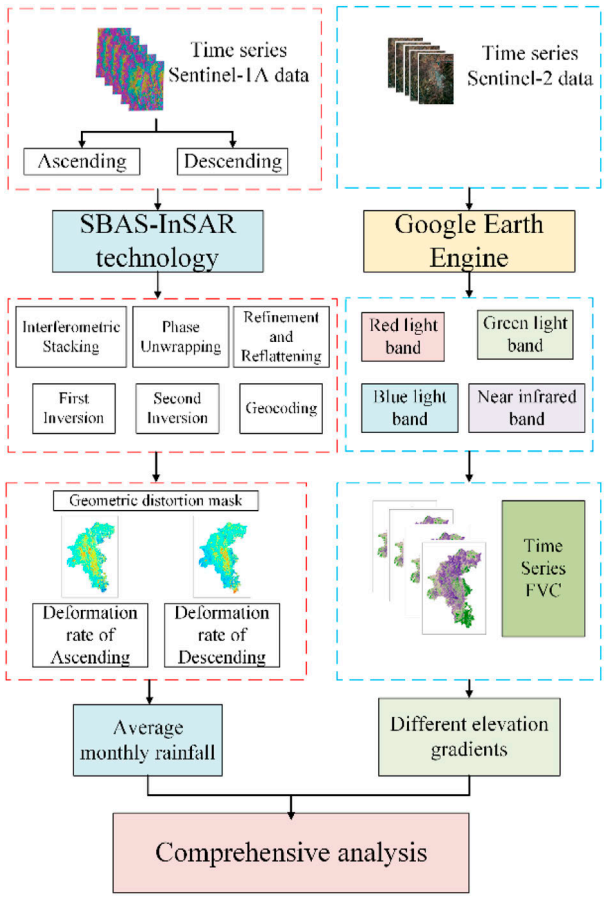

FIGURE 2
Technical roadmap.

is as Eq. 6

$$\begin{cases} 0° \le \theta \le 90° and\ \theta - \alpha < 0°, Foreshortening \\ \theta < 0°, Layover \\ \theta > 90°, Shadow \\ 0° \le \theta \le 90° and\ \theta - \alpha > 0°, Good\ visibility \end{cases} \quad (6)$$

As depicted in Figure 4, both ascending and descending orbit data displayed certain geometric distortions. Ascending orbit data mainly exerted layover effects, while descending orbit data displayed shadows predominantly. As indicated by the result, certain geometric distortions were inevitable during InSAR data processing in the complex geological conditions of the Yuanmou dry-hot valley region, due to the effect of radar satellite characteristics and the terrain morphology of the study area. Accordingly, prior to analyzing InSAR results, masking should be applied to the identified shadow and layover areas, as shown in Figure 5. This method can retain the valid InSAR observation areas and use a combined ascending and descending orbit method for comprehensive deformation analysis, thus ensuring the accuracy of land surface erosion and deformation monitoring.

Due to the lack of on-site monitoring data in the identical period, the InSAR results were validated using cross validation of the ascending and descending orbit deformation rates. The LOS deformation rate of the descending orbit data in the study area was taken as the *X*-axis, and the LOS deformation rate of the ascending orbit data was taken as the *Y*-axis. A scatter density map was drawn for a total of 5,297,742 points, as shown in Figure 6. The correlation coefficient R = 0.55 between the LOS deformation rate at the same point of the ascent and descent data, and most of the deformation rate values at the same point are not significantly different, suggesting a high correlation between the monitoring results of the two data in the study area, proving the feasibility of joint analysis of ascent and descent data.

3.2 FVC extraction based on pixel dichotomy method

Vegetation has been reported as an indispensable component of the geographical environment, and it takes on critical significance in the ecological system (Prach et al., 2001). Moreover, it is vital for surface energy exchange and the global water cycle. Vegetation is endowed with a crucial function of protecting against soil erosion, whereas soil erosion hinders vegetation from growing and developing. In general, FVC has been defined as the percentage of the vertical projected area of vegetation (e.g., leaves, stems, and branches) on the ground to the total study area. Moreover, FVC can represent the growth trend of vegetation to a certain extent, and it has been extensively employed in research regarding climate, hydrology, and soil (Zhang et al., 2019; Gao et al., 2020).

The pixel dichotomy model was presented as a linear model by Adams, Smith, and Johnson for the first time (Adams et al., 1986). The fundamental idea of this model aims at progressively approaching the roots of equations by repeatedly narrowing the interval where the potential root lies. It is assumed that the surface information of a pixel only comprises vegetation and soil, such that the proportion of vegetation information in the pixel is expressed as Eq. 7 (Li et al., 2014; Yang et al., 2023):

$$FVC = \frac{(S - S_{soil})}{(S_{veg} - S_{soil})} \quad (7)$$

Where S denotes a single pixel; S_{soil} represents soil information; and S_{veg} expresses vegetation information.

The Normalized Difference Vegetation Index (NDVI) is effective in representing vegetation status. Thus, with NDVI as a single pixel information, setting NDVIsoil as a pixel cumulative NDVI value of approximately 2% (i.e., soil information content), and adopting NDVIveg as a pixel cumulative NDVI value of 98% (i.e., vegetation information content), Eq. 7 is rewritten as Eq. 8:

$$FVC = \begin{cases} 0, NDVI \le NDVI_{soil} \\ \dfrac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}}, NDVI_{soil} \le NDVI \le NDVI_{veg} \\ 1, NDVI \ge NDVI_{veg} \end{cases} \quad (8)$$

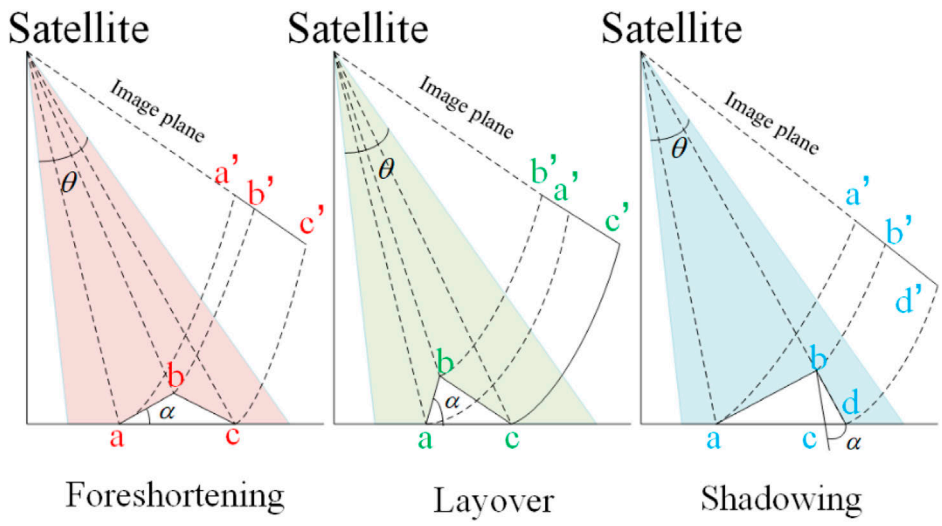

FIGURE 3
Geometric distortion of radar imaging.

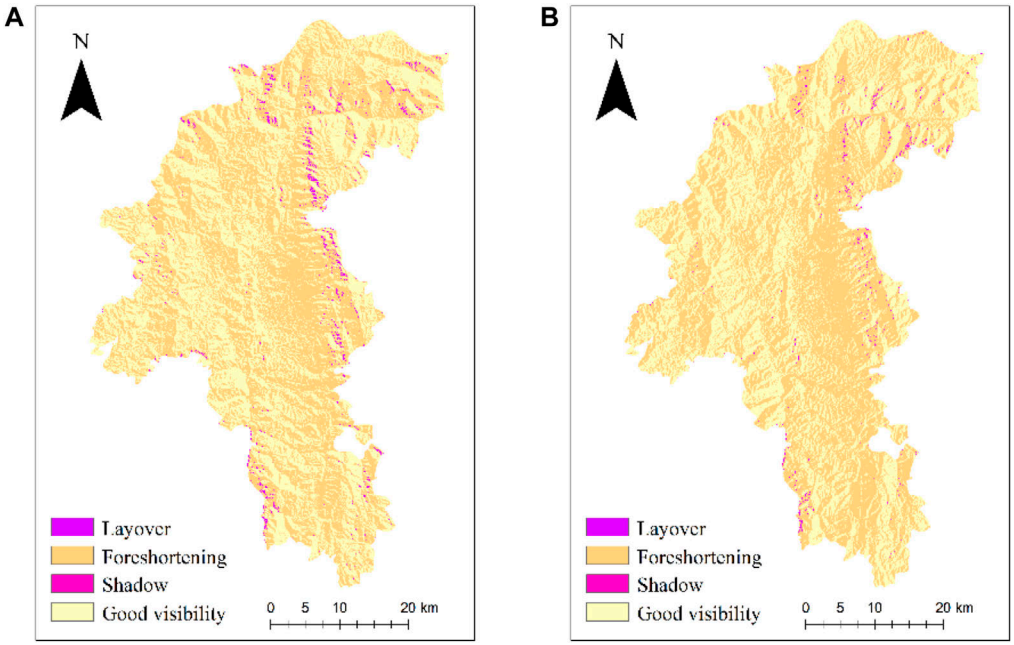

FIGURE 4
Analysis of radar visibility in the study area, **(A)** is the result of ascending, **(B)** is the result of descending.

The normalized difference vegetation index (NDVI) for the study area was calculated monthly on the Google Earth Engine platform, using Sentinel-2 optical remote sensing images from March 2018 to October 2022. Subsequently, the time series FVC for the study area was computed in accordance with the pixel dichotomy model principle. Figure 7 illustrates a portion of the FVC for the study area.

4 Result and analysis

4.1 Analysis of spatial characteristics of surface erosion deformation

Figure 8 presents the radar line of sight (LOS) surface deformation information of dry-red soil of the Yuanmou dry-hot

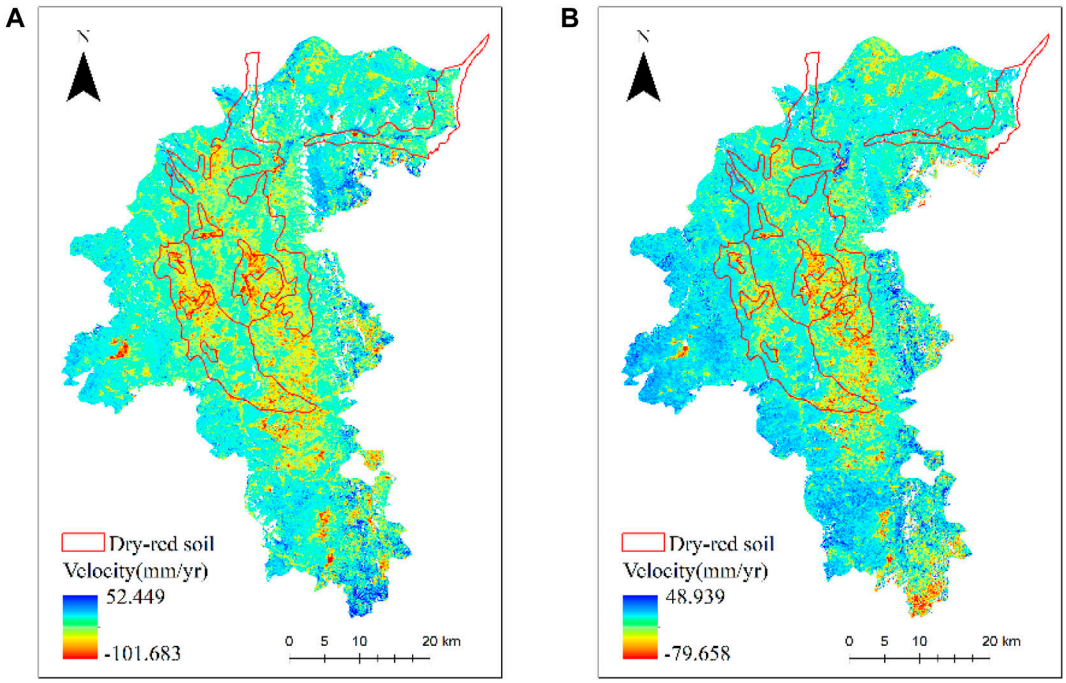

FIGURE 5
Deformation rate of the study area after mask processing, **(A)** is the result of ascending, **(B)** is the result of descending.

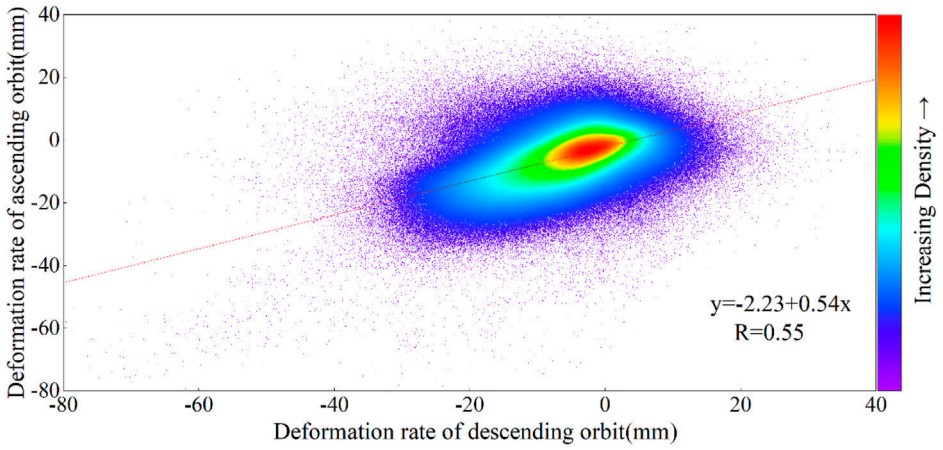

FIGURE 6
Scatter density map of points with the same name for ascending and descending.

valley, obtained using the SBAS-InSAR technology from March 2018 to October 2022. The overall deformation rate for the ascending orbit data ranged from −101.683 mm/yr to 30.570 mm/yr; for the descending orbit data, it ranges from −79.658 mm/yr to 41.942 mm/yr. It's important to note that InSAR results represent true surface deformation projected onto the LOS direction. A positive deformation rate indicates uplift towards the satellite, while a negative value indicates subsidence or erosion away from the satellite. The surface deformation information obtained from the ascending and descending orbit datasets does not perfectly correspond due to the side-looking imaging geometry of the Sentinel-1A satellite and the topographic variations in the study area. The Sentinel-1A satellite's ascending orbit data is acquired with the satellite flying from south to north, with the radar LOS direction on the right side of the satellite, while for the descending orbit, the situation is reversed. Thus, for detecting surface deformation in the complex geological conditions of the dry-hot valley area, a combination of data from different orbits should be utilized to ensure more accurate acquisition of surface deformation information.

To analyze the spatial distribution characteristics displayed by surface deformation in the Yuanmou dry-hot valley, the distribution

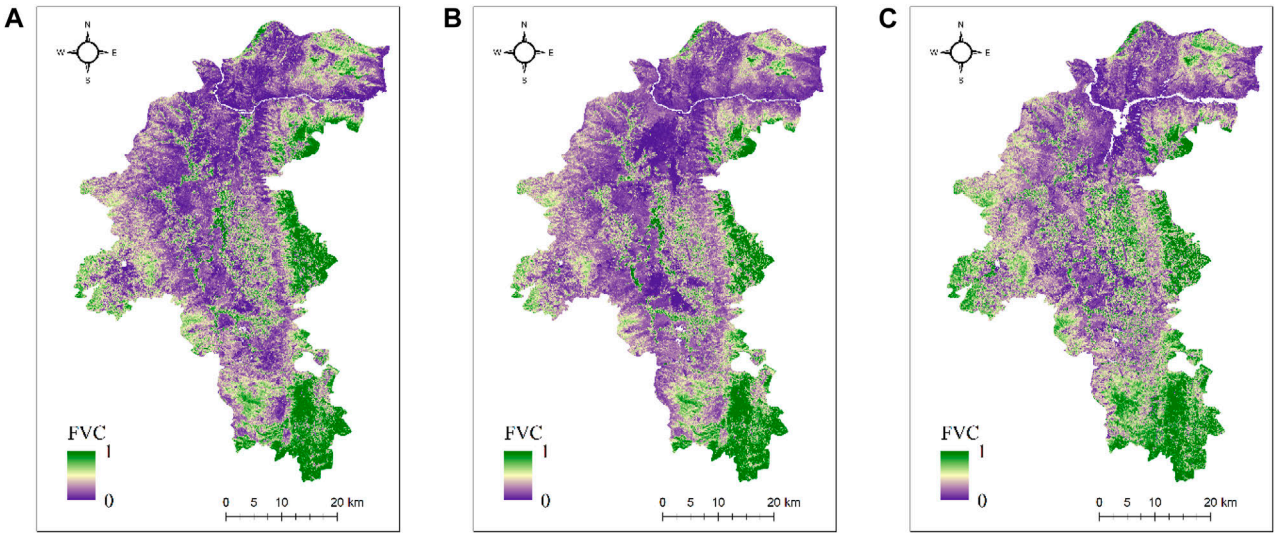

FIGURE 7
Partial FVC in the Study Area, **(A)** is the result for May 2018, **(B)** is the result for April 2020, **(C)** is the result for January 2022.

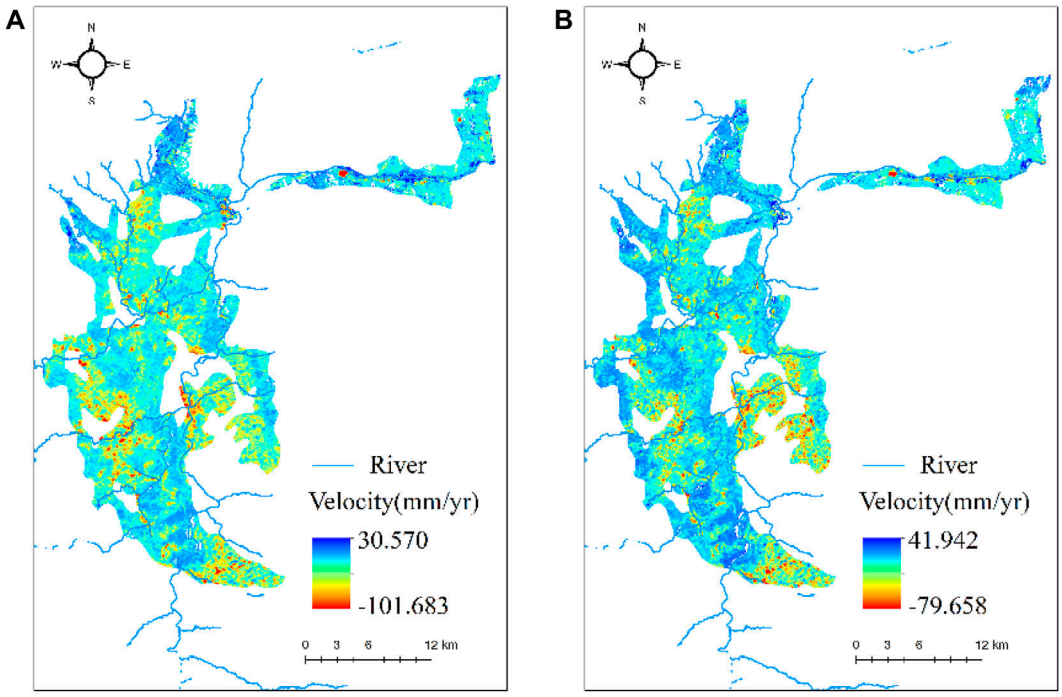

FIGURE 8
Surface deformation information of dry-red soil, **(A)** is the result of ascending, **(B)** is the result of descending.

of water systems in the study area was overlaid with the ascending and descending orbit deformation information (Figure 8). As depicted in Figure 8, the deformation features of the ascending and descending orbit data can be generally correlated spatially. In the region of dry-red soil distribution in the Yuanmou dry-hot valley, areas of surface uplift are mainly located in the northern Wudongde hydropower station reservoir area and the central region. The possible reason for this is the Wudongde hydropower station, situated at the border of Luliang County in Yunnan Province and Huidong County in Sichuan Province, which began reservoir filling at the end of 2019. Due to the larger particle size and loose structure of the dry-red soil, it can quickly absorb and store considerable water. Soil absorption and swelling can cause mountain uplift. When uplift reaches a critical threshold, the possibility of reservoir bank landslide disasters is significantly high. Thus, this area should be a focal point of observation in subsequent research.

TABLE 3 The average gradient of four different elevations.

Area name	Valley-dam area	Low mountain areas around the dam	Medium and low mountain areas	Medium and high mountain areas
Slope/°	12.33	13.80	20.93	21.79

Erosion-prone areas are primarily situated along the southern side of riverbanks and at the confluence of rivers. Yuanmou County is traversed by the Longchuan River from south to north, carrying away substantial sediment, sand, and gravel when flowing through. The water-absorbing and swelling nature of dry-red soil makes it more susceptible to erosion from river scouring, particularly at the confluence of rivers where the flow rate and velocity increase. Vortices and whirlpools can be formed sometimes, exerting a greater effect on the soil on the banks, thus enhancing the erosive capacity of the water on the soil.

4.2 Analysis of typical erosion deformation areas and characteristic points

In the four altitudinal gradients where dry-red soil is distributed, representative areas of erosion deformation were selected from both ascending and descending orbit data. Among these, A-D represent the selected typical erosion deformation areas from the ascending orbit data, while E-H represent those from the descending orbit data. It is worth noting that the main objective of this study is to explore the correlation between dry-red soil erosion at different altitudinal gradients in the Yuanmou dry-hot valley and its response to rainfall and FVC in its natural state. To eliminate the effect of non-natural factors such as human activities on soil erosion, the selection of typical erosion deformation areas attempts to avoid human-activity areas (e.g., farmlands and urban regions) as much as possible. Furthermore, a synchronous comparative analysis of surface deformation information from both ascending and descending orbits was employed for mutual validation (Figures 9, 10). The deformation rate monitoring points from the selected typical erosion deformation areas were overlaid with high-resolution optical images (Figures 11, 12).

To further analyze the response relationship between dry-red soil erosion at different altitudinal gradients in the Yuanmou dry-hot valley and rainfall and FVC, characteristic deformation points were selected in several typical erosion deformation areas. The above-mentioned points are numbered consistently with the typical erosion deformation areas. In conjunction with monthly average rainfall and time series FVC, time series curves of erosion deformation points from March 2018 to October 2022 were plotted, as shown in Figures 13–16. In addition, the average slope within the four altitude gradients was counted separately, and the slope factor was combined for auxiliary analysis. The statistical results are shown in Table 3.

A and E are the typical erosion deformation points of the ascending and descending orbits in the valley-dam area below 1,100 m elevation, respectively, and the maximum erosion amounts are about 80 mm. B and F are the typical deformation points of the ascending and descending orbits of the low mountain areas around

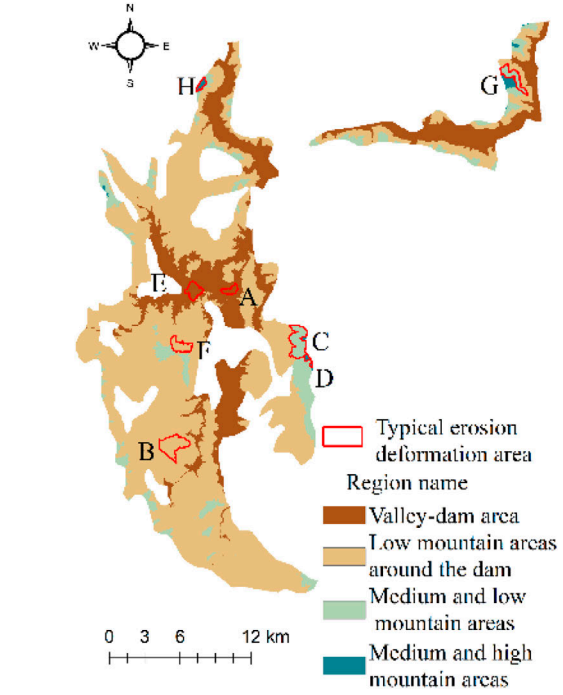

FIGURE 9
Typical erosion deformation areas at different altitudinal gradients.

the dam at elevations from 1,100 to 1,350 m, respectively. Compared with the valley-dam area, the erosion has slowed down somewhat, and the maximum amount of erosion is about 60 mm. The valley-dam area and the low mountain areas around the dam account for about 90% of the dry-red soil area in the Yuanmou dry-hot valley, and the average slope is 12.33° and 13.80°, respectively. Because the slope is slow, the sediment is less likely to be carried away by other erosion effects. The time series curve of typical erosion deformation points shows periodic changes, and the erosion and uplift amounts are roughly the same. Soil erosion intensifies during high vegetation coverage in rainy season, while soil erosion slows down during low vegetation coverage in dry season.

In general, under low FVC, the surface was mostly exposed and more susceptible to erosion and settling. When vegetation conditions were better, the soil's erosion resistance turned out to be stronger (Jacquemart and Tiampo, 2021; Yan et al., 2023). However, even during the rainy season with the higher FVC, soil erosion remained more pronounced. In contrast, in the dry season, erosion was reduced under low vegetation cover. As revealed by the above result, in the Yuanmou dry-hot valley below an altitude of 1,350 m, the response of dry-red soil erosion to rainfall became more

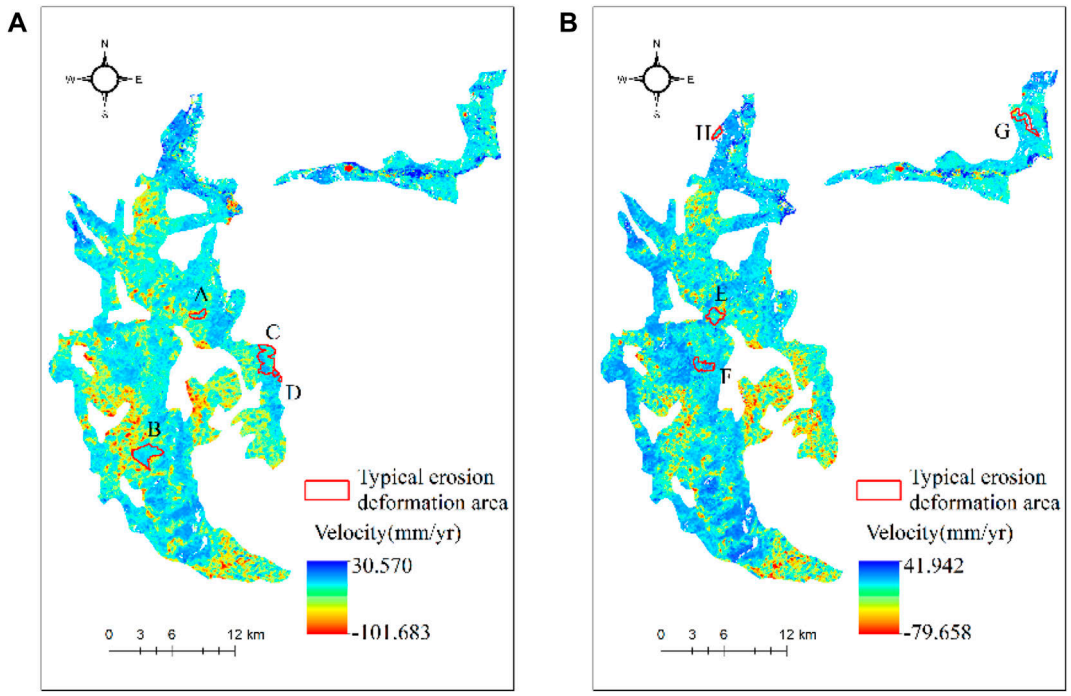

FIGURE 10
Typical erosion and deformation area for ascending and descending, **(A)** is the result of ascending, **(B)** is the result of descending.

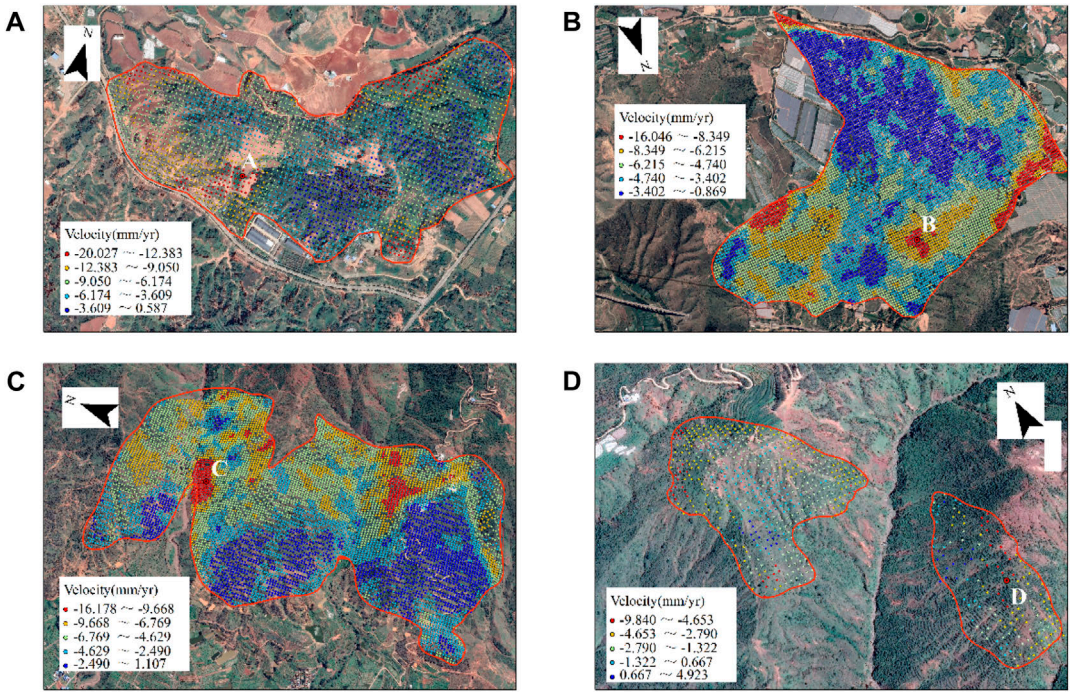

FIGURE 11
Typical erosion area deformation rate of ascending. **(A)** Typical erosion deformation zone A, **(B)** Typical erosion deformation zone B, **(C)** Typical erosion deformation zone C, **(D)** Typical erosion deformation zone D.

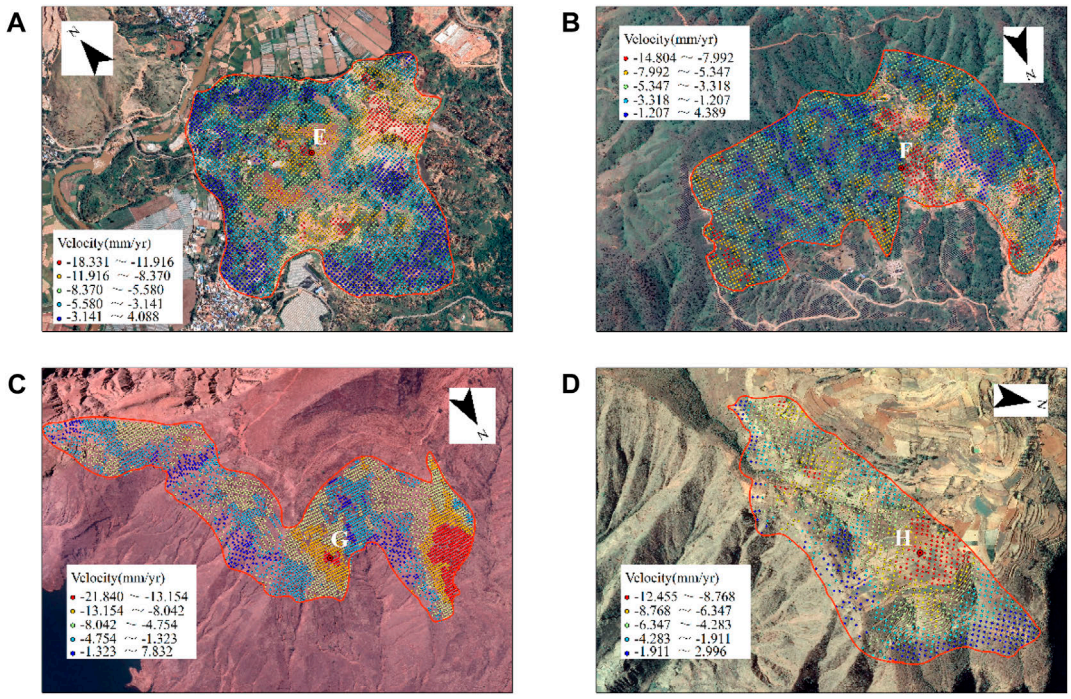

FIGURE 12
Typical erosion area deformation rate of descending. **(A)** Typical erosion deformation zone E, **(B)** Typical erosion deformation zone F, **(C)** Typical erosion deformation zone G, **(D)** Typical erosion deformation zone H.

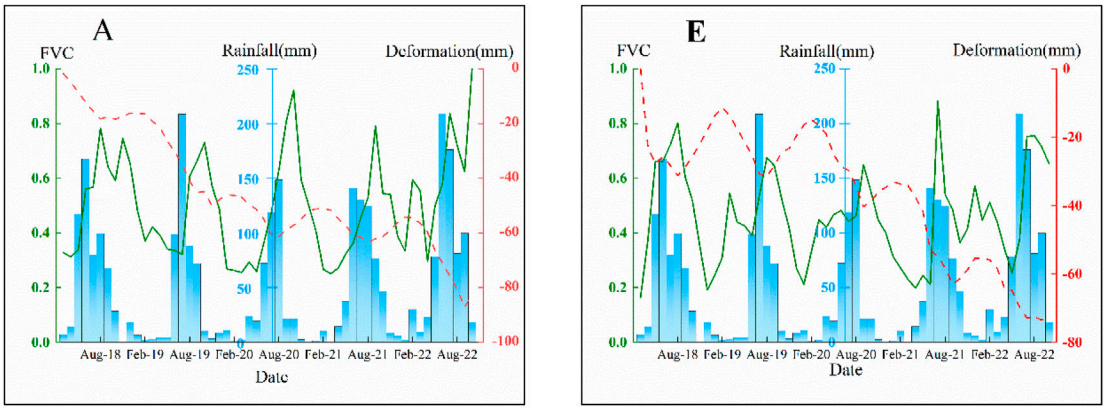

FIGURE 13
Time series curve of typical erosion deformation points in the valley-dam area. **(A)** Time series curve of typical erosion deformation point A, **(B)** Time series curve of typical erosion deformation point E.

pronounced, and vegetation cover exerted a limited effect on soil and water conservation. The reason is that vegetation below 1,350 m above sea level in Yuanmo dry-hot valley is mostly sparsely irrigated grass with short plants and underdeveloped roots. Under the action of rain, it is difficult to effectively fix soil and slow down erosion even if vegetation coverage is high. In addition, the surface temperature of the dry-hot valley is higher, especially in the low altitude area, the evapotranspiration capacity is stronger, and the soil water loss is faster. Therefore, during the dry season, the vegetation coverage decreases, and the soil water is lost under the action of strong evapotranspiration, resulting in soil expansion and surface uplift. Once continuous heavy rainfall occurs, the soil erosion amount will increase significantly.

C and G are the typical erosion deformation points of the ascending and descending orbits of the medium and low mountain areas at an altitude of 1,350–1,600 m, respectively. The medium and low mountain areas accounts for about 7% of the dry-red soil area of the Yuanmo dry-hot valley, with an average slope of 20.93°. Compared with the valley-dam area and the low mountain areas around the dam, the soil is more vulnerable to erosion due

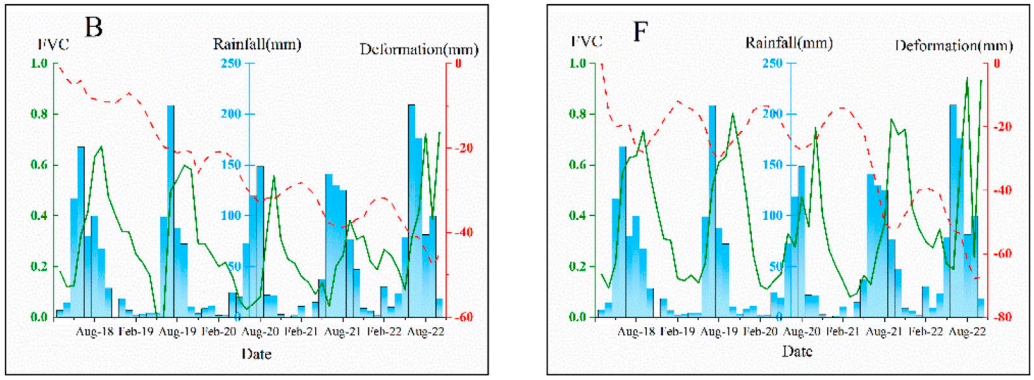

FIGURE 14
Time series curve of typical erosion deformation points in low mountain areas around the dam. **(A)** Time series curve of typical erosion deformation point B, **(B)** Time series curve of typical erosion deformation point F.

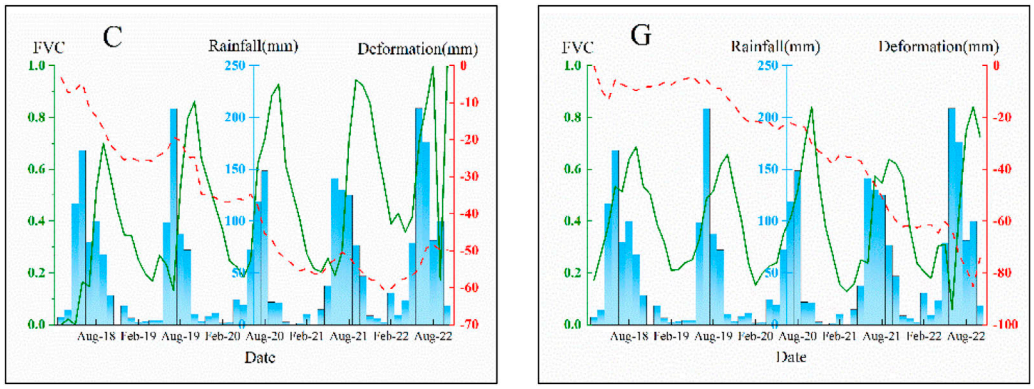

FIGURE 15
Time series curve of typical deformation points of dry-red soil in medium and low mountain areas. **(A)** Time series curve of typical erosion deformation point C, **(B)** Time series curve of typical erosion deformation point G.

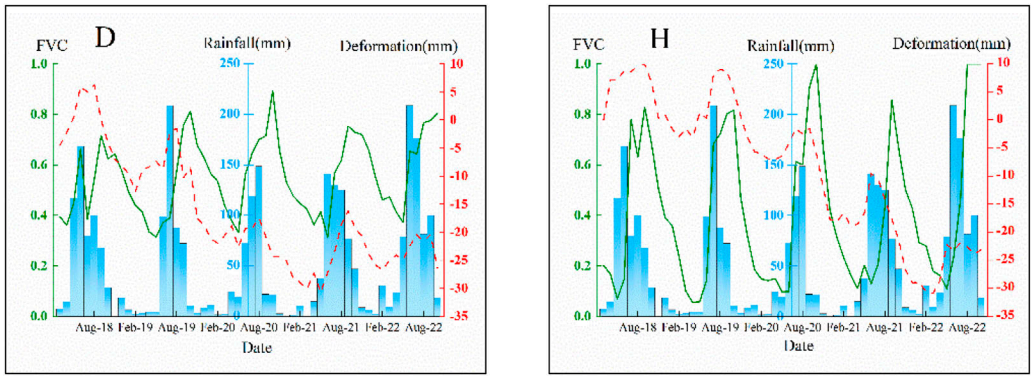

FIGURE 16
Time series curve of typical deformation points of dry-red soil in medium and high mountain areas. **(A)** Time series curve of typical erosion deformation point D, **(B)** Time series curve of typical erosion deformation point H.

to the increase of slope. The time series curve of typical erosion deformation points shows a continuous and oscillating decline. During the high vegetation coverage in rainy season, soil erosion slows down, while during the low vegetation coverage in dry season, soil erosion intensifies. It shows that vegetation coverage change is the main factor affecting soil erosion of dry-red soil in the medium and low mountain areas of Yuanmou dry-hot valley. The reason is that some evergreen broad-leaved forests with large plants begin to appear in the area above 1,350 m above sea level in Yuanmo dry-hot Valley. Vegetation develops during the rainy season with high vegetation coverage, and leaves play a certain role in intercepting the precipitation and slowing down soil erosion. During the dry season, the vegetation coverage decreases, and the water in the soil is lost under the action of evapotranspiration, resulting in the soil becoming loose. In the absence of vegetation protection, the soil is more difficult to resist the impact of external forces such as wind and water flow, and the erosion is intensified. Although vegetation slowed down soil erosion in the medium and low mountain areas to a certain extent, soil erosion increased year by year due to the steep slope in this area.

D and H are typical deformation points in the ascending and descending orbits of medium and high mountain areas with elevations above 1,600 m. These areas account for only 3% of the Yuanmou dry-hot valley with dry-red soil regions. With an average slope of 21.79°, they are the areas with the weakest soil erosion among the four elevation gradients. The time series curve of typical erosion deformation points shows a periodic continuous decline. During the rainy season, when vegetation coverage is high, soil erosion slows down, while during the dry season, when vegetation coverage is low, soil erosion intensifies. Similar to the medium and low mountain areas, soil erosion in the medium and high mountain areas of the Yuanmou dry-hot valley is mainly influenced by vegetation coverage. During the rainy season, with higher vegetation coverage, soil erosion is weaker, but during the dry season, soil erosion worsens due to reduced vegetation coverage. With the steepest slopes, overall, soil erosion increases year by year.

In this altitude range, besides evergreen broad-leaved forests, there were also some larger plant species of subtropical coniferous forests (e.g., pine and fir trees). Coniferous trees have well-developed root systems that penetrate deep into the soil, stabilizing soil structure and reducing soil loosening and collapse. Compared with broad-leaved forests, the needle-like leaves and branch structure of coniferous trees are more effective in intercepting rainfall, preventing direct contact of rainwater with the ground, and reducing water impact. As a result, the water flow velocity can be reduced. Furthermore, due to the higher altitude, surface temperature and evapotranspiration are relatively weaker compared with lower altitudes. Therefore, even in the dry season with low vegetation coverage, soil erosion is much less compared to the medium and low mountain areas.

5 Discussion

5.1 InSAR result analysis

In this study, the response relationship between dry-red soil erosion and rainfall and FVC was investigated using remote sensing techniques at different altitudinal gradients in the Yuanmou dry-hot valley. This study aimed at differentiating the contributions of rainfall and FVC to dry-red soil erosion in different altitudinal gradients. Accordingly, the accuracy and reliability of erosion deformation monitoring results using InSAR technology can directly affect the accuracy of this study. Given the lack of simultaneous ground measurement data, a cross-validation method using ascending and descending orbit datasets was adopted to validate the InSAR results. A comparison was drawn with InSAR results obtained by other researchers in the identical region (Peng, 2022) to further verify the accuracy of the InSAR results in this study, and the main differences are listed in Table 4. As depicted in the table, the InSAR results in this study were consistent in magnitude with previous research findings. Moreover, the error distribution curve was generated for the 5,297,742 co-located deformation points from ascending and descending orbit data in the study area (Figure 17). The measurement errors for ascending and descending data were primarily distributed between -5 mm and 5 mm, with a maximum error not exceeding 15 mm. The distribution conformed to a normal distribution curve, and the probability density of errors exceeding 5 mm was below 0.05. Furthermore, the dry-red soil erosion deformation patterns detected by ascending and descending data in the four different altitudinal gradients correspond to each other, with similar erosion rates, thus verifying the accuracy and effectiveness of the results in this study.

5.2 Analysis of the response relationship between dry-red soil erosion and rainfall and fractional vegetation cover in Yuanmou dry-hot valley

In this study, we employed SBAS-InSAR technology to investigate the relationship between soil erosion of dry-red soil and precipitation and vegetation coverage gradients in the Yuanmou dry-hot valley. Due to the unique geographical and climatic conditions of the Yuanmou dry-hot valley, different types of vegetation develop within different altitude gradients, exerting varying degrees of inhibition and protection against soil erosion of dry-red soil. Below an altitude of 1,350 m, the vegetation consists mainly of sparse shrubs and grasses. Even with relatively high vegetation coverage, it is difficult to effectively prevent soil erosion, with rainfall being the primary factor influencing erosion of dry-red soil—the greater the rainfall, the more severe the soil erosion. Above 1,350 m, larger vegetation begins to develop. When vegetation coverage is high, it effectively slows down soil erosion. Changes in vegetation coverage are the primary factor affecting soil erosion of dry-red soil—increased vegetation coverage leads to reduced soil erosion.

To further analyze the response relationship between dry-red soil erosion and rainfall and FVC in the Yuanmou dry-hot valley, our research results were compared with published similar studies, and the contributions and limitations of our study to existing research were summarized. SUN(Sun et al., 2013), in a study of the contribution of rainfall and vegetation cover to soil erosion in the Loess Plateau, suggested that variations in vegetation cover contribute more to soil erosion than rainfall. SUN's research covered the Loess Plateau as a whole, suggesting that in most

TABLE 4 Comparative study differences.

Comparative study	PENG (2022)	This study
Study area	Yuanmou dry-hot valley	Yuanmou dry-hot valley
Data type	Sentinel-1	Sentinel-1
Orbit type	Ascending and descending	Ascending and descending
Time span	2017.03–2021.10	2018.03–2022.10
Result of ascending (mm/yr)	−104.1-50.09	−101.449-52.449
Result of descending (mm/yr)	−66.04-44.98	−79.658-48.939

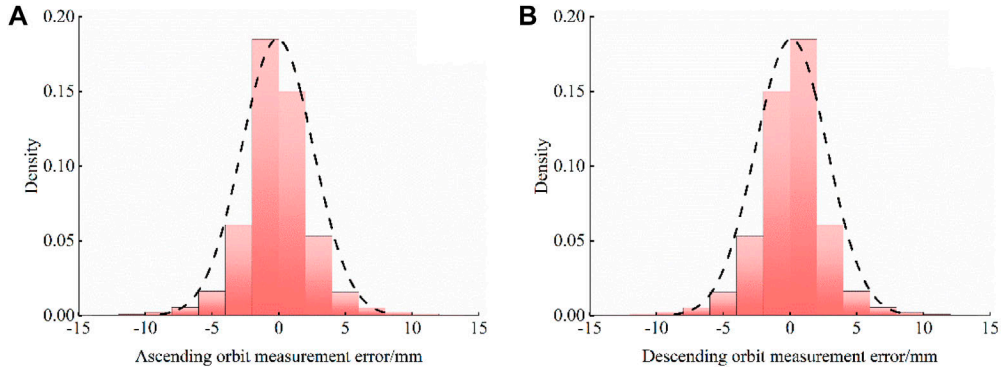

FIGURE 17
Measurement error of orbit ascending and descending data, **(A)** is the result of ascending, **(B)** is the result of descending.



FIGURE 18
Field survey photos.

areas of the Loess Plateau, variations in vegetation cover more signficiantly affected soil erosion than rainfall. In contrast, this study focused on different altitudinal gradients in the Yuanmou dry-hot valley, providing a more detailed spatial differentiation of the contributions of rainfall and vegetation cover to dry-red soil erosion. XU (Xu et al., 2019), in a study of Chen Town in Sanming City, Fujian Province, quantified the response relationship between vegetation cover and rainfall on soil erosion using a power-law regression model. XU proposed that when vegetation cover was less than 40%, and rainfall exceeded 80 mm, the risk of soil erosion increases sharply. When vegetation cover exceeded 40%, even heavy rainfall would not cause significant soil loss. In contrast, the contributions of vegetation cover and rainfall to soil erosion was only spatially differentiated, without further quantifying the relationships among the three factors. Exploring the quantitative relationship between rainfall, vegetation cover, and soil erosion in

different altitudinal gradients is an important avenue for future research.

Furthermore, to further validate the accuracy of the results of this study, field investigations were carried out in the middle and low mountain areas (altitude range: 1350m–1600 m) of Yuanmou. Field photographs were taken (Figure 18). As depicted in the photographs, dry-red soil with better vegetation cover was less susceptible to erosion, whereas areas without vegetation cover formed gullies and exhibited distinct signs of soil erosion.

6 Conclusion

In this study, the response relationship between dry-red soil erosion and rainfall and FVC was explored using remote sensing techniques at different altitudinal gradients in the Yuanmou dry-hot valley to clarify the sophisticated relationship between soil erosion, rainfall, and FVC. The study aimed to distinguish the contributions of rainfall and FVC to dry-red soil erosion at different altitudinal gradients. First, the SBAS-InSAR technology was used to acquire the surface deformation rates of dry-red soil erosion in the Yuanmou dry-hot valley from March 2018 to October 2022. Subsequently, a time series of FVC for the same period was calculated and extracted using pixel-based classification in the Google Earth Engine platform. Lastly, a comprehensive analysis was conducted, combining the surface deformation rates, time series of FVC, and rainfall data, to study the patterns of dry-red soil erosion at different altitudinal gradients. The results indicate that the dry-red soil erosion patterns detected by ascending and descending data at four distinct altitudinal gradients correspond to each other, with similar erosion magnitudes. The overall dry-red soil erosion deformation rates in the Yuanmou dry-hot valley range from −101.683 mm/yr to 30.57 mm/yr (Ascending),-79.658 mm/yr to 41.942 mm/yr (Descending). Areas with severe surface erosion are concentrated in the Longchuan River basin and a wide variety of river confluence zones, while areas with surface uplift are mostly found in the central and northern parts, specifically the Wudongde hydropower station reservoir area. The study reveals a noticeable altitudinal gradient effect on dry-red soil erosion in the Yuanmou dry-hot valley. The valley-dam area and the medium and low mountain areas were subjected to the most serious soil erosion, and the maximum erosion reached over 80 mm. Erosion was mitigated in the low mountain areas around the dam, with a maximum erosion of 60 mm. The medium and high mountain areas exhibit the weakest erosion, with a maximum erosion of only 30 mm. The correlation between dry-red soil erosion, rainfall, and FVC is divided by an altitude threshold of 1,350 m. Below 1,350 m, soil erosion is more strongly influenced by rainfall, whereas above 1,350 m, variations in FVC are the primary factors affecting soil erosion.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

JG: Writing–original draft. WX: Writing–review and editing. GHu: Writing–review and editing. GHe: Methodology, Writing–review and editing. LS: Validation, Writing–review and editing. ZY: Methodology, Writing–review and editing. ZD: Software, Writing–review and editing. LW: Data curation, Writing–review and editing. RC: Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Theoretical study on the mechanism of stick-slip instability occurrence on deep coal-rock structure

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Dynamic disasters seriously threaten the safety and effectiveness in deep mining. The mechanism of stick-slip instability occurrence on the deep coal-rock structure was studied in this paper through analyzing the occurrence condition of stick-slip in the weak surface and discussing the friction constitutive of the coal-rock structure. The result indicated that the grinding slip and the soft interlayer formation occurred in weak plane in the coal-rock structure in the process of diagenesis and strata movement, which is more likely to satisfy the stick-slip condition and then trigger dynamic disaster. Based on the mechanism study of coal-rock structure failure caused by stick-slip, it is proposed that the horizontal compression pulse caused by local stick-slip in coal seam could lead the layer-crack and fly out with the broken fragments. At the same time, it is pointed out that the scattering effect of the plane compression pulse in the propagation process induces the serial sliding instability of the coal-rock structure in many places, forming a large range of dynamic disasters. By means of numerical simulation of coal bump accident in a roadway in Yima Coal Mines, the dynamic process of sliding-slip instability of coal and rock mass is inverted, and the mechanism of sliding-slip instability of coal and rock structure is verified.

KEYWORDS

dynamic disaster, coal bump, stick-slip failure, layered structure weak plane, friction constitutive

1 Introduction

Coal-rock body comprises structure bodies and structure planes, and the slip and friction of structure planes in coal-rock body are its important mechanical properties (Guang-zhi et al., 2005). In seismic research, stick-slip occurrence on the friction surface is considered a mechanism of shallow-focus earthquakes, and has been introduced by scholars into the study of coal bumps. Qi et al. (Qing-xin et al., 1995) explored the mechanism of stick-slip occurrence, and introduced the mechanism of coal bump occurrence based on the stick-slip experiment of coal-rock combination. Jiang et al. (Yao-dong et al., 2005; Yao-Dong et al., 2013) established a three-dimensional model of instability of translatory coal bumps in gateways, and designed double-sided shear tests to verify the occurrence of coal-rock structural instability type coal bump induced by

stick-slip. The structural instability was summarized into three stages, and the stick-slip phenomenon was attributed to the different dynamic and static friction coefficients. Yin et al. (Guang-zhi et al., 2005) drew on the two-state variable constitutive model to describe the dynamic and evolutionary behavior of coal bumps, thereby more accurately reflecting the stick-slip characteristics of coal bump systems. Li et al. (Hai-tao et al., 2018) proposed a clamping model of coal seam roof and floor to coal seam, and held that coal seams may accumulate much energy under high stress. When weak structure planes are disturbed, stick-slip will occur, inducing the release of energy accumulated, causing large-scale structural instability, then resulting in coal mine dynamic disasters. Yan et al. (Yong-gan et al., 2010) built a mechanical model for the occurrence of coal body stick-slip relative to the roof and floor, studied the conditions for coal body stick-slip, and obtained the dynamic equation of the coal body after the occurrence of stick-slip. Despite their breakthroughs, the studies described above have mainly focused on the block structure of coal-rock, without giving sufficient attention to either the properties of the coal-rock structure plane itself or the specific mechanisms of its impact on stick-slip. As a result, they have failed to obtain further details on the coal bump induced by stick-slip.

For this reason, by taking the properties of coal-rock structure planes and their related influencing factors as the research object, and introducing the friction constitutive equation, this paper discusses the influence of structure plane properties on stick-slip and establishes the motion equation of horizontal compression pulse that it induces, so as to obtain the mechanism of coal-rock structure failure and instability caused by it. In addition, this paper also establishes a numerical calculation model based on on-site conditions for fitting and verification, thereby restoring the process of coal mine dynamic disasters.

2 Conditions for the occurrence of stick-slip on coal-rock structure plane

2.1 Characteristics of coal-rock structure

The rock body structure controls the deformation mechanism, failure mechanism, and mechanical properties of the rock body, and is composed of structure planes and structure bodies. Specifically, various complex geological interfaces within the rock body are collectively referred to as structure planes. The coal-rock body formed by sedimentation has obvious bedding structure, and structure planes are naturally formed between coal seams and rock layers. Meanwhile, the coal-rock body is connected together through cementation and compaction during the sedimentation process, forming a cohesive coal-rock body structure.

When the coal-rock body is in its original state, it is subjected to the combined action of overlying loads and horizontal tectonic stresses. The deformation of the coal-rock body is mainly elastic compression deformation. Microelements of the coal-rock body near the structure plane are selected, and their stress is shown in Figure 1A.

In the horizontal direction, the strain at a certain point of the structure plane is simultaneously affected by both coal and rock. However, due to the high strength of the rock body, it is assumed that the displacement of the structure plane varies with the strain of the rock body. If the structure plane is ideally smooth and the coal-rock body only undergoes compression deformation (Figure 1B), the black and gray areas represent the stress deformation of the coal-rock body, and their deformation amounts are as follows:

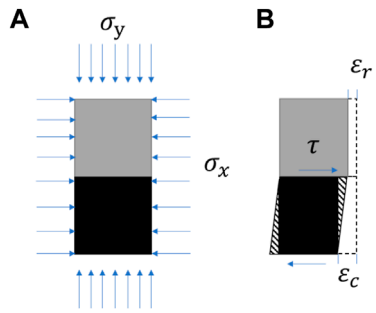

FIGURE 1
Stress analysis of structure face in the coal-rock body. **(A)** stress, **(B)** strain.

$$\begin{cases} \varepsilon_c = \sigma_x / E_c \\ \varepsilon_r = \sigma_x / E_r \end{cases} \tag{1}$$

Where $\sigma_x$is the horizontal tectonic stress; ε_c and $\varepsilon_r$are the strain of coal and rock bodies at the same point on the structure plane, respectively; and E_c and E_r are the elastic moduli of the coal and rockbodies, respectively, with a ratio of $E_r/E_c = 2 \sim 10$.

The strain of coal body can be expressed as follows:

$$\varepsilon_c = E_r/E_c * \varepsilon_r \tag{2}$$

Based on the assumption of smooth structure planes, the strain of coal body is greater than that of the rock body, and deformation incompatibility occurs between the structure planes of the coal-rock structure. However, the coal-rock body shows an apparent unity, and the displacement of the coal-rock body at the same point on the structure plane is consistent. The deformation of the coal body is shown as the sum of the black area and the dashed area in Figure 1B. It can be inferred from this that there must be a shear force (friction force) on the structure plane of the coal-rock body in the original rock state, which causes the displacement of the structure plane of the coal-rock body to be the same at the same point. As a result, shear deformation occurs in the coal body, leading to an increase in the elastic energy accumulated inside the coal body, and the stronger this constraint is, the more elastic energy accumulates. Considering the different properties of coal-rock, the coal body in the coal-rock combination has a larger deformation and thus becomes the carrier of energy storage. When the coal-rock body is excavated or disturbed, the structure plane is destroyed and unstable, and the constraint effect of the structure plane is either reduced or disappears completely. The elastic energy accumulated in the coal body will consequently be released, likely resulting in coal mine dynamic disasters. It can be seen that the key links in the formation of dynamic disasters are all directly related to the properties of structure planes. Therefore, it is necessary to study the stress situation and inherent properties of structure planes.

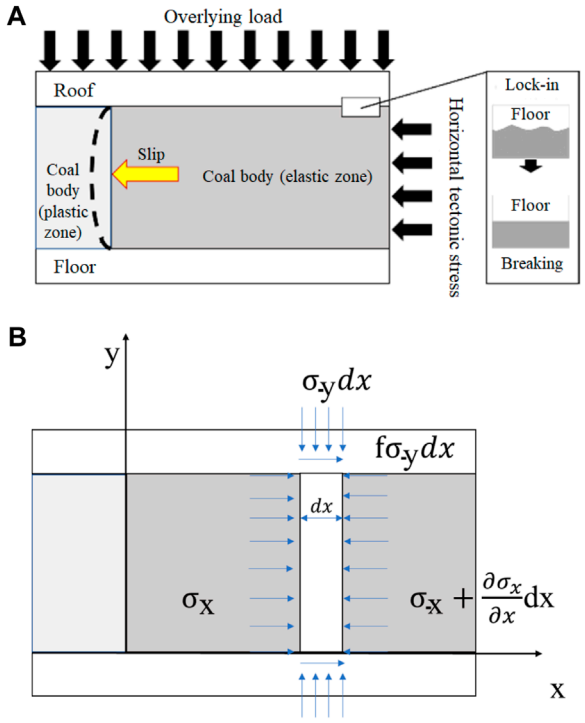

FIGURE 2
Force analyses of coal-rock slip (Yong-gan et al., 2010). **(A)** Loading, **(B)** stress state.

2.2 Stress analysis of coal-rock structure planes

In underground excavation engineering, the coal-rock body on the free face is subjected to an unloading effect, and the original stable coal-rock structure tends to slip toward the free face. From the free face to the inside, the coal body can be divided into the plastic zone and elastic zone (Yao-dong et al., 2005). As suggested in the above discussion, the stick-slip that may cause coal bump only occurs in the elastic zone (Yong-gan et al., 2010). Therefore, the interface between the elastic and plastic zones is taken as the Y-axis, with the upward side as the positive direction, while the interface between the coal seam and the floor is taken as the X-axis, with the positive direction deviating from the free face. The coal body with a length of dx in the elastic zone is taken as the research object, and the stress analysis is shown in Figure 2.

One of the most important mechanical properties of a structure plane is its shear strength, which is related to rock strength, structure plane roughness, and structure plane cohesion. According to Banton's formula, the shear strength of the coal-rock structure plane is as follows:

$$\tau = \sigma_n \left[JRC * \lg\left(\frac{JCS}{\sigma_n}\right) + \varphi_b \right] \tag{3}$$

Where JCS is the compressive strength of the structure plane; φ_b is the basic friction angle of the rock surface; and JRC is the roughness coefficient of the structure plane.

For coal-rock composite rock bodies, there are significant differences in their mechanical properties, due to differences in their diagenetic composition, cementing substances, and diagenetic environment. However, the strength and stiffness of coal body are generally less than those of the rock body, while the strength of JCS is similar to that of the coal body. The geometric shape of the structure plane of the coal-rock body is generally flat and wavy, with very few serration and step shapes, and its JRC value does not exceed 10.

On the premise of not considering the coal body failure, when the horizontal structural stress is greater than the sum of the cohesive force and static friction force of weak structure plane, the coal body will slip. The critical conditions for coal body slip are as follows:

$$M\frac{\partial \sigma_x}{\partial x}dx = f_0 \sigma_y(x)dx \tag{4}$$

Where σ_x is the horizontal tectonic stress; $\sigma_y(x)$ is the overlying load; f_0 is the static friction coefficient of the structure plane (assuming the friction coefficients of roof and floor are the same), $f_0 = \left[JRC * \lg\left(\frac{JCS}{\sigma_y}\right) + \varphi_b \right]$; and M is the mining height of the coal body.

2.3 Conditions for stick-slip occurrence on the coal-rock structure plane

When the coal-rock body satisfies Eq. 4, the coal body will slip, and the friction force it bears will change from static to dynamic friction force. However, the rock slip can be further divided into stable slip and stick slip, and not all slip will cause dynamic disasters in coal mines: only stick-slip instability may cause stress drop in the coal-rock body, after which elastic energy stored will be quickly release and dynamic changes will occur in the state of the coal-rock body. According to previous research, the slip friction force of rocks is related to their velocity, and the velocity-state friction constitutive law can be used to successfully predict the friction behavior of rocks, a method which has been widely applied in theoretical analysis and practical engineering (Dieterich, 1978; Chang-rong, 1999). Assuming that stress conditions are constant and normal, the velocity-state friction constitutive relation can be described as follows (Linker and Dieterich, 1992):

$$\mu = \mu_0 + a \ln(V/V_0) + b \ln(\theta/\theta_0) \tag{5}$$

Where μ_0 is the friction coefficient in a stable state at a speed of V_0; θ_0 is the reference rate; V_0 is the steady-state value of the friction coefficient and state variable, which is a constant, V is the slip velocity, and θ is the state variable; and a and b are two friction constitutive parameters, and can be obtained through least-squares iteration of the spring-and-block experiment results. When the state evolution equation is zero (i.e., $d\theta/dt = 0$), the steady-state friction coefficient μ_{ss} of the constitutive equation is obtained:

$$\mu_{ss} = \mu_0 + (a-b)\ln(V/V_0) \tag{6}$$

Where $(a-b) = d\mu_{ss}/d\ln V$ is the velocity dependence in a stable state. Ruina (Ruina, 1983) studied the stability of a single-degree-of-freedom system, and found that during linear stability analysis on fixed points under quasi-static conditions ignoring relations, only when $(a-b) < 0$ can small disturbances lead to unstable slip. The factors controlling the stability of friction slip

(i.e., positive or negative value of $a-b$) are quite complex, but a qualitative conclusion can still be drawn: In low-temperature environments (applicable to general working conditions in coal mines), stick-slip may easily occur on a polished friction surface or slip surface that has undergone running-in (Biegel et al., 1989). For non-smooth contact surfaces, the transition to a running-in state can be promoted by increasing pressure and the contact area of the friction surface, thereby enhancing the possibility of stick-slip (Wen-bin and Chang-rong, 2007; ZHANG et al., 2013). During the sedimentation and diagenesis process, coal-rock structures naturally have interconnected weak structure planes, including the contact surfaces between coal-rock layers and coal seam parting, providing the geological structure conditions for stick-slip occurrence on the coal-rock structure plane.

The deep mining of coal bodies is characterized by great burial depth and overlying load. If displacement occurs during the formation of coal-rock layers along the strata movement and when the structure plane is sheared, the surface of the coal body with lesser strength is more likely to have a breaking effect of the friction surface under the action of higher stress, due to the different strength of coal and rock in coal-rock combination. In addition, the bumps of the coal-rock body are sheared or smoothed, greatly reducing the overall strength of the shear surface and increasing the possibility of stick-slip occurrence, as shown in Figure 2A. This also explains the mechanism of higher stick-slip occurrence possibility under high stress conditions. Meanwhile, during the process of coal-rock body sedimentation or structure plane breaking, a weak plane interlayer composed of clast and debris is formed in the coal-rock structure plane, which weakens the strength of coal-rock contact surface to a certain extent, and large-scale dynamic disasters will also occur under low-stress conditions. It is worth noting that the mudded intercalation or fractured zone within the weak plane exhibits certain rheological behavior, and the long-term shear strength of the structure plane is 15%–20% lower than the instantaneous strength. As a consequence, the critical condition for stick-slip in the coal seam is reduced and the risk of dynamic disasters increases.

3 Mechanism of stick-slip instability occurrence on the coal-rock structure plane

If the stress state of the coal-rock body meets the condition of stick-slip occurrence on the weak structure plane, then when disturbed the roof and coal seam in the dx range ($x_1 \sim x_2$) of the elastic zone suddenly undergoes stick-slip, and the friction coefficient decreases from μ_0 to μ in an extremely short time Δt. At the same time, the elastic energy accumulated in the coal-rock body is released, generating a horizontal compression pulse in the coal seam, as shown in Figure 3.

Assuming it is a linearly decaying pulse waveform, the stress amplitude at any distance x from the wavefront is expressed as follows (Qi, 1996):

$$\sigma(x) = \sigma_m(1 - x/\lambda) \tag{7}$$

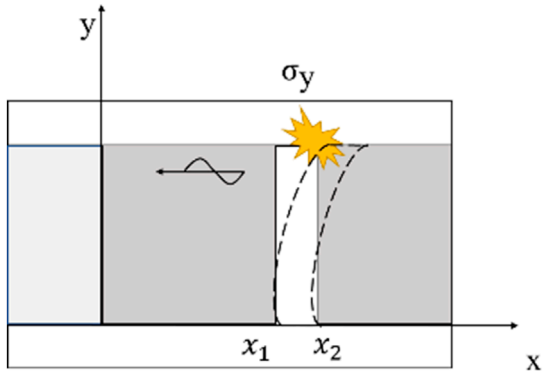

FIGURE 3
Stick-slip of the structure face in the coal-rock body.

Where λ is the pulse wavelength. Its peak intensity σ_m is expressed as follows:

$$\sigma_m = \int_{x_1}^{x_2} (\mu_0 - \mu)\sigma_y dx + G_0/\lambda \tag{8}$$

Where μ is the friction coefficient when stick-slip occurs on weak structure plane, and G_0 is the deformation energy of the coal body released.

Assuming that the time for the pulse wavefront to reach the free reflection surface is the starting point (t=0) and the stress wave velocity is C_0, then $x = C_0 t$ and $\lambda = C_0 \Delta t$ in Equation (x), and the time history curve can be expressed as follows:

$$\sigma(t) = \sigma_m(1 - C_0 t/\lambda) \tag{9}$$

The peak intensity is generally smaller than the compressive strength of the rock, and the horizontal stress on the free face is smaller than the internal horizontal stress of the coal body, which will not cause destruction to the coal body. When the compression wave reaches the free face, it is reflected as a tensile wave of equal intensity, leading to destruction near the end face. Assuming that the pulse wave decays linearly, the maximum tensile stress occurs at half-wavelength from the free face. When the tensile stress of the section reaches or exceeds the dynamic tensile strength of the rock σ_c, then layered cracking and failure occur.

Assuming that the distance between the wavefront of the reflected tensile wave and the free face is δ, the maximum tensile stress after superposition σ_s is expressed as follows:

$$\sigma_s = 2\sigma_m \delta/\lambda \tag{10}$$

Where when $\delta \le \lambda/2$ and $\sigma_m \ge \sigma_c$, δ is the crack thickness.

$$\delta = \lambda\sigma_c/2\sigma_m \tag{11}$$

According to the law of conservation of energy, the momentum G of a fractured fragment should be equal to the incident pressure pulse acting on the section δ:

$$G = \rho_0 \delta V_f = \int_0^{2\delta/C_0} \sigma(t)dt$$

$$= 2\delta\sigma_m(1-\delta/\lambda)\sigma_s \tag{12}$$

The velocity of fractured fragments is then obtained by combining Eq. 8 and Eqs. 11 and 12:

$$V_f = 2\sigma_m(1-\delta/\lambda)/\rho_0 C_0 = \left[2\int_{x_1}^{x_2}(\mu_0-\mu)\sigma_y dx + G_0/\lambda - \sigma_c\right]/\rho_0 C_0 \tag{13}$$

Eq. 13 above explains the disaster process caused by layered cracking and collapse of the coal-rock body on the free face after the occurrence of stick-slip instability in a single local area. The strength of the compression pulse and the dynamic tensile strength of the rock body determine if the coal body is destroyed, and also determine the corresponding extruding speed of the fractured coal body. The larger the overlying load is, the greater the difference between the static and stick-slip friction force, the higher the energy of the compression pulse, and the faster the rock body extruding speed will be.

In addition, when excavating gateways in deep mines, the coal-rock structure planes scattered in the mining space are likely in a critical state of slip due to the natural high stress state of the coal-rock body. In this case, the plane compression pulse induced by local stick-slip will not only cause destruction to the nearby coal-rock body, but will also form a larger range of interference due to the scattering effect of the pulse wave during the propagation process, inducing slip or even stick-slip of structure planes in critical state in other areas. Furthermore, multiple elastic stress waves will superimpose on each other in the mining space, thus triggering multiple chain reactions, in turn resulting in large-scale coal bumps. This complex multiple elastic wave action mechanism is difficult to accurately describe using mathematical expressions. However, it is clear that the damage and losses caused by such coal-rock dynamic disasters would be incalculable, and should be given sufficient attention in the actual production process.

4 Numerical simulation of disaster caused by stick-slip instability of the coal-rock body

During the excavation of the transportation roadway in the working face of a coal mine in Yima, Henan province, a coal bump accident occurred. Based on relevant data, FLAC^{3D} was used to perform numerical simulation, and the model is shown in Figure 4A. The model is a unit thickness plate model of 50 * 50 m, with the top and bottom layers as the top and bottom plates, which have high strength and dimensions of 23.5 * 50 m. After simplification, their mechanical properties are the same. The intermediate modelled coal seam has a relatively low strength, and a thickness of 3 m. A 3 * 5 m rectangular coal roadway is excavated in the middle of the model, and the physical and mechanical parameters of the model are shown in Table 1. The depth of the coal seam reaches $H = 800m$, and the pressure of the overlying strata is calculated according to $q = \gamma H$, where γ is the average bulk density of the overlying strata (taken as $2.5 * 10^4 N/m^3$).

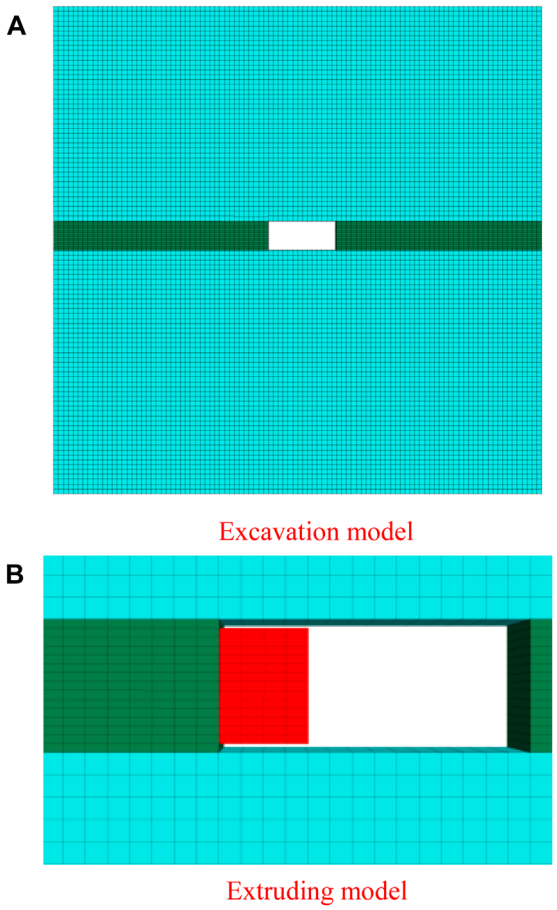

FIGURE 4
Calculation model. **(A)** excavation model, **(B)** extruding model.

According to the mechanism of stick-slip instability occurrence described above, when stick-slip occurs at a weak plane of the coal-rock body, a dynamic chain reaction will occur in the coal seam. The elastic energy accumulated by compression in the coal-rock layer will be transmitted to the gateway edge at an extremely high speed, and the coal body in the edge will be extruded out at high speed, thus resulting in dynamic disasters. For this reason, the loose coal body extruding out of the gateway edge was simplified as a block attached to the gateway wall, with a length of 2 m and height of 2.6 m, and without any contact with the roof and floor, as shown in Figure 4B.

To study the dynamic disasters caused by sudden stick-slip instability of coal-rock body, after the model reached equilibrium, the slip properties of the structure planes of coal-rock body were assigned by writing FISH language and referring to the stick-slip experiment results (Eq. (14)) described in Qi et al. [24]. When the shear force on the structure plane of the coal-rock layer reached its maximum friction force, it was suddenly initialized as residual friction force to simulate the occurrence of stick-slip instability.

$$\begin{cases} \tau_m = 0.2753\sigma_n + 0.3842 \\ \tau_c = 0.2309\sigma_n + 0.0150 \end{cases} \tag{14}$$

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TABLE 1 Modelled strata properties.

Strata	Density (kg/m^3)	Bulk modulus (GPa)	Shear modulus (GPa)	Friction angle (º)	Cohesion (MPa)
Roof	2,500	6.67	4	37	10
Coal	1,400	3.33	1.11	35	0.2
Floor	2,500	6.67	4	37	10

Where τ_m is the maximum friction force; τ_c is residual friction force; and σ_n is the normal stress of the structure plane.

When the structure of the coal-rock body becomes unstable, the loose coal body will be extruded out. Figure 5 shows the entire dynamic process of the stick-slip instability in the coal body. The friction force on the structure surface was reduced to zero, and the corresponding displacement and velocity of the coal body in each time period were displayed at intervals of 0.02 s, respectively represented by colors and arrows.

The velocity variation of the coal body on the free face and the right side of the extruded coal body over time is shown in Figure 6. After about 0.002 s of coal-rock structure stick-slip, the coal body transferred kinetic energy to the external extruded coal body through collision. After 0.007 s of coal-rock structure stick-slip, the velocity of the coal body was transmitted to the extruded coal body in the form of kinetic energy, and the velocity of the extruded coal body reached its maximum value, being pushed out at a maximum rate of approximately 2 m/s. At this time, the velocity of the coal body was reduced by half of the maximum value. Subsequently, the velocity of the coal body showed a fluctuating downward trend. After about 0.05 s, the velocity of the coal body decreased to 0. At this time, the displacement of the coal body reached its maximum value, and the displacement nephogram exhibited a distribution of elliptical envelope lines.

Throughout the impact process, the entire coal body moved toward the side of the adjacent gateway, and the loose coal body was extruded out at a high speed. There was strong friction between the coal seam and roof, along with obvious slip scratch and separation between the coal seam and the roof and floor. However, no obvious displacement between the roof and floor of the coal seam was observed. As shown in Figure 7, the arrows in the figure represent the displacement of the nodes. Depending on the different positions of loose blocks scattered in the gateway, the displacement of loose blocks decreased in a gradient from top to bottom, better corresponding to the form of coal body destruction in the gateway after coal bumps. The numerical simulation results are consistent with the previous description of coal bump (QI et al., 2003).

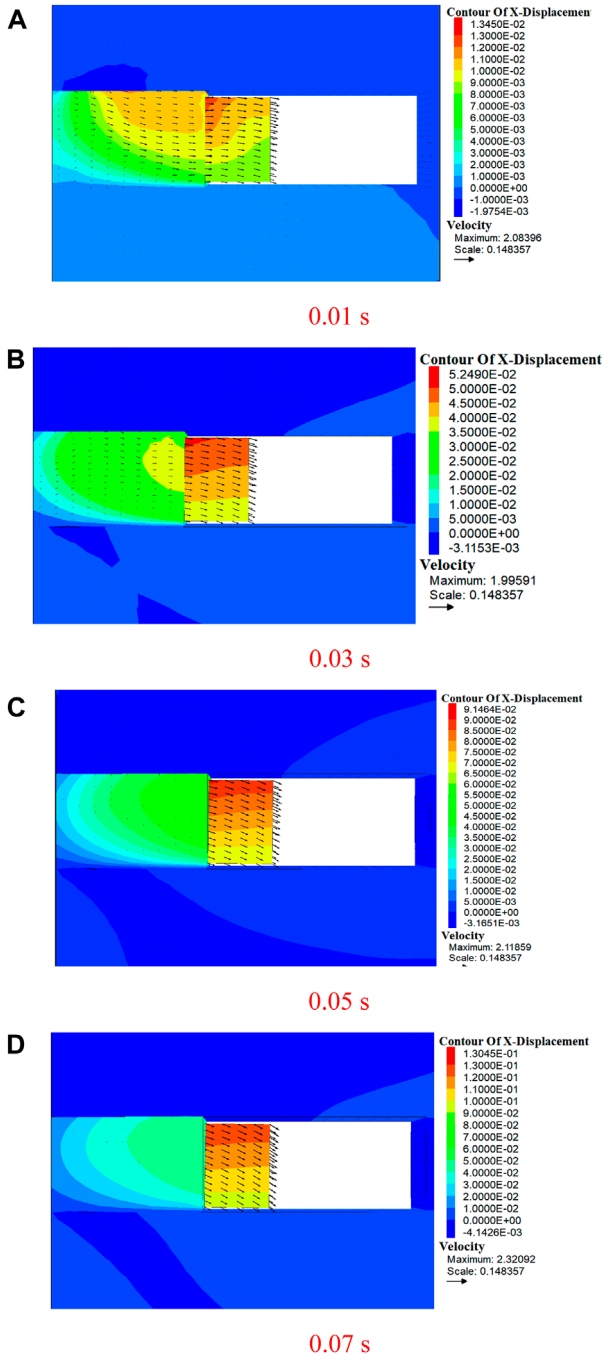

FIGURE 5
Dynamic process of coal-rock structure stick-slip instability. **(A)** 0.01s, **(B)** 0.03s, **(C)** 0.05s, **(D)** 0.07s.

5 Application of stick-slip mechanism

The stick-slip mechanism has opened up new avenues for the prevention of dynamic disasters. The stick-slip mechanism indicates that stick-slip instability is a dynamic phenomenon under certain conditions. Therefore, the prediction of disaster events can be achieved through the prediction of disaster occurrence conditions,

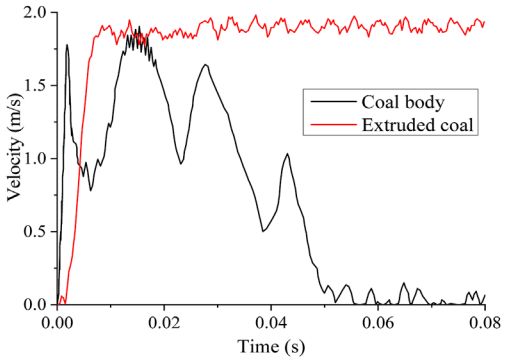

FIGURE 6
Velocity of the coal body and the extruded coal.

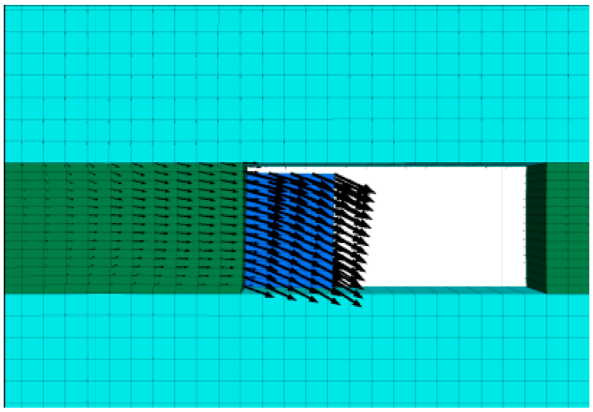

FIGURE 7
Simulated coal bump in the gateway.

and the comprehensive effects of disaster inducement factors can be determined to achieve the goal of disaster prediction. The process of preventing and controlling disasters is also a process of changing the conditions under which disasters occur. Through in-depth research on the conditions for disaster occurrence, effective measures can be taken to avoid such disasters and achieve effective prevention and control.

6 Conclusion

(1) There are natural joint faces in the structure planes of coal-rock bodies, but they generally show an apparent unity. Due to the constraint effect of the structure plane, uncoordinated deformation occurs near the structure plane of the coal-rock body, causing a certain amount of elastic energy to accumulate within the coal body. After being disturbed by stress, the constraint effect of the structure plane decreases, and the elastic energy is released.

(2) After the excavation of the coal-rock body, the occurrence of stick-slip instability must meet the critical condition of coal body slip, that is, the horizontal tectonic stress is greater than or equal to the friction force between the coal body and the roof and floor, and there is a trend of slipping towards the gateway. In addition, it must also satisfy the conditions for stick-slip occurrence.

(3) By introducing the rock friction constitutive equation, it is believed that there are many penetrating cracks in the layered structure of the coal-rock body. After slip and migration in the diagenesis process, the coal-rock structure planes undergo running-in or form weak interlayers, thus increasing the possibility of stick-slip.

(4) The application of elastic mechanics and elastic dynamics theory suggests that, due to the stick-slip between the coal seam and the roof and floor, horizontal compression pulses are formed in the coal body, and the energy accumulated in the coal seam is released, resulting in the fracturing and extruding of the coal-rock body on the free face. Due to the scattering effect of pulse propagation, large-scale disturbances are formed and lead to large-scale structural instability of coal-rock bodies, in turn causing serious dynamic disasters.

(5) A numerical simulation method was used to reproduce the coal bumps in the gateway of a mine in Yima. By assigning the structure plane with stick-slip characteristics, the stick-slip instability of coal-rock body was simulated. The results show that after 0.002 s of stick-slide, the coal body transferred kinetic energy to the loose coal body on the free face through collision and threw it out at a high speed, and after 0.05 s of stick-slide, the displacement of the coal body reached its maximum value and overall slip occurred toward the side of the adjacent gateway.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

ZZ: Writing–original draft. G Y: Conceptualization, Investigation, Methodology, Writing–original draft. YL: Writing–original draft. YC: Investigation, Writing–original draft, Writing–review and editing. CY: Writing–original draft. JZ: Writing–original draft.

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Conflict of interest

Authors ZZ, YL, and CY were employed by China National Coal Group Corporation. Author ZZ was employed by Coal Northwest Energy Co., Ltd. Author YL was employed by Inner Mongolia Coal Manda New Energy Chemical Co., Ltd. Author CY was employed by Ordos Branch of China Coal Energy Co. Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Slope deformation prediction based on noise reduction and deep learning: a point prediction and probability analysis method

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Slope deformation, a key factor affecting slope stability, has complexity and uncertainty. It is crucial for early warning of slope instability disasters to master the future development law of slope deformation. In this paper, a model for point prediction and probability analysis of slope deformation based on DeepAR deep learning algorithm is proposed. In addition, considering the noise problem of slope measurement data, a Gaussian-filter (GF) algorithm is used to reduce the noise of the data, and the final prediction model is the hybrid GF-DeepAR model. Firstly, the noise reduction effect of the GF algorithm is analyzed relying on two actual slope engineering cases, and the DeepAR point prediction based on the original data is also compared with the GF-DeepAR prediction based on the noise reduction data. Secondly, to verify the point prediction performance of the proposed model, it is compared with three typical point prediction models, namely, GF-LSTM, GF-XGBoost, and GF-SVR. Finally, a probability analysis framework for slope deformation is proposed based on the DeepAR algorithm characteristics, and the probability prediction performance of the GF-DeepAR model is compared with that of the GF-GPR and GF-LSTMQR models to further validate the superiority of the GF-DeepAR model. The results of the study show that: 1) The best noise reduction is achieved at the C1 and D2 sites with a standard deviation σ of 0.5. The corresponding *SNR* and *MSE* values are 34.91 (0.030) and 35.62 (0.674), respectively. 2) A comparison before and after noise reduction reveals that the R^2 values for the C1 and D2 measurement points increased by 0.081 and 0.070, respectively. Additionally, the *MAE* decreased from 0.079 to 0.639, and the *MAPE* decreased from 0.737% to 0.912%. 3) The prediction intervals constructed by the GF-DeepAR model can effectively envelop the actual slope deformation curves, and the *PICP* in both C1 and D1 is 100%. 4) Whether it is point prediction or probability prediction, the GF-DeepAR model excels at extracting feature information from slope deformation sequences characterized by randomness and complexity. It conducts predictions with high accuracy and reliability, indicating superior performance compared to other models. The results of the study can provide a reference for the theory of slope deformation prediction, and can also provide a reference for similar projects.

KEYWORDS

slope deformation prediction, deep learning, DeepAR model, Gaussian-filter algorithm, point prediction, probability analysis

1 Introduction

The stability of slopes is crucial for engineering safety (Peng et al., 2019; Qiu et al., 2024). Influenced by a variety of environments, the originally stable slopes are prone to lose their original equilibrium under the action of external or internal stresses, which may lead to disasters such as landslides and collapses. For example, in September 2008, landslides occurred in Jintou Mountain in the southern part of the Taipei Basin, which greatly impacted the safety of the residential community in the downslope location (Nguyen et al., 2022). On 17 September 2011, a landslide occurred in Baqiao District, Shaanxi, China, which causing severe casualties in terms of people and property (Lin et al., 2017), and on 28 June 2016, a landslide occurred in Xinlu Village, Shuicheng, Chongqing (Zuo et al., 2022). Currently, advance identification and trend prediction of disasters is one of the most important means to avoid losses and casualties caused by slope disasters. Slope deformation, as a key factor affecting its stability, has complexity and uncertainty, and mastering its future development pattern is crucial for early warning of slope instability disasters.

In recent years, many intelligent prediction algorithms have been applied to slope deformation prediction (Deng et al., 2021). Initially, more applications are static models such as the Support Vector Machine Regression (SVR) algorithm (Xu et al., 2022), the Autoregressive Moving Average (ARMA) algorithm (Shen et al., 2018), and the Backpropagation (BP) algorithm (Zhang et al., 2023). Since 2006, Deep Learning has achieved great success in the field of machine learning (Lasantha et al., 2023). Deep learning-based recurrent neural network (RNN) models with deeper network structures and more powerful representation learning capabilities are particularly favored by researchers (Cao et al., 2023). Currently, RNN models have achieved more research results in the field of slope deformation prediction (Xie et al., 2019). Long Short-Term Memory (LSTM) is a kind of RNN, Xi et al. (2023) established an LSTM slope deformation model based on the time-series deformation data from seven on-site monitoring points of Huanglianshu landslide and found that the prediction accuracy was better. Wang et al. (2024) used the LSTM algorithm to predict and analyze the deformation data of complex road graben slopes and compared it with other kinds of prediction models, and found that the LSTM slope deformation prediction model proposed in this paper is more accurate. Zhang et al. (2024) proposed a slope deformation prediction method based on LSTM for the stability of loosely stacked body slopes and demonstrated that the method can be used as an effective measure to mitigate landslide losses. The above studies demonstrate the applicability of deep learning models in slope deformation prediction and promote the progress of research work in this field, but there are still several problems need to be optimized. Firstly, although the LSTM model is capable of capturing the long-term dependence of slope deformation, it is relatively weak in handling mutations or outliers (Zhu et al., 2024), leading to limitations in its prediction accuracy (Chen et al., 2019). Secondly, the monitoring data used to train the prediction model is easily affected by conditions such as monitoring equipment and field environment, leading to the problem of data noise (Dong et al., 2023). This in turn affects the quality of the dataset and leads to unsatisfactory prediction results. Thirdly, the prediction results obtained from the existing studies are all point prediction results, resulting in low credibility of the results, which in turn limits the value of popularization and application.

DeepAR algorithm is an improved algorithm based on RNN and LSTM (Salinas et al., 2020). The algorithm was first proposed by Salina et al., in 2017 (Schaduangrat et al., 2023). The DeepAR algorithm contains a recurrent neural network structure inside, which has the same memory and parameter sharing as LSTM (Singh et al., 2024). In addition, DeepAR can adjust the probability distribution by probability modeling, which allowing it to learn the inherent laws and patterns of the slope deformation sequence data, rather than just simple linear relationships or trends. Hence, the DeepAR algorithm is able to capture this change and flexibly adjust according to the previously learned patterns, thus provide more robust predictions (Chang and Jia, 2023), when there is a sudden change in the original data. Currently, the DeepAR algorithm has been successfully applied in the fields of healthcare (Schaduangrat et al., 2023), finance (Soliman et al., 2023), and environmental protection (Jiang et al., 2021), and can also provide an effective means for accurate and reliable prediction of slope deformation. In addition, the current slope engineering measurement data are susceptible to noise problems due to a variety of conditions, limiting the accuracy of slope deformation prediction (Ma et al., 2021). Including deep learning algorithms such as RNN, LSTM, DeepAR, etc., the above-mentioned algorithms are single prediction algorithms and cannot pre-process for the dataset before doing prediction analyses. Therefore, it is of great significance to propose a hybrid algorithm that guarantees the quality of prediction input data and provides prediction analyses based on established high-precision prediction algorithms.

To address the above issues, a model for prediction and probability analysis of slope deformation points based on GF and DeepAR algorithms is proposed. The structure of the paper is organized as follows: Section 2 provides a detailed introduction to the newly proposed method, which consists of three parts: filtering and noise reduction processing based on the GF algorithm, slope deformation prediction based on DeepAR, and point prediction performance assessment and comparison analysis. Section 3 shows the noise reduction results, prediction results, and comparison analysis results of the GF-DeepAR model on two real slope engineering cases. Section 4 proposes a probability analysis framework for slope deformation based on the GF-DeepAR model and compares the performance of other probability analysis models to further validate the superiority of the GF-DeepAR model. Section 5 concludes this work. Section 6 compares the study in this paper with existing similar studies, and also compares the prediction accuracy at different time steps, and finally discusses the future research outlook.

2 Hybrid GF-DeepAR prediction approach

2.1 DeepAR algorithm

DeepAR is a time series prediction method based on deep learning, which has a significant advantage in predicting the nonlinear features of the series and can well perform point prediction and probability prediction (Cao et al., 2023). The

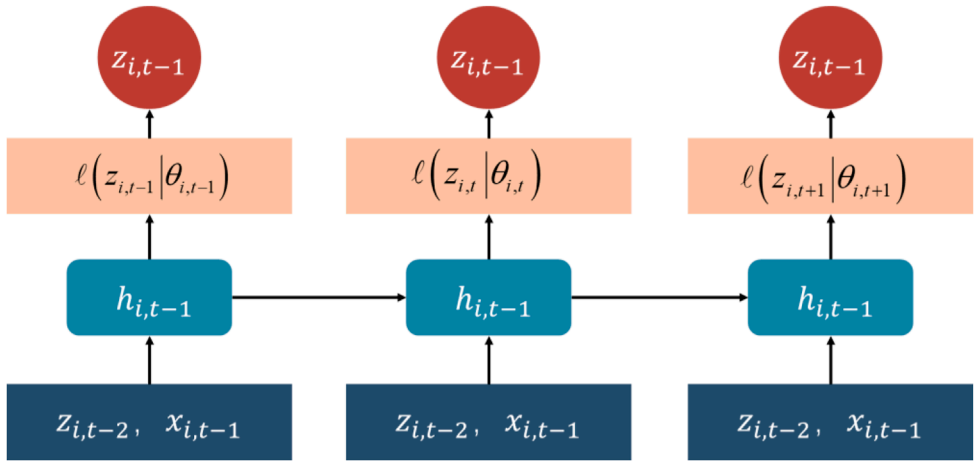

FIGURE 1
DeepAR network architecture.

structure of the DeepAR model is shown in Figure 1. Define the value of the ith slope deformation sequence at the moment t as $Z_{i,t}$. The goal of the prediction model is to obtain the joint probability distribution $P(z_{i,t:T}|z_{i,t-1}, z_{i,1:T})$ of the unknown sequence $Z_{i,t:T}$ through the known slope deformation data $Z_{i,1:t-1}$ and covariates $x_{i,1:T}$. Assume that the distribution of the unknown slope deformation sequence is $Q_\Theta(z_{i,t:T}|z_{i,t-1}, x_{i,1:T})$, and its probability distribution as shown in Eq. 1:

$$Q_\Theta(z_{i,t:T}|z_{i,t-1}, x_{i,1:T}) = \prod_{t=t_0}^{T} Q_\Theta(z_{i,t}|z_{i,1:t-1}, x_{i,1:T}) \tag{1}$$

And represent this distribution by a parametric likelihood function with, as shown in Eqs 2, 3:

$$\prod_{t=t_0}^{T} Q_\Theta(z_{i,t}|z_{i,1:t-1}, x_{i,1:T}) = \prod_{t=t_0}^{T} \ell(z_{i,t}|\theta(h_{i,t}, \Theta)) \tag{2}$$

$$h_{i,t} = h(h_{i,t-1}, z_{i,t-1}, x_{i,t}, \Theta) \tag{3}$$

Where h is the implied state function of the RNN neural network, θ is the output state function, and Θ is the network structure parameters.

It is worth noting that the model $\ell(z|\theta)$ should choose the likelihood function that best matches the statistical properties of the data, such as the Gaussian distribution likelihood function, the Bernoulli distribution likelihood function, and the negative binomial distribution likelihood function. Considering the characteristics of the data used in the study, Gaussian distribution is used as the likelihood model for slope deformation probability prediction, with the likelihood parameters $\theta = \{u, \sigma\}$, u as the expectation and σ as the standard deviation. Each likelihood function has its corresponding activation function, in which to ensure that σ is positive, the activation function of the output layer must be set as an exponential function (*exponential* activation function, *softplus* activation function), in this paper, we use the *softplus* as its activation function, as shown in Eq. 4:

$$\ell(z|u, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-(z-u)^2}{2\sigma^2}\right] \tag{4}$$

Where exp [] is a power function with e as the base.

2.2 GF algorithm

Gaussian-filter is a linear filtering technique with a probability density function obeying a normal distribution, which can be used to attenuate Gaussian noise interference in pit deformation data (Selva et al., 2020). The core idea of the Gaussian-filter algorithm is to iteratively convolve the original signal through the Gaussian kernel function, and use the weighted average of the neighborhood of a data point instead of that data point to obtain the filtered and noise-reduced signal.

Considering that the slope deformation data is a one-dimensional sequence, it is processed using a one-dimensional Gaussian function, as shown in Eq. 5:

$$g(t, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(t-t_0)^2}{2\sigma^2}\right) \tag{5}$$

Where: t is the sampling point for pit deformation monitoring, and t_0 is the mean value of t. Since the calculation takes the current sampling point as the origin, t_0 =0. Its first-order derivative $g^{(1)}(t, \sigma)$ is calculated as shown in Eq. 6:

$$g^{(1)}(t, \sigma) = \frac{-t}{\sqrt{2\pi}\sigma^3} \exp\left(-\frac{t^2}{2\sigma^2}\right) \tag{6}$$

Where: $g^{(1)}(t, \sigma)$ is a Gaussian filter, and the slope deformation sequence function $f(t)$ is noise-reduced by $g^{(1)}(t, \sigma)$, further, $S(t, \sigma)$ can be calculated as shown in Eq. 7:

$$S(t, \sigma) = f(t) * g^{(1)}(t, \sigma) \tag{7}$$

Where: $'*'$ is the convolution operator; σ is the standard variance of the Gaussian function; the smoothing effect of the

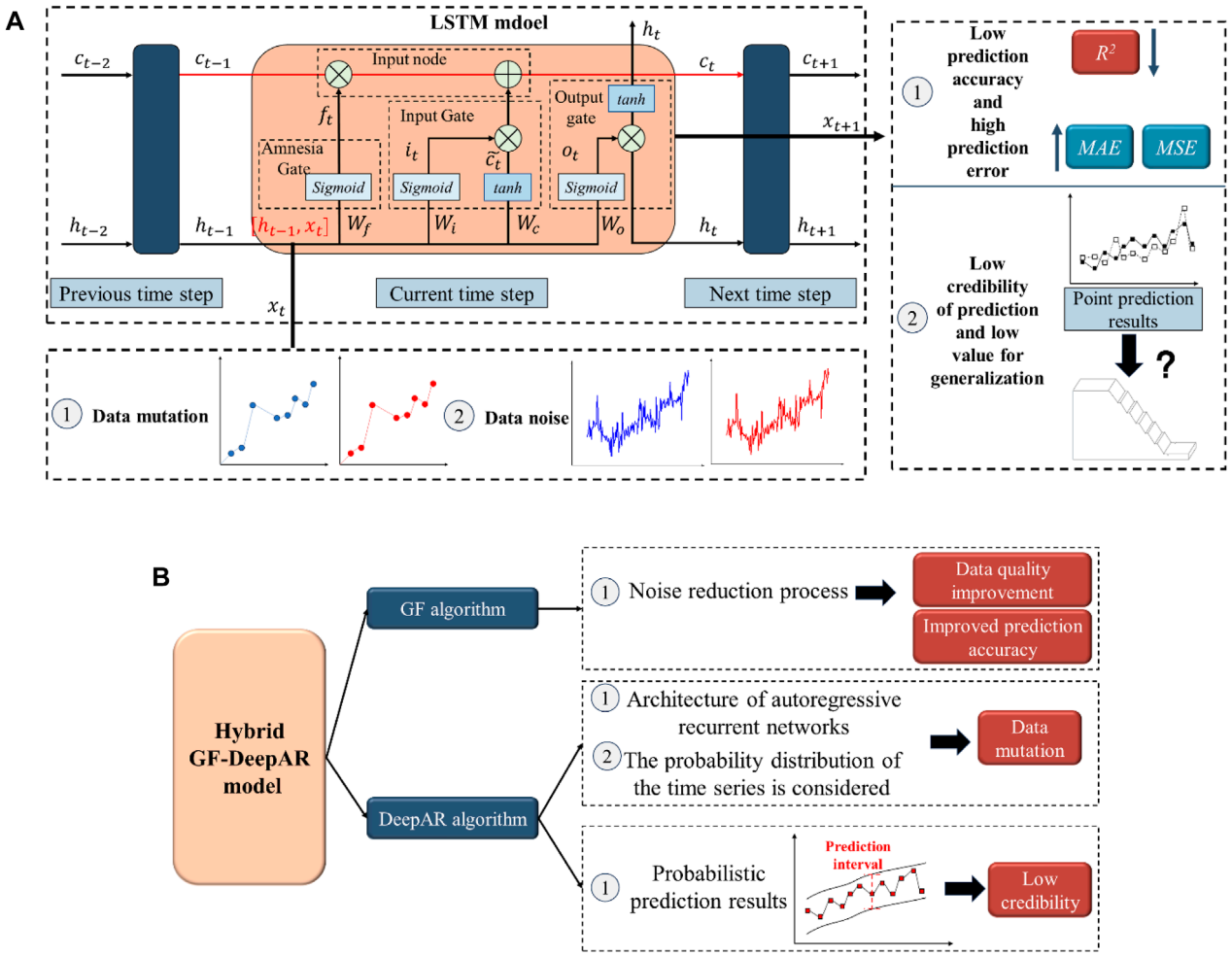

FIGURE 2
Problems with the LSTM model and advantages of the GF-DeepAR model **(A)** Problems with the LSTM model; **(B)** Advantages of the GF-DeepAR model.

Gaussian filter is characterized by σ. The larger σ is, the larger the local influence range of the Gaussian kernel function is, and the better the smoothing degree of the signal is, and the smaller σ is, the more the mutation information of the data is amplified.

2.3 GF-DeepAR hybrid model

Figure 2 shows the problems with the LSTM model and the advantages of the GF-DeepAR model. In view of the problems in previous studies, a model for point prediction and probabilistic analysis of slope deformation based on DeepAR deep learning algorithm (GF-DeepAR) is proposed. Firstly, the model can be used to reduce the noise of the monitoring data through the GF algorithm, which can improve the quality of the data on the one hand, and improve the prediction accuracy on the other hand. Secondly, the model is centered on DeepAR algorithm for slope deformation prediction, which can not only solve the problem of data mutation but also provide probability prediction results. Among them, the details about probability prediction will be elaborated in Section 4, and Sections 2 and 3 mainly elaborate point prediction related contents.

The GF-DeepAR hybrid model-building process is shown in Figure 3. It mainly includes three parts: filtering and noise reduction processing based on the GF algorithm, slope deformation prediction based on DeepAR, and point prediction performance evaluation and comparative analysis.

2.3.1 Filtering and noise reduction process based on GF algorithm

The core of the GF algorithm for noise reduction lies in determining the weight matrix of the Gaussian kernel function $w_k(x+i,\sigma)$. Firstly, the filter window length (2L+1), the number of iterations K, and the standard variance σ of the slope deformation sequence function $f(x)$ are defined. Calculate the weight matrix centered on the sampling point with Gaussian kernel function influence radius L. Normalise the weight matrix so that the sum of the weights is equal to 1 to get the final weight matrix, multiply the weight matrix with the corresponding points of the original data and then accumulate them to calculate the filtered output value

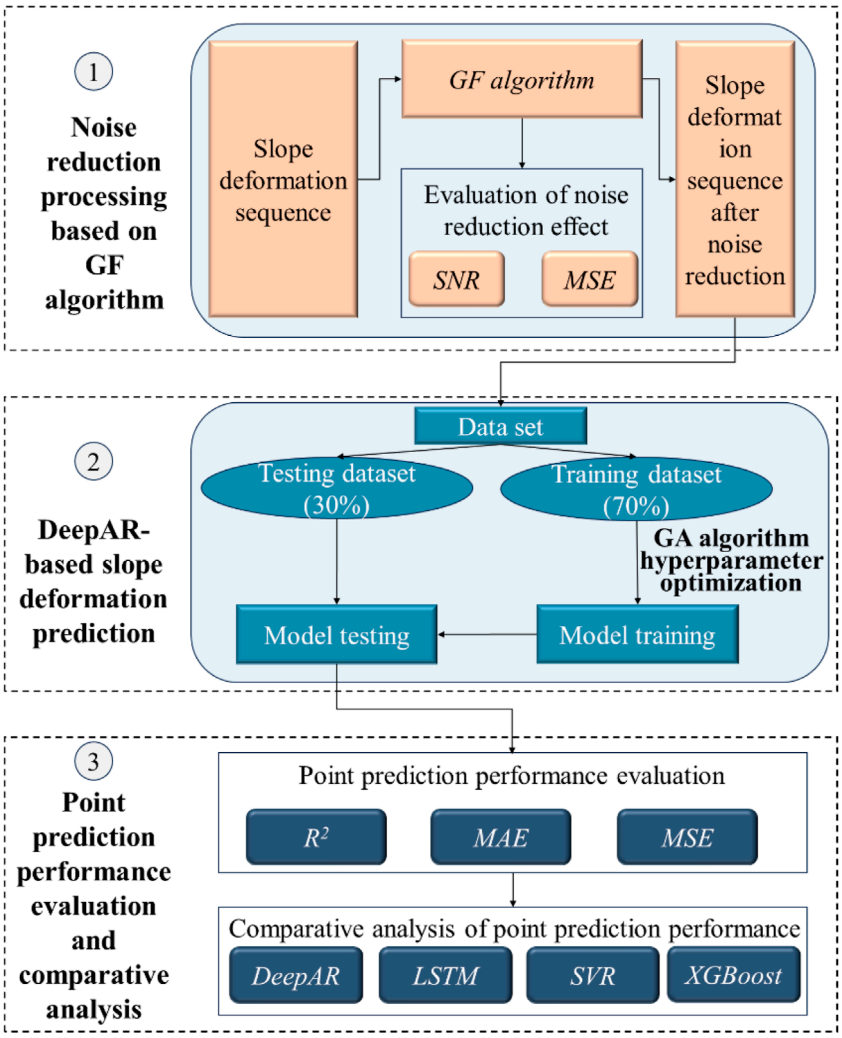

FIGURE 3
GF-DeepAR hybrid model.

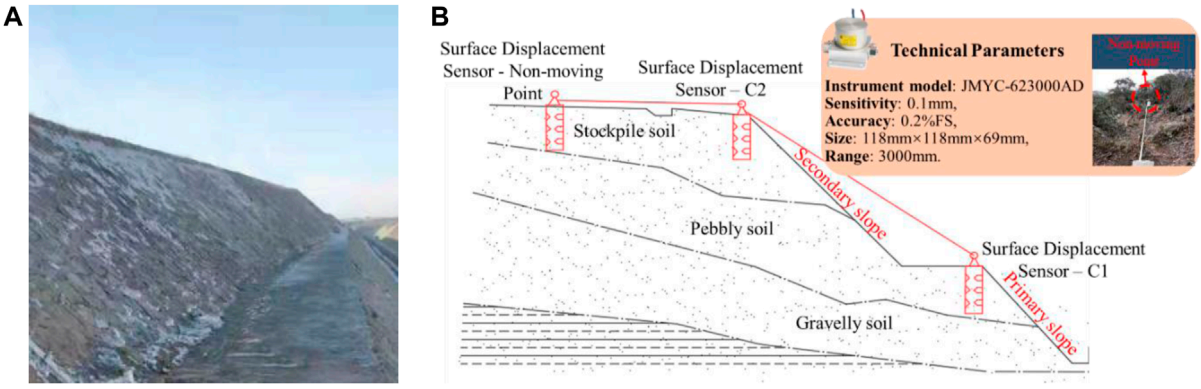

FIGURE 4
Slope engineering and deformation measurement point layout map-Case 1 **(A)** Actual site view; **(B)** Placement of deformation measurement points.

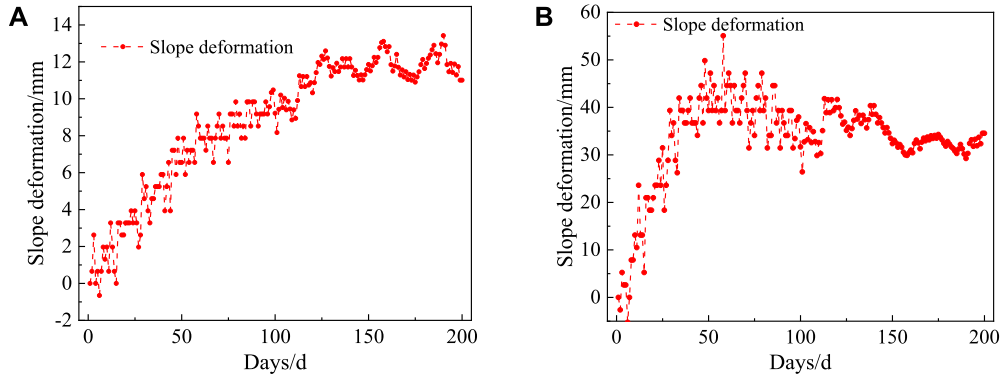

FIGURE 5
Change rule of slope cumulative deformation-Case 1 **(A)** C1 measurement point; **(B)** C2 measurement point.

$f_{k+1}(x)$ of the slope deformation sequence function $f(x)$, as shown in Eq. 8:

$$f_{k+1}(x) = \sum_{-L}^{L} f_k(x+i) w_k(x+i, \sigma) \tag{8}$$

Repeat the above steps until the number of iterations k=K to get the slope deformation sequence after noise reduction by the GF algorithm. The signal-to-noise ratio *SNR* and mean square error *MSE* are used as noise reduction performance evaluation metrics to select the optimal noise reduction data (Chicco et al., 2021; Kononchuk et al., 2022). Where *SNR* and *MSE* are defined, as shown in Eqs 9, 10:

$$\mathrm{SNR} = 10 * \lg\left[\sum_{i=1}^{N} x_i^2 / \sum_{i=1}^{N} (d_i - x_i)^2\right] \tag{9}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N} (d_i - x_i)^2 \tag{10}$$

Where: x is the initial slope deformation sequence, d_i is the slope deformation sequence after noise reduction, and N is the length of the slope deformation sequence. If the corresponding *SNR* and *MSE* of the noise reduction data are larger and smaller, it indicates that the noise reduction effect is better, and the data with the optimal noise reduction effect is selected for the next processing.

2.3.2 DeepAR-based slope deformation prediction

The noise-reduced slope deformation sequences are input into the DeepAR model and the data set is constructed based on the input sequences. In the specific construction process, the sliding window method is used to construct the input features and output features for slope deformation prediction. The input features $S_1, S_2, S_3 \ldots\ldots S_{t-1}$ of the data set consist of historical slope deformation values, and the time step of historical slope deformation is set to 8 with reference to the established research (Muneeb, 2022; Liu et al., 2024). The output features S_t consist of slope deformation values at time t. Further, the data set is divided on the basis of the constructed data set using the Holdout method (Mao et al., 2019), which divides the data set into training and testing sets in the ratio of 7:3 according to the chronological order.

The training set is input into the model to perform the training of the prediction model. It is worth noting that the DeepAR model has many hyperparameters, such as the number of network layers (num_layers), the number of cells (num_cells), the dropout rate (dropout_rate), the learning rate (learning_rate), and the number of training rounds (epochs). In this paper for more efficient implementation of hyperparameter setting, genetic algorithm (GA) (Cai et al., 2020) is introduced for hyperparameter optimization. After completing the DeepAR model training, the optimal hyperparameters and test set are sent to the model to perform test predictions of the model. In addition, the computing environment is configured in Windows 11 using python 3.10, Core i9-14900KF, RTX4090D, 64 GB DDR5. Computational libraries such as tensorflow, pandas, etc. are used during the computation.

2.3.3 Evaluation and comparative analysis of point prediction performance

The goodness of fit (R^2), mean absolute error (*MAE*), and mean absolute percentage error (*MAPE*) are selected to assess the point prediction performance of the model, which are defined as shown in Eqs 11–13:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_t - \hat{y}_t)^2}{\sum_{i=1}^{N} (y_t - \bar{y})^2} \tag{11}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |y_t - \hat{y}_t| \tag{12}$$

$$MAPE = \frac{100\%}{N}\sum_{t=1}^{N} \left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{13}$$

Where: the larger the value of R^2, the higher accuracy of the prediction model. *MAE* and *MAPE* are the error metrics, the smaller its value, the smaller the prediction error. N is the number of predicted samples, y_t is the measured slope deformation value, $\hat{y}_t$ is the predicted slope deformation value, and $\bar{y}$ is the average of the measured slope deformation value.

To further validate the prediction performance of the DeepAR model, the prediction performance of three typical prediction

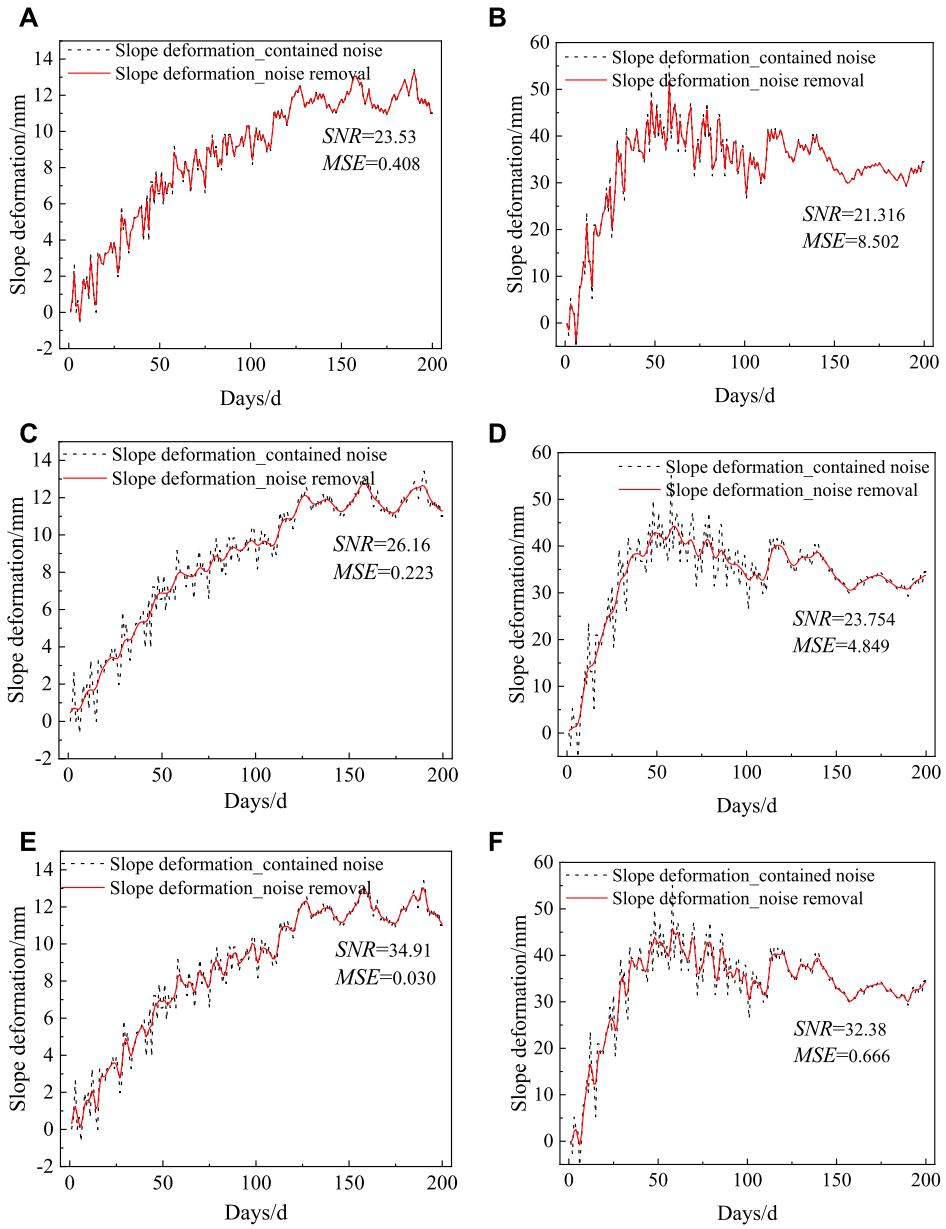

FIGURE 6
Noise reduction results of GF algorithm for slope deformation-Case 1 **(A)** C1 measurement point -σ2.0; **(B)** C2 measurement point -σ2.0; **(C)** C1 measurement point -σ1.0; **(D)** C2 measurement point -σ1.0; **(E)** C1 measurement point -σ0.5; **(F)** C2 measurement point -σ0.5.

algorithms, LSTM, XGBoost (Asselman et al., 2023), and SVR, was compared based on the above three metrics.

3 Case studies

3.1 Case 1

3.1.1 Overview of works

To verify the effectiveness of the proposed hybrid GF-DeepAR slope deformation prediction model, a cut slope is selected as an example of a work point. As shown in Figure 4A, the slope is a secondary slope with an overall height of 8–10 m, with a wide platform of about 1.5 m in the middle. The slope is composed of vegetative fill, pebble soil, and gravel soil in order from top to bottom. The slope is protected by a slurry masonry schist retaining wall, but under the influence of the external environment, there are localized outgrowths and damages of the schist on the slope surface, which seriously affects the overall stability of the slope and the retaining wall. Therefore, two surface deformation gauges of model JMYC-623000AD, C1 and C2, are deployed at the top of the primary and secondary slopes, to monitor the deformation values of the slopes. The monitoring cycle is 200d in total, the monitoring frequency is 4h/time, the monitoring frequency can

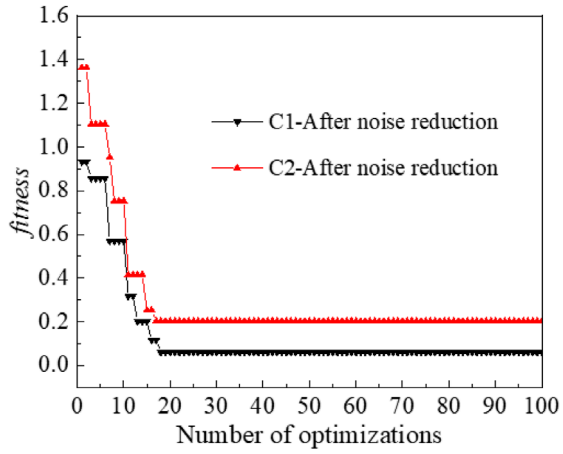

FIGURE 7
Optimization results of GA algorithm on C1 and C2 measurement points.

be appropriately strengthen according to the development of slope deformation, and the daily monitoring value is taken as the average of all the monitoring values of the day. The technical parameters of the surface deformation gauges and their specific placement can be found in Figure 4B.

The change rule of C1 and C2 measurement points is plotted as shown in Figure 5. The deformation of the secondary slope (measurement point C2) is larger than that of the primary slope (measurement point C1) in the figure, and this rule agrees with the established studies (Liu et al., 2024; Ye et al., 2024). Among them, the deformation of the C2 measurement point is gradually stabilized with the accumulation of time, but the fluctuation of the value before 100 days is larger, which is mainly considered to be caused by the freezing and expansion due to the environmental conditions of the site. Since then, the deformation of the C2 measurement point has gradually leveled off, but there is also a small fluctuation phenomenon, mainly considering the effect of noise (Ali et al., 2020; Duan et al., 2024). Similar to the C2 measurement point, the deformation of the C1 measurement point also tends to stabilize with time, and the cumulative deformation of the whole process is within 15 mm, but there are fluctuations in the value of the change process.

3.1.2 Results of noise reduction analysis

The GF-DeepAR hybrid model is used to firstly reduce the noise of the original monitoring data sets *Data_set_C1* and *Data_set_C2* of C1 and C2 measurement points respectively (the standard deviation σ is set to be divided into 2.0, 1.0, and 0.5), and then the relationship between the noise-reduced slope deformation series and the original noise-containing slope deformation series is shown in Figure 6.

As shown in Figure 6, the noise-reducing deformation series retains the characteristics of the deformation trend of the original series, and at the same time, the noise-reducing deformation series has a better smoothness than the original series, and the noise-reducing effect is better. At the C1 measurement point, *SNR* and *MSE* are 23.53(0.408), 26.16(0.223), and 34.91 (0.030) for the three different standardized variances, respectively. As the standard variance σ decreases, *SNR* gradually increases from 23.53 to 34.91, and *MSE* gradually decreases from 0.408 to 0.030, indicating that the noise reduction effect gradually becomes better, considering that the noise reduction effect obtained by continuing to reduce the standard variance σ is gradually stable, the noise reduction data under the condition that the standard variance σ is 0.5 can be selected as the data for the subsequent prediction and analysis of the C1 measurement points. At the C2 measurement point, *SNR* and *MSE* are 21.316(8.502), 23.754(4.849), and 32.38 (0.666) for the three different standardized variances, respectively. As the standard variance σ decreases, *SNR* gradually increases from 21.316 to 32.38, and *SNR* gradually decreases from 8.502 to 0.666, indicating that the effect of noise reduction gradually becomes better. Hence, the noise reduction data under the condition of standard variance σ of 0.5 is selected as the data for the subsequent prediction and analysis.

In summary, the data preprocessing part of the GF-DeepAR hybrid model can pre-filter the original monitoring data set, which retains the characteristics of the deformation trend containing the original series. At the same time, it can better eliminate the noise information hidden in it, which ensures the quality of the data for the subsequent deformation prediction and analysis of slope engineering.

3.1.3 Results of slope deformation prediction

The optimization results of the GA algorithm on the C1 and C2 measurement points are shown in Figure 7. The analysis shows that the fitness value (*MAE*) decays rapidly as the number of optimizations increases and stabilizes after 25 generations, indicating that the prediction error of the DeepAR model can be reduced by the GA algorithm. At the end of the optimization, the optimal hyperparameters on the C1 measurement point are obtained as num_layers=2, num_cells=120, dropout_rate=0.2, learning_rate=0.00136, and epochs=500, and the optimal hyperparameters on the C2 measurement point are obtained as num_layers=3, num_cells=200, dropout_rate=0.2, learning_rate=0.0008, epochs=500.

After obtaining the optimal hyperparameters, they are input into the DeepAR model. The D_{test_C1} and D_{test_C2} of C1 and C2 measurement points after the noise reduction process are input into the trained DeepAR prediction model respectively, and the corresponding slope deformation prediction results are calculated. To visualize the prediction ability of the GF-DeepAR model, the predicted results of the model at the C1 and C2 measurement points are plotted as shown in Figures 8A, B, with the horizontal axis representing the slope deformation obtained from the actual monitoring, and the vertical axis representing the slope deformation obtained from the prediction. Generally, a larger R^2 indicates a better nonlinear mapping ability of the model, and the noise-reduced values of C1 and C2 measurement points are 0.956 and 0.929, respectively, which are greater than 0.9, indicating a high prediction accuracy. Meanwhile, at the C1 and C2 measurement points, most of the data points are around the 45° median axis, indicating that the GF-DeepAR model has a strong ability to fit the nonlinearities against the slope deformation.

Further, the comparison of the predicted and measured values of slope deformation at the C1 and C2 measurement points are shown in Figures 8C, D. The analysis shows that the GF-DeepAR prediction model can well reflect the upward and downward fluctuations of slope deformation, and the predicted values match

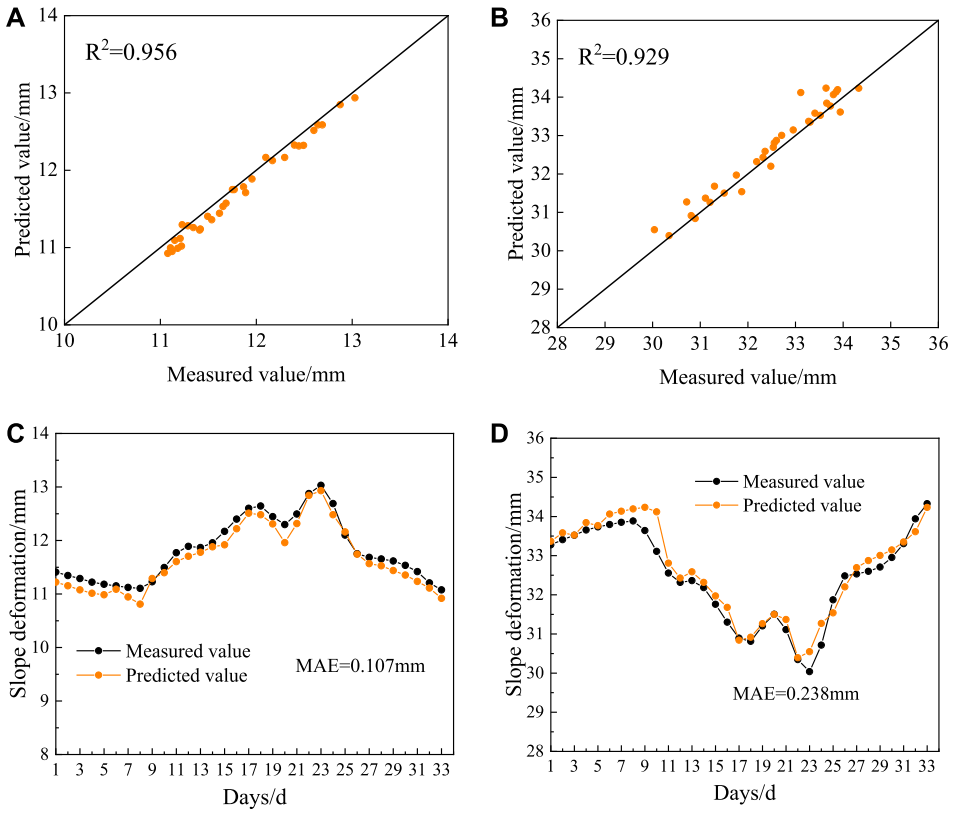

FIGURE 8
GF-DeepAR model slope deformation prediction results-Case 1 **(A)** C1 Measurement point- Scatter comparison of measured and predicted values; **(B)** C2 Measurement point- Scatter comparison of measured and predicted values; **(C)** C1 Measurement point- Comparison of measured and projected value trends; **(D)** C2 Measurement point- Comparison of measured and projected value trends.

the overall trend of the measured values with high correlation. Meanwhile, the residuals at the C1 and C2 measurement points are overall controlled within a small range, with a small mean absolute error *MAE* of 0.107 and 0.238, respectively.

In summary, the GF-DeepAR prediction model effectively solves the problem of accuracy improvement caused by poor data quality in slope engineering. The GF-DeepAR model shows high generalization ability on the two slope deformation measurement points, high overall prediction accuracy and small prediction error, which can well support the prediction of slope deformation.

3.1.4 Comparative analysis of slope deformation prediction before and after noise reduction

The results of the slope deformation prediction accuracy assessment before and after noise reduction at the C1 and C2 measurement points are shown in Figures 9A, B. The R^2, *MAE,* and *MAPE* obtained from the C1 measurement point before noise reduction are 0.875, 0.186, and 1.552%, respectively, and the R^2, *MAE,* and *MAPE* obtained after noise reduction are 0.956, 0.107, and 0.913%, respectively, with an increase of 0.081 in R^2, which indicates that the prediction accuracy of the C1 measurement point has been improved after the noise reduction treatment, while the *MAE* and *MAPE* have decreased by 0.079% and 0.639%, respectively. indicating that the prediction error of the C1 measurement point was controlled after noise reduction treatment. Similarly, after the noise reduction treatment, the C2 measurement point R^2 increased by 0.089, while *MAE* and *MAPE* decreased by 0.184% and 0.581%, respectively, indicating that the prediction accuracy and prediction error of the C2 measurement point were also improved after the noise reduction treatment.

This is mainly due to three advantages of combining GF algorithms with machine learning algorithms. Firstly, the noise in the slope deformation data can be removed by GF algorithm, making the slope deformation closer to the real situation (Innes et al., 2021; Richardson et al., 2022). Secondly, the GF algorithm not only reduces noise but also helps to highlight the intrinsic characteristics of the data (Noguer et al., 2022; Guan et al., 2024). During the filtering process, the algorithm is able to retain the main trends in the data while weakening random fluctuations. This makes it easier for machine learning algorithms to capture key information about the data during subsequent predictions, thereby improving prediction accuracy (Demšar and Zupan, 2021; Peng and Lee, 2021). Finally, with the GF algorithm, the risk of overfitting of machine learning predictive models can be reduced, and the generalization ability of the model can be improved so that it can maintain a high prediction accuracy in the face of new data.

The comparison between the predicted and measured values of slope deformation at C1 and C2 measurement points before noise reduction is shown in Figures 9C, D. The analysis shows

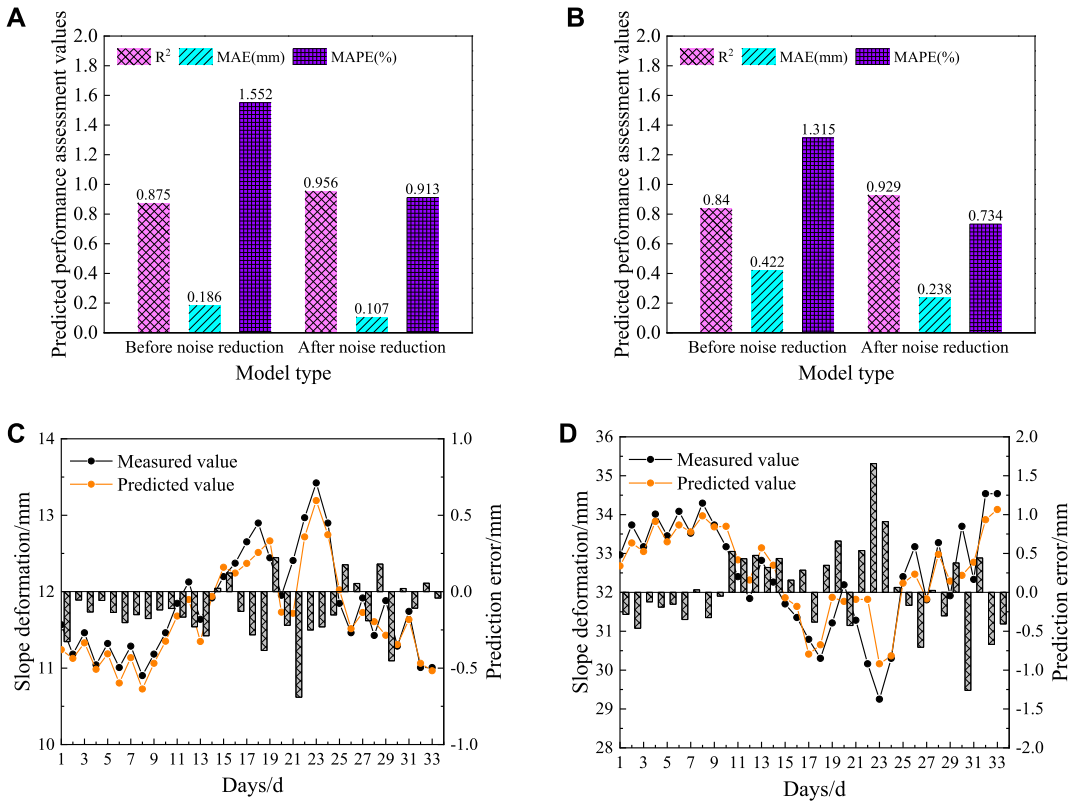

FIGURE 9
Comparison of slope deformation prediction results before and after noise reduction- Case 1 **(A)** C1 Measurement points - accuracy assessment of slope deformation prediction results before and after noise reduction; **(B)** C2 Measurement points - accuracy assessment of slope deformation prediction results before and after noise reduction; **(C)** C1 Measurement points - before and after noise reduction; **(D)** C2 Measurement points - before and after noise reduction.

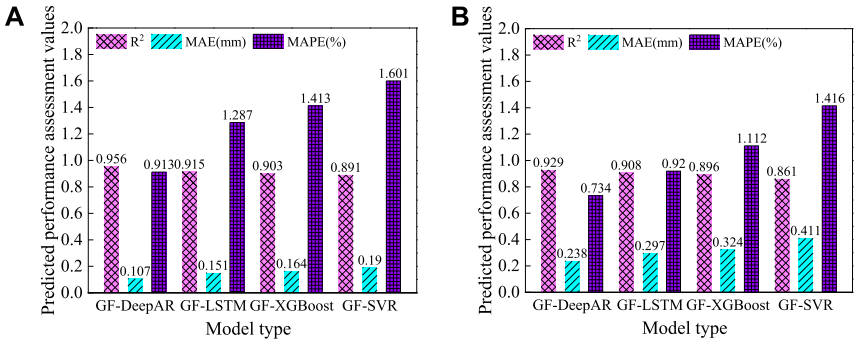

FIGURE 10
Comparison of prediction performance between different point prediction models **(A)** C1 measurement point; **(B)** C2 measurement point.

that although the prediction results and the measured values are more closely matched as a whole, there are fluctuations at more positions, i.e., the residuals of the data are larger, while the prediction results after noise reduction have a very high correlation between the predicted values and the measured values as a whole, and the prediction effect is better. In addition, the C1 and C2 measurement points experienced relatively large mutation phenomena in the interval segment from the 17th day to the 25th day, which is mainly considered to be the influence of the monitoring equipment, external environment (Yu et al., 2021; Yang et al., 2023). The GF-DeepAR prediction model can well control the unfavorable effects of the mutation data, and the prediction results still fit closely with the measured results. On the contrary, the single DeepAR prediction model without a noise reduction process has a large prediction error in this interval, limiting the overall prediction accuracy.

In summary, the GF-DeepAR prediction model can perform noise reduction for the original dataset, which guarantees the quality of the input dataset, and the resulting prediction accuracy is higher

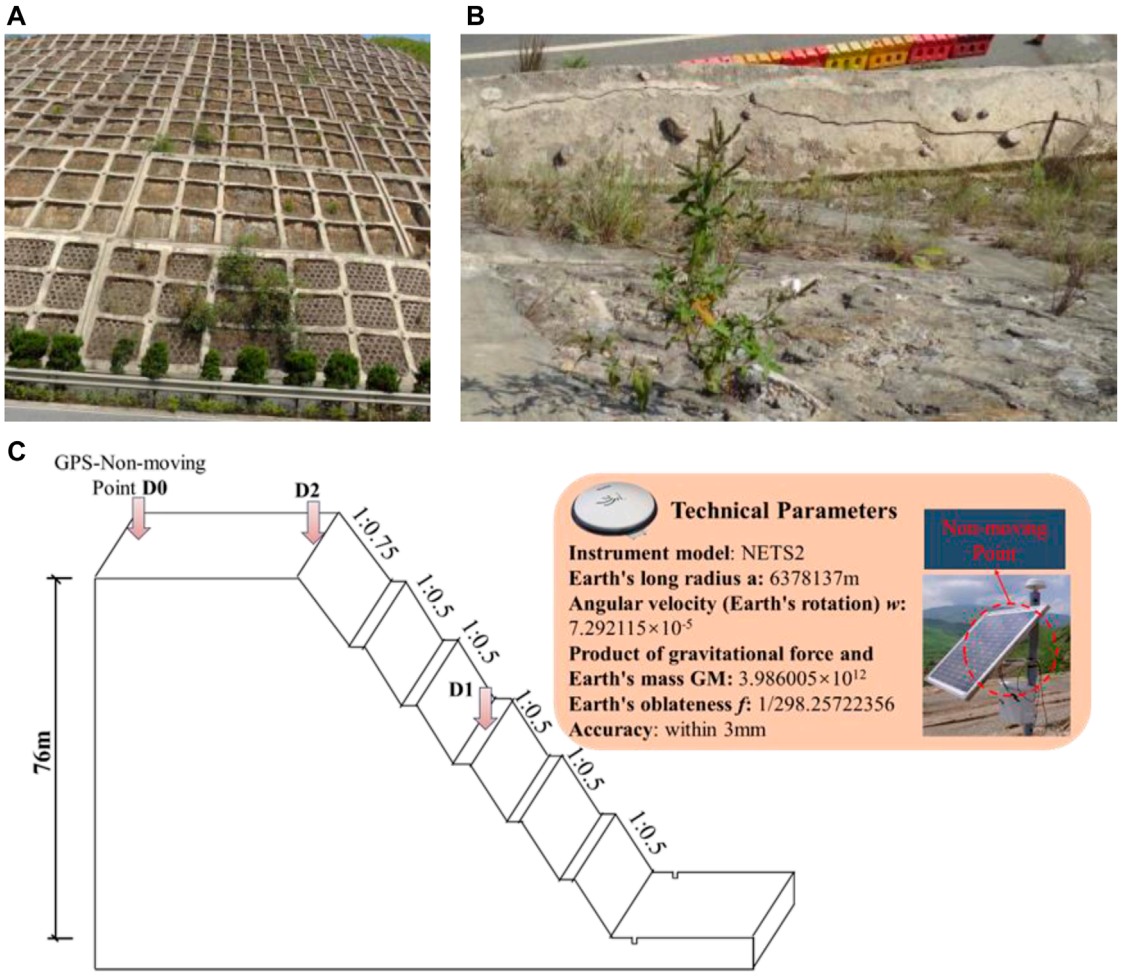

FIGURE 11
Slope engineering and deformation measurement point layout - Case 2 **(A)** High Steep Slope Site View; **(B)** Slope step cracks; **(C)** Deformation measurement point layout.

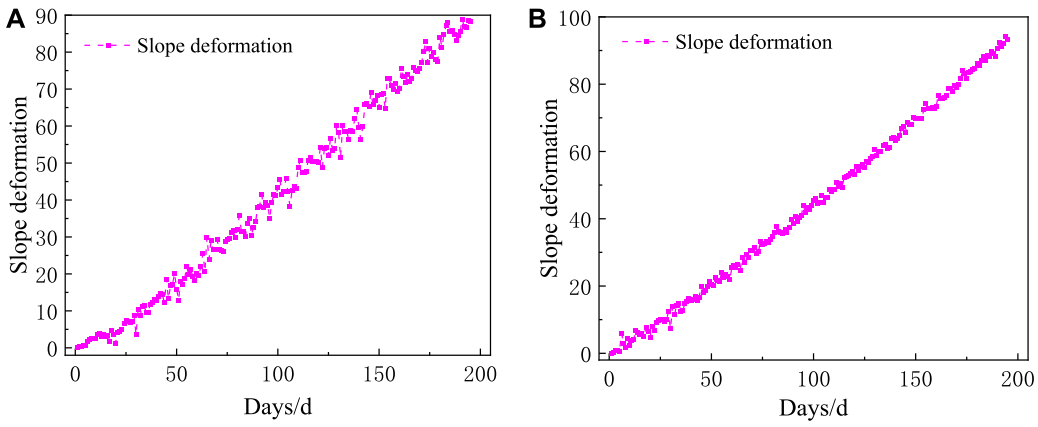

FIGURE 12
Change rule of slope cumulative deformation-Case 2 **(A)** D1 measurement point; **(B)** D2 measurement point.

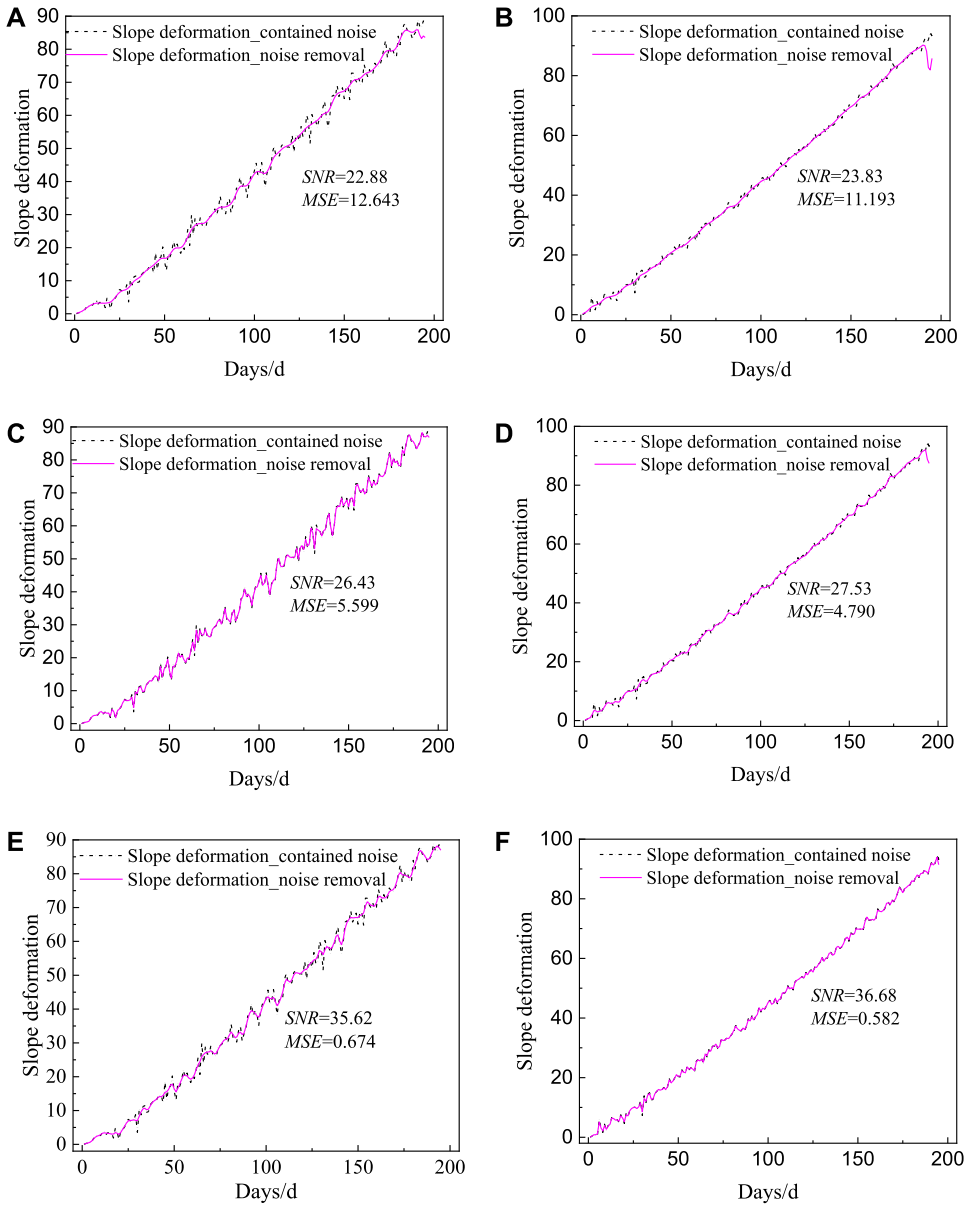

FIGURE 13
Noise reduction results of GF algorithm for slope deformation - Case 2 **(A)** D1 Measurement points -σ2.0; **(B)** D2 Measurement points -σ2.0; **(C)** D1 Measurement points -σ1.0; **(D)** D2 Measurement points -σ1.0; **(E)** D1 Measurement points -σ0.5; **(F)** D2 Measurement points -σ0.5.

than that of the single DeepAR prediction model, and the prediction error is lower than that of the single DeepAR prediction model.

3.1.5 Comparative analysis of the results of slope deformation prediction

To verify the superiority of the DeepAR model over the classical LSTM, XGBoost, and SVR prediction models, the same GF algorithm is used to optimize the LSTM, XGBoost, and SVR. A comparison analysis is performed with the GF-DeepAR hybrid model, and the results are shown in Figure 10. Taking the C1 measurement point as an example, the model with the smallest prediction error *MAE* and *MAPE* is the GF-DeepAR model, with *MAE* and *MAPE* of 0.107% and 0.913%, respectively, followed by the GF-LSTM model (0.151, 1.287%), then the GF-XGBoost model (0.164, 1.413%), and finally the GF-SVR model (0.891, 1.601%). Meanwhile, the prediction accuracy metric R^2 of each model is compared and it is found that the highest prediction accuracy is also achieved by the GF-DeepAR model. Hence, it can be obtained that the GF-DeepAR model has a better advantage in slope deformation point prediction than the classical LSTM, XGBoost and SVR models.

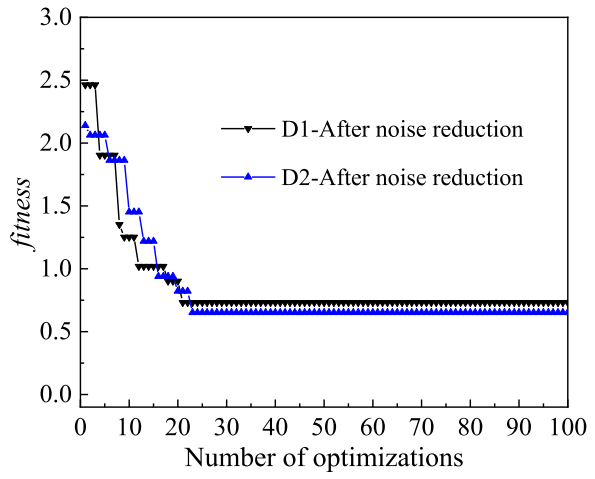

FIGURE 14
Optimization results of GA algorithm on D1 and D2 measurement points.

3.2 Case 2

3.2.1 Overview of works

Similarly, to verify the effectiveness of the proposed hybrid GF-DeepAR model, a high slope in a mountainous area is selected as an engineering example as shown in Figures 11A, B. The slope is a naturally high steep slope, the steepest part of the slope is as high as 76 m, according to the engineering geological conditions and the height of the slope to adopt step-type slope, the slope rate is set at 1:0.75 and 1:0.5. After operating for some time, there are large cracks appeared on the slope steps, and the whole slope is extruded and deformed at the foot of the slope after lateral shift, with poor slope stability. The slope is relatively high and steep, with a high-risk factor, and the consequences would be very serious in case of a landslide. To ensure the normal operation of the line, deformation monitoring is carried out for this slope.

Two GPS points, D1 and D2, are placed at the middle and top of the high slope to monitor the deformation value of the slope, where the GPS receiver is modeled as NETS2. The monitoring cycle is 195 d. The monitoring frequency is set to 6 h/time, influenced by the solution cycle, and the daily monitoring values are averaged over all the monitoring values for the day. The technical parameters of the surface deformation gauges and their specific placement can be found in Figure 11C.

The change rule of D1 and D2 measurement points is plotted as shown in Figure 12. In the figure, the deformation at the top of the slope (measurement point D2) is larger than the deformation in the middle of the slope (measurement point D1), and this pattern is consistent with measurement points C1 and C2. The deformations at both D1 and D2 measurement points are cumulative over time, and there are certain fluctuations, so D1 and D2 measurement points can be used as typical measurement points to verify whether the proposed GF-DeepAR model can accurately and reliably predict the development trend of cumulative deformation of slopes.

3.2.2 Results of noise reduction analysis

The GF-DeepAR hybrid model is used to first reduce the noise of the original monitoring data sets *Data_set_D1* and *Data_set_D2* at D1 and D2 respectively (the standard deviation σ is set to 2.0, 1.0, and 0.5), and the relationship between the noise-reduced slope deformation series and the original noise-containing slope deformation series is shown in Figure 13.

As shown in Figure 13, the noise-reduced slope deformation series retains the characteristics of the changing trend of the original series while better removing the noise information hidden in it as in Case 1. Taking the D1 measurement point as an example, under three different standard variances, *SNR* and *MSE* are 22.88(12.643), 26.43(5.599), and 35.62 (0.674) for the three different standardized variances, respectively. *SNR* gradually increases from 22.88 to 35.62, and *MSE* gradually decreases from 12.643 to 0.674 as the standard variance σ decreases, which indicates that the effect of noise reduction becomes better. Similarly, the results of the noise reduction performance of D2 and D1 are consistent. Considering that the noise reduction effect obtained by continuing to reduce the standard variance σ is gradually stable, the noise reduction data under the condition that the standard variance σ is 0.5 can be selected as the data for the subsequent prediction analysis of the D1 measurement point and D2.

3.2.3 Results of slope deformation prediction

Similarly, the optimization results of GA algorithm on D1 and D2 monitoring points are obtained as shown in Figure 14. Similar to the results for the C1 and C2 measurement points, the fitness value (MAE) decays rapidly as the number of optimizations increases and stabilizes after 25 generations. At the end of the optimization, the optimal hyperparameters on the D1 measurement point are obtained as num_layers=3, num_cells=67, dropout_rate=0.2, learning_rate=0.00230, and epochs=300, and the optimal hyperparameters on the D2 measurement point are obtained as num_layers=2, num_ cells=156, dropout_rate=0.2, learning_rate=0.0050, epochs=600.

Similarly, the sequences of D1 and D2 measurement points after the noise reduction process are input into the trained DeepAR prediction model respectively, and the corresponding slope deformation prediction results are calculated and plotted as shown in Figure 15A, B. The R^2 after noise reduction at the D1 and D2 measurement points are 0.968 and 0.974, respectively, which are greater than 0.95, indicating a high prediction accuracy. Further, the comparison of the predicted and measured values of slope deformation at the D1 and D2 measurement points are shown in Figures 15C, D. The analysis shows tat the GF-DeepAR prediction model can well reflect the upward and downward fluctuations of slope deformation, and the predicted values match the overall trend of the measured values with high correlation. Meanwhile, the residuals at the D1 and D2 measurement points are overall controlled within a small range, with a small mean absolute error *MAE* of 0.811 and 0.760, respectively.

In summary, the GF-DeepAR prediction model also effectively solves the problem of accuracy improvement due to data quality issues and the shortcomings of overfitting or underfitting of the prediction model in the high slope project in this mountainous area.

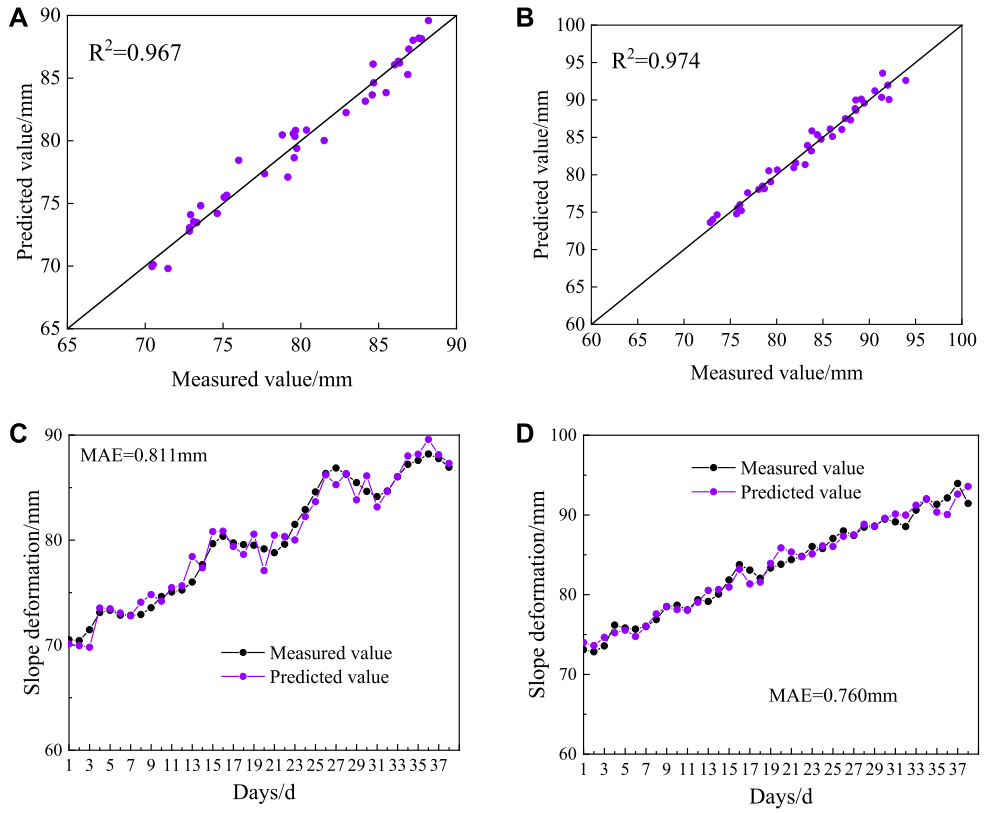

FIGURE 15
GF-DeepAR model slope deformation prediction results - Case 2 **(A)** D1 Measurement Points - Scatter Comparison of Measured and Predicted Values; **(B)** D2 Measurement Points - Scatter Comparison of Measured and Predicted Values; **(C)** D1 Measured points - comparison of measured and predicted trends; **(D)** D2 Measured points - comparison of measured and predicted trends.

3.2.4 Comparative analysis of slope deformation prediction before and after noise reduction

The results of slope deformation prediction accuracy assessment before and after noise reduction at D1 and D2 measurement points are shown in Figure 16A, B. Taking the D1 measurement point as an example, the R^2, *MAE* and *MAPE* obtained before noise reduction are 0.897, 1.548, and 1.929%, respectively, and the R^2, *MAE* and *MAPE* obtained after noise reduction are 0.967, 0.811, and 1.017%. The increase of R^2 by 0.070 indicates that the prediction accuracy of the D1 measurement point is improved after the noise reduction treatment, whereas the decrease of *MAE* and *MAPE* by 0.737% and 0.912%, respectively, indicates that the prediction error of the D1 measurement point is controlled after the noise reduction treatment. The same as Case 1, the prediction accuracy of GF-DeepAR model can be effectively improved because of the three advantages of reducing noise interference, highlighting data features and improving model generalization ability.

A comparison of the predicted and measured values of slope deformation at the D1 and D2 measurement points before noise reduction is shown in Figure 16C, D. Taking the D1 measurement point as an example, the analysis shows that the fluctuation between the prediction result and the measured value exists at more positions, and the R^2 is lower than 0.9, which mainly considers the influence of the data noise and restricts the fit between the prediction result and the measured value; while the overall correlation between the predicted value and the measured value after the noise reduction is extremely high, and the prediction result is better. In addition, D1 and D2 measurement points experienced relatively large mutations in the interval segment from the 16th day to the 27th day. As with the results obtained in Case 1, the GF-DeepAR prediction model can well control the unfavorable effects of the mutation data, while the single DeepAR prediction model without a noise reduction process has a large prediction error in this interval.

3.2.5 Comparative analysis of the results of slope deformation prediction

Similarly, to verify the superiority of the DeepAR model over the classical LSTM, XGBoost, and SVR models, the performance assessment results of each model are calculated as shown in Figure 17. Taking the D1 measurement point as an example, the model with the smallest prediction error *MAE* and *MAPE* is the GF-DeepAR model, with *MAE* and *MAPE* of 0.811% and 1.017%, followed by the GF-LSTM model (0.951, 1.197%), then the GF-XGBoost model (1.234, 1.501%), and finally the GF-SVR model (1.340, 1.723%). Similarly, the prediction accuracy metric R^2 of each model is compared and it is found that the highest prediction accuracy is also achieved by the GF-DeepAR model. Hence, it can be obtained that the GF-DeepAR model has a better advantage over the classical LSTM, XGBoost, and SVR models in the prediction of slope deformation points.

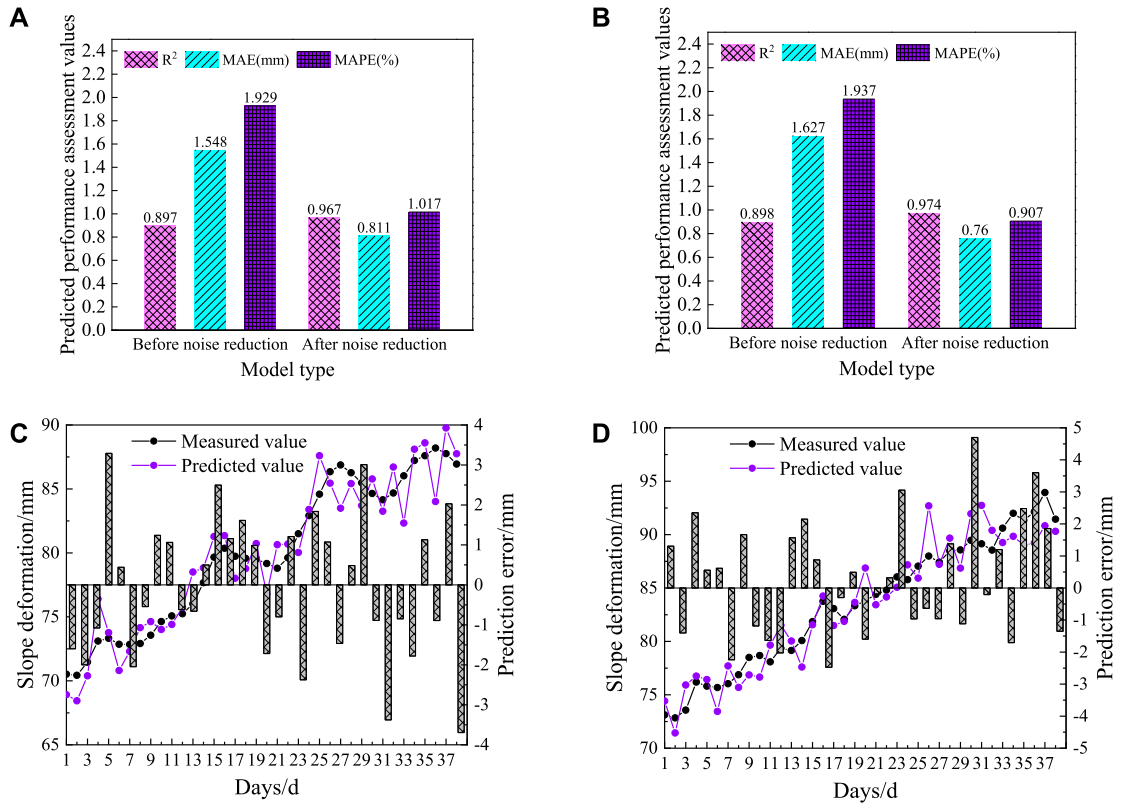

FIGURE 16
Comparison of slope deformation prediction results before and after noise reduction-Case 2 **(A)** D1 Measurement points - accuracy assessment of slope deformation prediction results before and after noise reduction; **(B)** D2 Measurement points - accuracy assessment of slope deformation prediction results before and after noise reduction; **(C)** D1 Measurement points - before and after noise reduction; **(D)** D2 Measurement points - before and after noise reduction.

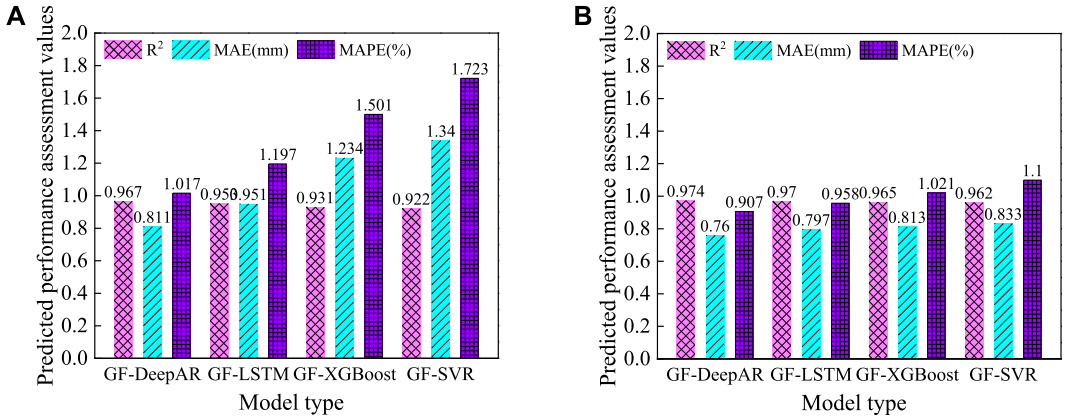

FIGURE 17
Comparison of prediction performance between different point prediction models **(A)** D1 measurement point; **(B)** D2 measurement point.

4 Framework for probability analysis of slope deformation based on the GF-DeepAR model

Compared with GF-LSTM, GF-XGBoost, and GF-SVR models, the GF-DeepAR model has better prediction performance. Moreover, the GF-DeepAR model can take into account the uncertainty of slope deformation prediction and provide the probability distribution of the slope deformation prediction results, which is more conducive to making safety precautionary decisions (Deng et al., 2023).

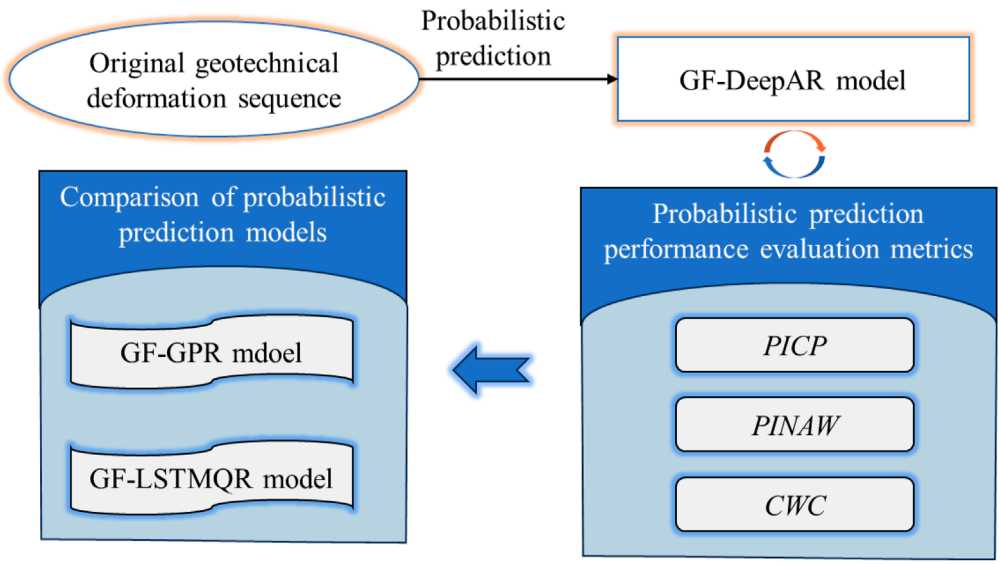

FIGURE 18
Framework for probabilistic analysis of the GF-DeepAR model.

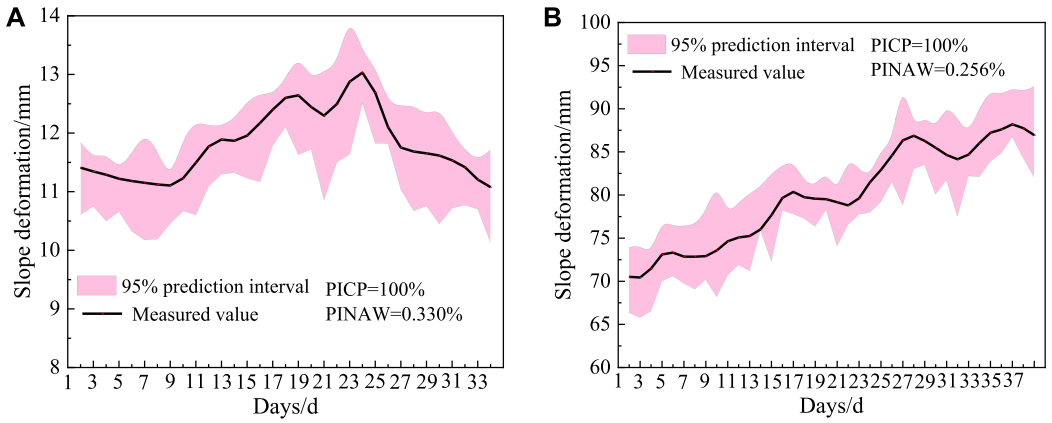

FIGURE 19
Probabilistic prediction results for C1 and D1 measurement points **(A)** C1 probability prediction results; **(B)** D1 probability prediction results.

The probability analysis framework of the GF-DeepAR model is shown in Figure 18. In this paper, we use historically measured slope deformation data to predict the slope deformation sequence probabilistically based on the GF-DeepAR model, and assess the prediction performance by using three metrics, namely, the prediction interval coverage (*PICP*), the normalized average width of the prediction interval (*PINAW*), and the coverage width criterion (*CWC*) (Shi et al., 2022; Schmidinger and Heuvelink, 2023). The specific calculations are as shown in Eqs 14–18:

$$PICP = \frac{1}{N}\sum_{k=1}^{N} R_k \tag{14}$$

$$R_k = \begin{cases} 1, Y(k) \in \left[Y_{low}, Y_{high}\right] \\ 0, Y(k) \notin \left[Y_{low}, Y_{high}\right] \end{cases} \tag{15}$$

$$PINAW = \frac{1}{N(Y_{\max} - Y_{\min})}\sum_{k=1}^{N}\left(Y_{high} - Y_{low}\right) \tag{16}$$

$$CWC = PINAW\left[1 + I(PICP)e^{-p(PICP-v)}\right] \tag{17}$$

$$I(PICP) = \begin{cases} 1, PICP < v \\ 0, Others \end{cases} \tag{18}$$

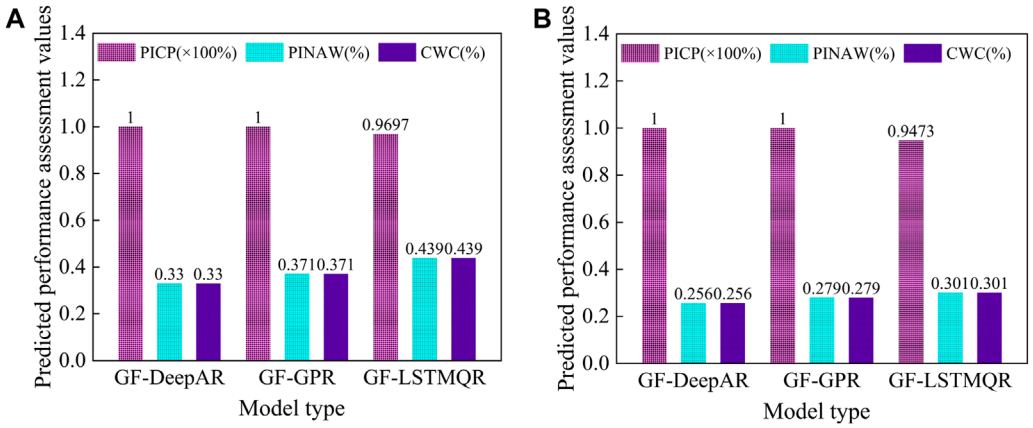

FIGURE 20
Comparison of prediction performance between different probabilistic prediction models **(A)** C1 measurement point; **(B)** D1 measurement point.

Where: Y_{high}, Y_{low} are the maximum and minimum values of a sample prediction interval in the slope deformation sequence Y_{max}, Y_{min} are the maximum and minimum values of all predicted samples. v is set as the nominal confidence level, p is the penalty parameter for the probability of failure intervals, which ranges from 50 to 100, and is taken as 50 here. A larger *PICP* indicates that there are more true values in the prediction interval, and a smaller *PINAW* has a smaller range of the prediction interval, which is more favorable for decision making. *PICP* and *PINAW* can be combined through *CWC*, and the smaller the value of *CWC*, the better.

The probability prediction analysis is carried out on the C1 and the D1 measurement point in Case 1 and Case 2, based on the GF-DeepAR model. The probability prediction results under the condition of 95% confidence are obtained as shown in Figure 19. The prediction intervals constructed in Figure 19, indicate that the *PICP* in both C1 and D1 measurement points are 100%, which is far from meeting the requirement of a 95% confidence level, implying that the prediction intervals constructed by the GF-DeepAR model can effectively envelope the actual slope deformation curves, and the *PINAW* are low, which are 0.330% and 0.256% respectively. It indicates that the upper and lower boundaries of the interval can be used as optimistic and conservative estimation quantities for slope deformation prediction. Taking the C1 measurement point shown in Figure 19A as an example, when the boundary value of the interval is lower than the corresponding engineering deformation warning index, it means that the actual deformation has a corresponding probability of being in the safe range. Hence, the probabilistic prediction provides an effective method for quantitatively evaluating the safety risk of slopes.

As shown in Figure 18, to verify the superiority of GF-DeepAR model in probability prediction, GF-GPR and GF-LSTMQR models are used for the comparation analysis of slope deformation probability prediction. The results of the comparison of prediction performance between different probability prediction models are obtained as shown in Figure 20. The *PICP* of the GF-DeepAR and GF-GPR models can reach 100% at both C1 and D1 measurement points, followed by the GF-LSTMQR model (C1: 96.97%, D1: 94.73%). Meanwhile, it can be found that the width of the GF-LSTMQR model is much larger than that of the remaining two types of models by *PINAW* values, which suggests that the GF-LSTMQR model has a larger degree of uncertainty. From the comparison analysis of the reliability and uncertainty of the intervals, the *CWC* values of the GF-DeepAR model proposed in this paper are 0.330% and 0.256% in the two measurement points of C1 and D1, respectively. They are smaller than the rest of the two types of models, indicating that the method in this paper not only meets the requirement of the reliability of the confidence level but also constructs intervals with the smallest uncertainty.

In summary, it indicates that the GF-DeepAR model is superior in probability prediction and better compared to the GF-GPR and GF-LSTMQR models. In addition, the GF-DeepAR probability prediction model also provides managers with an effective tool to quantify the uncertainty of the model output results, which can be used to analyze the main factors that cause uncertainty in the results on time according to the probability of interval coverage and the width of the intervals, to carry out timely regulation and reduce the risk of decision-making.

5 Discussions

In order to better highlight the research innovation of this paper, it is discussed and analyzed in three parts: comparison with similar studies, the processing of the input data comparison of prediction accuracy at different time steps and future outlook.

5.1 Comparison with similar studies

As shown in Table 1, a comparison of the established studies and the study in this paper is organized. The established studies include ACO-SVM model, SVM model, WD-IPSO-LSTM model, Transformer model and BiLSTM model, and in this paper, we study the GF-DeepAR model. By organizing the point prediction

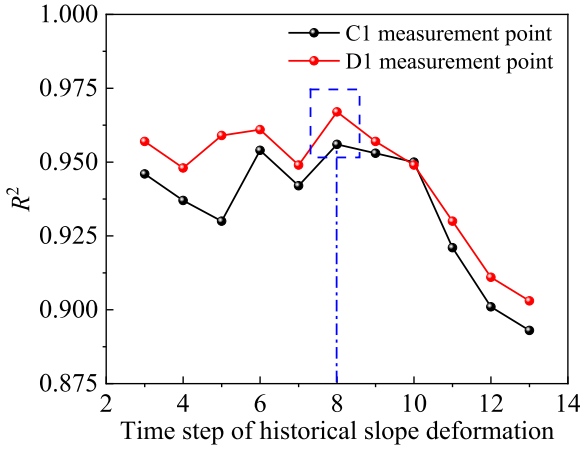

FIGURE 21
Different slope deformation time step under the R^2 change rule.

assessment results of each model, it is found that the R^2, *MAE*, and *MAPE* of the GF-DeepAR model are optimal, indicating that the GF-DeepAR model can achieve better prediction accuracy and lower prediction error. Meanwhile, another advantage of the GF-DeepAR model over established studies is the probability prediction, and the GF-DeepAR model can provide highly reliable and clear probability prediction results with a *PICP* of 100%.

5.2 The processing of the input data comparison of prediction accuracy at different time steps

In order to analysis the prediction performance of the GF-DeepAR model with different input parameters, the R^2 of the prediction results is calculated from the setup of different slope deformation time steps (3–13). Obtained different slope deformation time step under the R^2 change rule as shown in Figure 21, the analysis shows that when the time step between 3 and 8, R^2 fluctuates up and down, and reached the best when the time step is 8. Then, as the time step increases, R^2 gradually decreases, mainly considering that the longer and farther away from the predicted target time the slope deformation has less influence on the predicted target (Liu et al., 2020).

5.3 Future outlook

In this paper, a slope deformation prediction method based on the GF-DeepAR hybrid model is proposed, which can be used for noise reduction of slope noise data and provide highly accurate and reliable prediction results. However, the monitoring data of the underlying project only includes slope deformation data and the core point of this paper focuses on the noise reduction algorithm and prediction analysis, the input features of the GF-DeepAR hybrid model are only slope deformation, and the influencing factors of slope deformation are not considered. In general, water has a

TABLE 1 Accuracy assessment of slope deformation prediction results before and after noise reduction-Case 2.

N°	References	Input features	Model Type	Assessment metrics			Probability prediction assessment metrics	
				R^2	MAE(mm)	MAPE(%)	PICP(%)	PINA(%)
1	Chen et al. (2023)	Historical slope deformation	ACO-SVM	-	-	1.19	No probabilistic prediction function	
2	Jia et al. (2013)	Historical slope deformation	SVM	-	0.618	-		
3	Wang et al. (2023)	Historical slope deformation	WD-IPSO-LSTM	-	-	1.055		
4	Ning et al. (2023)	Historical slope deformation	Transformer/BiLSTM	0.8635/0.8365	2.4117/2.7548	-		
5	This paper	Historical slope deformation	GF-DeepAR	0.956/0.967	0.107/0.811	0.913/1.017	100/100	0.330/0.256

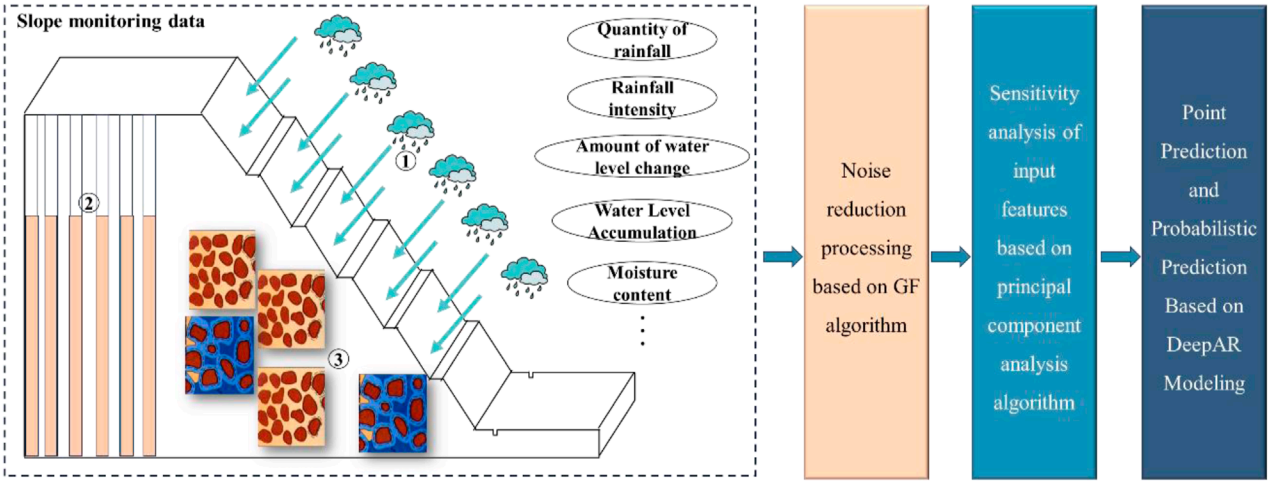

FIGURE 22
Future outlook.

great influence on soft rock slopes, loose accumulation slopes, and landslide slopes, etc. (Zhang et al., 2022; Yu et al., 2023). In addition, the deformation of slopes is susceptible to rainfall, water level, water content, and other factors related to water, which can lead to sudden changes or anomalies in deformation (Lo et al., 2023), which in turn affects the performance of slope deformation prediction models. It is worth noting that rainfall characteristics may contain multiple metrics such as rainfall intensity, rainfall on the same day, rainfall over multiple days, etc., and water level characteristics may also contain multiple metrics such as the amount of change in water level and the cumulative amount of water level. To represent the influence of the main control features of slope deformation more accurately, it is necessary to screen for numerous influencing factors (Mali et al., 2021; Zhuang et al., 2023) Hence, the sensitivity analysis method can be introduced based on the existing methods to optimize the best input features for slope deformation prediction, and then carry out the subsequent point prediction and probability prediction analysis, as shown in Figure 22.

6 Conclusion

It is important for early warning of slope instability risk to understand future patterns of slope deformation. Currently, the susceptibility of slope monitoring data to noise problems limits the accuracy and reliability of slope deformation prediction. In this paper, a slope deformation point prediction and probability analysis model based on the GF-DeepAR algorithm is proposed and validated relying on two real slope engineering cases. Some conclusions are as follows:

1) The best noise reduction is achieved at the C1 and D2 sites with a standard deviation σ of 0.5. The corresponding *SNR* and *MSE* values are 34.91 (0.030) and 35.62 (0.674).
2) A comparison before and after noise reduction reveals that the R^2 values for the C1 and D2 measurement points increased by 0.081 and 0.070, respectively. Additionnally, the *MAE* decreases from 0.079 to 0.639, and the *MAPE* decreases from 0.737% to 0.912%, which indicates that the accuracy of point prediction and prediction error of each measurement point is improved after noise reduction treatment.
3) The prediction intervals constructed by the GF-DeepAR model can effectively envelop the actual slope deformation curves, and the *PICP* in both C1 and D1 are 100%, which is far enough to meet the requirement of 95% confidence level. The *PINAW* is low, measuring 0.330% and 0.256% for C1 and D1, respectively.
4) Whether it is point prediction or probability prediction, the GF-DeepAR model excels at extracting feature information from slope deformation sequences characterized by randomness and complexity. It conducts predictions with high accuracy and reliability, indicating superior performance compared to other models.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MS: Conceptualization, Formal Analysis, Methodology, Software, Validation, Visualization, Writing–original draft. FL: Data curation, Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing–review and editing.

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Conflict of interest

Author MS was employed by Hunan Provincial Communications Planning, Survey and Design Institute Co., Ltd. Author FL was employed by Hunan Water Planning and Design Institute Co., Ltd.

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Landslide hazard assessment of the fault zone considering the fault effect: a case study of the Lixian–Luojiabu fault zone in Gansu Province (China)

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The earthquake landslide hazard assessment method is mainly based on the traditional Newmark model. However, when the landslide hazard assessment is carried out along the fault zone, the calculated results are often different from the actual situation because the influence of fault effect is not fully considered. Therefore, how to construct a landslide hazard assessment model suitable for the fault zone is a technical problem to be solved by researchers. Taking the Lixian–Luojiabu fault zone in Gansu Province in China as the study area, this paper put forward the concept of fault effect correction coefficient exploringly, systematically studied the relative distance relationship between the landslide and fault zone, and the relative position relationship between landslide and upper and lower sides of the fault zone. The value table of the fault effect correction coefficient along the Lixian–Luojiabu fault zone was established, and the corresponding distribution map of the fault effect correction coefficient was drawn. Based on this, an improved Newmark model for the landslide hazard assessment along the fault zone was constructed. On the basis of systematic analysis of the slope and engineering geological rock group in the study area, the traditional Newmark model and improved Newmark model considering fault effects were used, respectively, to carry out the earthquake landslide hazard assessment under the condition of 10% exceeding probability in 50 years, and the ROC curve and Kappa coefficient methods were used to compare and analyze the evaluation results. The results showed that the AUC value and Kappa coefficient of the danger area obtained by the improved model with the Newmark model were 0.841 and 0.822, respectively, which were significantly higher than the calculated values of the traditional Newmark model, indicating that the model had a good improvement effect. The Newmark improved model, considering the fault effect, fully considered the influence of distance from the fault zone and fault upper and lower side effects, and the research results can provide a new reference for the landslide hazard assessment along the fault zone.

KEYWORDS

hazard assessment, Newmark model, fault effect, fault zone landslide, earthquake, Lixian–Luojiabu fault

1 Introduction

China is a country with frequent earthquakes. Active fault zones and tectonic zones are widely distributed in the mainland of China. Both inter-plate and intra-plate tectonic activities are very strong. In particular, in the weak areas of active fault zones or tectonic zones, destructive earthquakes are more likely to occur, which has a great impact on the daily life of local residents (Wang, 2018). According to data statistics, strong ground vibration along the active fault zone not only causes serious dislocation deformation of buildings but also easily induces secondary geological disasters such as landslide, collapse, debris flow, and sand liquefaction (Huang and Li, 2009; Peng et al., 2009; Guo et al., 2020; Chen et al., 2022; Li C. H. et al., 2023a; Bai and Xu, 2023; Li Y. W. et al., 2023b). Among these secondary geological disasters, landslide is one of the most developed disasters along the active fault zone. In the last century, landslides triggered by earthquakes have claimed hundreds of thousands of lives and caused huge economic losses (Schuster and Alford, 2004; Dunning et al., 2007; Yin, 2008; Huang, 2009; Lan et al., 2013; Xu et al., 2014; Xu et al., 2018; Sidorin, 2020; Wang et al., 2020; Qiu et al., 2024).

In the late 1960s, researchers in developed countries such as the United States, Britain, and France began to explore how to scientifically and rationally use the mechanical analysis model to carry out the regional landslide hazard assessment. The most commonly used regional earthquake landslide hazard assessment method in the world is based on the Newmark cumulative displacement theory (Newmark, 1965), which further calculates the permanent displacement of slopes under earthquake conditions and takes it as the basis for earthquake landslide hazard zoning (Wu and Wang, 2008). Wilson and Keefer (1983) and Wilson and Keefer (1985) carried out a regional earthquake landslide hazard assessment of the slope zone along the fault zone in the Los Angeles area of the United States using the Newmark model. Ambraseys and Menu (1988) constructed an analysis model based on the critical acceleration ratio for the first time on the basis of fully collecting the monitoring records of the earthquake network from 1940 to 1981. Milesa and Ho (1999) integrated GIS software into Newmark calculation and analysis, used the displacement value calculated by the Newmark model to classify the earthquake and landslide hazard in the San Francisco East Bay mountains into four levels, and compiled the corresponding earthquake and landslide risk distribution map. Based on the Newmark cumulative displacement method, Jibson et al. (2000) conducted an inversion analysis of the earthquake landslide hazard induced by the 1994 Northridge earthquake in California, United States. Rathje and Saygili (2008) took into account the different transcendental probability factors under earthquake conditions, and based on the improvement of the existing Newmark model, they completed the earthquake landslide hazard assessment under different transcendental probability conditions in Southern California. Daniel et al. (2013) compared the landslide induced by the 1994 Northridge earthquake in California with the landslide based on the displacement prediction of the slider and discussed the accuracy of the evaluation model. Shinoda and Miyata (2017) based on the Newmark model, considered the slope failure direction on the basis of determining the slope azimuth angle, and improved the regional earthquake landslide hazard assessment method.

In China, research on the regional landslide hazard assessment using the Newmark model started relatively late, but the research results in this area are gradually increasing in the past 10 years. Based on the analysis of Wenchuan earthquake data, Xu (2010) modified the Newmark model coefficient and established a slope permanent displacement prediction model suitable for the Sichuan area. Wang et al. (2013); Wang et al. (2015) took 11 counties and cities in the Wenchuan Ms8.0 earthquake disaster area as an example, proposed a rapid emergency assessment method for the earthquake landslide hazard based on the simplified Newmark displacement model, and carried out an in-depth discussion on the concept of the earthquake landslide hazard and mechanical assessment methods. Chen et al. (2013), Chen et al. (2018), and Chen et al. (2019) studied the landslide hazard assessment of the Lushan earthquake affected area in Sichuan, Ludian earthquake affected area in Yunnan, and Jiuzhaigou earthquake affected area based on the Newmark model. Yang et al. (2017) used the Newmark model to quickly evaluate the spatial distribution of the landslide hazard induced by the Nepal Ms8.1 earthquake in 2015, and the evaluation results basically reflected the basic characteristics of the earthquake-induced landslide hazard distribution in the area. Taking the 2008 Wenchuan Mw 7.9 earthquake area as an example, Ma and Xu (2019) presented the landslide hazard assessment and slope failure function using two Newmark displacement models regressed by regional and global station records. Then, Ma et al. (2023) used the machine learning method to compare and analyze the new generation of the seismic landslide hazard model proposed by Xu Chong and the traditional Newmark model in the M_W 5.8 Lushan earthquake area, and discussed the accuracy and applicability of the two models. Zeng et al. (2023) proposed to combine the PMBM based on the Newmark method with EFBM to form the Newmark-information value model (N-IV), Newmark-logic regression model (N-LR), and Newmark-support vector machine model (N-SVM) for the earthquake landslide hazard assessment on the Ludian M_W 6.2 earthquake in Yunnan, and had achieved a better prediction effect.

In summary, scholars mainly use the Newmark mechanical analysis model to carry out the earthquake landslide hazard assessment. Based on this, the model coefficients are modified according to the characteristics of the research area, and the corresponding improved models are proposed. These research results extend the application scope of the Newmark model to a certain extent. However, active fault zones in China are widely distributed, especially the landslide along the fault zone is highly developed. How to scientifically and reasonably use the Newmark model to carry out the landslide hazard assessment along the fault zone and whether to establish an improved Newmark model suitable for the fault zone are technical problems to be solved by scientific researchers. Taking the Lixian–Luojiabu fault zone in Gansu Province in China as an example, this paper explores the concept of the fault effect correction coefficient and constructs an improved Newmark model suitable for the landslide hazard assessment along the fault zone, in order to provide

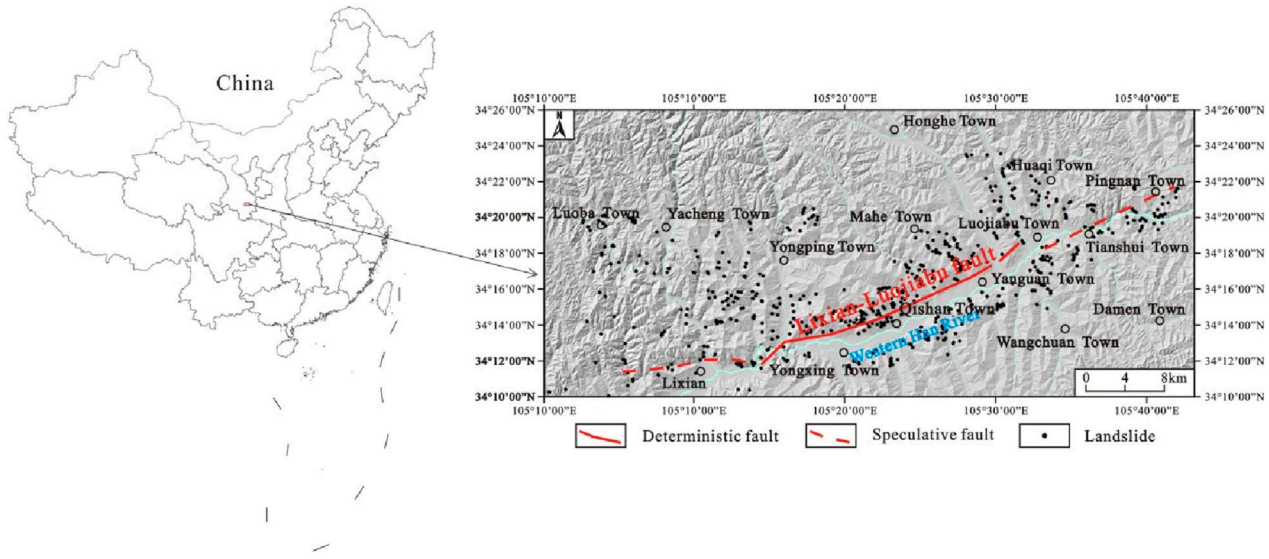

FIGURE 1
Landslide distribution map in the study area.

scientific basis for local government disaster prevention and mitigation.

2 Study area

The Lixian–Luojiabu fault zone in the Gansu Province of China starts from Tanchang in the west; passes through Taoping, Lixian, and Luojiabu; and extends to Jiezikou in the east, with a total length of approximately 150 km. It is characterized by both inclinative and left-handed development. The fault zone is mainly composed of three oblique secondary fault segments on the plane. The western segment starts from the east of Tanchang and ends to the east of Lixian, which is approximately 90 km long. The middle section starts from the south of Lixian and ends to the northeast of Luojiabu, which is approximately 40 km long. The eastern section starts from the west of Tianshui Town and ends to the east of Pingnan Town, which is approximately 20 km long. This paper takes the key area (the middle section) of the fault zone as the study area, which is located at the junction of the northern Lixian of Longnan City and the southwestern Qindu District of Tianshui City. It is the seismogenic fault of the 1654 Luojiabu 8.0 earthquake. The epicenter is located near the Luojiabu Town in the eastern section of the fault zone, and the maximum intensity can reach XI (Han, et al., 2001; Yang et al., 2015). The lithology of the strata exposed in the area includes Yanshanian biotite porphyritic granite, Devonian sandstone and slate, Carboniferous siltstone and limestone, Paleogene conglomerate and sandstone, Neogene red clay, Middle-late Pleistocene loess, and Holocene alluvial gravel. There are a large number of landslides along the fault zone. According to data collection, remote sensing interpretation and field investigation, it was found that 588 landslides have occurred on both sides of the Lixian–Luojiabu fault zone and the density of landslides is very high (Figure 1).

3 Assessment methodology

3.1 Calculation of the fault effect correction coefficient

For the Lixian–Luojiabu fault zone, the author carried out research on the fault effect of seismic geological disasters based on GIS technology and achieved research results on the correlation between landslide development and the fault zone (Feng et al., 2021). Through further analysis, it is found that the development of landslide is most affected by the distance from the fault zone and the relative position of the upper and lower sides. These two factors are static factors, while the direction of landslide movement and seismic intensity are dynamic factors that are difficult to predict. Therefore, the influence of the first two factors on the development of landslide should be considered. In order to carry out the landslide hazard assessment along the fault zone more accurately, the author puts forward the concept of the fault effect correction coefficient, which is a comprehensive correction coefficient value obtained by considering the two factors of the distance from the fault zone and the relative position of the upper and lower sides, and the parameter is expressed by β. The specific calculation method of the fault effect correction coefficient is represented as follows:

First, according to the relative distance between the landslide and the Lixian–Luojiabu fault zone, the density of landslide distribution points under different fault distance classification conditions is calculated (Figure 2). Because the landslide in the area 10 km away from the fault zone is the weakest controlled by the fault, the landslide point density value in the area >10 km away from the fault zone is used as the reference value, and the ratio of the landslide point density value in each fault distance classification to the landslide point density value in the area >10 km away from the fault is used as the correction value of the fault distance. The maximum amplification effect of the fault distance

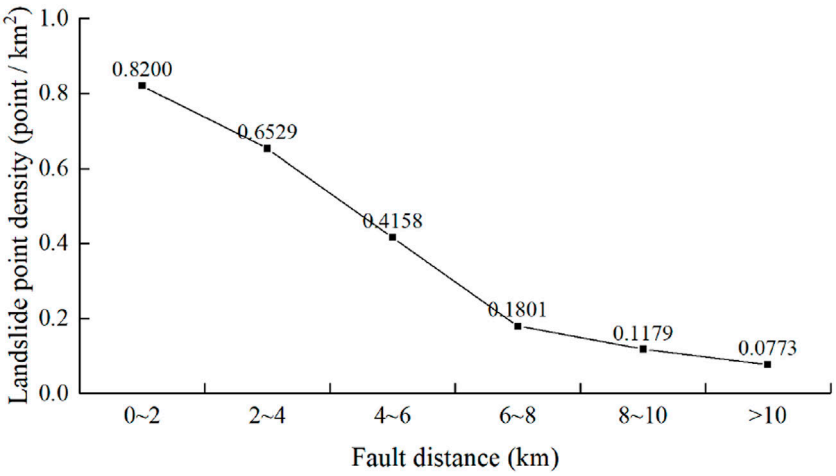

FIGURE 2
Graph of the relationship between the landslide point density and fault distance.

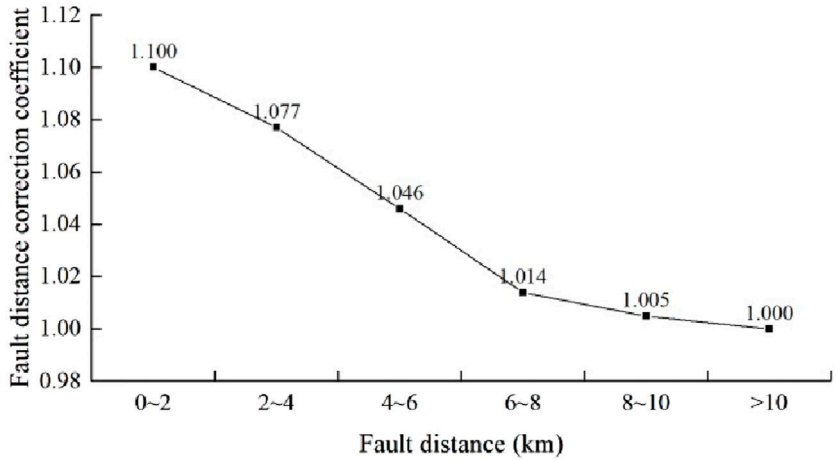

FIGURE 3
Fault distance correction coefficient graph of landslide.

on the landslide development is 1.1. The correction value of the fault distance under all fault distance classification is normalized (normalized interval 1–1.1), and the fault distance correction coefficient graph of the landslide along the Lixian–Luojiabu fault zone is obtained (Figure 3).

Second, according to the relative position relationship between the landslide and the upper and lower sides of the Lixian–Luojiabu fault zone, the density of landslide points in the upper and lower sides of the fault zone is calculated (Figure 4). It is worth noting that when point density analysis is carried out because the landslide in the area outside 10 km from the fault zone is weakly controlled by the fault and when the density value of the landslide point is carried out, the study area is divided into three grades: the upper wall area within 10 km from the fault zone, the lower wall area within 10 km from the fault zone, and the area beyond 10 km from the fault zone. Because the landslide in the area 10 km away from the fault zone is weakly controlled by the fault, the landslide point density value corresponding to the area 10 km away from the fault zone is taken as the reference value, and the ratio of the landslide point density value corresponding to the upper and lower sides classification area to the landslide point density value corresponding to the area 10 km away from the fault zone is taken as the upper and lower side correction value. The maximum amplification effect of the upper and lower side positions on the landslide development is limited to 1.1. The upper and lower side correction values in all classification areas are normalized (normalized interval 1–1.1), and the upper and lower side position correction coefficient graph of the landslide along the Lixian–Luojiabu fault zone is obtained (Figure 5).

Finally, the correction coefficient of the fault distance in Figure 3 and the correction coefficient of the upper and lower side position in Figure 5 are multiplied to obtain the value table of the correction coefficient of the fault effect (Table 1) and the value distribution map of the fault effect correction coefficient (Figure 6) along the Lixian–Luojiabu fault zone.

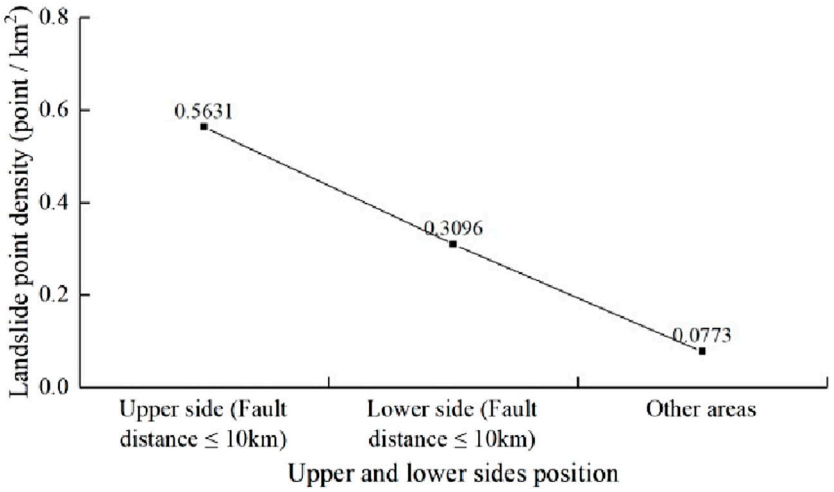

FIGURE 4
Graph of the relationship between the landslide point density and the upper and lower side positions.

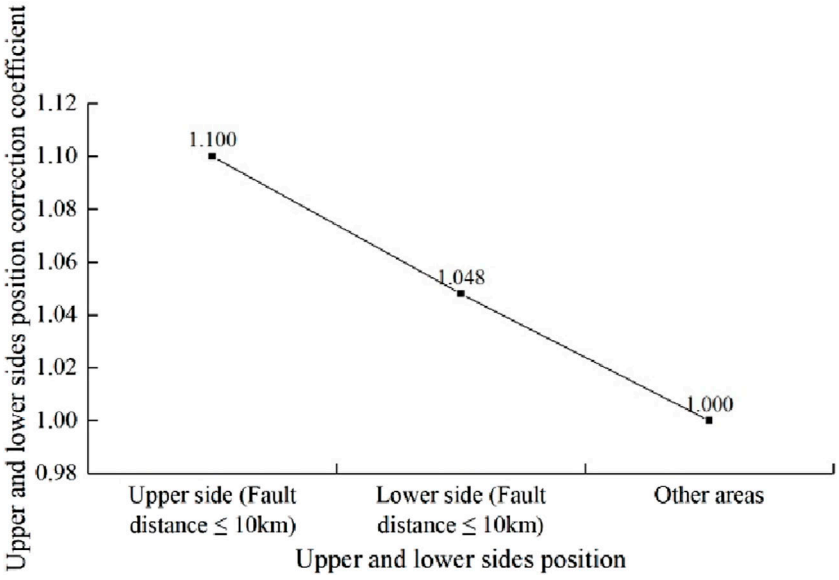

FIGURE 5
Upper and lower side position correction coefficient graph of landslide.

3.2 Construction of the Newmark improved model considering the fault effect

3.2.1 Newmark traditional model

In 1965, Newmark proposed the method of simulating landslide by the movement of rigid bodies on the slope surface, which later evolved into the famous Newmark model (Newmark, 1965). The model is based on the limit equilibrium theory. It is assumed that the sliding body is a rigid body and there is no deformation inside the sliding body. When the external force is less than the critical acceleration, the slope does not produce displacement. When the external force is greater than the critical acceleration, a finite displacement will occur. The model evaluates the stability of the slope by calculating the permanent displacement accumulated by the sliding body during the acceleration of the ground motion. At present, it has been widely recognized by scholars in the prediction of earthquake-induced landslides.

The corresponding calculation process can be summarized as five steps: (1) calculate the static safety factor of regional slope; (2) calculate the critical acceleration of the slope; (3) calculate the permanent displacement value of the slope; (4) calculate the probability of earthquake landslide occurrence; (5) complete the earthquake landslide hazard assessment.

TABLE 1 Value table of the correction coefficient of the fault effect (Lixian–Luojiabu fault zone of Gansu Province).

Distance from the fault zone / Relative position of the fault	0~2 km	2~4 km	4~6 km	6~8 km	8–10 km	>10 km
Upper side	1.210	1.185	1.150	1.115	1.106	1.000
Lower side	1.153	1.129	1.096	1.062	1.054	1.000

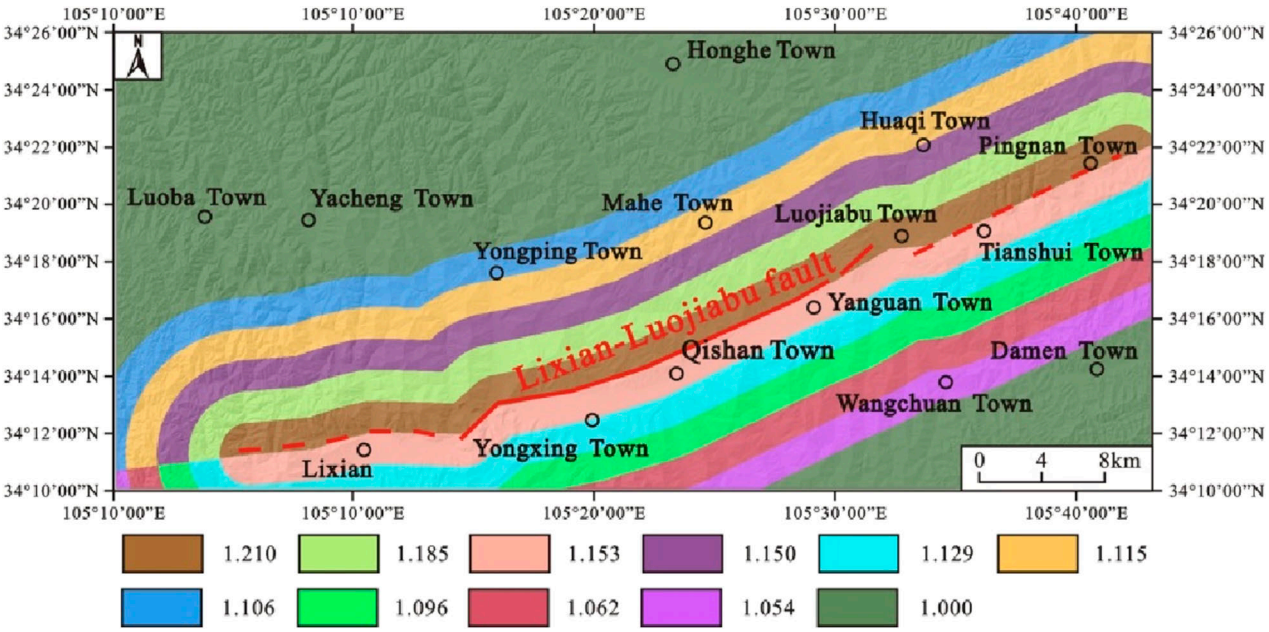

FIGURE 6
Value distribution map of the fault effect correction coefficient (Lixian–Luojiabu fault zone of Gansu Province).

When calculating the static safety factor of the regional slope, the safety factor formula proposed by Jibson et al. (2000) considering the influence of rainfall infiltration is generally used, and its stress analysis diagram is shown in Figure 7.

$$F_s = \frac{c'}{\gamma t \sin\alpha} + \frac{\tan\varphi'}{\tan\alpha} - \frac{m\gamma_w \tan\varphi'}{\gamma \tan\alpha} \quad (1)$$

where φ' is the effective internal friction angle (°), c' is the effective cohesion (kPa), α is the slope angle (°), γ is the weight of slope material (kN/m^3), γ_w is the weight of water (kN/m^3), t is the thickness of the slope body (m), and m is the ratio of the buried depth of groundwater above the damaged surface to the depth of the damaged surface.

The critical acceleration is expressed as

$$a_c = (F_s - 1)g \sin\alpha \quad (2)$$

where g is the acceleration of gravity (m/s^2).

The Newmark displacement calculation adopts the empirical formula obtained by Jibson and Harp et al.:

$$\lg D_n = 1.521 \lg I_a - 1.993 \lg a_c - 1.546 \quad (3)$$

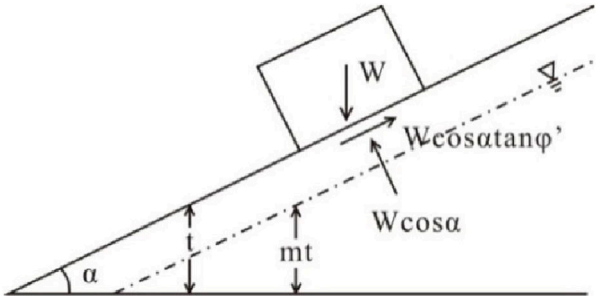

FIGURE 7
Static force analysis diagram of the Newmark model.

where D_n is the Newmark cumulative displacement (m) and I_a is the earthquake intensity (m/s).

The general formula of I_a is

$$I_a = \frac{\pi}{2g} \int_0^{T_d} [a(t)]^2 dt \quad (4)$$

where $a(t)$ is the time program column of single-component ground motion acceleration in a strong earthquake (m/s^2), T_d is the total duration recorded for ground motion acceleration (s), and t is time (s).

From Formula (4), the Newmark cumulative displacement calculation needs to input the complete ground motion acceleration time series curve, but this is difficult to achieve in the real process. Therefore, in the absence of the ground motion acceleration time series curve, people generally use the empirical formula to calculate the I_a value. In this paper, the Arias strength is calculated by using Roberto to analyze the empirical formula of 190 acceleration time history records of 17 strong earthquakes in Italy (Roberto, 2000):

$$I_a = 0.004(PGA)^{1.668} \tag{5}$$

where PGA is the peak ground acceleration (m/s^2).

In fact, the cumulative displacement D_n calculated by the above Newmark model is not completely corresponding to the slope instability, and the area where the cumulative displacement occurs does not necessarily have a landslide. Only when the slope displacement accumulates to a certain extent, the slope will be unstable and lead to landslide. For this reason, Jibson et al. (2000) proposed a formula for calculating the probability of earthquake landslides. This formula can reasonably reflect the internal relationship between slope displacement and landslide occurrence, which is convenient for people to further carry out the hazard assessment on the basis of calculating the probability of earthquake landslides. The specific calculation formula of the earthquake landslide probability is as follows:

$$P(D_n) = k\left[1 - exp\left(-aD_n^b\right)\right] \tag{6}$$

where $P(D_n)$ is the probability of the occurrence of an earthquake landslide; and k, a, and b are constant parameters in the fitting function. In this paper, k is 0.335, a is 0.048, and b is 1.565.

3.2.2 Newmark improved model considering the fault effect

In this paper, combined with the characteristics of landslide development along the fault zone, the static safety factor formula of the Newmark model is improved, and the fault effect correction coefficient is introduced. Because the larger the safety factor is, the better the stability of the slope is, and the correction coefficient is essentially the amplification coefficient of the fault effect; the safety factor should be reduced to a certain extent. Here, the reciprocal of the correction coefficient of the fault effect is taken for reduction. The specific expression is

$$F_s = \frac{1}{\beta} \bullet \left(\frac{c'}{\gamma t sin\alpha} + \frac{\tan\varphi'}{\tan\alpha} - \frac{m\gamma_w \tan\varphi'}{\gamma \tan\alpha} \right) \tag{7}$$

where β is the correction coefficient of the fault effect and its value can be referred to the calculation method in Section 2.

The calculation steps of the landslide hazard assessment using this method are similar to the Newmark traditional model, and the specific calculation method is no longer repeated.

4 Landslide hazard assessment of the fault zone

4.1 Parameter selection

4.1.1 Terrain slope

Slope is a key factor affecting the development of landslide, which directly affects the stability of the slope (Hürlimann, et al., 2022; Yang, et al., 2023). ArcGIS software was used to reclassify the slope of the study area according to 1:50,000 DEM data, and it was divided into six sections: 0°–10°, 10°–20°, 20°–30°, 30°–40°, 40°–50°, and above 50° (Figure 8). Among them, the size of the grid value is set to 25 m × 25 m, and the study area is divided into 3,080,572 grid units.

4.1.2 Engineering geological rock group

The engineering geological rock group is the material foundation of landslide, which directly affects the stress state and weathering degree of rock and soil on the slope (Liu, et al., 2024; Ye, et al., 2024). When selecting the parameters of the engineering geological rock group, the stratum lithology in the study area is simplified and classified into five rock groups, which are the hardest rock group, the harder rock group, the softer rock group, the weak rock group, and the loose rock group (Figure 9). At the same time, 64 sets of undisturbed rock and soil samples were taken in different rock group units along Luojiabu Town, Yanguan Town, Tianshui Town, Yongping Town, Luoba Town, Yacheng Town, and Lixian County, and the corresponding rock and soil mass shear test was carried out. The gravity, cohesion, and internal friction angle of the five types of rock group units were tested, and the mechanical parameters of the engineering geological rock group were finally obtained (Table 2).

4.2 Calculation of regional critical acceleration

When analyzing the stability of the landslide, the sliding body state is considered according to the dry state. The ratio of the thickness of the saturated part of the potential sliding body to the total thickness of the sliding body (m) is 0, and the thickness of the sliding body (t) is approximately 10 m. Based on the Newmark model and the grid calculator of ArcGIS, the static safety factor F_s of the regional slope body of the traditional model and the improved model is calculated by Formula (1) and Formula (7), and then, the corresponding regional critical acceleration distribution value is obtained by Formula (2). The natural breakpoint classification method is used to divide the regional critical acceleration value into four intervals: (0, 0.05 g), (0.05 g, 0.15 g), (0.15 g, 0.25 g), and greater than 0.25 g, forming a distribution map of regional critical acceleration (Figure 10).

4.3 Hazard assessment

According to the ground motion parameter zoning map under the condition of 10% exceeding probability in 50 years in the study area compiled by the Lanzhou Earthquake Research

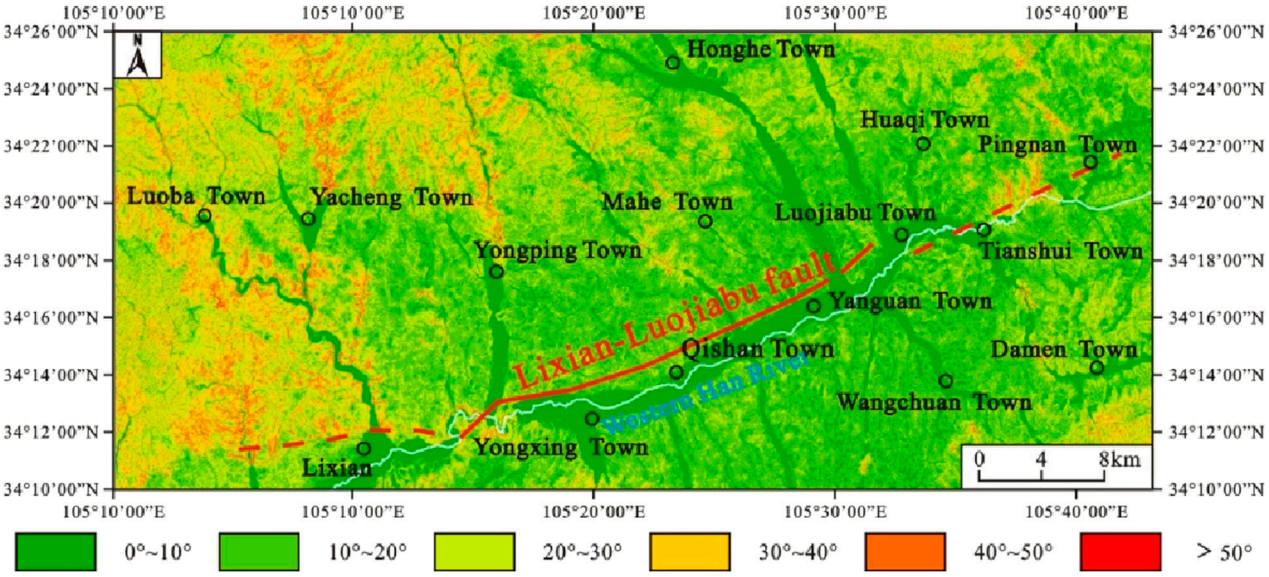

FIGURE 8
Map of slope in the study area.

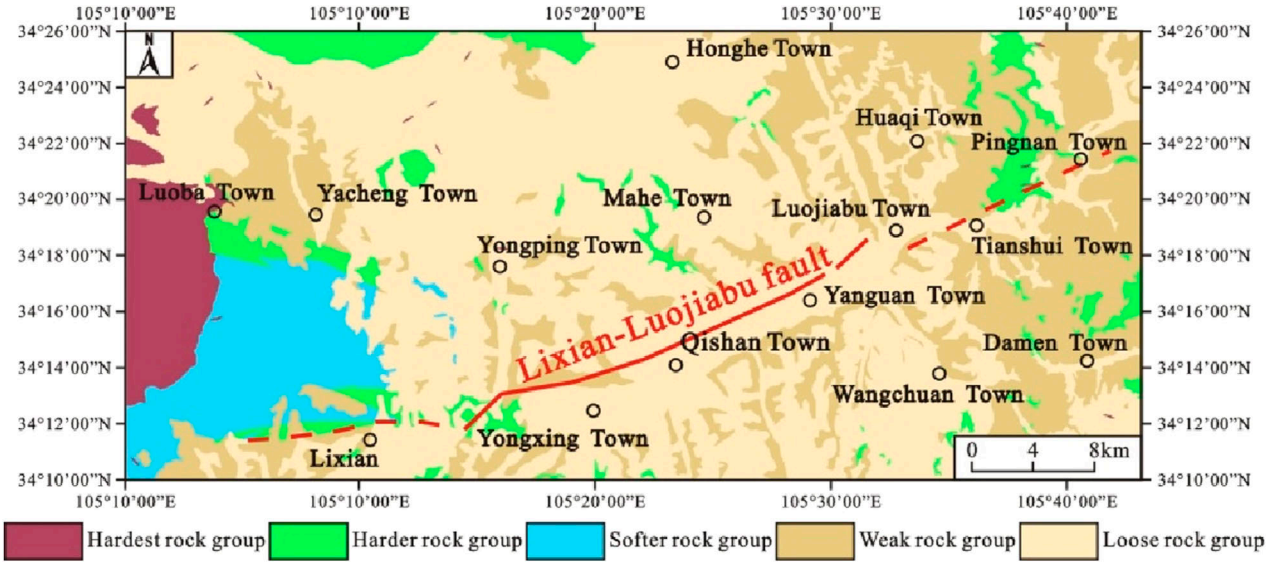

FIGURE 9
Map of engineering geological rock group in the study area.

TABLE 2 Empirical value of mechanical parameters about the engineering geological rock group.

Serial number	Rock group type	c' (kPa)	φ' (°)	γ (kN/m^3)
1	Hardest rock group	140	48	26
2	Harder rock group	70	32	23
3	Softer rock group	50	28	22
4	Weak rock group	28	23	20
5	Loose rock group	24	20	19

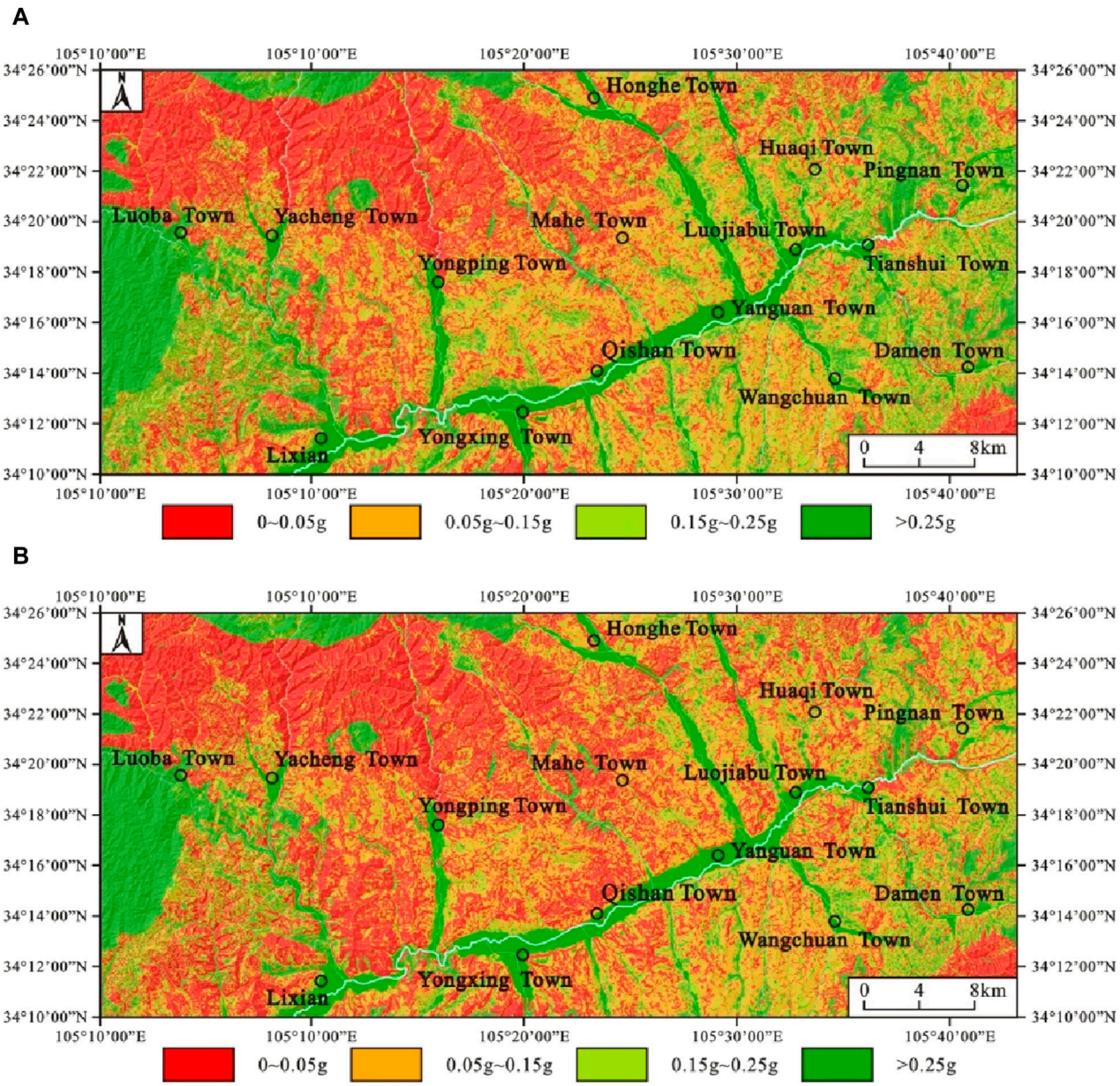

FIGURE 10
Distribution map of regional critical acceleration. **(A)** Newmark traditional model. **(B)** Newmark improved model.

Institute of China Earthquake Administration, the I_a value in the study area is calculated by Formula (5). Substituting the I_a value and a_c value into Formula (3), the Newmark cumulative displacement value of the study area under the condition of 10% exceeding probability in 50 years is obtained. According to specifications for the risk assessment of geological hazard (GB/T 40112-2021) and the research results of earthquake landslide hazard zoning (Jibson et al., 2000; Yang et al., 2021), the probability of the earthquake landslide occurrence is calculated according to formula (6). The earthquake landslide hazard level is divided into high-hazard areas (earthquake landslide occurrence probability is greater than 25%), medium-hazard areas (earthquake landslide occurrence probability is 15–25%), low-hazard areas (earthquake landslide occurrence probability is 5–15%), and extremely low-hazard areas (earthquake landslide occurrence probability less than 5%) (Figure 11).

4.4 Comparative analysis

Through analysis and calculation, the statistical tables of landslide hazard assessment zoning with different evaluation methods are summarized (Table 3). It is found that the evaluation results of the two models are mainly medium-hazard areas and extremely low-hazard areas, followed by high-hazard areas, and finally low-hazard areas. Among them, the high-hazard areas calculated by the Newmark improved model considering the fault effect accounts for about 22.85% of the total areas of the study area,

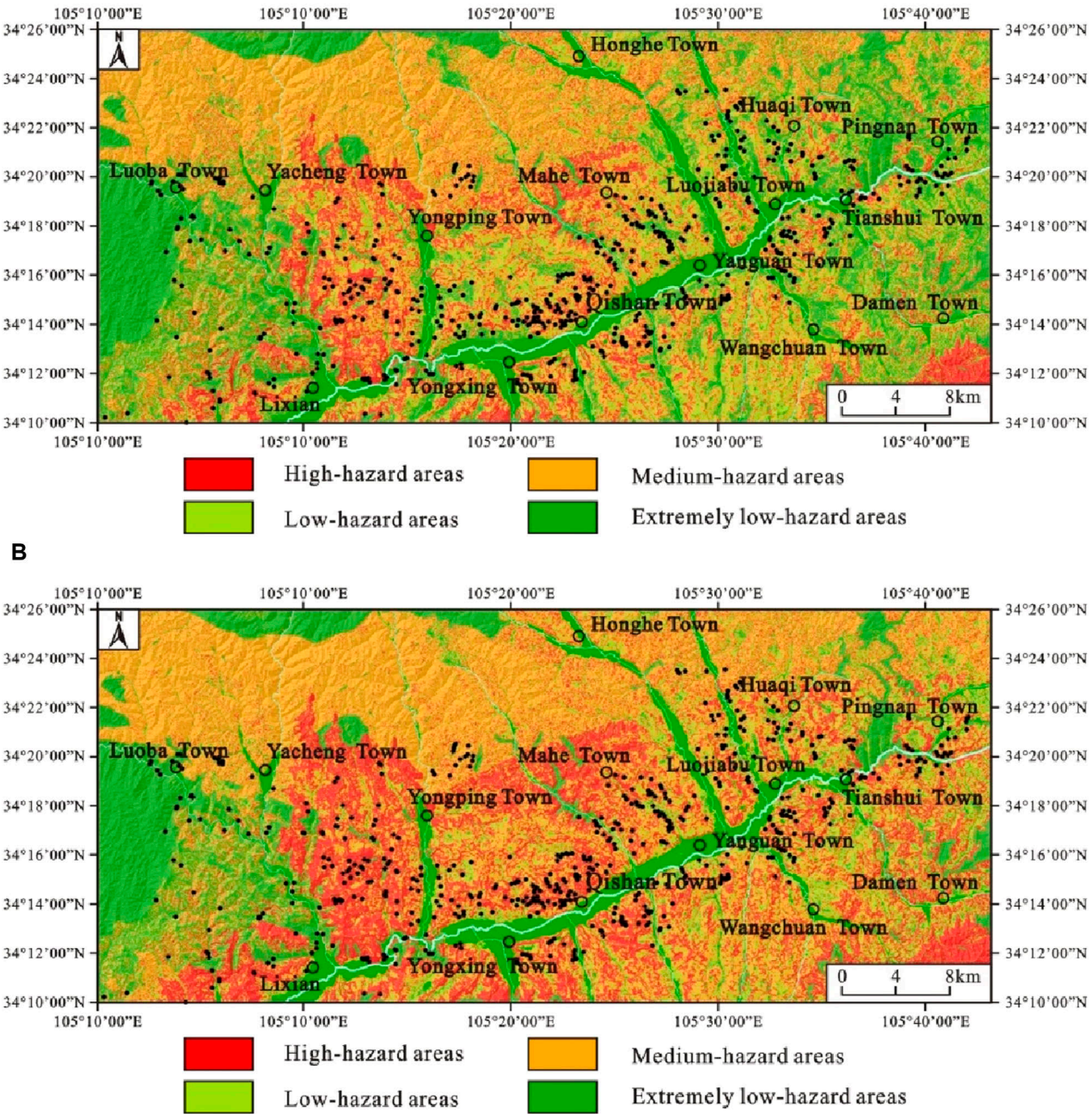

FIGURE 11
Hazard assessment map of earthquake landslide under the condition of 10% exceeding probability in 50 years. **(A)** Newmark traditional model. **(B)** Newmark improved model.

and the high-hazard areas calculated by the Newmark traditional model account for about 16.90% of the total areas of the study area. In the evaluation results of the two models, the existing landslides are concentrated in high-hazard areas and medium-hazard areas, and the landslide point density shows a gradual increase from extremely low-hazard areas to high-hazard areas. Among them, the landslide point density in the high-hazard areas calculated by the Newmark improved model considering the fault effect is relatively larger, up to 0.9417 point/km^2. From Figures 10, 11, it can be seen that the critical acceleration value calculated in the upper side area of the fault in the study area, especially near the fault zone, is significantly lower than that before the improvement, which leads to a significant increase in the probability of landslide occurrence calculated in this area.

In order to verify the scientificity and reliability of the model, the landslide hazard assessment results obtained by the above two models are tested by the ROC curve method and Kappa

TABLE 3 Landslide hazard zoning summary table of different model evaluation methods.

Evaluation model	Hazard zoning	Division area (km^2)	Proportion of the partition area (%)	Landslide number (point)	Proportion of landslides (%)	Landslide point density (point/km^2)
Newmark traditional model	High-hazard areas	324.35	16.90	292	49.66	0.9003
	Medium-hazard areas	738.41	38.46	212	36.05	0.2871
	Low-hazard areas	204.25	10.64	46	7.82	0.2252
	Extremely low-hazard areas	652.73	34.00	38	6.46	0.0582
Newmark improved model considering the fault effect	High-hazard areas	438.57	22.85	413	70.24	0.9417
	Medium-hazard areas	716.17	37.31	119	20.24	0.1662
	Low-hazard areas	175.17	9.12	31	5.27	0.1770
	Extremely low-hazard areas	589.83	30.72	25	4.25	0.0424

TABLE 4 Statistical table of AUC values and Kappa coefficient values of different models.

Testing method	Newmark traditional model	Newmark improved model considering the fault effect
ROC curve method	0.786	0.841
Kappa coefficient method	0.763	0.822

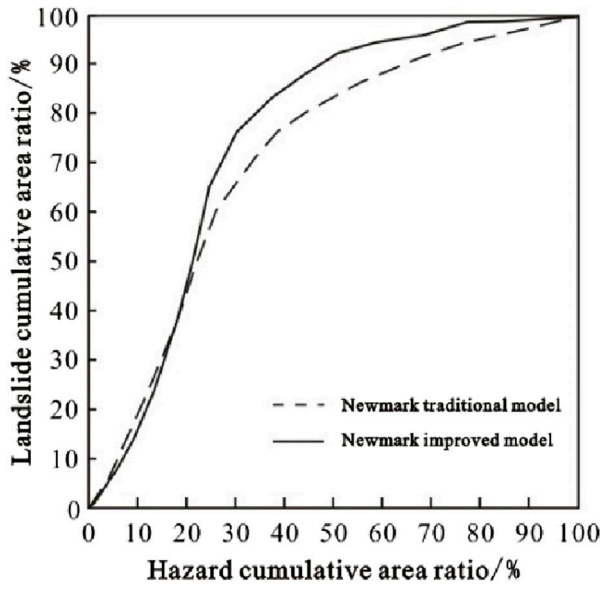

FIGURE 12
Comparison of ROC curves about different model evaluation methods.

coefficient method, respectively. When using the ROC curve method to test, scholars generally use the area under ROC curve (AUC) as an important indicator to measure and compare the prediction accuracy of the model (Swets, 1988; Guo et al., 2023; Guo et al., 2024). When the AUC value is 0.5, the prediction results of the model have no practical value. When the AUC value is between 0.5 and 0.7, the accuracy of the model prediction results is relatively low. When the AUC value is between 0.7 and 0.9, the accuracy of the model prediction results is relatively high. When the AUC value is above 0.9, the accuracy of the model prediction results is very high. The Kappa coefficient method is a classification accuracy evaluation index based on the confusion matrix algorithm, which reflects the consistency between the observed values and the simulation results, also known as the consistency test (Lee and Pradhan, 2007). When the Kappa coefficient value is between 0.2 and 0.4, the consistency of the model prediction results is relatively low. When the Kappa coefficient value is between 0.4 and 0.6, the consistency of the model prediction results is moderate. When the Kappa coefficient value is between 0.6 and 0.8, the consistency of the model prediction results is relatively high. When the Kappa coefficient value is between 0.8 and 1, the consistency of the model prediction results is very high.

From Table 4 and Figure 12, it can be seen that the AUC value and Kappa coefficient value of the hazard area obtained by the Newmark improved model considering the correction coefficient of fault effect are 0.841 and 0.822, respectively, which are significantly higher than the calculated values of the Newmark traditional model, indicating that the improvement effect of the model is better. It is objectively proved that the advantage of using the Newmark improved model considering the correction coefficient of fault effect

to evaluate the landslide hazard along the Lixian–Luojiabu fault zone in Gansu Province is more obvious.

5 Conclusion and future remarks

Taking the Lixian–Luojiabu fault zone in Gansu Province in China as the study area, based on the analysis of the research results of the correlation between landslide development and the fault zone, the concept of the fault effect correction coefficient was innovatively proposed, the value table of the fault effect correction coefficient along the Lixian–Luojiabu fault zone in Gansu Province was created, and the corresponding distribution map of the fault effect correction coefficient was drawn. On this basis, an improved Newmark model for the landslide hazard assessment along the fault zone was constructed. The earthquake landslide hazard assessment under the condition of 10% exceeding probability in 50 years was carried out by using the Newmark traditional model and Newmark improved model considering the fault effect, respectively. The evaluation results were compared and analyzed by the ROC curve method and Kappa coefficient method.

The results showed that the high-hazard areas calculated by the Newmark improved model considering the fault effect accounted for about 22.85% of the total areas of the study area, and the high-hazard areas calculated by the Newmark traditional model accounted for about 16.90% of the total areas of the study area. In the evaluation results of the two models, the existing landslides were concentrated in high-hazard areas and medium-hazard areas, and the landslide point density showed a gradual increase from extremely low-hazard areas to high-hazard areas. However, the landslide point density in the high-hazard areas calculated by the Newmark improved model considering the fault effect was relatively larger, up to 0.9417 point/km^2. This is mainly because in the upper side area of the Lixian–Luojiabu fault, especially in the area near the fault zone, the fault effect correction coefficient is relatively larger, and the calculated critical acceleration value is significantly lower than that before the improvement, which leads to a significant increase in the probability of landslide occurrence calculated in this area. The AUC value and Kappa coefficient of the hazard zone obtained by the Newmark improved model were 0.841 and 0.822, respectively, which were significantly higher than the calculated values of the Newmark traditional model, indicating that the improvement effect of the model was better.

The Newmark improved model considering the fault effect fully considered the influence of distance from the fault zone and fault upper and lower sides' effect, and the research results can provide a new reference for the landslide hazard assessment along the fault zone. However, it is worth noting that the fault effect correction coefficient proposed in this paper only considered the two key factors, the distance from the fault zone and the relative position of the upper and lower sides, and whether other factors should be considered remains to be further studied. In addition, the improved model belongs to the mechanical analysis model, which takes limited geological background factors into consideration in the calculation process, which only considers the influence of the slope and engineering geological rock group, and does not analyze the existing landslide sample data. These shortcomings should be further remedied in future research work.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

WF: investigation, methodology, resources, writing–original draft, and writing–review and editing. YT: funding acquisition, investigation, resources, and writing–review and editing. HM: data curation, supervision, and writing–review and editing. BH: funding acquisition, validation, and writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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UAV and field survey investigation of a landslide triggered debris flow and dam formation in Eastern Carpathians

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In the May–August period of 2010, major heavy rains impacted the Eastern Carpathians (Northeastern Romania), leading to flash floods and triggering numerous landslides. The extreme weather conditions caused damage to the road network, extensive forest destruction, and lead to formation of impounded lakes. One of the hardest-hit areas was the mountain tributaries catchments of the Bistrița watershed. Particularly, the most significant landslide-triggered debris flow event occurred in the upper Iapa valley (Neamț County). The landslide process started near the top of the Drumul Chinezilor ridge in the Goșmanu-Geamăna Massif (Tarcău Mountains), at an elevation of 875 m a.s.l., and the flow-slide fan obstructed a 300-m section of the Iapa watercourse at 615 m a.s.l. This study compiles the climatic, anthropogenic, geological, and geomorphological evidence gathered during the field investigation in the October 2023 and utilizes Unmanned Aerial Vehicle (UAV) data collected to reconstruct the occurred debris flow-slide event. Additionally, it explores considerations regarding the reactivation of landslide processes, dam stability, and the future evolution of the impounded lake (Făgețel Lake: water surface area of 9,500 m^2; maximum depth 10 m). Furthermore, the lessons learned and future actions required to prevent further mass movement associated with debris flow-slide processes in prone areas of the Eastern Carpathians are discussed.

KEYWORDS

weather-induced landslides, landslide-triggered debris flow (LDF), dam formation, impounded lake, UAV, Eastern Carpathians

1 Introduction

In recent decades, the escalating frequency of extreme rainfall as a consequence of ongoing climate change has been linked to an observed increase in the occurrence and magnitude of various types of geomorphological (e.g., erosion, landslides) and hydrological (e.g., floods, flash floods) hazards (Neumayer and Barthel, 2011; Diffenbaugh and Field, 2013; Gariano and Guzzetti, 2016). This trend also includes the catastrophic events triggered by landslides leading to debris flows (Yang et al., 2020; Yang et al., 2023). In this context, if landslides can be triggered by various climatic,

geomorphological, seismic, or anthropogenic factors (Cruden and Varnes, 1996; Hungr et al., 2014), debris flows occur only when a mixture of earth material, water, and air rapidly surges down steep drainage paths (over 25°), with their primary trigger being high-intensity rainfall (Hürlimann et al., 2019; Scheip and Wegmann, 2022; De Falco et al., 2023). Therefore, in this specific weather and geomorphic conditions, the combination of landslides and debris flow (debris flow-slide) in the same event poses a higher threat to human life and infrastructure, owing to their sudden occurrence, high mobility, volume, impact energy, and extensive run-out distance (Gariano and Guzzetti, 2016). However, whether landslides and debris flows occur separately or in combination, triggering each other (Iverson et al., 1997; Sassa and Wang, 2005), they are responsible for thousands of casualties and economic losses every year (Costa and Schuster, 1988; Kahn, 2005; Petley, 2012).

Generally, the term debris flow is associated with a wide variety of hydrogeomorphic processes and phenomena (e.g., debris torrents, debris slides, mudflows, debris floods, mudslides), usually specific to steep slopes (e.g., mountains, cliffs) frequently impacted by extreme weather conditions (Santangelo et al., 2021; Ortiz-Giraldo et al., 2023). In this context, the interactions between debris flows induced by heavy rainfall and hydrographic network are topics of great relevance for understanding slope evolution, as well as the implications for flood hazards within exposed watersheds (Korup, 2005; Chien-Yuan et al., 2008; Cao et al., 2011a; Cao et al., 2011b; Marchi, 2017). However, the main issue with these types of hydrogeomorphic processes is their relative difficulty in prediction and monitoring due to their rapid manifestation. Therefore, the utilization of remote sensing techniques and optical imagery derived from Unmanned Aerial Vehicles (UAV) surveys has become a very useful tools for observing and monitoring the areas affected by landslides, debris flow and rockfalls (Blanch et al., 2024). Furthermore, recent advancements in GIS algorithms, coupled with the ability to obtain images from UAVs (Colomina and Molina, 2014), are driving significant advances in various geoscience applications such as automatically calculating the volume of material eroded in gullies (Neugirg et al., 2016), multitemporal monitoring of landslides (Blanch et al., 2021; Fang et al., 2024) or shoreline transformation rates (Yermolaev et al., 2021), and flood monitoring using aerial images and videos (Eltner et al., 2021).

In the Carpathians, as is other mountainous regions of Europe (Tiranti et al., 2018; Frank et al., 2019; De Falco et al., 2023; Tichavský et al., 2023), debris flow is one of the most frequent processes threatening local communities (Ilinca, 2014; Vădean et al., 2015; Mihu-Pintilie et al., 2016; Pop et al., 2019). This hazard is due to their high mobility induced by rainfall, which particularly affects flysch deposits and can cause damage not only within and adjacent to the flow-slide sector, but also in the depositional area (Santo et al., 2018). Furthermore, in some specific morpho-hydrological conditions, debris fans can temporarily block valleys, leading to the formation of dams and impounded lakes (Costa and Schuster, 1988; Evans, 2006; Fan et al., 2020). In these cases, the risk of dam failure exposes downstream communities and infrastructure to flash floods (Costa and Schuster, 1988; Dai et al., 2005; Cao et al., 2011a; 2011b), mudflows (Sepúlveda and Padilla, 2008; Tannant and Skermer, 2013), and other destructive events associated with lateral erosion (Zhao et al., 2022). Consequently, detailed hazard assessments are needed, firstly to the flow-slide sector and depositional area to protect people and infrastructure from future events, and secondly for dam stability to better manage the associated risks.

In the flysch belt of the Eastern Carpathians (Romania) (Belayouni et al., 2009; Miclauș et al., 2009), where the study site is located (Figure 1A) most landslides and landslide triggered debris flow occur in remote locations and usually do not pose a significant hazard (Mihu-Pintilie et al., 2014b; Mihu-Pintilie et al., 2016) (Figure 1B). However, some debris flow-slide events have impacted road infrastructure located at the base of slopes and caused extensive forest destruction, with a moderate impact on the local economy (Pop et al., 2017). In some cases, the debris fan deposits lead to the formation of temporary or, very rarely, long-term water accumulation behind the dams (Mihu-Pintilie, 2018a). One of the most recent landslide and rainfall-induced debris flow events occurred in the summer of 2010, in the upper Iapa valley, a right tributary of the Bistrița River (Figure 1C). Initially starting as a landslide process near the top of the Goșmanu-Geamăna Massif (Tarcău Mountains) at an elevation of 875 m a.s.l., the debris flow deposits obstructed a 300-m section of the Iapa watercourse at 615 m a.s.l., forming a 10 m depth lake, currently known as Făgețel Lake (Figure 1D). The main trigger was the heavy rains that impacted the entire region during the May-July period of 2010 (Romanescu et al., 2017; Romanescu et al., 2018a), but the high density of the forest paths and extensive deforestation in the Limpedea logging area have also a significant contribution in geomorphological process that affect the southern slope of the Drumul Chinezilor ridge. However, the most interesting aspect related to the Iapa landslide triggered debris flow (Iapa LDF) is that of more than 20 large landslide dams formed due to extreme hydro-climate conditions in the Carpathian Mountains, investigated and reported in various studies (Năstase, 1949; Ciornei, 1959; Tövissi, 1964; Pop, 1970; Decei, 1981; Ichim and Rădoane, 1996; Ilinca and Gheuca, 2011; Șerban et al., 2012; Romanescu et al., 2013; Mihu-Pintilie, 2014a; Mihu-Pintilie et al., 2014b; Stoleriu et al., 2014; Mihu-Pintilie et al., 2016; Lesenciuc et al., 2017; Mihu-Pintilie et al., 2018a; Romanescu et al., 2018b), the Iapa LDF event is the singular one in the Eastern Carpathians that has formed a long-term lake (more than 10 years) due to a debris flow-slide dam (Table 1).

In this work, the rainfall data collected during the May–August period of 2010 are reported for the first time in order to describe the Iapa LDF occurrence scenario and Făgețel Lake formation. This case study is of interest to the international community because these hazardous phenomena occur in many places on Earth where debris materials and loose soils cover steep bedrocks, posing a threat to the communities living in the affected areas or along the dammed valleys. The paper includes descriptions of rainfall data, the anthropogenic impact on destabilized slopes, and the geological, geomorphological and hydrological setting. Additionally, it focuses on the UAV methodology employed in the post-event survey to produce the accurate maps of the entire affected area. Finally, in the concluding remarks section, the lessons learned and future actions needed to prevent the further reactivation of the Iapa LDF are discussed.

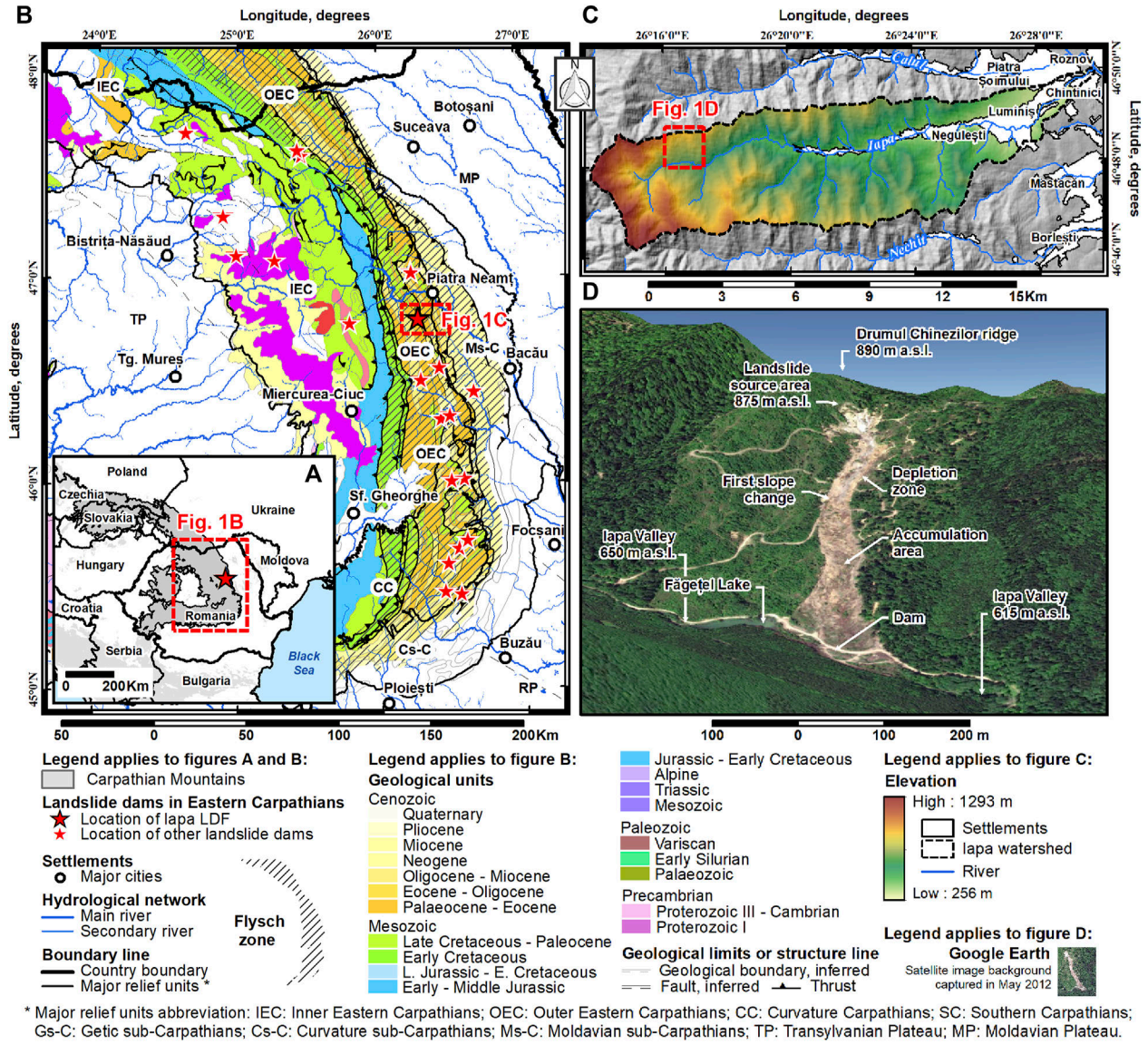

FIGURE 1
Geographic location of the Iapa LDF. **(A)** and other landslide dams (see Table 1), **(B)** in the flysch zone of the Eastern Carpathians. In **(C)**, the UAV mapped area is highlighted in the upper Iapa watershed, represented in **(D)** as 3D image.

2 Study area and regional setting

The investigated Iapa LDF, occurred in the upper part of the Iapa watershed (46°48′34″N/26°16′19″E) which drains the northeastern side of the Goșmanu-Geamăna Massif (eastern Tarcău Mountains), part of the central group of the Eastern Carpathians. With a total length of 25.3 km, the Iapa River flows from west to east and serves as a right-side tributary of the Bistrița River, joining it near Roznov (Neamț County). Downstream of the Iapa LDF dam, four settlements are potentially at risk in the event of a dam failure: Negulești (639 inhabitants), Luminiș (2,295 inhabitants), Piatra-Șoimului (4,015 inhabitants), and Chintinici (823 inhabitants) (Figure 1C). In the forthcoming subsections, we will delve into the geological, climatic, hydrological, and anthropogenic factors that significantly contributed to the formation of the LDF dam and Lake Făgețel (Figure 2).

2.1 Geological background

The upper Iapa watershed is located within the Bistrița Half-window (Outer Carpathians Flysch Zone), where the Tarcău and Vrancea Nappe's (Outer Moldavides), are exposed. Dominating the landscape are vertical or reversed anticlines and synclines, which took shape during the Upper Cretaceous to Lower Miocene period. Overall, the geological formations exhibit a distinct north-south orientation, with faulted flanks characterized by a vertical or reversed configuration (Brustur et al., 2019).

TABLE 1 Examples of rainfall-induced landslide dams and lake formations in the Eastern Carpathians.

Lake name	Mountain unit	River	Location (UTM)	Landslide age	Landslide type	Dam failure	Supporting references
Făgeţel L.	Goşmanu Mts.	Iapa	5245552/1360319	2010	Rock slide and debris flow	Did not fail	Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Palcău L.	Vrancea Mts.	Palcău	5129688/1402860	2008	Rock slide	Failed	Mihu-Pintilie (2018a)
Topliţa L.	Goşmanu Mts.	Topliţa	5220820/1375442	2005	Rock slide	Did not fail	Mihu-Pintilie (2018a)
Lacul cu Boglari	Berzunţi Mts.	Strâmba	5210377/1395619	2002	Slide	Partial fail	Mihu-Pintilie (2018a)
Agăş L.	Tarcău Mts.	Muncel	5212655/1366174	2000	Rock slide	Partial fail	Mihu-Pintilie (2018a), Romanescu et al., (2018b)
Cuejdel L.	Stânişoarei Mts.	Cuejdel	5270636/1275295	1991	Rock slide	Did not fail	Ichim and Rădoane (1996), Mihu-Pintilie (2018a), Mihu-Pintilie (2018b), Mihu-Pintilie et al. (2014a), Mihu-Pintilie et al. (2014b), Mihu-Pintilie et al. (2016), Stoleriu et al. (2014)
Constellation L.	Stânişoarei Mts.	Cuejdel	5269954/1353255	1991	Rock slide	Did not fail	Ichim and Rădoane (1996), Mihu-Pintilie (2018b), Mihu-Pintilie et al. (2016)
Lacul fără nume	Vrancea Mts.	Zăbala	5124514/1398789	1977	Rock slide	Did not fail	Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Old Green L.	Vrancea Mts	Lepşa	5160653/1389939	1971	Rock slide	Failed	Mihu-Pintilie (2018a), Romanescu et al. (2018b), Tövissi (1964)
Betiş (Novăţ) L.	Maramureş Mts.	Novăţ	5329417/1221978	1957	Rock slide	Failed	Ciornei (1959), Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Green L.	Vrancea Mts.	Chiua Mica	5162508/1396776	1940	Rock slide	Failed	Decei (1981), Mihu-Pintilie (2018a), Romanescu et al. (2018b)

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TABLE 1 (*Continued*) Examples of rainfall-induced landslide dams and lake formations in the Eastern Carpathians.

Lake name	Mountain unit	River	Location (UTM)	Landslide age	Landslide type	Dam failure	Supporting references
Bolătău L.	Nemira Mts.	Izvorul Negru	5193224/1379992	1883	Rock slide	Failed	Nastase (1949), Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Red L.	Hășmaș Mts.	Bicaz	5238159/1323933	1837	Rock slide	Did not fail	Mihu-Pintilie (2018a), Romanescu et al. (2013), Stoleriu et al. (2014)
Iezerul Sadovei	Obcina Feredeului	Iezerul	5346677/1288023	? (1600)	Rock slide	Partial fail	Lesenciuc et al. (2017), Mihu-Pintilie (2018a), Mîndrescu et al. (2013), Stoleriu et al. (2014)
Bolătău L.	Obcina Feredeului	Holohoșca	5327708/1283078	?	Rock slide	Did not fail	Mihu-Pintilie (2018a), Mîndrescu et al. (2013), Stoleriu et al. (2014)
Iezerul Călimani	Călimani Mts.	Puturosu	5266740/1278858	?	Rock slide	Did not fail	Mihu-Pintilie (2018a)
Taul Zânelor	Călimani Mts.	Bistrița	5266840/1257806	?	Rock slide	Did not fail	Decei (1981); Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Izvorul Măgurii	Bârgău Mts.	Leșu	5277968/1243179	?	Rock slide	Did not fail	Decei (1981); Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Dofteana L.	Nemira Mts.	Seaca	5195639/1384520	?	Slide	Failed	Mihu-Pintilie (2018a)
Black L.	Buzău Mts.	Brebu	5115608/1394034	?	Rock slide	Failed	Decei (1981); Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Mocearu L.	Buzău Mts.	Sărățel	5100017/1403183	?	Rock slide	Partial fail	Decei (1981); Mihu-Pintilie (2018a), Romanescu et al. (2018b)
Hânsaru L.	Buzău Mts.	Bâsca	5100313/1394535	?	Rock slide	Partial fail	Decei (1981); Mihu-Pintilie (2018a), Romanescu et al. (2018b)

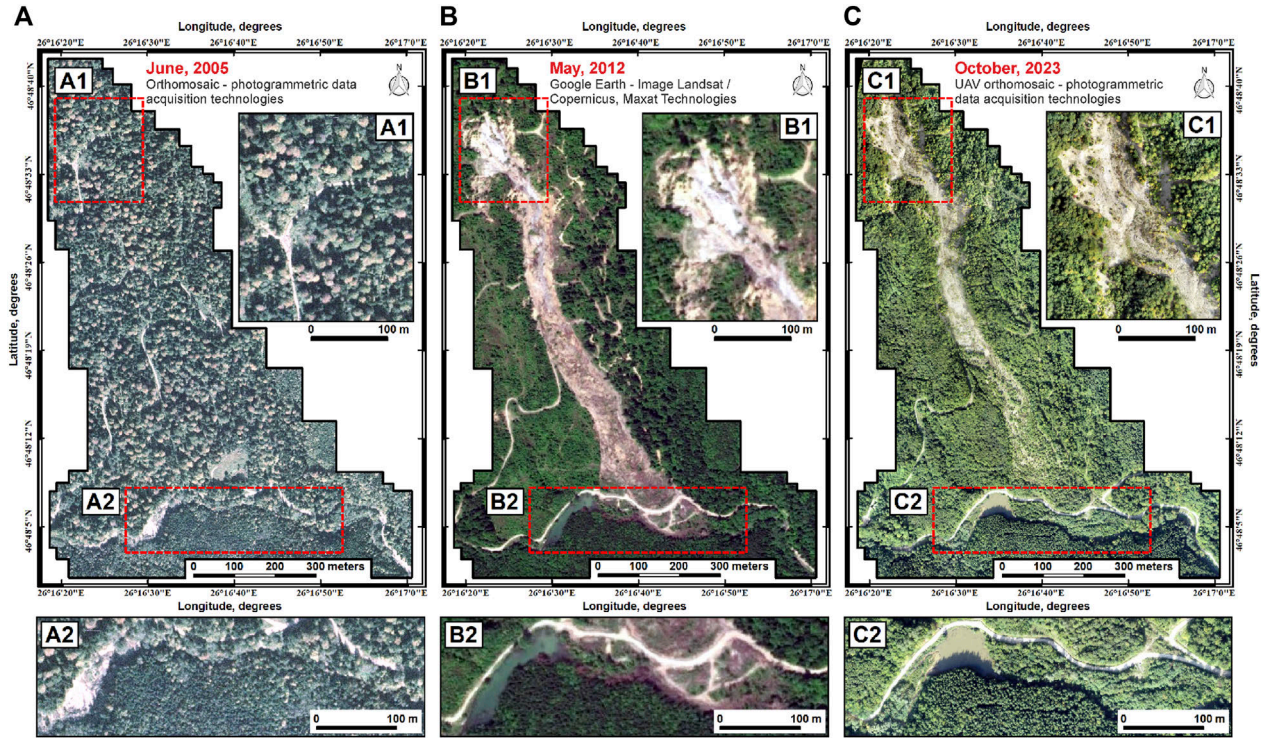

FIGURE 2
Aerial images showing the mountain slope before the landslide-triggered debris flow event **(A)**, the Iapa LDF in 2012 two years after the mass movement occurred **(B)**, and UAV orthomosaic in 2023 **(C)**. The landslide source area **(A1, B1, C1)**, and impoundment/dam area **(A2, B2, C2)** are highlighted in each map.

The Tarcău Nappe, which is of interest for the present study, comprises two main units: the Tarcău Sandstone Digitation, formed by the Lower Tarcău Formation (Paleocene-Lower Eocene); and the Strigoiu Scale, composed of: Putna Formations (Paleocene-Lower Eocene), Straja Formation (Lower Eocene-Middle Eocene), and Ciunget Formation (Lower Eocene-Middle Eocene). The Strigoiu Formation marked the frontal part of the Tarcău Nappe that thrusted towards east the Vrancea Nappe along the Vaduri Digitation (Guerrera et al., 2012). Within this lithological configuration, the landslide that triggered the Iapa LDF in 2010 (Figures 2A, B) occurred in the Ciunget Formation and Straja Formation deposits (Figures 3A, B), very close to the contact with the Putna Formation lithofacies, which consists of dark-greyish clays, calcarenites, and limestone with a thickness of 4-5 m on the left flank of the Iapa LDF (Figure 3C).

The Ciunget Formation (Lower Eocene-Middle Eocene) is represented by a flysch lithofacies with intercalations of microconglomerates and thin layers of red clays. The main predominantly pelitic mass consists of Tarcău sandstones, occurring in beds that reach 10–12 m in thickness. Intermittently, alongside the sandstones, there are also beds of organogenic microconglomerates, with thicknesses ranging from 0.15–0.20 m, containing green schists. Towards the upper part of the lithological succession, there are also beds of friable conglomerates, mainly composed of well-rounded white quartzite fragments, alongside fragments of metamorphic rocks embedded in a silty matrix (Grasu et al., 1988).

The Straja Formation (Lower-Middle Eocene) stands out as a lithological and structural unit marked by a diverse sandstone lithofacies. Therefore, from a petrographic standpoint, the formation exhibits four distinct lithofacies: quartz-arenites, gaizes and spongolites, siltstones, as well as green and dark-red clays (Grasu et al., 1988). The quartz-arenites, which are the main lithological component in the LDF source area, are fine greenish, glassy sandstones with a sharp fracture, form the basal turbidites components. Microscopically, these sandstones predominantly feature quartz grains and cherts, accompanied by lesser amounts of muscovite, feldspars, chloritized biotite, zircon, and pyrite. Gaizes and spongolites make up either the basal layers of specific turbidites or the upper sections in sequences of calcareous microconglomerates and sandstones. Meanwhile, siltstones may manifest as slender interlayers within red and green shale or as more substantial turbidite beds displaying parallel to convolute lamination. In both instances, the matrix is composed of clay-sericite or clay-carbonates. The clays lithofacies encompass a significant proportion, accounting for 62% of the Straja Formation column. In the study area, these clays are observed in distinct layers measuring 5–20 cm, displaying varying shades of red or green (Grasu et al., 1988). However, the stratigraphy of the Tarcău sandstones (Figure 3D) in both the Ciunget Formation and Straja

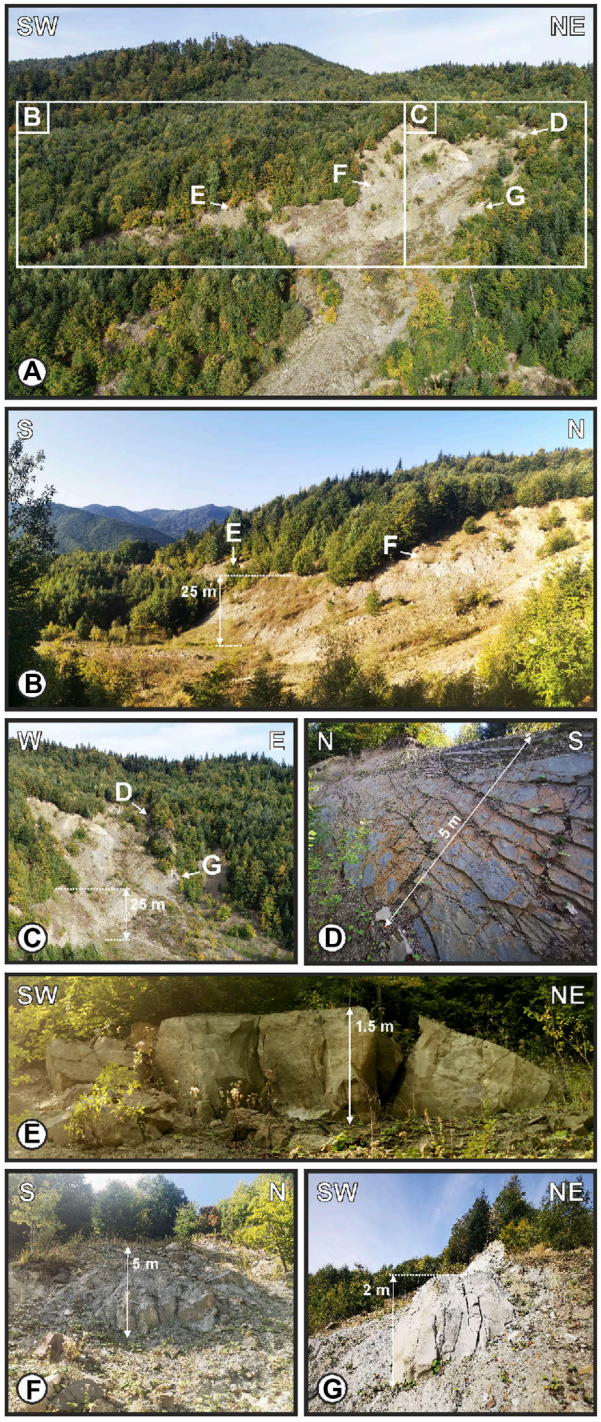

FIGURE 3
Lithology of the Iapa LDF source (see A1, B1 and C1 in Figure 2): **(A)** aerial view of the landslide scarps area near Drumul Chinezilor ridge; **(B)** west; and **(C)** north aerial views of the main scarp area with **(D)** outcrops of Tarcău sandstone of the Straja Formation, and **(E)** medium, **(F)** high, and **(G)** very high desegregated sandstone deposits during the Iapa LDF event.

Formation, with varying thicknesses and hardness (Figures 3E–G), and interspersed with siltstone and clay layers, was the main lithological factor of Iapa LDF event in the synoptic context of the summer of 2010.

2.2 Climate condition

In documenting the direct relationship between climatic conditions and landslide processes that occurred in the upper Iapa watershed, we utilized both general data characterizing the climate on the eastern flank of the Goșmanu Mountains (Apostol, 2004) and local data recorded at the Luminiș pluviometric station (46°48′01″N/26°28′53″E) from the lower Iapa watershed (Cojoc et al., 2015). Therefore, the general climatic characteristics include annual mean temperatures ranging between 5°C (Nechit, 450 m a.s.l.) and 8°C (Săvinești, 280 m a.s.l.) at lower altitudes in the region, and between 2.5°C and 3°C at the meteorological station located above 1,500 m a.s.l. (e.g., Ceahlău Mts.). In both cases, the annual thermal characteristics are associated with a higher value of humidity. The mean precipitation amounts range between 600 mm (Moldavian Subcarpathians) and 900–1,000 mm (upper Iapa watershed). The snow cover duration ranges between 80 and 82 days, but in the case of upper part of the mountains valleys, like the Iapa, Calu and Nechit rivers, the snow cover duration can exceed 90 days due to shelter conditions. Overall, this type of climate is characteristic of mountains with moderate altitudes and corresponds to the mixed forest zone in the Eastern Carpathians (Cheval et al., 2014; Cojoc et al., 2015).

Regarding the precipitation regime in the trigger zone of the Iapa LDF, the data recorded at the Luminiș pluviometric station (300 m a.s.l.) between 1971 and 2021 indicate that the mean precipitation amount is 703.5 mm, with June (108.5 mm) and July (107 mm) being the wettest months of the year (Supplementary Table S1). However, the annual rainfall amount increases with altitude, especially from east to west, where in the study area, these values frequently exceed 1,000 mm. This phenomenon also occurred in 2010, when according to data recorded in Iapa wathershed, 12 km downstream of the Iapa LDF, the annual precipitation amount was 1,007 mm (Cojoc et al., 2015; Romanescu et al., 2018a). Moreover, only during the June-August interval of 2010, when the LDF occurs, the cumulative precipitation amount accounts for 70% of the total precipitation recorded during the entire year. However, this pluviometric regime indicates direct control of climatic conditions on geohazard manifestations (Mihu-Pintilie, 2018a), as well as an indirect causality between the occurrence of landslides and debris flow triggered by extreme rainfall in areas without forest vegetation (Lesenciuc et al., 2017).

2.3 Hydro-morphological characteristics

The Iapa River, along with the Calu River to the north and the Nechit River to the south, are the main tributaries of the Bistrița River from the northeastern flank of the Goșmanu Massif. All three watercourses flow from west to east, perpendicular to the general orientation of geological strata (Brustur et al., 2019). Consequently, the entire hydrographic network is concentrated on the main valley with a few short and low-discharge tributaries. Also, due to the north-south orientation of the geological structures, the main watercourses are segmented by numerous lithological thresholds (e.g., Duraș waterfall on the Iapa River; Brustur et al., 2019).

In this hydro-morphological configuration, the lowest point in the Iapa watershed (76.01 km^2) lies at the confluence of the Bistrița River (264 m a.s.l.), while the highest point is situated in the western part of the basin at Murgoci Peak (1,293 m a.s.l.). The Iapa watershed exhibits a slightly asymmetrical catchment basin, characterized by a parallel hydrographic network type (Jung et al., 2019). The left slope, covering a width of 1–2 km, lacks permanent tributaries. In contrast, the right slope, extending 3–4 km, is drained by several significant streams, including Mânza, Măniș, and Mălina. However, in the area where the LDF occurs, specifically on the southern slope of the Drumul Chinezilor ridge, the hydrographic network consists solely of temporary streams (e.g., Limpedea brook), all of which are collected by the Iapa River. Consequently, the Făgețel Lake, formed by the LDF dam obstructing a 300 m long-section of the Iapa Valley (see A2, B2 and C2 in Figure 2) at 20.5 km upstream of the confluence with the Bistrița River, lacks any other permanent tributary.

Concerning the flow rate data of the Iapa watercourse, groundwater contributes with 40% to the annual discharge (Cojoc et al., 2015). Therefore, from 1950 to 2021, the multi-annual discharge at the Luminiș gauging station averaged 0.63 m^3/s, with a minimum mean discharge rate of 0.2 m^3/s in 2013 and a maximum mean discharge rate of 1.7 m^3/s in 1970 (Supplementary Table S2). However, climatic conditions, which control the rest of 60% of the flow rate and are often influenced by extreme rainfall events, make the maximum discharge data more representative for the present study. In this context, the highest discharge values recorded on the Iapa River at the Luminiș gauge station occurred on 8 June 1969 (75.3 m^3/s), 28 May 1972 (65.8 m^3/s), 12 July 2005 (58.8 m^3/s), and 2 June 2016 (68.6 m^3/s). In 2010, the maximum flow rate was recorded on 26 June, reaching 40 m^3/s. However, a detailed analysis of this flash floods event and its correlation with LDF and Făgețel Lake formation will be detailed in next sections.

2.4 Land use and anthropogenic activity

The vegetation within the upper Iapa watershed consists of 95% mixed forests, and two distinct zones are observed: the spruce zone (*Picea abies*, *Picea excelsa*) and the beech zone (*Fagus sylvatica*), both occasionally associated with herbaceous vegetation. The spruce zone constitutes over 50% of areas situated above 1,000 m a.s.l., particularly in the high and middle sections of the main ridges. Consequently, spruce stands in these zones are either pure or nearly pure, characterized by dense forest masses, with a sparse or underdeveloped herbaceous or shrub layer. At lower elevations (850–900 m a.s.l.), the spruce mixes with fir (*Abies alba*) and beech. Notably, in the area of the landslide source of the Iapa debris flow (875–800 m a.s.l.), pine (*Pinus sylvestris*) also appears. At altitudes ranging from 450 m a.s.l. to 600 m a.s.l., corresponding to the elevation of Făgețel Lake (615 m a.s.l.), the emergence of the beech zone is influenced by continental and foehn-like climatic factors, albeit covering a smaller surface area. In some areas, the beech forests at these elevations also incorporate specimens of elm (*Ulmus montana*) and sycamore (*Acer pseudoplantanus*). Within the shrubbery along the Iapa watercourse, noteworthy species include rowan (*Sorbus aucuparia*), hazel (*Corylus avellana*), spindle (*Euonymus europaea*), red elderberry (*Sambucus racemosa*), and black elderberry (*Sambucus nigra*). However, in the water mass accumulated behind the Iapa LDF dam, of the tree species mentioned earlier, currently, only the trunks of spruce are still visible above the water's surface.

Overall, being an intensively forested area, the main and only industrial activity in the region is the exploitation and valorization of timber. Thus, satellite images reveal numerous areas where the forest has been clear-cut in longitudinal strips towards the valleys of the Iapa, Manzu, and Maniș rivers, extending almost to the alignment of the main ridges. The most heavily exploited area was identified in the upper sector of the Iapa River, specifically on the eastern slope of the Murgoci Peak (1,293 m a.s.l.), the entire left slope of the Mânzu stream (Mânzei ridge), and in the study area, formerly known as the Limpedea logging zone or Drumul Chinezilor ridge. In this context, being an area with limited accessibility and steep slopes, heavy forest tracks was used for timber extraction, forming paths that have turned into deep cutting rigoles, gully and landslide scarps. However, only in the investigated area, the density of the road and paths network used for timber exploitation is 4.5 km/km^2. As we will see in the upcoming subsections, the exploitation paths network and the deforested areas was one of the main factors that triggered the Iapa LDF in the summer of 2010.

3 Data collection and methods

In this study, to generate detailed maps and specific charts, including the geomorphological sketch of the affected area, longitudinal topographic sections and cross-sections, the thickness of erosion and deposition map derived from the difference of two successive DEMs (DOD), and the water surface evolution of the Făgețel Lake from formation to the present, we utilized a variety of data sources such as aerial (Figure 2A) and satellite (Figure 2B) imagery, UAV-derived orthomosaic (Figure 2C) and old cartographic products (topographic maps, scale 1:5,000). Therefore, all data, whether produced during the field survey investigation by direct measurements or acquired from various sources and used as background to highlight the formation and evolution of the Iapa LDF, are detailed in Table 2.

3.1 UAV and field survey investigation

The field survey campaign took place in October 2023 and covered an area of approximately 15 ha on foot and 20 ha through UAV mapping, including the landslide source area, the debris flow paths, the fan area (LDF dam), and the water surface of the impoundment. The primary objective was to investigate the triggering in the crown area, track the flow-slide evolution in terms of both erosion and accumulation, and assess the damage in the flooding area caused by LDF dam formation. All data, including pictures, waypoints, and topographical measurements, were subsequently geolocated using a accurate GPS. Regarding the aerial measurements, the use of UAV techniques was possible in such a forested area due to the fact that the 2010 debris flow-slide event created a scar in the forest vegetation. However, after the rainfall-induced debris flow-slide event in 2010, the broken trees were collected by the forest administrators.

TABLE 2 UAV, satellite imagery and cartographic products used to investigate the Iapa LDF, dam formation and impounded lake evolution.

Data type	Name of cartographic products	Date of acquisition/edition	Source
Aerial imagery	UAV-derived orthomosaic	October, 2023	Field survey, direct acquisition
	Orthophoto (0.5 m resolution)	June, 2005	
Satellite imagery	Orthophoto (2 m resolution)	May, 2012	Google Earth satellite view
		April, 2014	
		May, 2017	
		September, 2019	
	Landsat 7 ETM+ normalized difference moisture index (50 m resolution)	03 July, 2010	Copernicus Open Access Hub
		20 August, 2010	
Topographic map, scale 1:5,000	L-35-041-D-a-1-III	1975	National Agency for Cadastre and Land Registration of the Borrower, Neanț County, Romania
	L-35-041-D-a-1-IV		
Topographic map, scale 1:25,000	L-35-041-D-a	1984	National Agency for Cadastre and Land Registration of the Borrower, Neanț County, Romania
Geological map, scale 1:50,000	Sheet 48 days Tazlău (L-35-41-D)	1983	Geological Institute of Romania

Currently, the forest growing on the surface of the LDF is young and dispersed.

The photogrammetric data acquisition stage consisted of using a high-performance DJI Phantom 4 Pro drone with a full-frame digital camera with a 20-megapixel CMOS sensor. The flight plan was designed to perform successive flights with 70% overlap between photos. Flights were conducted at a relative altitude of 110 m above the slope where the Iapa LDF occurred, correlated with mountain topographic variation, in order to obtain a ground sampling distance (GDS) of 2 cm. The photogrammetric area surveyed is 20 ha, of which the affected area by debris flow-slide is 13.5 ha and by flood approximately 2.5 ha. The photos obtained are automatically georeferenced by the drone using the on-board RTK system to record precise geographic coordinates for each photo. A total of 571 photos were obtained, which were processed using automated procedures with appropriate spatial alignment algorithms. In Figure 4A the Projection Center Point (PCPs) coordinates of each UAV photo are indicated.

The dense point cloud, mesh, texture, tiled model and digital surface model (DSM) algorithms implemented in Agisoft Metashape Pro v.1.6.5 software were used to produce the orthomosaic (2 cm spatial resolution) (Figure 2C) and UAV-derived DSM (10 cm spatial resolution) of the Iapa LDF area. Spatial analyses were performed using Esri ArcGIS v.10.2. The DSM was resampled to a spatial cell size of 1 m^2. In the final stage of data processing, to capture all topographic details within and in the vicinity of the LDF body, the final DEM was filtered to exclude vegetation (e.g., trees, shrubs) or any other point elevation that does not relate to the land surface (Figure 4A).

3.2 DEM-derived from old maps and DOD

In order to obtain the thickness of erosion and deposition map derived from the difference of two consecutive DEMs (DOD) (De Falco et al., 2023), an elevation model before the Iapa LDF event was needed for comparison with the UAV-derived DEM obtained for 2023. Therefore, the best option for extracting altitudinal information was the topographic maps at a 1:5,000 scale, considering the low resolution of other available elevation models like SRTM or ASTER (Khasanov, 2020) in the investigated region. In this context, two topographic maps corresponding to the study area were acquired from the National Agency for Cadastre and Land Registration of Neamț County, Romania (Table 2). The contours with 2.5 m equidistance were manually digitized, along with other point elevation information (e.g., mountain peks, elevation of hydrographic network), using the old maps as a background. Based on this shapefile elevation data, a DEM with a 1 m cell size, similar to the resolution of the UAV-derived DEM, was generated using the Topo to Raster interpolation tool in ArcGIS 10.2 (Figures 4B, C).

Regarding the DOD methodology, which is a widely adopted tool for volumetric data in geomorphic change detection (GCD) (De Falco et al., 2023), especially in areas affected by landslides (Jaboyedoff et al., 2012) and debris flows (Bull et al., 2010; De Long et al., 2012), it was employed to identify the primary areas of erosion and accumulation in the case of the Iapa LDF. The difference between the 2023 UAV-derived DEM and the 1975 old maps-derived DEM was computed using the Raster Calculator tool in ArcGIS 10.2 (Figure 4D). The resulting raster was used to obtain morphometric values for the detached, transported,

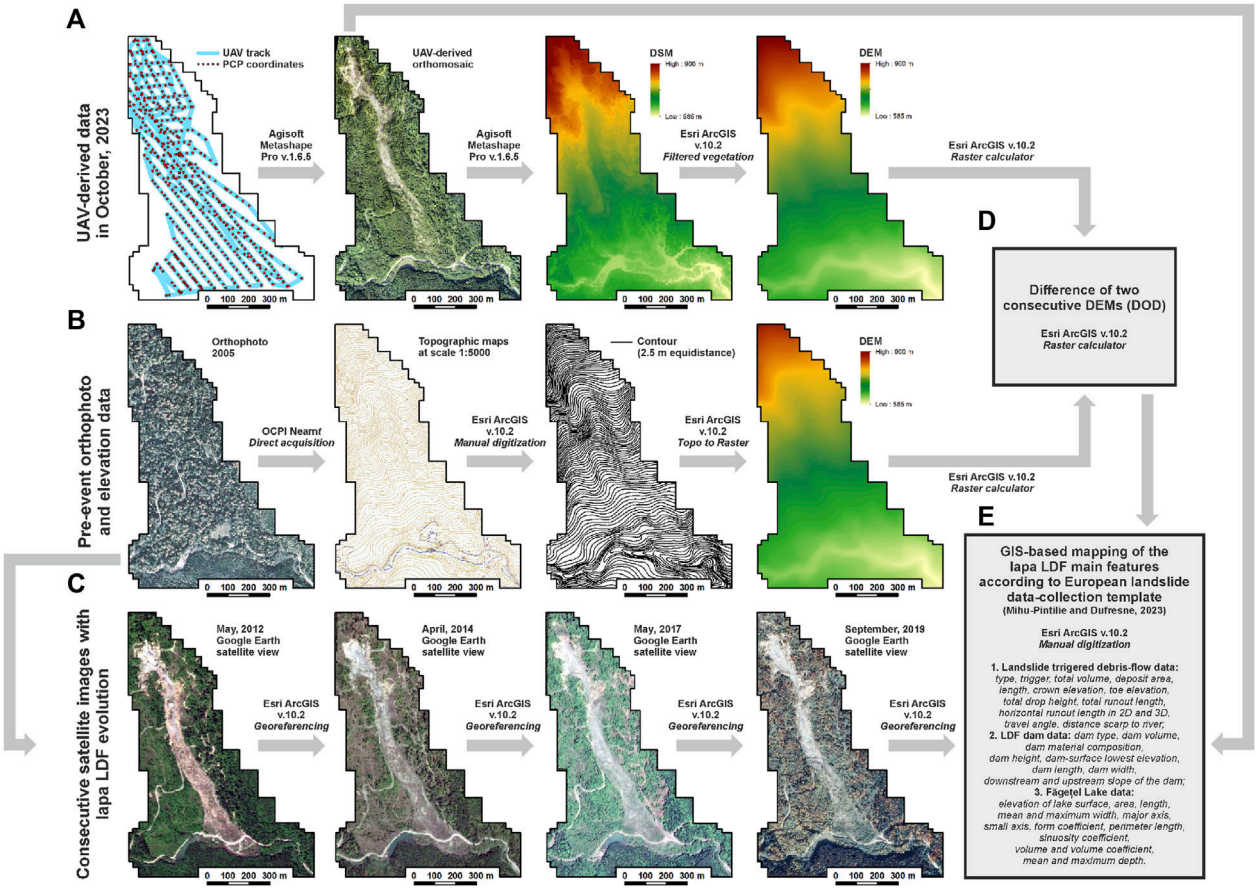

FIGURE 4
Workflow chart followed in this study to obtain the Iapa LDF geodetic data: **(A)** The area covered by 2023 UAV measurements, including PCP coordinates of each vertical photo, the UAV-derived orthomosaic, DSM derived from UAV survey, and the resulting DEM obtained after filtering the DSM to exclude vegetation and other non-elevation surfaces; **(B)** Pre-event orthophoto, the 2.5 m equidistance contours manually digitized using old topographic maps as background, and the resulting DEM with pre-event slope characteristics; **(C)** Consecutive satellite images (Google Earth georeferenced screenshots) used for the evolution characterization of the Iapa LDF; **(D)** Difference (DOD) between the 2023 UAV-derived DEM and the old maps-derived DEM used to delineate erosion and deposition areas; **(E)** GIS-based mapping of the Iapa LDF according to the European landslide data-collection template (Mihu-Pintilie and Dufresne, 2023).

and deposited terrigenous material. Additionally, it facilitated the accurate delineation of the morphological features of the Iapa LDF. Furthermore, by utilizing successive Google Earth satellite views from 2010 to the present (Figure 4C), along with DOD data, we managed to identify other episodes of debris flow-slide that occurred in the crown area of the Iapa LDF after the 2010 event.

3.3 Hydro-morphological data collection

The delineation of the Iapa LDF features for hydrological and geomorphological mapping was conducted through field descriptions correlated with the geodetic data (e.g., UAV-derived orthomosaic and DEM). The measurements improve the estimate of the shape, surface area, and volume of both the initial and recently reactivated debris flow-slide in the study area. Moreover, since the present case study will be included together with other examples in an upcoming European landslide dams database, the delineation of geomorphological features to obtain accurate morphometrical values was achieved according to a specific data-collection template (Mihu-Pintilie and Dufresne, 2023) (Figure 4E). The summary of this data-collection includes informations related with: 1) Landslide triggered debris-flow data: type, trigger, total volume, deposit area, length, crown elevation, toe elevation, total drop height, total runout length, horizontal runout length in 2D and 3D, travel angle, distance scarp to river (Cruden and Varnes, 1996; Hungr et al., 2014); 2) LDF dam data: dam type (Costa and Schuster, 1988), dam volume, dam material composition, dam height, dam-surface lowest elevation, dam length, dam width, downstream and upstream slope of the dam (Fan et al., 2020); 3) Făgețel Lake data: elevation of lake surface, area, length, mean and maximum width, major axis, small axis, form coefficient, perimeter length, sinuosity coefficient, volume and volume coefficient, mean and maximum depth (Mihu-Pintilie, 2018b; Romanescu et al., 2018b).

4 Results and discussions

4.1 The rainfall-triggered Iapa LDF event

As presented in the introduction section, during the summer of 2010, significant heavy rainfall impacted the northeastern part of the Goșmanu Massif, leading to several flash floods along the Iapa Valley. The highest precipitation amounts were recorded in three intervals: 16–22 May (115.8 mm), 22–27 June (195.8 mm), and 25–27 July (70.4 mm). Overall, from May to August 2010, the cumulative precipitation amounted to 599.1 mm, which represents 70% of the total precipitation recorded throughout the entire year (Figure 5A). These weather conditions also induced historically high discharge rates on the Iapa River as a response to rainfall events: 16.4 m^3/s on 22 May, 40 m^3/s on 26 June, and 12.6 m^3/s on 27 July (Figure 5B). According to locals, during these periods, the Iapa River flooded several courtyards and damaged several bridges and roads in settlements downstream of the Iapa LDF location, especially in Neguleşti and Luminiș.

However, based on discussions with stakeholders, including the foresters whose ranger office house is located 8 km downstream from the LDF dam, it could not be precisely determined which of the three rainfall events triggered the debris flow-slide event. Under these circumstances, we attempted to correlate satellite imagery with the possible weather interval when the mass-movement occurred. Therefore, due to the fact that the Iapa LDF event left a scar in the forest vegetation, the best option was to investigate successive Landsat 7 ETM+ Normalized Difference Moisture Index (NDMI) images with a resolution of 50 m per pixel (Figure 5C). In practice, NDMI is generally used to determine vegetation water content (Ochtyra et al., 2020), which, in the case of the present study, can indicate when forest vegetation was removed from the area affected by the debris flow-slide. In this framework, the analysis of NDMI rasters indicates that the Iapa LDF occurred between 03 July and 20 August, and most probably the rainfall event from 27 July was the one that triggered the LDF. Furthermore, even though the most severe meteorological conditions of 2010 were not recorded at that time, the initiation of landslide processes can be attributed to the 27 July event, although the decisive factor was the large quantities of precipitation that saturated and weighed down the southern slope of Drumul Chinezilor ridge throughout the entire summer season.

Interestingly, it should be noted that during the period of 25–27 July 2010, when it is also considered that Făgețel Lake was formed, the discharge data on the Iapa Valley did not show a proportional increase directly corresponding to the amount of precipitation that fell, as was the case with previous rainfall events. In this context, we consider that the blocking of the Iapa Valley by the LDF fan caused the accumulation of water behind the dam, creating a delay of several hours between the high quantities of precipitation and the discharge response. This delay most likely corresponds to the filling duration of the newly formed lacustrine depression, estimated to be between 2 and 4 h. After the watercourse resumed its flow over the dam surface, the discharge data recorded at the Luminiș gauge station showed a progressive increase, reaching a maximum of 12.6 m^3/s.

4.2 DOD-base LDF characteristics

The difference of DEMs (DOD) methodology used for GCD across the Iapa LDF area was primarily applied to obtain volumetric data and secondarily to confirm the field survey observations and measurements. In this regard, the difference between the two rasters of 2023 UAV-derived DEM and the 1975 old maps-derived DEM indicates a total volume of 782,500 m^3 of displaced materials, of which more than 450,000 m^3 represents the volume of the Făgețel Lake dam. The erosion and deposition thickness values range between −28 m in the source area and +30 m in the deposition area (Făgețel Lake dam). The mean thickness value is approximately ±3.4 m, suggesting that, apart from the crown area and the obstructed river sector where the erosion and accumulation amplitudes are high, the rest of the Iapa LDF exhibits a relatively shallow depth configuration (Figure 6A).

The cross section locations of the field observations and UAV-derived GPS measurements used to validate the DOD outcomes are also indicated in Figure 6B. They show values ranging between 15 m and 25 m of erosion in the landslide-triggering area and on the debris flow-slide flanks, while erosion values ranging between 2 m and 4 m are observed in the main channel of the flow-sliding area. Regarding the deposition values, they are more representative in the LDF dam area, where the flow-slide accumulation reported thickness exceeding 25 m between the valley floor and the top of the obstructed dam. However, when comparing the field measurement results with the DOD values, the errors do not exceed 1 m, especially in the deposition area, and this is a consequence of the fact that direct measurements could not capture the entire flow-sliding plane at all analyzed points. In the erosional area, the errors were minimal (less than 0.5 m), including here also the debris flow events post-2010, which are quite visible in the LDF source area.

Overall, the DOD map accurately indicates all details related to the thickness of the mass movement in terms of erosion and accumulation areas. This analysis permitted the identification of important geomorphological aspects, such as the presence of channels where major erosion occurred (C1–C7), the first slope change at the foothill (C8), the upper part of the debris flow-slide area (C9–C12), or the precise limit of the obstructive dam (C13–C15) (Figure 6B).

4.3 Hydrological and geomorphological characterization of Iapa LDF

For a more comprehensive hydrological and geomorphological characterization of the Iapa LDF, we divide the investigated area into three landform parts: 1) Landslide triggered debris-flow area; 2) Iapa LDF dam area; 3) Lake area. All morphometric values will be recorded in an upcoming landslide dams database, alongside other representative landslide.

4.3.1 Landslide source and debris-flow area

The topography of the south-facing slope of the Drumul Chinezilor ridge, loose material on its surface and anthropogenic impact as a consequence of intensive deforestation provide very

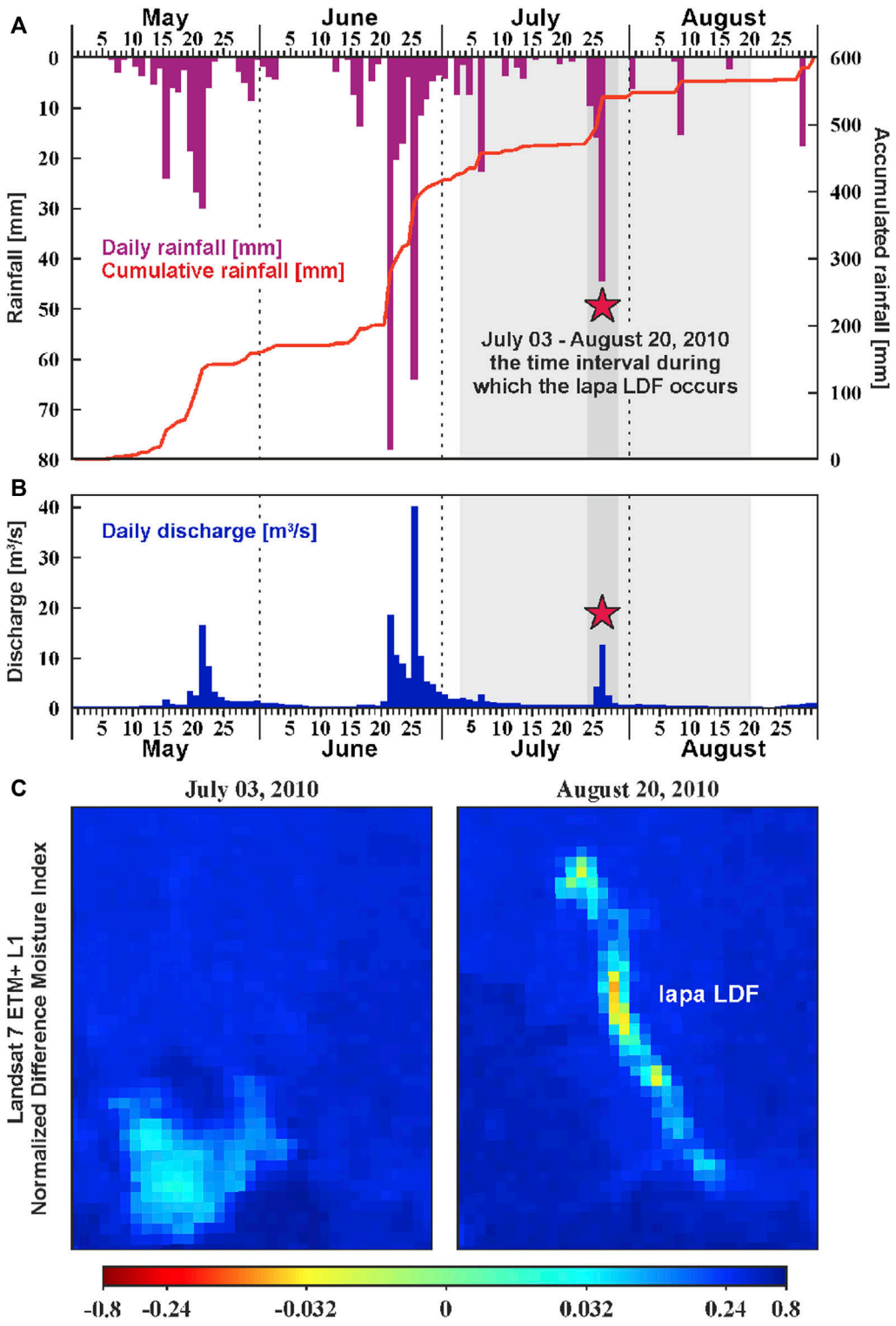

FIGURE 5
The rainfall event that triggered the Iapa LDF: daily and cumulative precipitation (mm) in the May–August interval of 2010 **(A)**, and correlation with daily maximum discharge (m^3/s) at the Luminiș gauging station (see Figue 1C) **(B)**. In **(C)** Landsat 7 ETM+ L1 NDMI imagery indicating that the Iapa LDF occurred between July 3 and August 20 interval of 2010. The red star indicates July 27 as the most probable date.

favorable conditions for a wide range of geomorphological processes such as landslides and debris flows (Figure 7A; Table 3). Therefore, the landslide process that triggered the debris flow-slide in 2010 started at an altitude of 875 m a.s.l. and affected an area of 13.5 ha. The height of the main scarps ranges from 25 m in the central part of the crown area to 10 m on the secondary scarps located on both

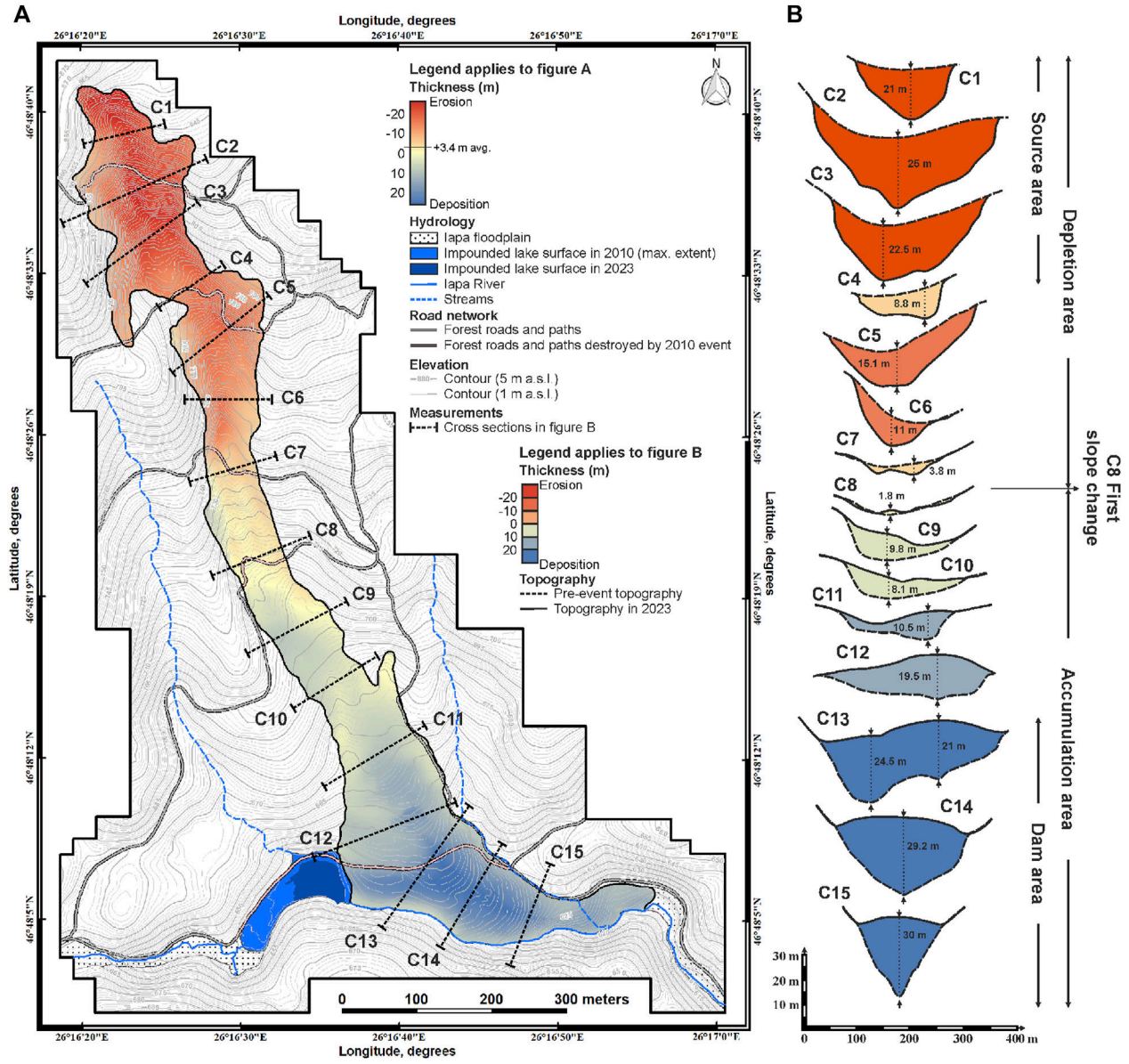

FIGURE 6
The difference of DEMs (DOD) map of the Iapa LDF **(A)**. In **(B)**, 15 transversal cross sections highlight the main erosion and deposition areas along the affected slope.

flanks of the landslide depression. The slope of the main scarps ranges between 60° and 90° and are still very active (Figure 7B).

The debris flow-slide area started in two confined channels and joined in the middle of the landslide depression at 780 m a.s.l., approximately 300 m below the upper limit of the crown area. The slope consists of very poorly sorted sediments with a predominance of sand and sandstone clasts, making it particularly susceptible to flow-sliding processes. For this reason, the investigated mass-movement was classified as a debris flow-slide based on sediment texture, geomorphological characteristics of both depletion and accumulation zones, and especially due to the rapid course of the flow-slide event. Furthermore, the presence of erosional channels and small debris fans formed post-2010 in the initial landslide area indicates that the current processes belong only to the channelized form of debris flow.

The depletion zone comprises a steep scarp and multiple old-to-new channel-like transport areas, deeply incised into the valley slope. The slope gradient is highest in the upper part and gradually diminishes further down the slope. The rugged relief of the depletion area is accentuated by the presence of structural steps, leading to significant changes in slope gradient. For instance, the floor of the middle channel incision descends by 5 m as it traverses the bedrock outcrop in the central part of the depletion zone. The depth varies along the central line in the upper part of the depletion zone and along the two lateral channels after the main channels split 180 m before the onset of the debris flow

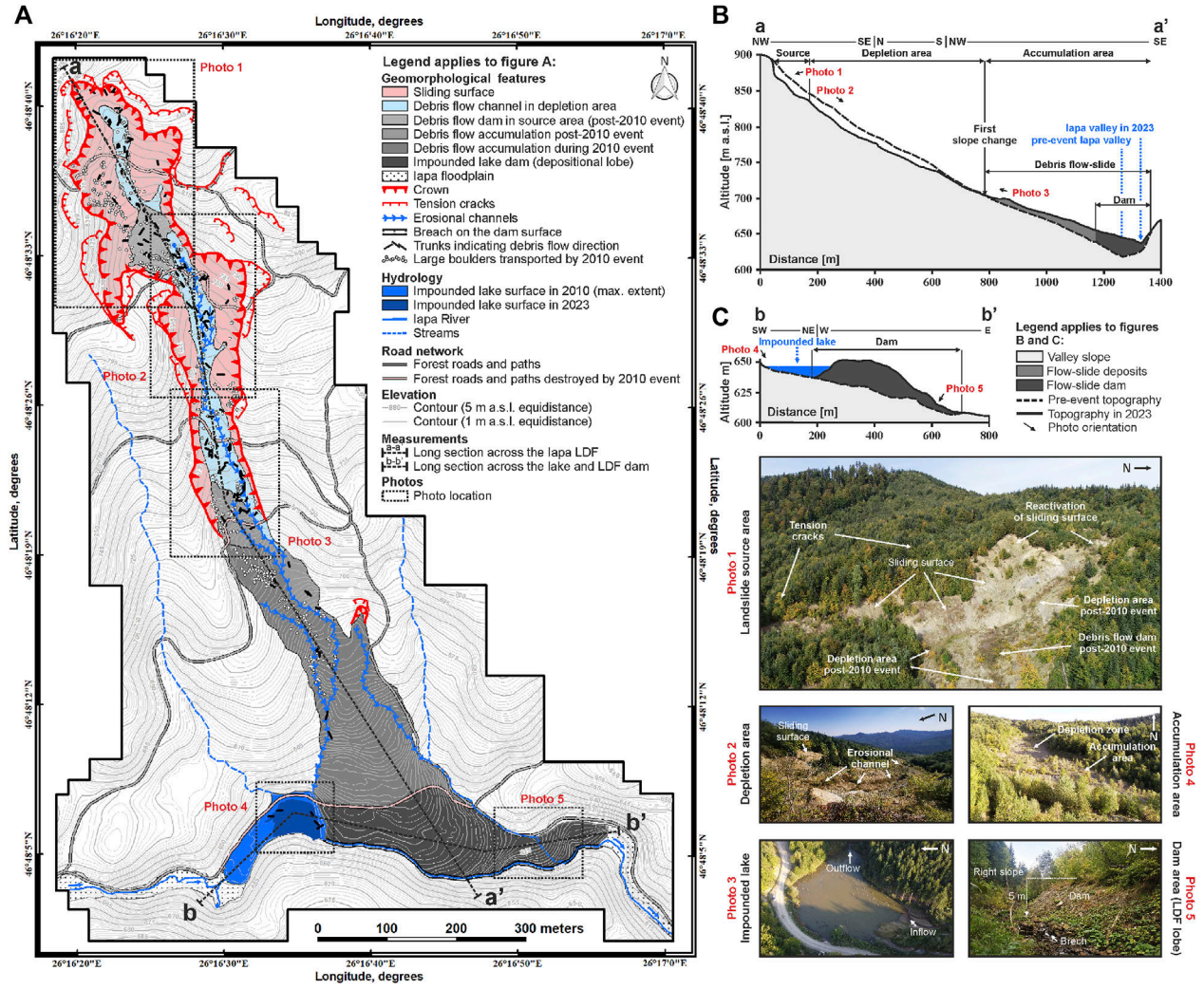

FIGURE 7
The simplified geomorphological sketch of the Iapa LDF **(A)**. Long section (a-a') across the landslide source area, depletion zone, and accumulation area (vertical exaggeration 1:2.5) **(B)**. Long section (b-b') across Făgețel Lake and debris flow-slide dam (vertical exaggeration 1:3) **(C)**. The main morphological features indicating the slope failure processes and the main debris flow characteristics are highlighted in photos.

accumulation. The maximum width of the depletion zone measures 90 m, while its length along the central line extends to 490 m. The elevation difference between the upper and lower parts is approximately 85 m a.s.l.

The debris flow-slide accumulation area begins in the lower part of the depletion zone. The upper part of the accumulation has an elongated fan shape that transforms into a lobe-like accumulation confined within the Iapa Valley. In the longitudinal section a–a' measured across the entire Iapa LDF area, the current topography of the fan surface indicates a relatively 15° gradient, characteristic of fans resulting from flow-sliding processes (Figure 7B). The lower part of the accumulation area indicates that deposits impacted the right slope of the Iapa Valley during the 2010 event. However, in October 2023 when field measurements were conducted, the materials impinged on the opposite slope had mostly eroded due to changes in Iapa watercourses on the dam surface. Additionally, the lateral development of the accumulation front, measured from the apex, is considerably larger on the right side, in the direction of the Iapa River flow. This asymmetry indicates both the transport capacity during flood events and the dynamic processes of debris flow, which continued for approximately 100 m along the valley. Overall, the Iapa LDF transported a large amount of material for over 750 m, with the total length of the accumulation from the upper part to the obstructed river bed being 550 m, and 200 m along the Iapa Valley. The maximum width reaches 330 m, with a thickness of about 30 m in the dam area. The matrix-rich debris flow contains large floating sandstone boulders, most of them concentrated at the toe of the debris flow. However, a significant area of large boulders is also located in the upper part of the accumulation area, indicating other post-2023 mass movements of lesser intensity. Along the long section of the lobe, the variety of clasts indicates a cohesive type of debris flow. Overall, the total volume of the accumulation area is 782,500 m^3 (Figure 7A; Table 3).

TABLE 3 Morphometric characteristics of the Iapa LDF area.

Parameter of Iapa LDF	Value
Affected area (A_{LDF})	13.5 ha
Deposit area (A_D)	8.1 ha
Deposit length (L_D)	750 m
Landslide crown elevation (LC)	875 m a.s.l.
Landslide toe elevation (LT)	615 m a.s.l.
Drop height (H or LC/LT)	260 m a.s.l.
Total runout length (L)	1,250 m
Horizontal runout length in 2D (L_{2D})	1,320 m
Horizontal runout length in 3D (L_{3D})	1,400 m
Travel angle (H/L)	0.26
Distance scarp to river (L_{sr})	1,160 m
Volume of displaced materials (V_D)	782,500 m^3

TABLE 4 Morphometric characteristics of the dam area.

Parameter of the dam	Value
Dam area (A_{dam})	2.5 ha
Percentage of LDF deposit area	30%
Dam height (H_{dam})	30 m
Dam-surface lowest elevation (D_{low})	615 m a.s.l.
Dam-surface height elevation (D_{high})	654 m a.s.l.
Dam length (L_{dam})	50 m
Dam width (W_{dam})	330 m
Downstream slope	35°
Downstream slope length	270 m
Upstream slope	65°
Upstream slope length	60 m
Dam volume (V_{dam})	450,000 m^3

4.3.2 Iapa LDF dam area

Generally, a landslide dam is the lower part of the accumulation area, which forms a barrier that can hold back water above the obstructed river level (Fan et al., 2020). In this context, the most widely accepted morphological characterization involves the shape, size, and composition of landslide dams in relation to the size of the blocked valley (Costa and Schuster, 1988). In the case of the Iapa LDF, the obstructed dam is represented by the lower part of the debris lobe, which fills the Iapa Valley. The accurate delineation of the initial shape of the obstructed valley sector was performed in ArcGIS based on the 1975 old maps, also used for DOD. Therefore, according to Costa and Schuster (1988) landslide dam classification, the Iapa LDF dam falls into the second category of dams, occupying the entire section of the obstructed valley. The matrix composition of the dam is mixed, ranging from 1 m floating sandstone boulders to fine debris deposits resulting from disaggregated sandstone, siltstone and clay rocks and topsoils transported during the LDF event. However, due to the mass movement type, together with the dam's lithological characteristics and the fact that it formed a long-term lake, the Iapa LDF is quite unique in the landscape of the Eastern Carpathians. Usually, the other examples of landslide dams that did not fail after a few days have been formed by rock slides, which confer high stability due to the lithological composition and morphological characteristics (Mihu-Pintilie, 2018a; Romanescu et al., 2018b).

Regarding the morphometric parameters of the Iapa LDF dam, the surface is 2.5 ha (30% of the accumulation area), and the volume was estimated to 450,000 m^3. The maximum dam height is 30 m, measured from the initial dam apex (654 m a.s.l.), now 4 m flattened by the reconstruction of the road destroyed during the 2010 event, down to the corresponding lower elevation of the Iapa riverbed. At present, the dam surface elevation ranges from 650 m a.s.l. to 610 m a.s.l. The maximum length of the dam, which corresponds to the maximum width of the filled river sector, is around 50 m. The dam width measured from the impounded lake outflow location up to the downstream limit of the dam is 330 m, of which the upstream slope is short (60 m) and steep (65°), and the downstream slope is much longer (270 m) and less steep (35°) (Figure 7C; Table 4).

Regarding dam stability, the main erosional process is the overtopping, represented by the Iapa watercourse, which creates a channel 1.5 m deep and 5 m wide on the dam surface. However, despite the erosive down-cutting, this breach ensures the drainage of water from Făgețel Lake, particularly during periods of rainfall, thereby mitigating flash floods. Additionally, the entire surface of the dam has been replanted with trees, which currently provide additional stability to the dam due to the root network that anchors the upper part of the dam, and by attenuating the direct impact of precipitation.

4.3.3 Iapa LDF lake area

In the case of the lakes formed behind the landslide dams, various terms have been adopted in the scientific literature (e.g., landslide lake, impoundment lake, landslide-dammed lakes) (Fan et al., 2020). In this approach, we consider the most appropriate term to describe the uniqueness of Făgețel Lake as the landslide-triggered debris flow-slide lake, or abbreviated LDF lake. Related to the hydronym Făgețel Lake, this name was given by the locals because the place where the lake formed was previously known as a young beech forest area ("fag" means "beech" in Romanian).

Related to the morphometrical parameters of the LDF lake, in 2023, when the UAV and field survey were carried out, the surface area of the lake was much smaller than its initial size. Therefore, in the following, we will present the morphometric parameters of the lake 2 years after its formation using satellite images available on

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TABLE 5 Evolution of morphometric and morpho-bathymetric parameters of the Făgețel Lake.

Parameter of the lake	Year 2010	Year 2023
Elevation of lake mirror	651 m a.s.l	645 m a.s.l.
Water surface (A_{lake})	9,500 m^2	3,100 m^2
Length (L_{lake} or A/W_{avg})	250 m	90 m
Maximum width (W_{max})	60 m	55 m
Average width (W_{avg} or A/L)	38 m	34.4 m
Major axis (AX_{max})	210 m	68 m
Small axis (AX_{small})	78 m	44 m
Form coefficient (AX_{small}/AX_{max})	0.32	0.61
Perimeter length (P)	600 m	260 m
Sinuosity coefficient ($P/\sqrt{3.14A}$)	3.47	2.63
Volume (V)	50,000 m^3	10,000 m^3
Maximum depth (H_{max})	10 m	6 m
Average depth (H_{avg} or V/A)	5.3 m	3.2 m
Volume coefficient ($3H_{avg}/H_{max}$)	1.59	1.6

the Google Earth platform, as well as the morphological parameters measured in 2023 (Figure 4C; Table 2). In this context, the initial surface area of the lake mirror was estimated at 9,500 m^2, with a length of 250 m and a maximum width of 60 m. In October 2023, these parameters had drastically decreased (surface area 3,100 m^2, length 90 m), except for the width, which remained the same. The perimeter of the lake also experienced the same decreasing trend, respectively from 600 m to just 260 m. The considerable reduction in the water surface area is a consequence of the breach on the surface of the dam, leading to a decrease in the maximum depth from 10 m (651 m a.s.l. of the water surface) to only 6 m in 2023 (645 m a.s.l. of the water surface). As for the volume of water at the time of dam formation, it was estimated around 50,000 m^3, but in 2023, it had reduced to only 10,000 m^3. Additionally, the shape of the lake has changed considerably, transitioning from an elongated shape along the flooded valley (sinuosity coefficient of 3.47) to an almost circular shape in 2023 (sinuosity coefficient of 2.63). This trend is also indicated by the ratio of the major and minor axes of the lake, which reveals an evolution of the form coefficient from 0.32 in 2012 to 0.61 in 2023, but not by the volume coefficient, which remains constant around 1.6 values. The volume coefficient indicates that the Făgețel lacustrine basin evolution is very similar to other landslide lakes in the Eastern Carpathians, which maintain the maximum depth at the bases of submerged dam slopes and a constant ratio between the volume and area of the lake. However, the comprehensive evolution of all morphometric and morpho-bathymetric parameters of Făgețel Lake is presented in Table 5.

According to the evolution of morphometric and morpho-bathymetric parameters of Făgețel Lake, our estimation of the lake's lifespan is approximately 20 years (another 6 or 7 years from now) (Figure 8). However, this theoretical estimate does not account for the reactivation of landslide processes, dam destruction due to a major flash flood event, or anthropogenic intervention. All of these factors could lead to the evacuation of water within a few hours or maintain water retention at current levels for an extended period. In either scenario, the hydrological hazard posed by dam destruction no longer represents a threat to population located downstream of the lake due to the considerable reduction of the stored water volume. In any case, it appears that local authorities are making efforts to maintain the lake at its current parameters by clearing trees from the water body, landscaping the shores and access routes to the lake, as well as managing forestry waste.

4.4 Lessons learned

The location of the Iapa LDF in the flysch zone of the Eastern Carpathians, a mountainous area frequently affected by extreme rainfall events with high erosional impact in deforested locations, constitutes the main premise for triggering the recent mass-movement processes that have occurred in the upper Iapa Valley. Even though the debris flow-slide event that occurred in the summer of 2010 was extremely dynamic, a stabilized appearance of vegetated landforms in the LDF accumulation area indicates that shallow landslides and debris flows are currently active only in the source and depletion area. However, a new episode of heavy rainfall that affected the southern slope of the Drumul Chinezilor ridge can occur at any time. This hazard threat arises from the analysis of climatic conditions during the May-August period of 2010 when the time lag between the long-lasting rain culmination and the landslide triggering suggests that the debris flow-slide initiation was connected with cumulative precipitation over the 3 months in the study area. Therefore, lessons learned and future actions needed to prevent the further reactivation of the Iapa LDF suggest that local authorities should avoid clear-cutting forests on exposed slopes prone to landslide processes. Additionally, the network of forest exploitation paths should be minimized on steep slopes, as the density of these timber transportation routes has been the primary anthropogenic trigger leading to the occurrence of the Iapa LDF.

Regarding the Iapa River sector obstructed by 2010 LDF event and the formation of Făgețel Lake, although this type of landslide lakes are not unique in the landscape of the Eastern Carpathians, the uniqueness and hazardous threat arise from the dam composition and stability characteristics. Usually, the lifespan of dams formed by debris flow-slide processes is short (a few hours) due to the low cohesion of the debris matrix. Therefore, the long-term presence of Făgețel Lake and the relatively stability of the dam indicate, but only in this case, that the potential flood hazard threat was partially diminished. However, this does not guarantee that in the event of other similar occurrences, the formed dams will not fail, affecting the population located downstream. For this reason, in the watershed of the Iapa river, in addition to the area affected by debris flow-slide in 2010, other areas susceptible to landslides should also be monitored in the future. In this study, we identified three possible other areas where mass movement processes could occur on a similar or even

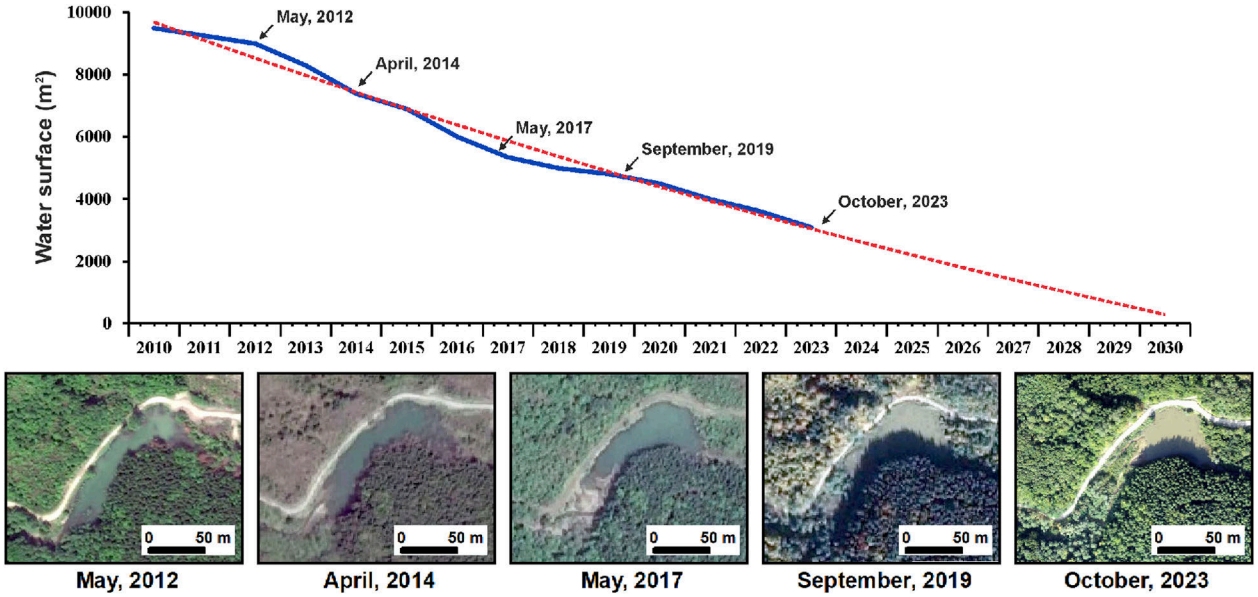

FIGURE 8
Water surface evolution of the Făgețel Lake between 2010 and 2023 (blue line) and the lifespan estimation (dotted red line) using water surface extent delineated based on five consecutive aerial images.

larger scale than Iapa LDF. However, we anticipate that the outcomes of this approach will aid in enhancing the emergency response plan in the event of any other potential destructive hydro-morphological events linked to heavy rainfall in the surveyed region.

4.5 Limitation of UAV survey methodology

From the perspective of UAV survey methodology used in this study, both for extracting the main morphological and morphometric parameters of the Iapa LDF and for understanding the mechanism of the impoundment and formation of Lake Făgețel, there were several limitations that need to be addressed. The UAV survey conducted to obtain a DEM as accurate as possible with the topographic reality in 2023 was hindered by the forest vegetation that had spread over the area. This aspect made the generation of the DEM using DTM-derived from successive orthomosaic aerial images a time-consuming process, involving the identification and filtering of non-elevation data (e.g., tree canopy). However, in the future, we intend to use LiDAR technology to reconstruct the terrain elevation model in the area affected by the Iapa LDF, a technology that will streamline both the processing and filtering stages of geospatial data, significantly improving the accuracy of the resulting DEM. Despite these drawbacks, the use of DEM-derived from UAV survey and corrected on the ground with GPS measurements has yielded satisfactory results.

5 Conclusion

The mass movement that occurred on July 27, 2010, in the upper Iapa Valley (Goșmanu Massif, Eastern Carpathians) can be classified as a landslide triggered debris flow (Iapa LDF). The landslide that triggered the debris flow processes began at an altitude of 875 m a.s.l., affecting an area of 13.5 ha and transporting a large amount of material for over 1.4 km up to 615 m a.s.l. The total volume of transported material was approximately 782,500 m^3. The lower part of the accumulation area, namely, the dam area (450,000 m^3), filled a 330 m narrow sector of the Iapa watercourse and formed an impoundment. The water storage above the debris flow-slide dam caused the formation of a elongated lake (250 m length, 9,500 m^2 water surface), currently known as Făgețel Lake. Measurements conducted in 2023 using UAV survey indicate that the lake size has drastically reduced, with the current water surface area being only 3,100 m^2. This considerable reduction is a consequence of the breach on the dam surface, leading to a decrease in maximum depth from 10 m to only 6 m in 2023. Under these morphological and hydrological conditions, the lake is projected to be completely drained in 6 or 7 years.

Overall, being a consequence of extreme rainfall events with high erosional impact in deforested locations where Iapa LDF occurred, the entire area affected by mass-movement remains vulnerable to reactivation under similar rainfall-induced landslide conditions, as observed in 2010 (599.1 mm cumulative precipitation recorded in the May to August interval). Therefore, future actions necessary to prevent further reactivation of the Iapa LDF suggest that local authorities should stop the clear-cutting forests on exposed slopes prone to landslide processes. Additionally, the network of forest exploitation paths should be minimized on steep slopes, as the density of these timber transportation routes has been the primary anthropogenic trigger leading to the occurrence of the Iapa LDF. Furthermore, while the long-term presence of Făgețel Lake and the relative stability of the dam indicate, but only in this case, a partial diminishment of the potential flood hazard

threat, it does not guarantee that formed dams will not fail in other similar occurrences, potentially affecting downstream populations. Therefore, in the Iapa watershed, areas susceptible to landslides should be continuously monitored in addition to the area affected by the 2010 debris flow-slide for future risk mitigation efforts.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

AM-P: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. CS: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. AU: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Glossary

a.s.l.	Above Sea Level
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
DEM	Digital Elevation Model
DTM	Digital Terrain Model
DOD	DEM of Difference
GCD	Geomorphic Change Detection
GIS	Geographic Information System
GDS	Ground Sampling Distance
GPS	Global Positioning System
LDF	Landslide triggered debris flow
NDMI	Normalized Difference Moisture Index
PCP	Projection Center Point coordinates
RTK	Real-Time Kinematic
SRTM	Shuttle Radar Topography Mission
UAV	Unmanned Aerial Vehicle

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A method for rapidly assessing landslide hazard—taking the landslide in Yongxing town, Mingshan area as an example

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To overcome the reliance on large samples and high-quality data in existing evaluation methods, while also improving evaluation efficiency and accuracy, this paper proposes a method for rapid landslide hazard assessment. This method utilizes existing research findings and specific analytical techniques for the study area to conduct rapid assessments. Taking the landslide in Yongxing Town, Mingshan Area, Ya'an City, Sichuan Province as an example, the Analytic Hierarchy Process (AHP) is combined with the Information Value (IV) method, Certainty Factor (CF) method, and Frequency Ratio (FR) method from previous studies, The AHP-IV and AHP-FR methods assess the study area as a moderately hazardous zone, while the AHP-CF method assesses it as a slightly hazardous zone. Affected by the strong 2013 Lushan earthquake, the landslide in the study area caused permanent damage. Field investigation results show that the landslide hazard in the study area is moderate, and the AHP-IV and AHP-FR methods are more consistent with the actual field results. The AHP-CF method, due to not considering the water system factor and having certain errors in its discrimination method, leans towards a safer assessment, The results of the three evaluation methods are somewhat consistent.

KEYWORDS

hazard assessment, analytic hierarchy process, information value method, certainty factor method, Frequency Ratio method, peak ground acceleration

1 Introduction

China, with its vast territory and complex geological environment, frequently experiences various geological disasters, causing significant economic losses and casualties. According to the "National Geological Disaster Bulletin" for 2007–2016, there are over 8,000 geological disasters in China each year, with landslide disasters occurring more than 5,000 times annually (Figure 1A). Landslides account for over 50% of geological disasters. As shown in the proportion of landslides in geological disasters over the past decade, landslides account for as much as 76%. The direct economic losses and casualties caused by geological disasters in China in recent years are shown in Figure 1B. Annually, landslides in China cause direct economic losses of about 4.446 billion yuan and 1,073 casualties. In recent

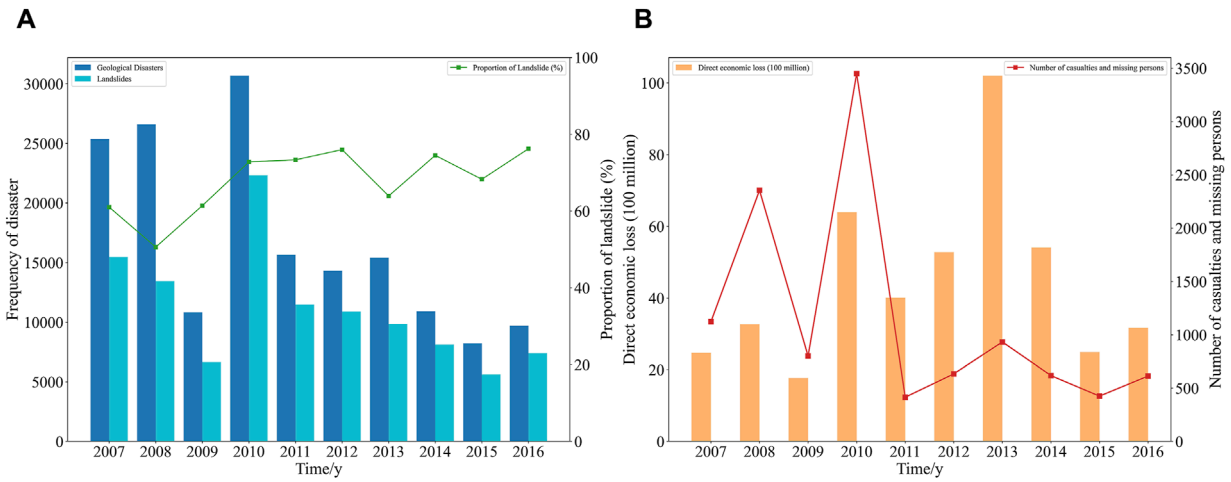

FIGURE 1
(A) Frequency of disaster and Proportion of landslides **(B)** Economic loss and casualties.

years, China has experienced several major landslide events: In 1989, a torrential rain triggered the Xikou landslide, causing direct economic losses of over 6 million yuan and 221 casualties, making it the largest landslide disaster in China in the late 1980s; in September 2011, thousands of gentle slope landslides occurred in Nanjiang County, Sichuan, severely affecting villages and farmland; in September 2014, a gentle slope landslide occurred in Xiangjiaping, Jiangkou Town, leveling an entire residential area; the "6·24" major landslide in Maoxian, Sichuan in 2017 resulted in 83 casualties; in November 2018, a gentle slope landslide in Yutai Village, Toutuo Town, Chongqing, posed a huge threat to local residents and construction projects in progress (Zhu, 2022).

In the study of landslide hazard assessment (Cheng et al., 2024; Marín-Rodríguez et al., 2024), two research methods have been widely applied: one is the empirical rule analysis method based on expert knowledge, and the other is the data-driven statistical regression analysis method. The first type, empirical rule analysis, is characterized by its simplicity and independence from data samples. By utilizing expert knowledge to compare the relationships between various factors one by one, it can also effectively reduce human error and achieve relatively accurate and reliable hazard analysis. Among these, the Analytical Hierarchy Process (AHP) has been widely applied, which involves selecting typical landslide predisposing environmental factors and triggering factors based on expert experience, and determining the contribution weights of different factors before conducting an overlay analysis assessment (Feizizadeh and Blaschke, 2014; Mandal and Mandal, 2018). Wu et al. used the AHP to compile a landslide susceptibility map for Gangu County, China, providing an important reference for geological disaster management and risk assessment (Wu et al., 2016) Sandeep Panchal et al. applied the AHP for landslide disaster assessment on National Highway 5 in India, determining the weights of each factor through a hierarchical structure and pairwise comparison matrix, and generated a landslide hazard distribution map (Panchal and Shrivastava, 2022). Chunhung Wu et al. combined rainfall and six site factors, and through the AHP, obtained landslide susceptibility assessment results for different areas in central Taiwan and mapped the susceptibility distribution (Wu and Chen, 2009).

The advantage of the second type, statistical regression analysis lies in its ability to reveal relationships between variables and to make predictions and inferences. By calculating parameters and conducting significance tests, the importance of influencing factors can be determined. Additionally, statistical regression analysis is highly interpretable, explaining the impact of independent variables on dependent variables, which aids in further exploring the relationships between variables. Among these, Lee et al. used the Frequency Ratio (FR) and Logistic Regression (LR) to assess landslide susceptibility in the Selangor area of Malaysia, comparing the applicability of these two methods in landslide susceptibility mapping (Lee and Pradhan, 2007). Shraban Sarkar used the Information Value (IV) method for landslide susceptibility assessment in parts of the Darjeeling Himalayas (Sarkar et al., 2013). Zhang et al. optimized the Frequency Ratio method and applied it to landslide susceptibility assessment in the Caiyuan Basin in the southeast mountainous region of China (Zhang et al., 2020). Bai used the Logistic Regression method to analyze landslide susceptibility in the Youfang River basin (Bai et al., 2015). Xing used a modified LR method to assess the susceptibility of rainfall-induced landslides (Xing et al., 2021). Abdo employed both the Frequency Ratio and Statistical Index methods to analyze the impact of different factors on landslide susceptibility, proposing corresponding susceptibility distribution maps and suggestions (Abdo, 2022). Wang et al. evaluated landslide hazard in Wen County, northwest China, using the IV, Weights-of-Evidence (WOE), and Certainty Factor (CF) methods (Wang et al., 2019). Chen et al. compared the application of the Frequency Ratio model, Statistical Index model, and Weights-of-Evidence model in landslide susceptibility mapping, providing a basis for comparison and selection in landslide susceptibility assessment (Chen et al., 2016a).

The advantage of the first type, empirical rule analysis is very extensive, but its weight assignment relies on the subjective judgment of decision-makers, making it highly subjective. The advantage of the second type, statistical regression analysis, which

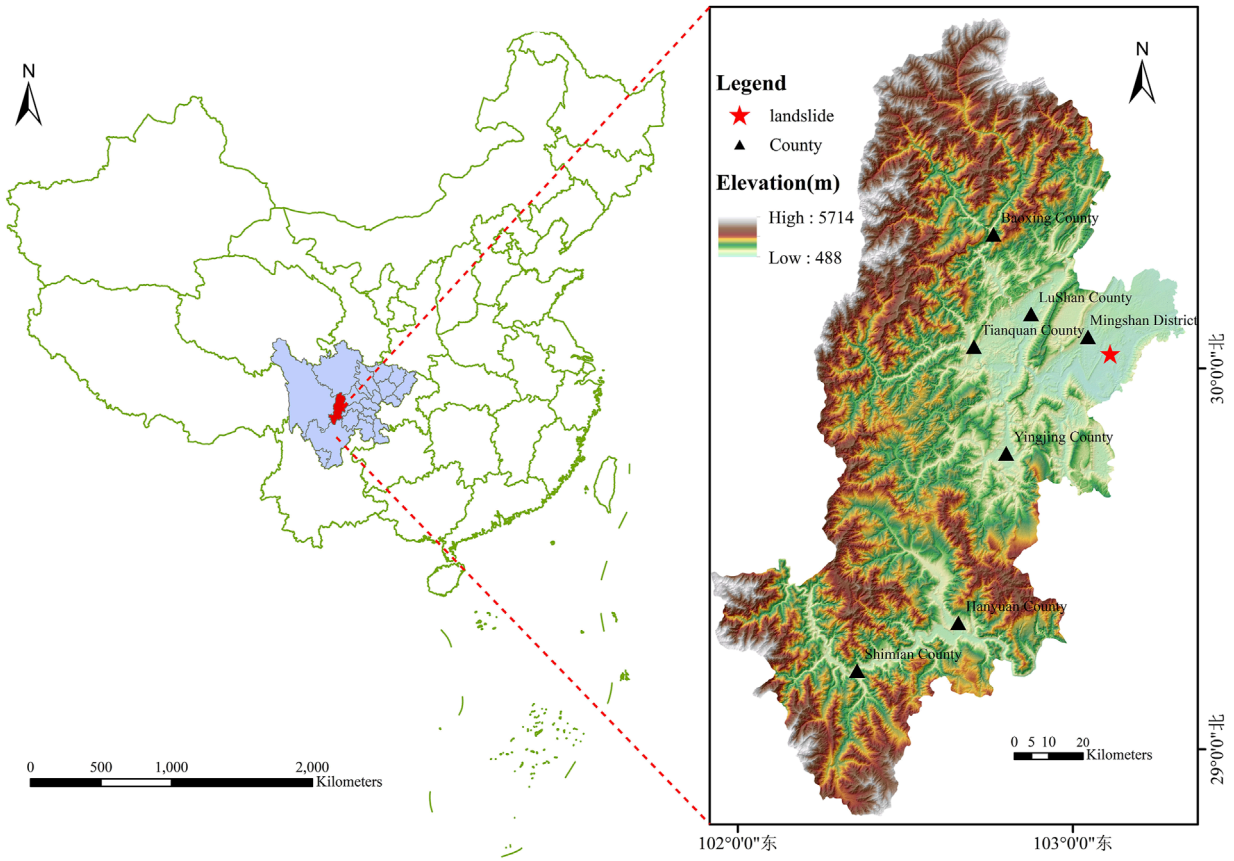

FIGURE 2
Location of the study area.

starts from the statistical information of a large amount of data, is highly objective. However, mathematical statistical models have limitations in precisely expressing the nonlinear relationship between factors and landslide hazards (Chen et al., 2021). To further enhance the accuracy of landslide hazard assessment, some scholars have combined empirical rule analysis with statistical regression analysis. Chen et al. used the AHP and CF methods to map landslide susceptibility in the Baozhong area of Baoji City, China (Chen et al., 2016b). Ionut Cristi Nicu applied the AHP, FR, and Statistical Index methods for landslide susceptibility assessment (Nicu, 2018). Guoliang Du et al. compared the effects of the AHP-IV and LR-IV methods in the susceptibility distribution map of the Himalayan convergence zone in China (Du et al., 2019).

Statistical regression analysis requires a large sample size and high-quality data. Landslide data are often limited and exhibit spatial and temporal unevenness, which may lead to inaccuracies or significant biases in the results of statistical regression analysis. When studying individual landslides, researchers often do not use this method due to its high data requirements. Today, for regional landslide hazard assessments, many researchers have applied statistical regression analysis to obtain evaluation results. If the results of previous studies can be appropriately applied when studying individual landslides, it can overcome the drawbacks of data requirements in statistical regression analysis and significantly improve the efficiency of landslide hazard assessment. If the first type of empirical rule analysis method based on expert knowledge is also applied, the accuracy of landslide hazard assessment can be enhanced.

This article focuses on the landslide in Yongxing Town, Mingshan Area, Ya'an City, Sichuan Province. By selecting statistical regression analysis results from similar areas, it obtains the IV, CF, and FR values. It combines previous research results with the AHP method in empirical rule analysis, using AHP-IV, AHP-CF, and AHP-FR methods to assess the landslide hazard in Yongxing Town. The AHP-IV and AHP-FR methods assess the landslide in the study area as moderately hazardous, which is more consistent with field survey results. The AHP-CF method, due to not considering factors such as rainfall and distance from water system, and having errors in its discrimination method, assesses the area as slightly hazardous, leaning towards less safe assessment.

2 Overview of the study area

2.1 Basic characteristics

The landslide is located on the south side of the Mingshan-Cheling County Road in Huacheng Village, Yongxing Town, Mingshan Area, Ya'an City, Sichuan Province, with coordinates at East Longitude 103°09′41″ and North Latitude 30°02′51″ (Figure 2). The landslide

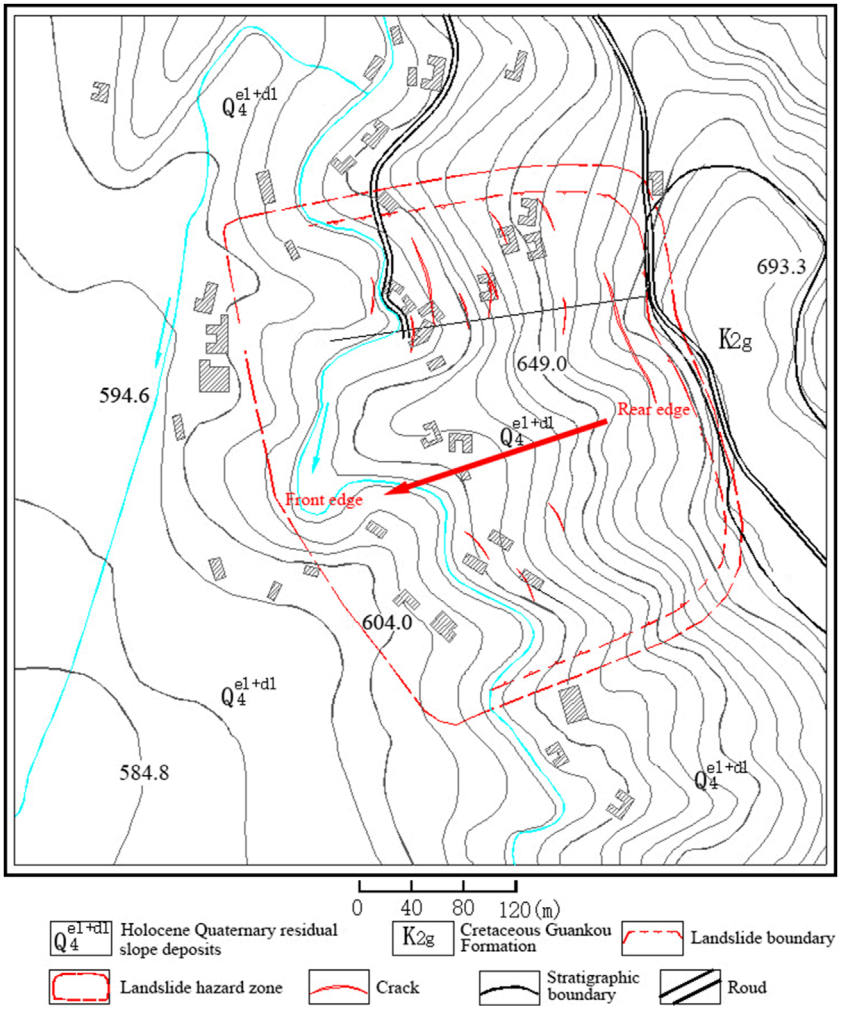

FIGURE 3
Engineering geological plan of the landslide.

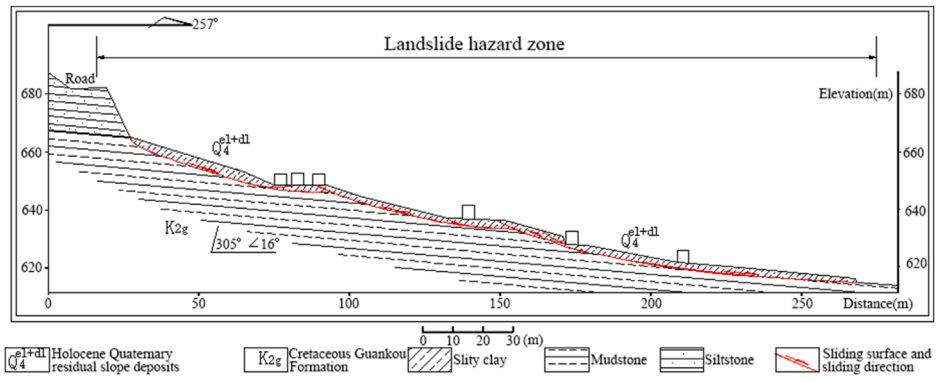

FIGURE 4
Engineering geology profile of the landslide.

has an irregular planar shape, mainly sliding along two gullies. The rear edge of the landslide is below a steep slope formed by bedrock ridges, with an elevation of 665 m, while the front edge is at the foot of the slope with an elevation of 615 m, bounded on both sides by bedrock ridges. The landslide has a length of 250 m, an average width of about 500 m, an average thickness of about 4.0 m, covering an area of 125,000 square meters and a volume of 500,000 cubic meters, classified as a medium-sized traction-type soil landslide.



FIGURE 5
(A) Foundation settlement **(B)** Cracking damage of the houses.

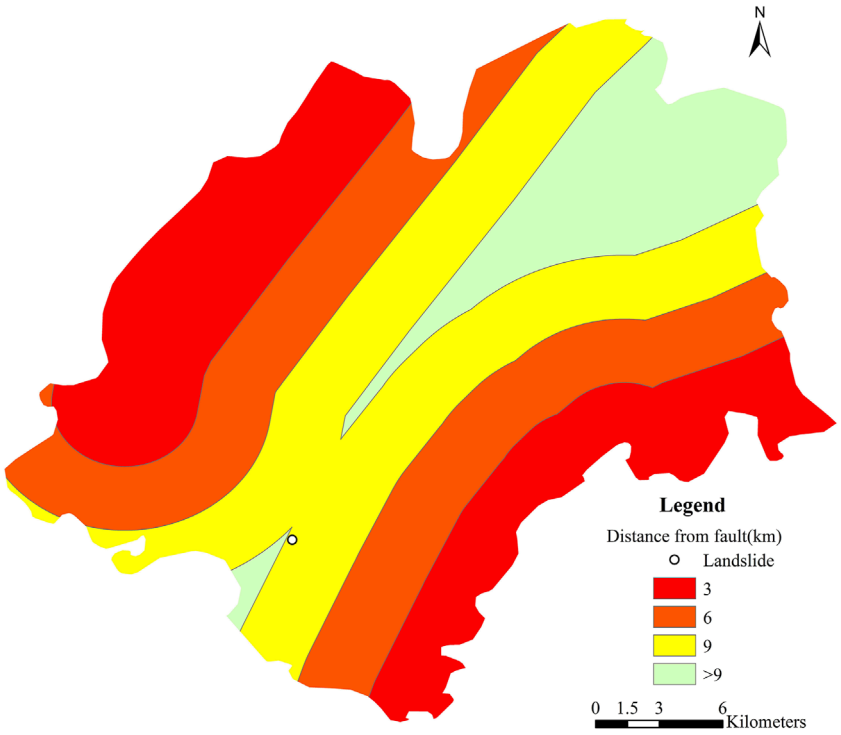

FIGURE 6
Influence range of faults in Mingshan District.

The landslide is located to the east of Group 2 of Huacheng Village in Yongxing Town. The rear edge of the slope is formed by a bedrock ridge, 3–30 m high with a slope of 30°–60°, forming the rear boundary of the landslide. The middle part of the slope forms a ridge, with gullies on both sides. The rear edge of the gully has a slope of about 15°–18° and a width of about 50–60 m. Near the middle ridge, the slope is gentler at 8°–12°. The middle part of the gully is relatively gentle, with a slope of about 12°–14° and a width of 50–60 m, with some areas flattened for housing construction. The middle front edge of the terrain is steeper, with a slope of about 14°–18° and a width of 30–50 m, with some parts forming steep steps of 3–5 m due to cutting. The front edge of the terrain is gentler, with a slope of about 11°–13° and a width of about 80 m. The landslide slope faces 257°, underlain by mudstone and siltstone of the Cretaceous Guankou Formation, with rock layer attitude 305°∠16°, forming a dip-slope (Figure 3).

The landslide mass consists of Quaternary residual slope deposit fine clay Q_4^{el+dl}, with a layer thickness of 3–6 m, and is plastic. The landslide sliding surface is above the interface formed by the mudstone and siltstone of the Cretaceous Guankou Formation (k_2g), with a slope of about 257°∠12°. Its typical structural cross-section is shown in Figure 4.

2.2 Deformation and damage characteristics

The landslide first occurred in 2001, with deformation mainly distributed in the gullies on both sides, causing effects such

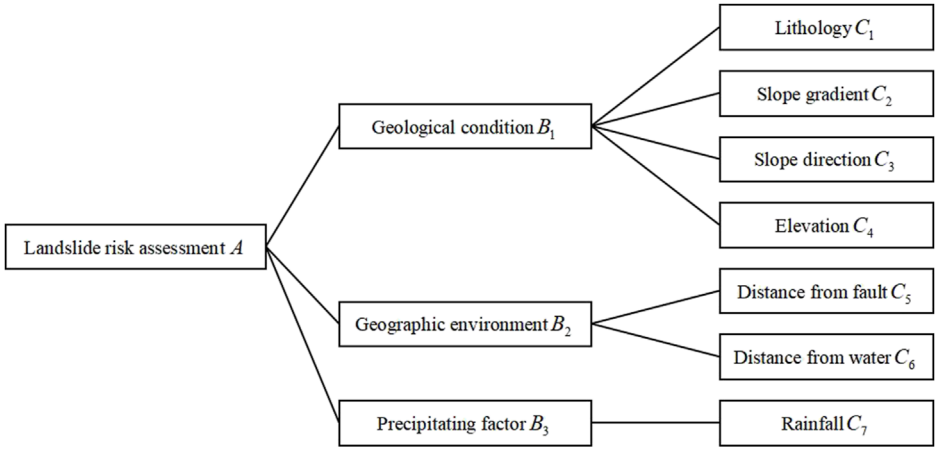

FIGURE 7
Hierarchical structure model.

TABLE 1 Description of judgment matrix.

Scale	Meaning
1	i and j are equally important
3	i is slightly more important than j
5	i is significantly more important than j
7	i is strongly more important than j
9	i is extremely more important than j
2, 4, 6, 8	Represents the median value of the above neighboring judgments
reciprocal	If the ratio of the importance of i to j is B_{ij}, then the ratio of the importance of j to i is B_{ij}

as cracking of residential walls and ground fissures, leading to the relocation of 12 households with 56 villagers. The landslide undergoes slow creep annually, particularly intensifying during heavy rain. Current landslide deformations include subsidence at the front edge, with farm roads and house foundations sinking 10–30 cm (Figure 5A), causing cracks in roads and houses; cracking of houses in the middle, with ground fissures opening 1–5 cm wide and extending 2–10 m; partial slumping at the steep step behind the houses in the middle-front, compressing the houses; and in the middle-rear part of the landslide, partial collapse of the slope, house cracking with openings of 0.5–3 cm (Figure 5B), extending 1–3 m, and ground bulging.

2.3 Impact of earthquakes on landslides

Newmark's method (Newmark, 1965) is commonly used to determine the stability of slopes under seismic activity. Its main principle is that under the coupled effect of seismic acceleration, the slope undergoes instantaneous displacement along the sliding surface, accumulating continuously. When the applied peak seismic acceleration exceeds the critical acceleration of the slope, a landslide is triggered. This is determined by performing a double integration of the difference between these two accelerations to obtain the cumulative displacement value (Jibson, 2007; Roy et al., 2016; Ma and Xu, 2019). If the cumulative displacement is small, the slope will recover after the seismic activity stops, without suffering damage. However, if the cumulative displacement exceeds the critical displacement, the slope is considered to have suffered permanent damage (Wang et al., 2010).

When using the Newmark method, it is necessary to obtain both the critical acceleration of the slope and the peak seismic acceleration. The critical acceleration of a slope is the minimum seismic acceleration needed to overcome shearing resistance of the soil and initiate sliding under seismic activity. It reflects the maximum acceleration the slope can withstand and is an inherent parameter of the slope (Li and Su, 2021). The critical acceleration of a slope is related to the material composition of the slope, its geometric shape, and factors such as the cohesion, friction angle, density and the slope angle (Wang and Lin, 2010) The more loose the slope material and the steeper the slope angle, the smaller the magnitude of critical acceleration required to generate large movements and the poorer the seismic resistance; conversely, for materials with good cohesion, the critical acceleration is larger, and the seismic resistance is better (Qiu et al., 2024). The critical acceleration of a slope needs to be determined for specific slopes through repeated experiments and is unknown for most cases (Maharjan et al., 2021). According to field survey results, the overall stability of the landslide in the study area is poor, and the slope is steep. Referring to the research results from Wang et al. (2010), a critical acceleration of 0.1 g (98 cm/s^2) can be assumed for the landslide in this study area. The peak seismic acceleration can be determined using empirical attenuation relationships of seismic acceleration (Yu and Wang, 2004). The attenuation relationship for the peak seismic acceleration along the major axis is given by Eq. 1, and along the minor axis by Eq. 2.

TABLE 2 Average random consistency index.

The order of the judgment matrix	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

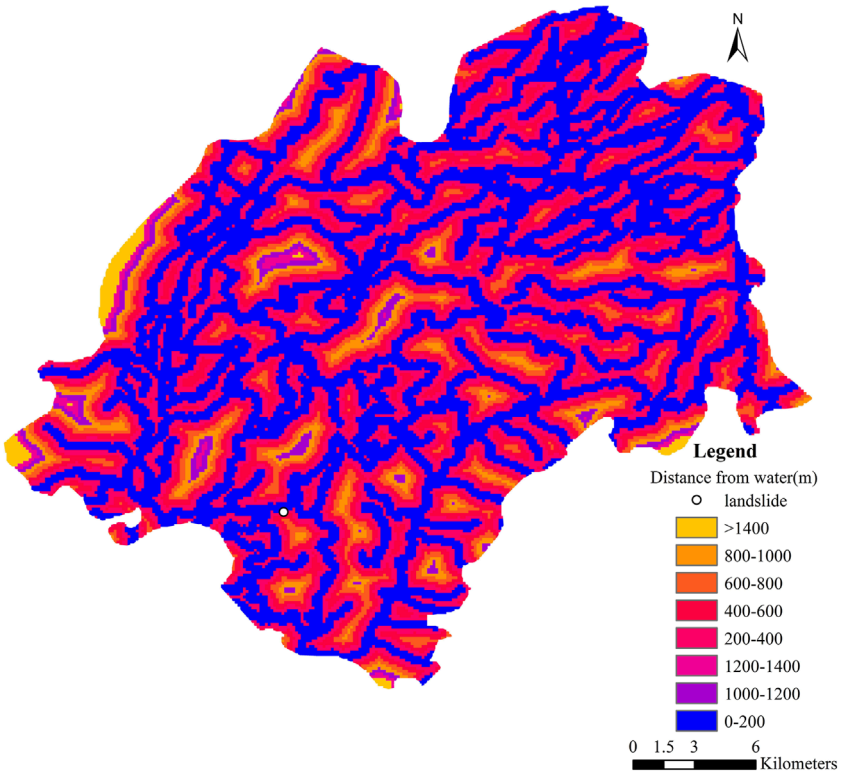

FIGURE 8
Influence range of water system in Mingshan District.

TABLE 3 Combination of evaluation factors.

Combination sequence number	List of evaluation factors
1	Lithology, slope gradient, elevation, distance from fault, distance from water system
2	Lithology, slope gradient, slope direction, elevation, distance from fault
3	Lithology, slope gradient, slope direction, elevation, distance from fault, distance from water system, rainfall

$$\lg^{al\,\max} = 0.617 + 1.163M - 0.046M^2 - 2.207\lg\left[D + 1.694e^{(0.446M)}\right] \quad (1)$$

$$\lg^{al\,\max} = -0.644 + 1.080M - 0.043M^2 - 1.626\lg\left[D + 0.255e^{(0.570M)}\right] \quad (2)$$

However, in earthquakes that occur in mainland China, there is some uncertainty in the direction of the earthquake fault and the orientation of the long and short axes of the isoseismal lines. To consider the relationship between the orientation of the long and short axes of the isoseismal lines and the azimuth of the seismic impact point, the peak accelerations along the long and short axes are calculated separately, and their geometric mean is used as the reference value for the peak acceleration at the seismic impact point (He et al., 2023). The calculation process is given by Eq. 3.

$$a_{\max} = \sqrt{al\,\max \times aw\,\max} \quad (3)$$

In Eqs 1–3: D is the horizontal distance from the study area's slope to the epicenter; M is the magnitude of the earthquake; al max is the peak seismic acceleration on the long axis; aw max is the peak seismic acceleration on the short axis; $a_{\max}$ is the peak seismic acceleration.

Based on the principles of the Newmark method, it is known that when the peak ground acceleration of an earthquake exceeds the critical acceleration of a slope, it will cause permanent

TABLE 4 Judgment matrix of combination 1 (AHP-IV).

Index	Lithology	Slope gradient	Elevation	Distance from fault	Distance from water system
Lithology	1	2	3	0.5	2
Slope gradient	0.5	1	3	1	2
Elevation	0.333	0.333	1	0.25	0.5
Distance from fault	2	1	4	1	2
Distance from water system	0.5	0.5	2	0.5	1

TABLE 5 Judgment matrix of combination 2 (AHP-CF).

Index	Lithology	Slope gradient	Slope direction	Elevation	Distance from fault
Lithology	1	2	3	3	0.5
Slope gradient	0.5	1	3	3	1
Slope direction	0.333	0.333	1	2	0.25
Elevation	0.333	0.333	0.5	1	0.25
Distance from fault	2	1	4	4	1

TABLE 6 Judgment matrix of combination 3 (AHP-FR).

Index	Lithology	Slope gradient	Slope direction	Elevation	Distance from fault	Distance from water system	Rainfall
Lithology	1	2	3	3	0.5	2	2
Slope gradient	0.5	1	3	3	1	2	1
Slope direction	0.333	0.333	1	2	0.25	0.5	0.333
Elevation	0.333	0.333	0.5	1	0.25	0.5	0.333
Distance from fault	2	1	4	4	1	2	1
Distance from water system	0.5	0.5	2	2	0.5	1	0.5
Rainfall	0.5	1	3	3	1	2	1

damage to the slope. Earthquake data were obtained from the National Earthquake Science Data Center. Calculations show that the peak ground acceleration caused by the severe "4.20" Lushan earthquake in 2013 in this study area was 183.11 cm/s^2, which is greater than the critical acceleration of the slopes in the study area (98 cm/s^2). Therefore, it would cause permanent damage at the study site. Additionally, there are faults near the study area (Figure 6), and the influence of earthquakes should be considered when assessing landslide risks in this area.

3 Research methods

Numerous scholars in China and abroad have conducted a series of studies on landslide risk assessment (Qiu et al., 2022).

TABLE 7 Analysis results of AHP hierarchy method (AHP-IV).

Evaluation factor	Weight value of each factor (%)	Value of CI
Lithology	25.917	0.039
Slope gradient	22.548	
Elevation	7.328	
Distance from fault	31.01	
Distance from water system	13.197	

TABLE 8 Analysis results of AHP hierarchy method (AHP-CF).

Evaluation factor	Weight value of each factor (%)	Value of CI
Lithology	26.538	0.049
Slope gradient	23.185	
Slope direction	9.511	
Elevation	7.103	
Distance from fault	33.663	

TABLE 9 Analysis results of AHP hierarchy method (AHP-FR).

Evaluation factor	Weight value of each factor (%)	Value of CI
Lithology	21.454	0.038
Slope gradient	17.026	
Slope direction	6.427	
Elevation	5.201	
Distance from fault	22.833	
Distance from water system	10.034	
rainfall	17.026	

Among them, empirical rule analysis based on expert experience and knowledge, and statistical regression analysis based on a large amount of data and statistical information, have been widely applied. Empirical rule analysis can select landslide disaster-causing factors and quantify their weights, offering intuitive and interpretable results. Statistical regression analysis reveals the relationships between variables, enabling prediction and inference. However, empirical rule analysis is highly subjective and statistical regression analysis struggles to precisely express the non-linear relationship between factors and landslide risks. This paper adopts a combination of both methods, using the Analytical Hierarchy Process (AHP) in empirical rule analysis combined with the Information Value Method, Certainty Factor Method, and Frequency Ratio Method from statistical regression analysis. Specifically, it employs AHP-IV, AHP-CF, and AHP-FR methods to assess landslide risk in Yongxing Town, Mingshan District, Ya'an City.

3.1 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP), developed in the 1970s by the American operations researcher Saaty (1977), has evolved over the years into a mature methodology. Its basic principle is to decompose the elements of the evaluation system's alternative solutions into levels such as objectives, criteria, and plans, and then conduct qualitative and quantitative decision-making analysis. This method is characterized by mathematizing the decision-making process of decision-makers using a limited amount of quantitative information, based on in-depth analysis of the influencing factors and internal relationships of complex decision making problems. This provides a convenient decision-making tool for complex problems having multiple objectives, multiple criteria, or unstructured characteristics (Vaidya and Kumar, 2006).

The application of AHP generally involves the following three steps:

(1) Establishing a hierarchical structure model. This includes the goal layer, criteria layer, and plan layer (Figure 7).
(2) Constructing a judgment matrix. Constructing the judgment matrix is a key step in AHP decision-making. Starting from the goal layer, each element within the same layer is compared pairwise to determine their relative importance (Table 1).
(3) Consistency test. To ensure the reliability of the matrix, the consistency of the judgment matrix is tested by calculating its consistency index:

$$CI = (\lambda_{max} - n)/(n-1) \tag{4}$$

where λ_{max} is the largest eigenvalue of the judgment matrix; n is the order of the judgment matrix; CI is the consistency index of the judgment matrix. When $CI = 0$, the judgment matrix has complete consistency; otherwise, the larger the CI is, the poorer the consistency of the judgment matrix. RI represents the average random consistency index of the judgment matrix (Table 2) (Kayastha et al., 2013).

3.2 Information Value method

The Information Value (IV) method, introduced in 1948 by the American mathematician and founder of information theory, Shannon, in his paper "A Mathematical Theory of Communication," employs probability theory and logical methods to derive the formula for calculating information value (Shannon, 1948). In the 1980s, Professor Yan Tongzhen first introduced information theory into landslide disaster prediction research (Yin, 1988), and later it was widely applied by experts and scholars in the field of disaster assessment. The concept of information prediction suggests that

TABLE 10 Analysis results of AHP-IV method.

Factor	Class	Information value				AHP weightage	The product of information value and AHP weightage
		Ni/km	Si/km	Ni/Si	Results		
Lithology	Cretaceous mudstone, sandstone	0.261	32.903	0.79	0.05112	0.26	0.01329
	Jurassic mudstone, sandstone	0.016	4.401	0.36	−0.73481		−0.19105
	Quaternary	0.000	0.504	0.00	0.00000		0
	Paleogene mudstone	0.040	4.423	0.90	0.18148		0.04718
Slope gradient/°	<10	0.061	16.172	0.38	−0.68075	0.23	−0.15657
	10~20	0.084	9.983	0.84	0.11248		0.02587
	20~30	0.097	11.409	0.85	0.12432		0.02859
	30~40	0.038	3.467	1.1	0.38215		0.08789
	40~50	0.023	0.878	2.62	1.25001		0.2875
	50~60	0.014	0.322	4.35	1.75701		0.40411
Elevation/m	500~1,000	0.101	25.784	0.39	−0.65470	0.07	−0.04583
	1,000~1,500	0.215	16.223	1.33	0.57202		0.04004
	1,500~2,000	0.001	0.224	0.45	−0.51167		−0.03582
Distance from fault/km	<3	0.001	0.347	0.29	−0.95104	0.31	−0.29482
	3~6	0.212	23.205	0.91	0.19253		0.05968
	6~9	0.104	18.679	0.56	−0.29298		−0.09082
Distance from water system/km	<0.2	0.119	26.271	0.45	−0.51167	0.13	−0.06652
	0.2~0.4	0.069	6.722	1.03	0.31640		0.04113
	0.4~0.6	0.071	4.077	1.74	0.84072		0.10929
	0.6~0.8	0.054	2.669	2.02	0.98994		0.12869
	0.8~1.0	0.001	1.546	0.06	−2.52657		−0.32845
	1.0~1.2	0.003	0.764	0.39	−0.65477		−0.08512
	1.2~1.4	0.000	0.182	0.00	0.00000		0

the occurrence of a landslide disaster is related to the quantity and quality of information obtained during the prediction process and is measured by the amount of information. The greater the information value, the more conducive it is to the occurrence of a disaster (Sharma et al., 2015). The calculation of information value can be expressed by the following formula:

$$I(Y,x_1,x_2,\cdots x_n) = \ln \frac{P(Y,x_1,x_2,\cdots x_n)}{P(Y)} \quad (5)$$

where $I(Y,x_1,x_2,\ldots x_n)$ represents the information value provided by the combination of factors $x_1,x_2,\ldots x_n$ for geological disasters such as landslides and collapses; $x_1,x_2,\ldots x_n$ is the probability of geological disasters occurring under the condition of the factor combination $x_1,x_2,\ldots x_n$; $P(Y)$ is the probability of geological disasters occurring in the entire study area. The total information value within a single evaluation factor can be simplified and represented by the following formula:

TABLE 11 Analysis results of AHP-CF method.

Factor	Class	Area of class/km^2	Number of landslide	Certainty factor	AHP weightage	The product of certainty factor and AHP weightage
Engineering geological group	Soft and hard intersand mudstone group	1012.50	137	0.2538	0.27	0.0685
	Hard basalt group	244.86	20	−0.2012		−0.0543
	Hard stratified limestone group rock, dolomitic limestone group	195.97	8	−0.5010		−0.1353
	Hard - semi-hard sandstone group	324.87	14	−0.6990		−0.1887
	Soft rock group	90.32	16	0.4316		0.1165
	Soft and hard tuff	38.21	0	−1.0000		−0.027
	Semi-cementation group	0.27	0	−1.0000		−0.027
Slope gradient/°	<10	190.90	17	−0.2316	0.23	−0.0533
	10~20	497.15	78	0.3222		0.0741
	20~30	620.30	77	0.2071		0.0476
	30~40	438.61	20	−0.4983		−0.1146
	40~50	138.49	3	−0.8235		−0.1894
	>50	21.54	0	−1.0000		−0.023
Slope direction	North	237.61	17	−0.5370	0.09	−0.0483
	North-East	229.75	17	−0.2019		−0.0182
	East	264.22	29	−0.0747		−0.0067
	South-East	223.00	23	0.0879		0.0079
	South	213.81	23	0.0795		0.0072
	South-West	228.02	22	0.1118		0.0101
	West	269.04	42	0.3331		0.0300
	North-West	241.54	22	−0.0384		0.0035
Elevation/m	<1,250	18.04	8	0.7892	0.07	0.0552
	1,250~1,500	73.97	60	0.8685		0.0608
	1,500~1,750	127.88	39	0.6513		0.0456
	1,750~2,000	181.76	38	0.5495		0.0385
	2,000~2,250	260.21	31	0.2116		0.0148
	2,250~2,500	277.74	10	−0.6479		−0.0454
	>2,500	967.41	9	−0.9368		−0.0656

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TABLE 11 (*Continued*) Analysis results of AHP-CF method.

Factor	Class	Area of class/km^2	Number of landslide	Certainty factor	AHP weightage	The product of certainty factor and AHP weightage
Distance from fault/km	<0.5	577.04	108	0.4381	0.34	0.149
	0.5~1	372.13	44	0.1047		0.0356
	1~1.5	272.36	20	−0.1921		−0.0653
	1.5~3	476.60	19	−0.5896		−0.2005
	>3	208.88	4	−0.7659		−0.2604

$$I_i = \sum_{i=1}^{n} \ln \frac{N_i/N}{S_i/S} \tag{6}$$

Where I_i is the total information value of a single evaluation factor; N_i is the area of the geological disaster body within the graded region; N is the area of the graded region; S_i is the total area of the geological disaster body in the study area; and S is the total area of the study area (Zhang et al., 2014).

3.3 Certainty Factor method

The Certainty Factor (CF) method is a common method for assessing landslide susceptibility, based on the probability function of landslide occurrence. It calculates the certainty factor of the evaluation factor using the following formula:

$$CF = \begin{cases} \dfrac{PP_a - PP_s}{PP_s(1 - PP_a)} (PP_a < PP_s) \\ \dfrac{PP_a - PP_s}{PP_a(1 - PP_s)} (PP_a \geq PP_s) \end{cases} \tag{7}$$

Where CF represents the certainty factor of landslide occurrence; PP_a is the ratio of the number of landslides to the area of a in factor grade category a, representing the conditional probability of landslides occurring in factor grade category a; PP_s is the ratio of the total number of landslides to the total area of the study region, representing the prior probability of landslides occurring in the entire study area.

The range of CF is $[-1, 1]$. A positive value indicates an increased certainty of landslide occurrence, with values closer to 1 indicating a higher likelihood of landslides. A negative value indicates decreased certainty, with values closer to −1 indicating a lower likelihood of landslides. A value of 0 indicates that the conditional probability and prior probability are the same, and it is uncertain whether a landslide will occur (Xiong et al., 2022).

3.4 Frequency Ratio method

The Frequency Ratio (FR) method calculates the probability of landslides occurring for each influencing factor within different grading intervals, analyzing the spatial relationship between the distribution of landslides and the gradation of each influencing factor. The frequency ratio is the ratio of the area where landslides occur in a particular grading interval of an influencing factor to the total landslide area of the study area, and the ratio of the area under that grade to the total area of the study area (Solaimani et al., 2013; Panchal and Shrivastava, 2021) The formula and calculation process of the frequency ratio are as follows:

$$FR = \frac{N_{ij}}{N_r} / \frac{A_{ij}}{A_r} \tag{8}$$

In the formula: FR is the frequency ratio value; N_{ij} is the area of landslides occurring in the j -th category of the i-th influencing factor; N_r is the total landslide area of the study area; A_{ij} represents the area of the j-th category of the i -th influencing factor; and A_r represents the total area of the study area.

Methods such as AHP, IV, CF, and FR are applicable for evaluating the impact of various factors on outcomes, each with its unique advantages and limitations. AHP is easy to understand and suitable for complex decisions, but it may be influenced by subjective biases; IV is simple to operate and effective for large data sets, but it relies on the quality of the data; CF is intuitive and effective for rapid analysis, but it can distort results when factor correlations are high; FR effectively analyzes the relationship between event frequency and factors, but it requires extensive historical data. The choice of method should consider the research needs and data conditions comprehensively to ensure the accuracy and practicality of the evaluation results.

4 Selection of evaluation factors

The selection of evaluation factors is fundamental to landslide risk assessment. Choosing and analyzing these factors is key to quantifying the occurrence and evolution of landslides. By considering different evaluation factors, one can gain deeper insights into the potential risks and evolutionary trends of landslides. This paper comprehensively evaluates landslide risks in the study area using seven evaluation factors: lithology, slope, aspect, elevation, distance from faults, distance from hydrological systems, and rainfall. The data on lithology, slope, aspect, and elevation are obtained from field survey results. The distance from faults is indicated in Figure 6, the distance from hydrological systems is shown in Figure 8, and rainfall data is available from the Mingshan District annals.

TABLE 12 Calculation results of AHP-FR method.

Factor	Class	Area of landslide/km^2	Percentage of landslide A/%	Area of class/km^2	Percentage of class B/%	Frequency ratio	AHP weightage	The product of frequency ratio and AHP weightage
Stratum	Middle Devonian Series	1.603	12.020	507.556	9.558	1.258	0.22	0.27676
	Upper Devonian Series	0.112	0.842	18.918	0.356	2.364		0.52008
	Lower Carboniferous Series	2.379	17.835	497.575	9.370	1.903		0.41866
	Middle Carboniferous Series	0.723	5.424	112.000	2.109	2.572		0.56584
	Upper Carboniferous Series	0.305	2.284	98.950	1.863	1.226		0.26972
	Lower Permian Series	2.243	16.820	996.733	18.770	0.896		0.19712
	Upper Permian Series	0.259	1.945	64.492	1.214	1.601		0.35222
	Lower Triassic Series	0.436	3.271	72.256	1.361	2.404		0.52888
	Middle Triassic Series	3.994	29.946	2085.908	39.280	0.762		0.16764
	Upper Triassic Series	1.262	9.464	821.252	15.465	0.612		0.13464
	Neogene Upper Series	0.020	0.149	13.699	0.258	0.577		0.12694
	Quaternary system	0.000	0.000	21.042	0.396	0.000		0
Slope gradient/°	0°~10°	0.170	1.273	152.948	2.880	0.442	0.17	0.07514
	10°~20°	0.781	5.856	584.679	11.010	0.532		0.09044
	20°~30°	2.201	16.499	1434.790	27.019	0.611		0.10387
	30°~40°	5.000	37.485	2022.487	38.086	0.984		0.16728
	40°~50°	3.472	26.030	891.345	16.785	1.551		0.26367
	50°~60°	1.304	9.779	184.702	3.478	2.812		0.47804
	60°~70°	0.353	2.648	35.506	0.669	3.960		0.6732
	>70°	0.058	0.431	3.923	0.074	5.836		0.99212

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TABLE 12 (*Continued*) Calculation results of AHP-FR method.

Factor	Class	Area of landslide/km^2	Percentage of landslide A/%	Area of class/km^2	Percentage of class B/%	Frequency ratio	AHP weightage	The product of frequency ratio and AHP weightage
Slope direction	Flat land	0.000	0.000	1.117	0.021	0.000	0.06	0
	North orientation	0.765	5.733	665.384	12.530	0.458		0.02748
	Northeast orientation	1.170	8.771	676.752	12.744	0.688		0.04128
	East orientation	2.008	15.058	677.632	12.761	1.180		0.0708
	Southeast orientation	2.909	21.808	675.454	12.720	1.715		0.1029
	South orientation	2.308	17.306	635.714	11.971	1.446		0.08676
	Southwest orientation	2.275	17.060	727.937	13.708	1.245		0.0747
	West orientation	1.337	10.024	655.879	12.351	0.812		0.04872
	Northwest orientation	0.566	4.241	594.510	11.195	0.379		0.02274
	<0	6.343	47.556	2229.319	41.980	1.133		0.06798
Elevation/m	0~500 m	0.356	2.669	81.305	1.531	1.743	0.05	0.08715
	500~1,000 m	1.584	11.877	320.780	6.041	1.966		0.0983
	1,000~1,500 m	1.566	11.743	753.194	14.183	0.828		0.0414
	1,500~2,000m	2.253	16.890	1213.738	22.856	0.739		0.03695
	2,000~2,500 m	4.775	35.799	1575.787	29.674	1.206		0.0603
	2,500~3,000 m	2.659	19.932	1183.677	22.290	0.894		0.0447
	3,000~3,712 m	0.145	1.091	181.898	3.425	0.318		0.0159

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TABLE 12 (*Continued*) Calculation results of AHP-FR method.

Factor	Class	Area of landslide/km^2	Percentage of landslide A/%	Area of class/km^2	Percentage of class B/%	Frequency ratio	AHP weightage	The product of frequency ratio and AHP weightage
Distance from fault/km	<1 km	3.767	28.243	1002.251	18.873	1.496	0.23	0.34408
	1~2 km	2.118	15.876	758.290	14.279	1.112		0.25576
	2~3 km	1.525	11.435	623.934	11.749	0.973		0.22379
	3~4 km	1.492	11.186	530.660	9.993	1.119		0.25737
	4~5 km	0.798	5.980	419.050	7.891	0.758		0.17434
	5~6 km	0.647	4.850	328.398	6.184	0.784		0.18032
	6~7 km	0.554	4.153	276.041	5.198	0.799		0.18377
	7~8 km	0.308	2.308	231.572	4.361	0.529		0.12167
	8~9 km	0.355	2.665	199.378	3.754	0.710		0.1633
	9~10 km	0.218	1.631	123.794	2.331	0.700		0.161
	>10 km	1.557	11.675	817.014	15.385	0.759		0.17457
Distance from water system/km	<0.2	0.716	5.365	245.590	4.625	1.160	0.10	0.116
	0.2~0.4	0.800	5.999	238.648	4.494	1.335		0.1335
	0.4~0.6	0.797	5.974	232.695	4.382	1.363		0.1363
	0.6~0.8	0.734	5.501	231.177	4.353	1.264		0.1264
	0.8~1.0	0.631	4.733	225.306	4.243	1.115		0.1115
	1.0~1.2	0.571	4.279	220.747	4.157	1.029		0.1029
	1.2~1.4	0.558	4.183	219.267	4.129	1.013		0.1013
	1.4~1.6	0.454	3.405	213.747	4.025	0.846		0.0846
	1.6~1.8	0.679	5.092	415.799	7.830	0.650		0.065
	1.8~2.0	0.708	5.308	396.861	7.473	0.710		0.071
	>2	6.690	50.160	2670.543	50.289	0.997		0.0997

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TABLE 12 (*Continued*) Calculation results of AHP-FR method.

Factor	Class	Area of landslide/km^2	Percentage of landslide A/%	Area of class/km^2	Percentage of class B/%	Frequency ratio	AHP weightage	The product of frequency ratio and AHP weightage
Rainfall/mm	<560	0.369	2.765	296.956	5.592	0.494	0.17	0.08398
	560~575	1.335	10.008	824.627	15.529	0.644		0.10948
	575~590	3.109	23.312	1251.821	23.573	0.989		0.16813
	590~605	5.627	42.188	1487.127	28.004	1.506		0.25602
	605~620	2.391	17.923	1161.925	21.88	0.819		0.13923
	620~635	0.440	3.302	194.999	3.672	0.899		0.15283
	635~650	0.023	0.169	80.298	1.512	0.112		0.01904
	>650	0.045	0.334	12.627	0.238	1.404		0.23868

TABLE 13 Calculation results and risk identification methods.

Methods	Results	Evaluation result
AHP-IV	−0.06965	No-danger zone, Low risk area, Medium danger zone and High risk area. The corresponding ranges are: 5.10552~−1.99811, −1.99811~−0.68084, −0.68084~−0.70398, −0.70398~3.54118 (Zhang D et al., 2014)
AHP-CF	0.0154	The range value of CF is [−1, 1], and a positive value indicates that the certainty of landslide occurrence increases, and the closer it is to 1, the easier prone to landslide. A negative value indicates that the certainty of landslide occurrence decreases, and the closer it is to −1, the less likely landslide is to occur. A value of 0 means that the conditional probability is the same as the prior probability, and it is uncertain whether a landslide will occur
AHP-FR	0.77294	The corresponding frequency ratios of very low risk area, light risk area, medium risk area, high risk area and very high risk area were 0.073, 0.235, 0.608, 1.404, and 5.363, respectively (Zhang et al., 2020a)

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The selection of evaluation factors is subjective, and the combination of single evaluation factors is limited. Based on the analysis of landslide formation mechanisms and previous research experience (Liu et al., 2024; Qiu et al., 2024; Ye et al., 2024), this paper selects three types of combinations of evaluation factors (Table 3). By using multiple combinations of different evaluation factors and comprehensively considering various factors, a more thorough understanding and assessment of landslide risks are achieved. Such an integrated evaluation approach helps to reduce the subjectivity and one-sidedness of single-factor evaluations, enhancing the reliability and accuracy of the assessment results. By comparing results from different combinations, the relative importance of each evaluation factor in different contexts can be explored, thus providing more targeted suggestions and decision-making support for landslide prevention and disaster management.

5 Landslide risk assessment

5.1 Determining the weight of evaluation factors using the Analytical Hierarchy Process (AHP)

(1) The results of pairwise comparisons of evaluation factors were obtained through expert argumentation, Constructing the judgment matrix (Tables 4–6):
(2) Result verification (refer to Eq. 4 for the calculation method): $CI(AHP-IV) = 0.039 < 1.12$, $CI(AHP-CF) = 0.049 < 1.12$, and $CI(AHP-FR) = 0.038 < 1.32$, indicating that the entire hierarchical model has good consistency, and the judgments are reasonable (results shown in Tables 7–9).

5.2 AHP-IV method

Some scholars have used the Information Value method for landslide risk assessment (Sarkar et al., 2013; Zhang et al., 2014; Du et al., 2019; Wang et al., 2019). This paper combines the information values from the article by Zhang et al. (2014) with the weights of the AHP method, by selecting relevant factors (see Table 3) and conducting overlay analysis, the information value of each factor category is calculated. Then, these information values are multiplied by the weights from the Analytic Hierarchy Process (AHP) and aggregated to assess the landslide susceptibility of specific locations, with the detailed calculation process shown in Table 10, refer to Eqs 5, 6 for the calculation method.

5.3 AHP-CF method

Some scholars have used the Certainty Factor method for landslide risk assessment (Chen et al., 2016b; Wang et al., 2019; Xiong et al., 2022) This paper combines the certainty factor values from the article by Xiong et al. (2022) with the weights of the AHP method, by analyzing the spatial distribution of factors related to landslides (see Table 3), the certainty coefficients of these factors are calculated. Then, these certainty coefficient values are multiplied by the weights from the Analytic Hierarchy Process (AHP) and aggregated to assess the landslide susceptibility of specific locations, with the detailed calculation process shown in Table 11, refer to Eq. 7 for the calculation method.

5.4 AHP-FR method

Some scholars have used the Frequency Ratio method for landslide risk assessment (Lee and Pradhan, 2007; Chen et al., 2016a; Nicu, 2018; Zhang et al., 2020; Zhang et al., 2020; Abdo, 2022). This paper combines the frequency ratio values from the article by Zhang Qiukai (Zhang et al., 2020) with the weights of the AHP method, by analyzing the classification of factors related to landslides (see Table 3), the frequency ratio for each factor category is calculated. Then, these frequency ratios are multiplied by the weights from the Analytic Hierarchy Process (AHP) and aggregated to assess the landslide susceptibility of specific locations, with the detailed calculation process shown in Table 12, refer to Eq. 8 for the calculation method.

5.5 Evaluation results

The calculation results and risk identification methods of the three approaches are shown in Table 13.

6 Results and discussion

6.1 Results analysis

The AHP-IV and AHP-FR methods classify the area as a moderate-risk zone, while the AHP-CF method assesses it as a low-risk zone.

The landslide in question first occurred in 2001, causing damage to 12 residential houses. It has been sliding annually in recent years, particularly during the “4.20” Lushan earthquake in 2013, where the peak ground acceleration caused by the earthquake was greater than the critical acceleration of the landslide, resulting in permanent damage. Field investigations reveal that the stability of landslide is currently poor. Under the action of rainfall, it is highly susceptible to overall sliding. The assessments of the AHP-IV and AHP-FR methods, categorizing the area as a moderate-risk zone, align more closely with the actual situation. The AHP-CF method, assessing it as a low-risk zone, shows some variance from the other two methods’ results. This discrepancy mainly arises from two aspects: Firstly, the AHP-CF method did not consider rainfall and proximity to the water source as evaluation factors for this landslide, even though both are significant influence factors. Rainfall increases pore water pressures in the soil, leading to a reduction in effective stress and reduced shear strength, thus triggering landslides. Areas close to water systems often have higher groundwater levels and hence lower effective stresses, thus increasing the probability of landslides. The exclusion of these factors in the AHP-CF method leads to an “apparently” safer assessment of the study area. Secondly, the judgment method of the AHP-CF method

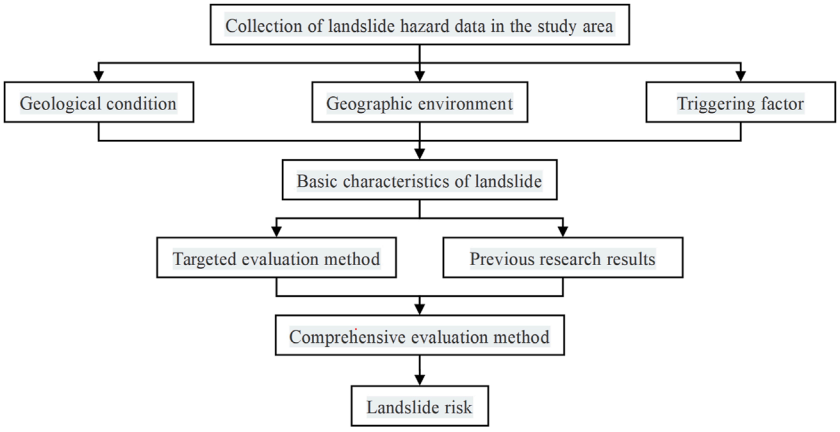

FIGURE 9
Flow chart of rapid landslide risk assessment method.

is derived from the inherent nature of the CF method itself. Applying the results of this study directly into it may introduce certain errors.

To improve the accuracy of the AHP-CF method for landslide risk assessment, the following improvements can be made: Firstly, more comprehensive evaluation factors should be selected, considering hydrological factors like rainfall and proximity to the water system. Secondly, the judgment method of the AHP-CF method should be adjusted according to the actual situation, to be better align with the reality of the study area, thereby enhancing the accuracy of the assessment. Finally, integrating other assessment methods, such as AHP-IV and AHP-FR, and considering various factors, the AHP-CF method can be continuously optimized.

6.2 Discussion

The geographical and geological conditions of different study areas may significantly vary. Directly applying the results of one study to another area may not yield safe evaluations. This paper, while using previous research results, uses the AHP method to better adapt these results to the current study area. However, the judgment of the AHP-IV approach is derived from the Information Value (IV) values cited in the original article, which did not use the AHP. Therefore, directly applying the AHP-IV method's evaluation results to the cited article's IV evaluation method can lead to a certain errors. The same applies to the judgment results of the AHP-FR method. The judgment of the AHP-CF method, derived from the inherent nature of the CF method, allows for only a general judgment, and its accuracy remains to be verified. Nevertheless, the evaluation results of all three methods show high consistency and align with the actual conditions of the landslide in the study area. Therefore, despite some errors, the evaluation results are still considered reasonable.

Landslide risk assessment has always been a hot topic in the field of geological disaster research. To improve evaluation efficiency and accuracy, this paper proposes a rapid method for landslide risk assessment. This method comprehensively considers various factors such as geological conditions, geographical environment, and triggering factors. It utilizes existing research conclusions and study methods specific to the study area for quick calculation and evaluation. The method involves the following steps (Figure 9):

(1) Collect data on geological disasters in the study area, including geological conditions, geographical environment, and triggering factors.
(2) Summarize the basic characteristics of the landslide.
(3) Choose targeted methods for analysis based on the basic characteristics of the landslide.
(4) Use suitable research results from similar areas.
(5) Establish a comprehensive evaluation method based on targeted evaluation methods and previous research findings.
(6) Apply the comprehensive evaluation method, combined with the basic characteristics of the landslide, to assess its risk.

Currently, for regional landslide risk assessment, many researchers have applied statistical regression analysis to obtain evaluation results. If appropriate previous research results are applied to individual landslide studies, it can overcome the shortcomings of statistical regression analysis in terms of data requirements and greatly improve the efficiency of landslide risk assessment. For example, in this study, after seven data including lithology, slope, aspect, elevation, distance from faults, distance from hydrological systems, and rainfall were easy to obtain, we can make a rapid assessment of landslide risk.

It is important to note that when applying previous research results to different study areas, the accuracy of landslide risk assessment needs to be verified. To enhance accuracy, this paper selected research results from three similar areas and combined them with the AHP method. Ultimately, the three evaluation results showed high consistency, thus considered reasonable. However, due to the lack of an appropriate judgment method, the research results of this method may still contain some errors.

7 Conclusion

Through the landslide risk evaluation, the risks associated with the landslides in the study area were assessed, leading to the following conclusions.

(1) The study employed three landslide risk assessment methods: AHP-IV, AHP-CF, and AHP-FR. Both AHP-IV and AHP-FR methods assessed the study area as a moderate-risk zone, while the AHP-CF method rated it as a low-risk area.

(2) Field investigation results classified the landslide risk in the study area as moderate. When these findings were combined with the cumulative displacement caused by earthquakes in the surrounding areas, the assessments of the AHP-IV and AHP-FR methods, categorizing the area as a moderate-risk zone, were found to be more consistent with the actual situation. The AHP-CF method, which assessed the area as low-risk, was analyzed for its error sources, and suggestions for improvement were proposed.

(3) The study proposed a rapid method for landslide risk assessment. This method takes into account various factors including geological conditions, geographical environment, and triggering factors. It utilizes existing research findings and methods tailored to the study area to quickly evaluate landslide risk.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

NH: Investigation, Writing–review and editing. XG: Formal Analysis, Methodology, Writing–original draft. WZ: Conceptualization, Writing–review and editing. LX: Conceptualization, Writing–original draft. FG: Supervision, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Investigation of the rock mass state in the near-wall part of the quarry and its stability management

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Introduction: The research is aimed to identify the vulnerable areas of quarry slopes through the creation of a stress-strain state model for the rock mass at the Vostochny quarry, East Saryoba field of the Zhi-landy Group of cupriferous sandstones, as well as their subsequent strengthening.

Methods: The research is based on the development of a database containing information on mining-geological, geophysical, geodetic and aerospace surveys. The authors of the research use modern geodetic, aerospace and geophysical technologies for scientifically based predicting of technogenic disasters and the rock mass stress-strain state modeling to ensure safe and optimal mining of fields in difficult mining-geological conditions.

Results: The results obtained show that the strengthening of weakened quarry slopes based on the rock mass stress-strain state modeling contributes to the scientific-practical profitability of field mining and provides safe mining in difficult mining-geological conditions.

Discussion: Novelty is in the scientific substantiation of the method for strengthening quarry slopes, which is based on the rock mass stress-strain state modeling. The research is of great practical importance, as the rock mass stress-strain state modeling increases the reliability of predicting the rock mass state during its mining. Strengthening of quarry slopes using the proposed method reduces risks and increases safety and economic efficiency of mining the solid mineral deposits in difficult mining-geological conditions.

KEYWORDS

slope, modeling, stress-strain state, rock mass, quarry, geomechanics, laser scanning

1 Introduction

A characteristic peculiarity of open-pit mining of mineral deposits is that as the depth of quarries increases, so does the service life of quarry slopes placed in a limiting position. In addition, mining operations are intensified and concentrated, and mining occurs in difficult mining, geological and hydrogeological conditions (Tyo and Zeitinova, 2023;

Wang et al., 2023; Zhe et al., 2023). In Kazakhstan, more than 70% of quarries reach a depth of 200 m or more, sometimes up to 700 m (Kassymkanova et al., 2020; Tolovkhan et al., 2023). Therefore, in order to ensure safe and complete mining of deposits, increasing technical-economic performance of the mining enterprise in the conditions of open-pit mining, it is of course necessary to ensure the stability of quarry slopes (Pysmennyi et al., 2020; Taiwo et al., 2023). When planning, it is necessary to reliably determine the optimum parameters of quarry slopes to ensure their long-term stability while minimizing the volume of stripping operations (Rysbekov et al., 2020).

Numerous studies performed to ensure the quarry slope stability require improvement in the present realities due to the rapid development of equipment and technologies (Moldabayev et al., 2021; Bazaluk et al., 2023; Fandy et al., 2024). In Kazakhstan, geomechanical and geodynamic research using modern technologies and methods is conducted at mining enterprises, but technogenic disasters cannot be prevented (Nurpeisova et al., 2021; Tolovkhan et al., 2022; Issatayeva et al., 2023). Modern mining facilities are a kind of laboratories where geomechanical and geodynamic processes are studied using space, geodetic, geological, etc., Methods.

When mining mineral deposits, the rock mass is out of its natural position and to understand the geomechanical processes occurring in it, it is important to conduct studies of fracturing in the rock mass before and during its mining, since with increasing depth of mining operations, the mining-geological conditions become more difficult (Pivnyak et al., 2012; Kalybekov et al., 2020; Malanchuk et al., 2022; Petlovanyi et al., 2023). During large-scale mining operations at Zhezkazgan, Akbakai, Maikain, Maleevsk and other fields, there is a change in the geodynamic regime of the rock mass geological environment, as evidenced by scientific research conducted by a group of scientists of Satbayev University (Aidarbekov et al., 2021; Nurpeissova et al., 2021; Aidarbekov and Istekova, 2022; Sedina et al., 2022).

When ensuring industrial safety of subsoil mining, reliable information on the rock mass state in the subsoil is an urgent task (Bazaluk et al., 2022a; Baltiyeva et al., 2023). In this case, it is necessary to distinguish those factors that have a great influence on the geomechanical processes occurring in the rock mass, in specific mining-geological conditions (Kalybekov et al., 2015; Bazaluk et al., 2022b). Since the stability loss of quarry slopes in their limiting position leads to various kinds of deformations that destroy transport routes in the quarry, disable mining equipment and often lead to human casualties (Sdvyzhkova et al., 2022; Saik et al., 2023). Pipatpongsa et al., (Pipatpongsa et al., 2024), investigates the critical conditions leading to reverse toe sliding in laterally confined low wall slopes subjected to counterweight fill, providing novel insights into enhancing slope stability in mining operations. Modelling stands as a pivotal tool in comprehending and mitigating landslide hazards, offering a nuanced perspective on the intricate dynamics of landslide processes under various triggering factors (Fang et al., 2023).

The rock mass stress-strain state (SSS) changes under the influence of technogenic factors, as well as under the influence of natural factors–current geodynamic movements along tectonic disturbances (Pysmennyi et al., 2022). Thus, the stability of quarry slopes depends on the rock mass SSS. Therefore, control over the rock mass state can be positively solved through innovative monitoring methods, as well as by creating a database of geological, geophysical and geodetic information to model the rock mass SSS during its mining for making managerial decisions on strengthening weakened rock mass areas (Nurpeissova et al., 2020; Kassymkanova et al., 2023a; Kassymkanova et al., 2023b).

To perform the SSS modeling of quarry slopes, it is necessary to have a 3D model of the quarry with a structural characteristic of quarry slopes by the degree of their disturbance (Sdvyzhkova et al., 2020; Zerradi et al., 2023). This model can be derived from performing laser scanning of the quarry (Aukazhieva and Darkenbayeva, 2021; Pasierb et al., 2024). Unmanned aerial survey is used in the analysis of hazardous areas in open-pit mining (Cao et al., 2023; Liu et al., 2024). Laser scanning is a modern survey method that provides high accuracy and density of 3D data points containing information on the spatial structure of quarry slopes. This method is widely used in the mining industry (Li et al., 2023; Zhang et al., 2023).

Earlier terrestrial scanning systems included only laser scanners, but later GPS receivers were added to many models, allowing data to be obtained in an external coordinate system in real time and after processing (Apollo et al., 2023). In contrast, airborne and mobile laser scanning systems are more complex and require additional data preprocessing, but their accuracy is lower compared to terrestrial scanning systems (Medic et al., 2023). Typically, airborne laser scanning systems include the laser scanner itself, GPS-system and Inertial Navigation System (INS), a digital camera and a control unit (Coccia et al., 2022).

The choice of laser scanning method depends on the tasks set and desired data accuracy. Terrestrial laser scanning provides the highest accuracy within 2–5 mm over spatial distances of up to 1 km. Mobile laser scanning has an accuracy of 5 cm, while airborne laser scanning has an accuracy of 15–20 cm. Terrestrial laser scanning is ideal for creating millimeter-accurate 3D models of various objects, such as assessing the quarry slope deformations. In addition, point coordinates derived from traditional geodetic methods can serve as reference points to assess the scan data accuracy, and not only for their correction (Adebiyet et al., 2022; Castillón et al., 2022).

The Zhilandy Group of cupriferous sandstone deposits covers an extensive area and includes the Itauz, West Saryoba, East Saryoba, Kipshakpai, Karashoshak fields and the Kokdombak, Donyzauz, Kulzhan, Airanbay, Taldybulak and Konkuduk ore occurrences, confined to the wings of the northern part of the Zhezkazgan syncline (Skrinnik et al., 2020; Zeylik et al. 2021; Akpanbayeva and Issabek, 2023). About 30 points of the State Geodetic Network (SGN) are located in this area, as well as the developed surveying reference network, which includes several dozens of points. In the area of the East Saryoba field of the Zhilandy Group of cupriferous sandstone deposits, geodetic measurements are conducted at the SGN points located within and outside the East Saryoba field at a distance of about 20 km (Kuttykadamov et al., 2016). Using the satellite positioning method, measurements are performed at 5 SGN points. All coordinates and heights of ground reference marks are determined using the Global Navigation Satellite System (GNSS) by measurements from starting points at a distance of no more than 5 km. Measurements are performed in Static mode, using the network positioning method. The following necessary observation conditions are fulfilled during the work: maximum distance between receivers is 5.0 km; minimum number of observed

satellites for processing–8; recording interval–5 s; elevation angle mask is 10°; accuracy of obtaining horizontal coordinates is 0.002 m; in height–0.002 m; GDOP (satellite geometry) is less than 5; duration of observations at the point is 70 min.

The GNSS measurements confirm high efficiency in solving geomechanics problems at mining enterprises in Kazakhstan. They can be used not only for discrete measurements, but also for continuous monitoring of deformations and stresses occurring both in the earth's crust and in the near-wall rock masses during open-pit mining of mineral deposits.

This manuscript aims to present a novel and systematic approach to managing the quarry slope stability in challenging mining-geological conditions. By integrating advanced geodetic, geological, and geophysical technologies, we aim to develop a comprehensive stress-strain state model of the rock mass at the Vostochny quarry, East Saryoba field. Our methodology emphasizes the practical application of predictive modeling to identify vulnerable areas within quarry slopes and inform strategic decision-making for slope strengthening measures. By integrating multiple data sources and applying cutting-edge techniques, this research contributes to the advancement of sustainable mining practices and enhances the safety and economic viability of mineral mining.

2 Materials and methods

2.1 Research stages

The authors of this paper propose a five-stage modeling method for the rock mass SSS during open-pit mining of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones for making managerial decisions on strengthening weakened quarry slope areas placed in a limiting position.

At the first stage, the geological and structural characteristics of Zhilandy Group deposits of cupriferous sandstones are studied according to the Republican Geological Fund reports to create a geophysical-geological information database of the studied object to identify the internal structure and geometrization of the spatial position of tectonic disturbance planes, geological dislocations, zones of heterogeneity and structural rock mass disturbance. Based on the performed analysis of mining-technical and geomechanical documentation of previously conducted research, potential rock mass zones prone to failure are identified due to the redistribution of stresses in the near-wall rock masses during mining of mineral deposits. In addition, the physical-mechanical rock mass properties of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones are studied.

At the second stage, laser scanning and UAV (Unmanned Aerial Vehicle) surveying is conducted to perform spatial coordinate referencing to the surveying reference network points of the Vostochny quarry. The study is performed according to the saved SGN coordinates during the intensive mining of the Vostochny quarry using the satellite positioning method. The measurements use GNSS geodetic class satellite navigation equipment: Leica GPS GX-1230 and Leica TS06 plus 5. Measurements are performed statically with a 2-s data recording interval, with receivers located at each of the points delimiting each side of the geodetic network. Based on the obtained coordinate differences in space, changes in line lengths and heights between geodetic network points are calculated. Full vectors of point displacements are then plotted, reflecting the trend movements that occur over this time and the deformations they cause.



FIGURE 1
Location of the study area: Yellow markers–surveyor reference points; pink markers–state geodetic points.

Two methods are used to align geodetic measurements. The first method involves centering and orienting the network relative to a "conditionally fixed" point. The second method consists of free network alignment followed by centering and orienting using the least squares method, taking into account minimizing the sum of squares of the displacement vector values.

In the third stage, a 3D quarry with structural characteristic of the quarry slopes by the degree of their disturbance can be obtained by conducting laser scanning of the surface of the quarry slopes placed in a limiting position.

At the fourth stage, a database of actual material on laser scanning and geological-geophysical information of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones is created in order to model the natural-technogenic rock mass state to identify the pattern of formation of the near-wall mass destruction zones, taking into account the rock mass SSS and time factor.

At the fifth stage, the rock mass SSS of the Vostochny quarry is modeled.

The sixth stage involves development and patenting a method for strengthening stationary quarry slopes.

2.2 Study area

The research object is the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones, which is located in the northern area of the Zhezkazgan ore district (Figure 1).

The geological structure of the area involves Precambrian, Poleozoic, Mesozoic and Cenozoic formations. All the Zhilandy Group fields are spatially confined to grey sandstones of the Taskuduk horizon of the Taskuduk Formation and underlying sediments represented by interlayered greenish-grey and grey sandstones, intraformational conglomerates and dark grey or black siltstones and argillites with interlayers of limestone with fauna.

TABLE 1 This is a table. Tables should be placed in the main text near to the first time they are cited.

Point name	Ellipsoid WGS - 84		Ellipsoid mark WGS - 84
	Latitude	Longitude	H, m
Bezyimyannaya	47°59′50.88126″ N	67°30′46.96248″E	367,6874
Burovaya	48°08′12.72727″ N	67°27′41.60400″E	420,506
Dangauz	48°13′31.26746″ N	67°22′48.58769″E	445,4592
Itauzbulak	48°07′06.78362″ N	67°20′27.10405″E	517,2728
Musulmanskoe	48°12′37.19979″ N	67°28′18.06175″E	410,9155

TABLE 2 Point data after balancing and determination of conversion parameters.

No	Point name	Class	Geographic coordinates on an ellipsoid WGS-84		Ellipsoid mark WGS-84
			Latitude	Longitude	H, m
1	Poselkovyiy	4	48°08′47.43544″N	67°29′36.25553″E	402,7452
2	Aslanbek	4	48°11′24.85021″N	67°35′48.34038″E	427,2772
3	4,735	4	48°09′17.91359″N	67°28′38.42796″E	402,7452
4	5,784	4	48°09′48.06852″N	67°27′00.26502″E	434,6978
5	Burovaya	4	48°08′12.72727″N	67°27′41.60400″E	420,4767

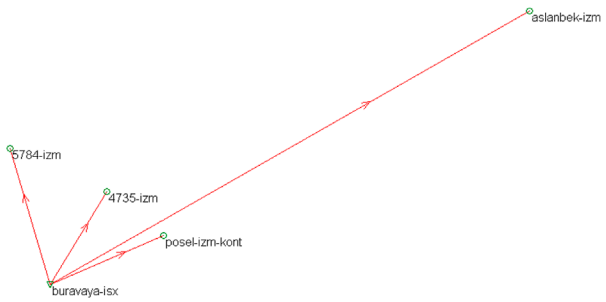

FIGURE 2
Scheme for conducting observations.

The East Saryoba field, like the rest of the Zhilandy Group fields, is confined to the Zhezkazgan syncline wings. The manifestation of Hercynian tectogenesis has led to the formation of structures here, complicated by longitudinal flexural shear zones and disjunctive faults. The field area is a zone of the highest stresses, which have led to the formation of both folding and discontinuity faults.

The mining-technical conditions of the East Saryoba and West Saryoba fields are characterized by the following indicators.

- ore bodies have a sheet-like shape;
- ores and host rocks are stable and strong;
- by thickness, the ore deposits are low thickness (m<3 m), medium thickness (m = 3–8 m), thick (m = 8–18 m and m>18 m);
- by incidence angle, the deposits are flat-bedding (α<15°), low-inclined (α=15°–20°), inclined (α = 20°–35°) and in flexures represented by steeply inclined occurrence;
- ore is of medium value in terms of content of useful components.

Ore deposits are a sheet-like form of flat-bedding and inclined bedding (90%), as well as steeply inclined bedding and in flexural areas (10%). The thickness of ore bodies varies from 0.6 m to 18.44 m.

Currently, the East Saryoba field is engaged in tunneling and mining operations using both open-pit and underground mining methods.

The ore field of the East Saryoba contains 11 ore deposits with 109 ore bodies explored. The largest deposits are confined to the Taskuduk horizon. They have a north-eastern strike, up to 3,200 m long, 0.5–17 m thick, up to 1,400 m of dip size.

The geological structure is complicated by a series of tectonic faults. The largest of them is the Central Saryoba transpressional fault, which is located between the West and East Saryoba fields. In addition to it, small discontinuities are mapped in the fields.

In this regard, for safe mining of the field, it is necessary to conduct geomechanical research on a permanent basis using various methods, including surveying and geodetic studies. Based

Onestep - Transformation Report

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Project Information

	System A	System B
Project name:	Jylandy_izm_GGS_izm_trans	Jylandy_msk_GGS_katalog

Coordinate System Information System B

Coordinate system name:	Ничего
Created:	-
Transformation name:	-
Transformation type:	-
Height mode:	-
Residuals:	-
Local Ellipsoid:	-
Projection:	-
Geoid model:	-
CSCS model:	-

Transformation details

Height mode: Orthometric

2D-Helmert transformation

Number of common points:	5		
Sigma a priori:	1.0000		
Sigma a posteriori:	0.0413		
Rotation origin:	X0:	1.3384 m	
	Y0:	-1.1039 m	

No.	Parameter	Value	rms
1	dE	113096.9309 m	0.0185 m
2	dN	58758.8791 m	0.0185 m
3	Rotation	0° 00' 11.27461"	0° 00' 00.86583"
4	Scale	10.4439 ppm	4.1976 ppm

Height transformation

Number of common points:	5		
Mean transformation accuracy:	0.0516 m		
Parameters:	-0.00007098	0.00001378	29.3885 m
Inclination of height in X:	-0° 00' 14.64068"		
Inclination of height in Y:	0° 00' 02.84233"		

Residuals

Grid:

System A	System B	Point type	dE [m]	dN [m]	dHgt [m]
4735-izm	4735	Position + height	-0.0247 m	-0.0330 m	-0.0550 m
5784-izm	5784	Position + height	0.0156 m	0.0421 m	0.0195 m

FIGURE 3
Parameters for conversion from WGS-84 to the local coordinate and height system.

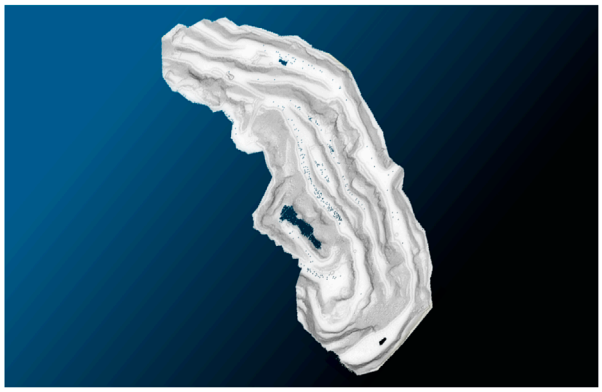

FIGURE 4
3D model of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones.

on geospatial data obtained from surveying and geodetic studies, geological models of fields can be developed to determine the direction of structures and characteristics of deposits.

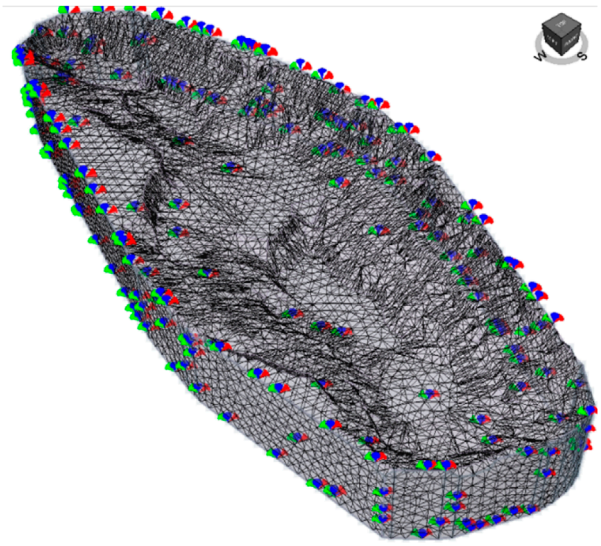

FIGURE 5
Finite element analysis calculation scheme.



FIGURE 6
Weakened area of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones.

2.3 Surveying and geodetic studies

To obtain a three-dimensional model of the quarry walls to identify deformed areas, terrestrial laser scanning is applied at the Vostochny quarry. In order to obtain a three-dimensional model of the Vostochny quarry with millimeter accuracy, surveying and geodesic studies are conducted in the area of determining the coordinates and heights of the surveying reference network points at the quarry using Global Navigation Satellite System (GNSS) technologies. Subsequently, the digitized contours of the Vostochny quarry are used to develop a geomechanical model. Satellite measurements are performed in Static mode, and the work in this mode implies conditional subdivision into two stages: field work and office studies.

The following necessary observation conditions are fulfilled during the work: maximum distance between receivers is 5.0 km; minimum number of observed satellites for processing–8; recording interval–5 s; elevation angle mask is 10°; accuracy of obtaining

TABLE 3 Physical-mechanical properties of rock mass composing the quarry slope.

No	Rock type	Cohesion coefficient, KPa	Internal friction angle, deg
1	Limestone	250	30
2	Limestone mass	350	29
3	Sandstone	388	31
4	Red limestone	488	32
1	Limestone	250	30

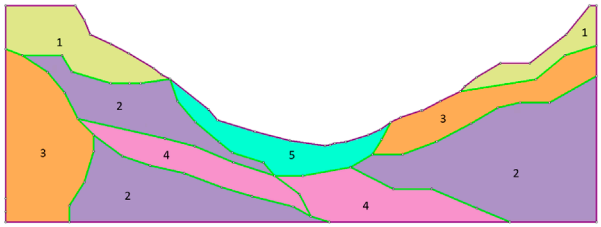

FIGURE 7
2D model geometry with indication of rock types: 1–limestone; 2–limestone mass; 3–sandstone; 4–red limestone; five–ore.

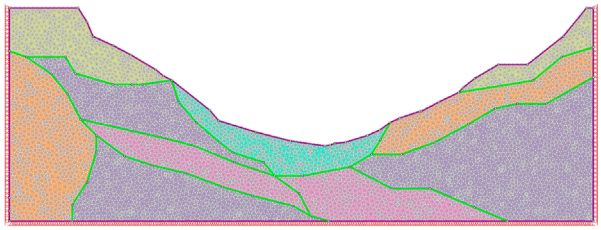

FIGURE 8
2D model calculation scheme.

horizontal coordinates is 0.002 m; in height–0.002 m; GDOP (satellite geometry) is less than 5; duration of observations at the point is 80 min.

Triangulation points of the State Geodetic Network provided by the branch of the National Centre of Geodesy and Spatial Information are used as starting points. The Burovaya State Geodetic Network point is used as a base point and for conversion to WGS 84. Initial data are given in Table 1.

Point data after balancing and determination of conversion parameters are given in Table 2.

The Burovaya State Geodetic Network point is chosen as the starting point for installing the base reference station. All static measurements are made using the baseline to a given point. The scheme for conducting observations is shown in Figure 2.

Field data from points of International Ground Station (IGS) world network are included in post-processing to obtain precise coordinates and altitudes (Orynbassarova et al., 2022). Processing and equalization of this network is performed at the points on this network on a permanent basis. Referencing of points to the above-mentioned network provides high accuracy and consistency of the obtained coordinates in the WGS84 system. Also, to improve the accuracy of the final results before processing, the project includes such data as accurate satellite ephemerides, ionospheric maps, tropospheric state maps and updated satellite clocks for the period of field work. Parameters for conversion from WGS-84 to the local coordinate and height system are given in Figure 3.

Reference bases are established at the Poselkovyiy and Burovaya State Geodetic Network points. The balanced coordinates of points are taken as the initial data, according to certain parameters for conversion from WGS-84 to the local system of coordinates and heights, which are the geodetic basis for performing terrestrial laser scanning, the results of which form the basis for SSS modeling of the Vostochny quarry slopes, East Saryoba field of the Zhilandy Group of cupriferous sandstones.

Scanning is conducted in safe areas of shedding walls, as well as in areas that the STONEX300 terrestrial scanner is capable of capturing. The quarry is also surveyed using a UAV. In this case, the MATRICE 300 RTK, designed on the basis of an updated hardware and software platform and equipped with a wide range of functions based on artificial intelligence, is used. The drone is equipped with a built-in RTK module that provides the most accurate course data for positioning. In addition, more accurate positioning data is also provided by using the high-precision mobile DJI D-RTK two satellite positioning systems in conjunction with UAV.

The UAV imagery is processed in Agisoft Metashape. The scanner imagery is processed in Reconstructor. Both images are merged into one by the Cloud Compare software. The point cloud and 3D model are created based on two measuring tools (scanner + UAV) and are presented in Figure 4.

A 3D model of the Vostochny quarry has been obtained based on the instrumental survey of the quarry using a Stonex 300 laser scanner and MATRICE 300 RTK industrial flight platform.

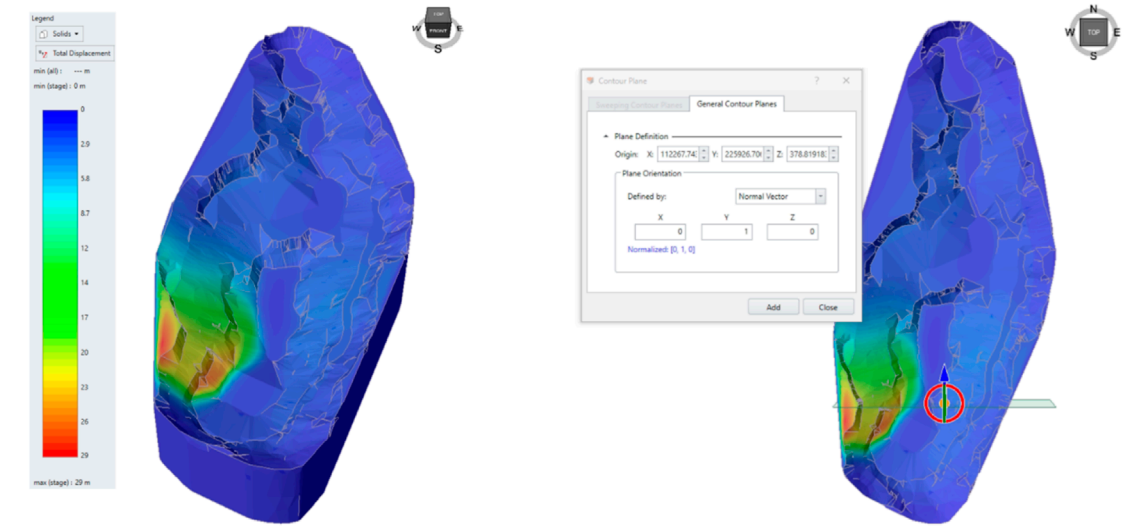

FIGURE 9
Displacement distribution in the Vostochny quarry model **(A)** and creation of a plane section to determine the slip surface **(B)**.

2.4 Geomechanical modeling

Digitized contours of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones are used to construct the geomechanical model (Figure 4). A homogeneous 3D finite-element model of the field has been created by combining these contours in reference to the coordinate system. When modeling a three-dimensional mass area, the boundary conditions are determined by fixing the displacements of the model.

- the XY plane (model bottom) is fixed in the X, Y and Z-axes;
- the YZ plane is fixed in the X and Y-axes;
- the XZ plane is fixed in the Y-axis.

The finite element mesh of the model (Figure 5) has been obtained by uniformly partitioning the domain into 10-node tetrahedra. The number of elements for the model below is 767,552.

To determine the rock mass SSS and the main characteristic determining the stability of the quarry walls–the safety factor (SF), a well-tested numerical finite element method is used, implemented in the licensed RS3 software (Rocscience, Canada).

The solution is performed in the elastic-plastic formulation using The Mohr–Coulomb (MC) failure criterion (Eq. 1):

$$\tau = c + \sigma_n tg\varphi, \tag{1}$$

where τ–tangential stress (shear stress), MPa; σ_n–normal stress, MPa; φ–internal friction angle, deg; c–cohesion, MPa.

SF is the most significant numerical modeling result, indicating that the wall can be operated at specified geometric parameters (Eq. 2):

$$F = \frac{Material\ (rock, bottom) resistance\ to\ shear}{Resistance\ to\ shear required\ for\ equilibrium}, \tag{2}$$

The "strength reduction" procedure, used in the RS3 code, is well adapted for determining the SF value. If the slope is in a limiting state, the Mohr–Coulomb failure criterion can be represented as follows (Eq. 3):

$$\frac{\tau}{F} = \frac{c}{F} + \frac{\tan\varphi}{F}, \tag{3}$$

Thus, the slope safety factor is the value of F by which the initial rock shear resistance parameters should be divided in order for the slope to fail. This interpretation makes it possible to determine the safety factor by consistently reducing the real strength characteristics of the rocks composing the slope by F times to such "reduced" (factorized) c_f and ϕ_f values, at which the slope stability with a given geometry becomes impossible, that is, the slope failure occurs. Mathematically, this means a divergence of the iteration process in the numerical solution. When the algorithm fails to converge within the maximum number of iterations set by the user, no stress distribution can be obtained that simultaneously satisfies both the Mohr–Coulomb failure criterion and the global equilibrium condition.

During a visual inspection of the Vostochny quarry slopes, East Saryoba field of the Zhilandy Group of cupriferous sandstones, weakened areas have been noted (Figure 6). Physical-mechanical properties of the weakened Vostochny quarry slope area with a height of 15 m according to geological exploration data are given in Table 3.

Physical-mechanical properties of the Vostochny quarry slope weakened area (Table 3) are used to develop a 2D model (Figure 7).

The imported section from the RS3 program into RS2 and the drawing of material lines to separate rock layers are shown in Figure 7 with the indication of rock types. The calculation scheme of the model with boundary conditions and partitioning into triangular finite elements is presented in Figure 8.

Thus, the divergence of the iteration process in the numerical solution physically means slope failure. The value of the strength reduction factor F, at which collapse in the solution occurs, is taken as the slope safety factor.

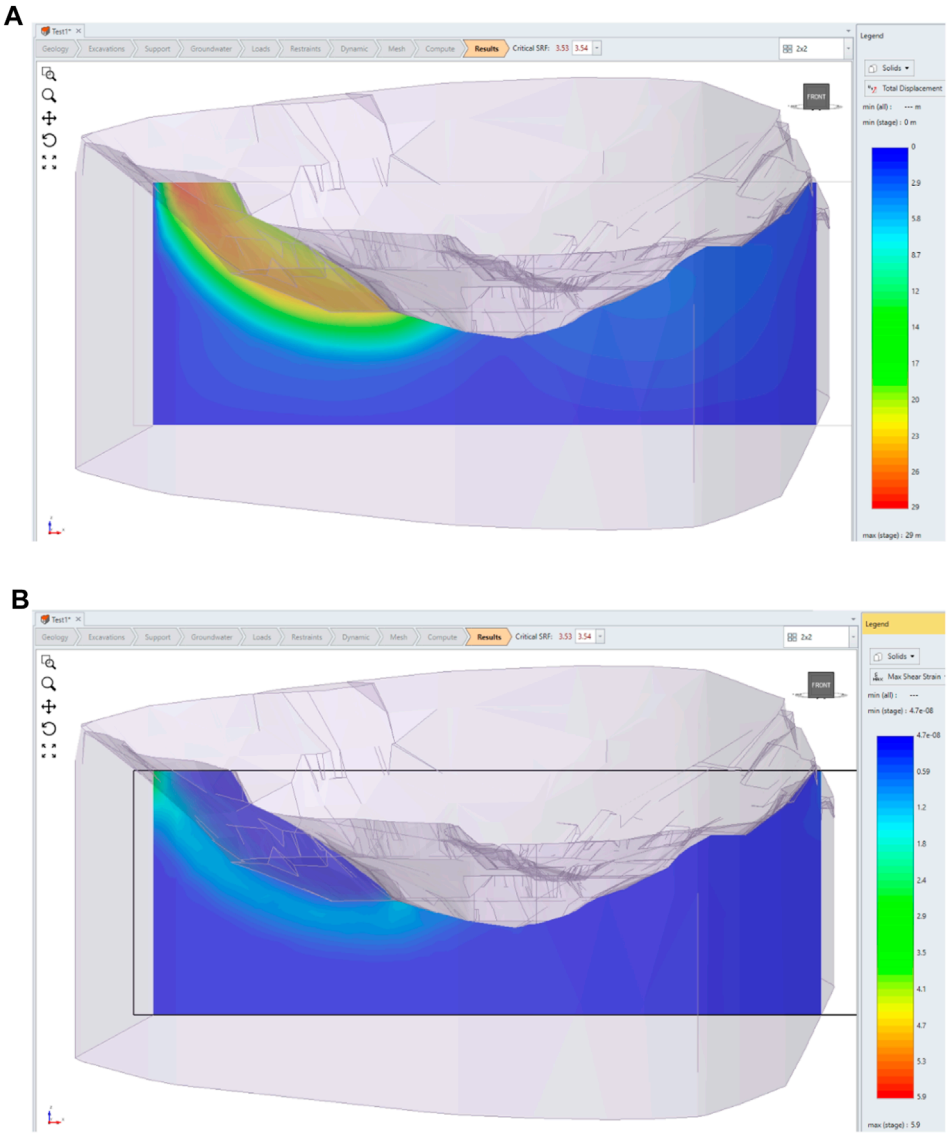

FIGURE 10
Slip surface modeling results: **(A)**–expressed in displacements; **(B)**–expressed in maximum shear deformations.

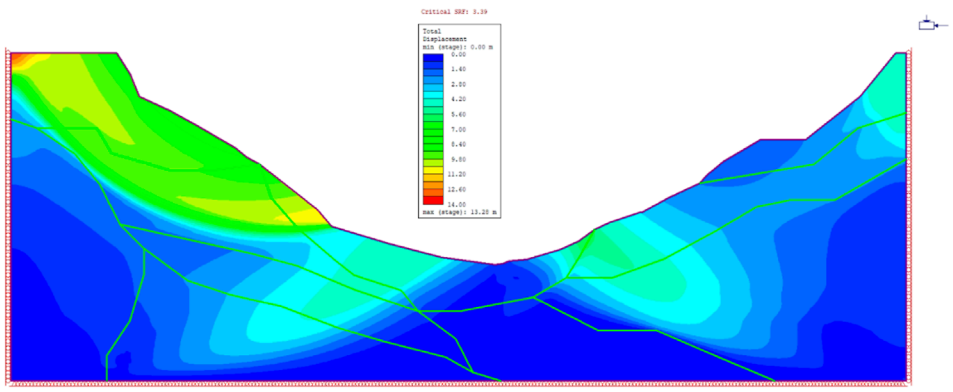

FIGURE 11
Total potential displacements of the slip surface expressed in shears.

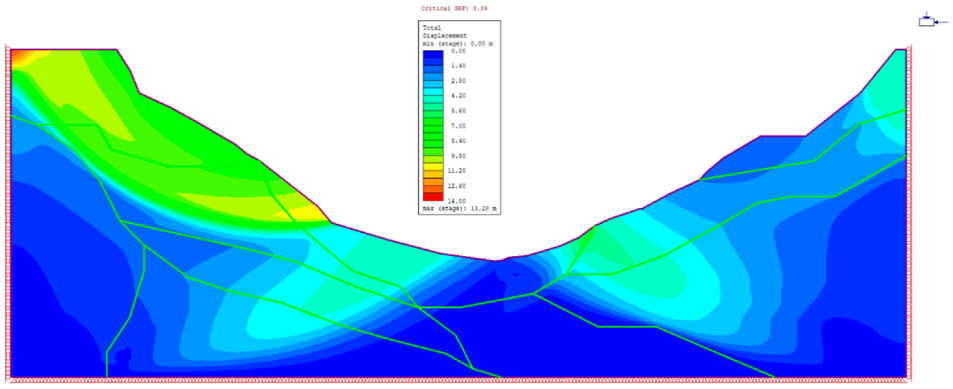

FIGURE 12
Maximum shear deformations and potential slip surface.

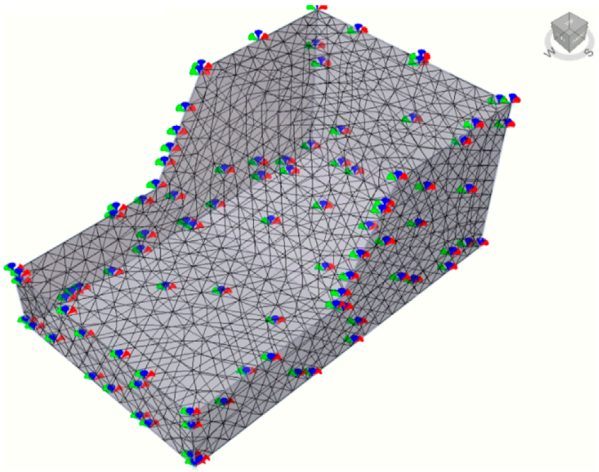

FIGURE 13
Calculation scheme of verification model.

3 Results and discussion

Performed calculations show that the south-western area is the most potentially hazardous area of the Vostochny quarry, East Saryoba field of the Zhilandy Group of cupriferous sandstones (Figure 9A). However, in this case, it is possible to speak only about a "potential" hazard since the SF exceeds 3 (SF ≥ 3). To identify a potentially hazardous slip surface, a 3D model section is made along the most hazardous area (Figure 9B). The potential slip surface is presented in Figure 10A,B.

Research conducted on a homogeneous macro-level model has shown that, taking into account only the quarry geometry factor and physical-mechanical properties (Table 3) of the rock mass at the current stage of mining operations, the south-western area of the Vostochny quarry is potentially hazardous. In this case, it is possible to speak only of a "potential" hazard, as the safety factor is 3.53.

The results of finite element modeling are given in Figure 11 and Figure 12. The safety factor decreases to the value of SF = 3.39 when the problem is solved in two-dimensional formulation and physical-mechanical properties of rock layers are taken into account (Table 3). Taking this value as a safety factor, it is this value that should be considered when developing methods for quarry wall protection. This result correlates well with studies conducted in (Wang et al., 2023), which show that the transition to a two-dimensional layered model leads to a decrease in SF by no more than 10%.

Figure 11 and Figure 12 show the total displacements and maximum shear deformations for the section of the most potentially hazardous area. As with the three-dimensional problem, the largest potential displacements are to be expected in the western (left) area of the slope, where the resulting angle is 390° (300° in the right wall). The safety factor (SF) of the quarry wall, calculated based on the Strength Reduction procedure described above, is 3.39. This means that the displacements shown in Figure 11 as well as the potential slip line (Figure 12), will occur if the strength characteristics are reduced by 3.39 times. In the real situation, the quarry wall is quite stable.

The pattern of displacements and maximum shear deformations is caused by the area geometry and by the fact that the slope angle exceeds the internal friction angle of the rocks. Zones of increased shear deformations and displacements within the mass are explained by the presence of contacts of rock layers having different physical-mechanical properties.

After identifying the Vostochny quarry weakened areas by means of SSS modeling, a method for strengthening stationary quarry slopes has been developed and patented (Rysbekov et al., 2023). The essence of the method is to create a crushing zone by drilling shielding inclined wells parallel to the future slope surface and blasting them, with additional drilling of wells, installing reinforcement in them and filling them with strengthening solution. This method differs from existing ones in that additional wells are inclined and drilled between inclined shielding wells at approximately the same angle as the shielding inclined wells. It is important that the filling with strengthening solution is performed after the crushing zone has been created. In this case, the reinforcement of additional inclined wells is installed in such a way that it is adjacent to the well wall from the side of the future slope surface. After removing the blasted mass and cleaning the surface of the slope, rods or hooks are welded to the reinforcement of additional inclined wells, on which a metal mesh is fixed over

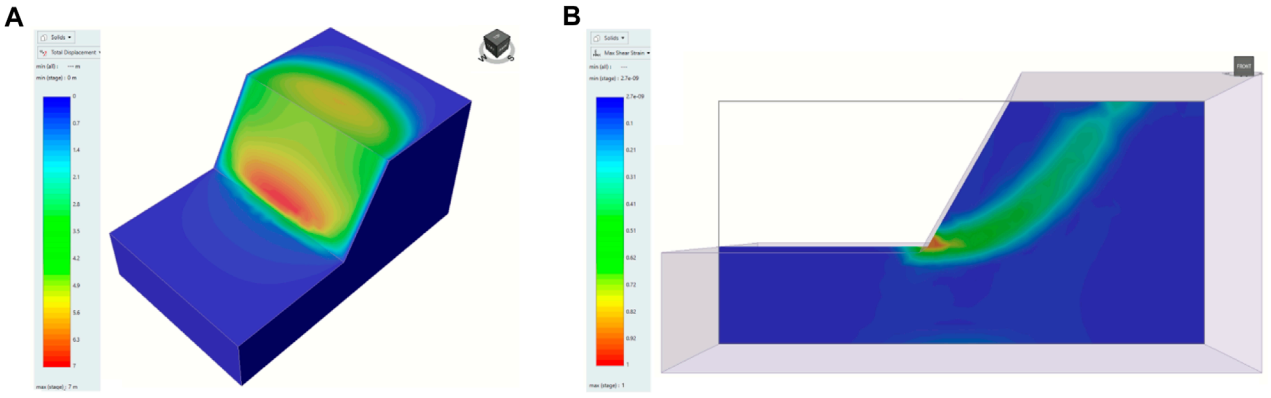

FIGURE 14
Results of modeling the slope without strengthening: **(A)** potential displacements; **(B)** maximum shear deformations.

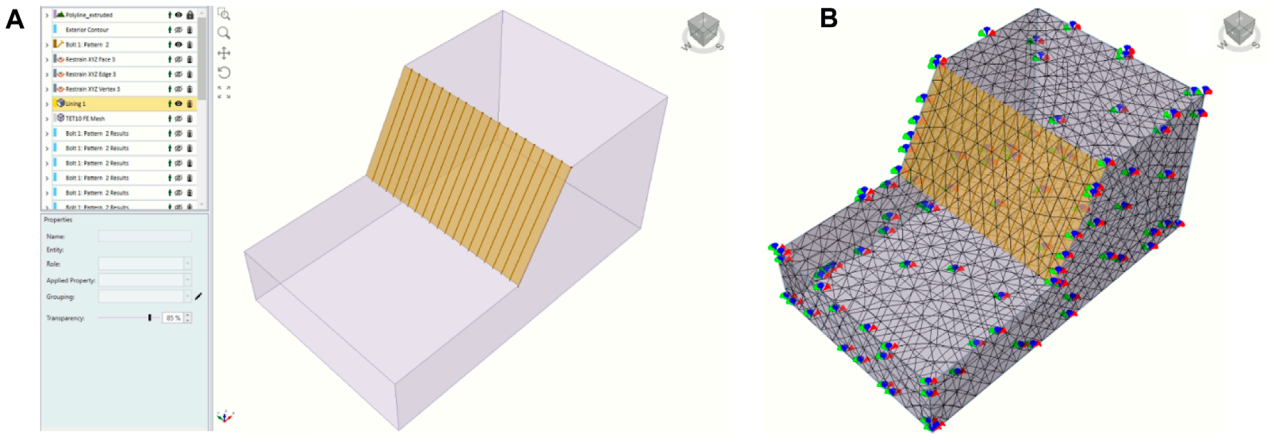

FIGURE 15
Scheme for reinforcement installation and application of strengthening solution **(A)** and calculation scheme of the model simulating the new slope strengthening method **(B)**.

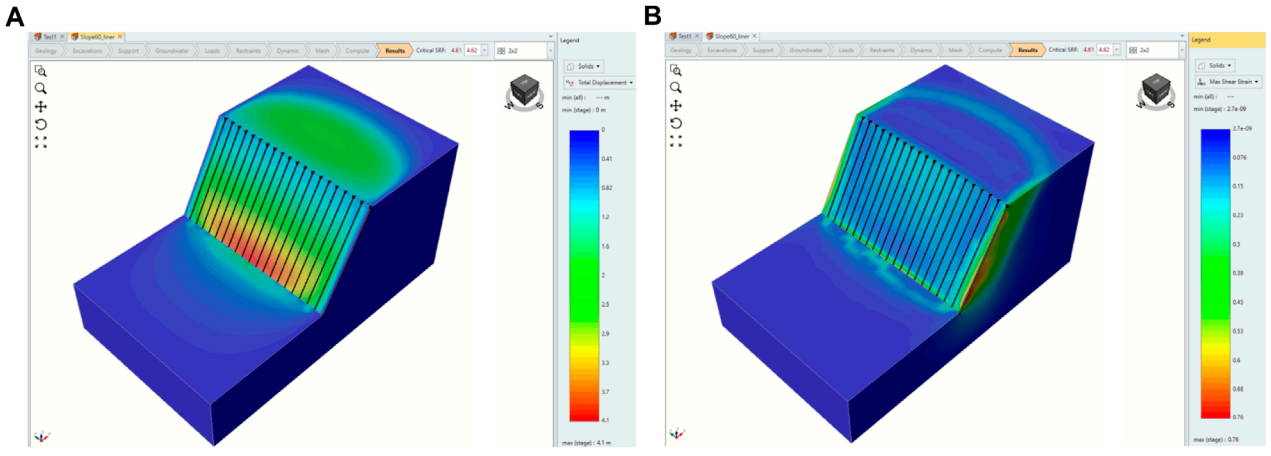

FIGURE 16
Strengthened slope modeling results: **(A)** potential displacements; **(B)** maximum shear deformations.

TABLE 4 Multi-variant modeling results.

No	Cohesion	SF	SF after strengthening the slope	Increase in SF, %
1	150	2.08	2.56	23.08
2	250	2.96	3.61	21.96
3	350	3.82	4.61	20.68
4	450	4.65	5.58	20.00
5	550	5.46	6.53	19.60
6	650	6.26	7.46	19.17
7	750	7.05	8.39	19.01

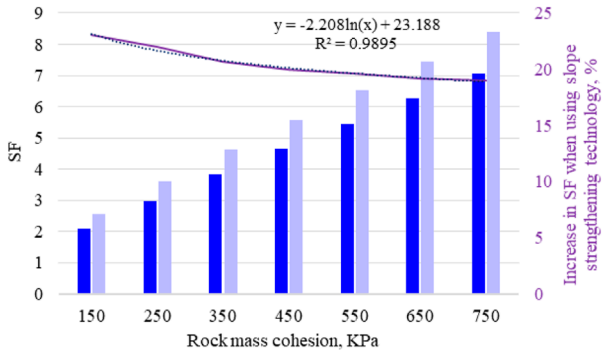

FIGURE 17
Calculation scheme of verification model.

the entire slope surface. Then a layer of strengthening solution is applied to it.

To verify this method for strengthening stationary quarry slopes, a 3D geomechanical model of the slope located at an angle of 60° to the horizontal surface is constructed. The calculation scheme for the corresponding finite element model with the indication of boundary conditions and finite element partitioning is given in Figure 13.

Physical-mechanical rock mass properties are used for modeling (Table 3). The results of modeling the slope without strengthening are shown in Figure 14.

The Strength Reduction procedure for the area presented in Figure 14A results in a strength reduction factor of 3.83. It is this value that is considered as a safety factor. Thus, for the slope without strengthening, SF = 3.83 at the resulting slope angle of 60°. The area of maximum shear deformations determining the potential slip surface, which is hypothetical to occur at this stage of mining due to a 3.83-fold decrease in the mechanical properties of the rocks, is shown in Figure 14B.

Standard support tools implemented in the RS3 software package are used for modeling the strengthening of stationary quarry slopes according to the developed and patented method. Drilling additional wells, installing reinforcement in them and filling them with strengthening solution are simulated using the Bolt tool according to the method described in (Tereshchuk et al., 2018).

Figure 15 shows the scheme after this modeling stage has been performed. When blasting shielding wells, when the quarry slope is placed in a limiting position, with a mesh of 3 m between inclined wells, half of the well remains on the quarry slope. The reinforcement is placed in this recess. Then, according to the strengthening method, a metal mesh is attached to the reinforcement of inclined wells over the entire slope surface and then a layer of strengthening solution is applied to it. This stage is simulated using the Lining tool. The use of this tool is shown in Figure 15A. The calculation scheme of the finite element model simulating a new method for strengthening slopes with indication of boundary conditions and finite element partitioning is given in Figure 15B.

The modeling results of the new slope strengthening method are shown in Figure 16.

The safety factor after slope strengthening increases by 21% to a value of 4.61, indicating the significant effectiveness of the proposed slope strengthening method.

To study the rock cohesion influence on the effectiveness of the proposed method of slope strengthening, seven options for calculating of this slope stability have been performed. The cohesion varies in steps of 100 KPa from a value of 150–750 KPa. The multi-variant modeling results are shown in Table 4. The interpretation of the multi-variant modeling results is graphically summarized in Figure 17.

When generalizing the modeling results, a regression dependence of the new method effectiveness on cohesion of the rocks composing the slope has been obtained (Eq. 4):

$$E(\%) = -2.08 \ln(K) + 23.188 \quad (4)$$

where K–rock cohesion (KPa).

Apply this technology to a quarry-scale model. Model the strengthened area in the south-western wall of the quarry, as shown in Figure 18A. Modeling results are given in Figure 18B.

The analysis of the modeling results of the new slope strengthening method on a quarry-scale shows a significant increase in the safety factor of the quarry wall up to the value of SF = 5.19.

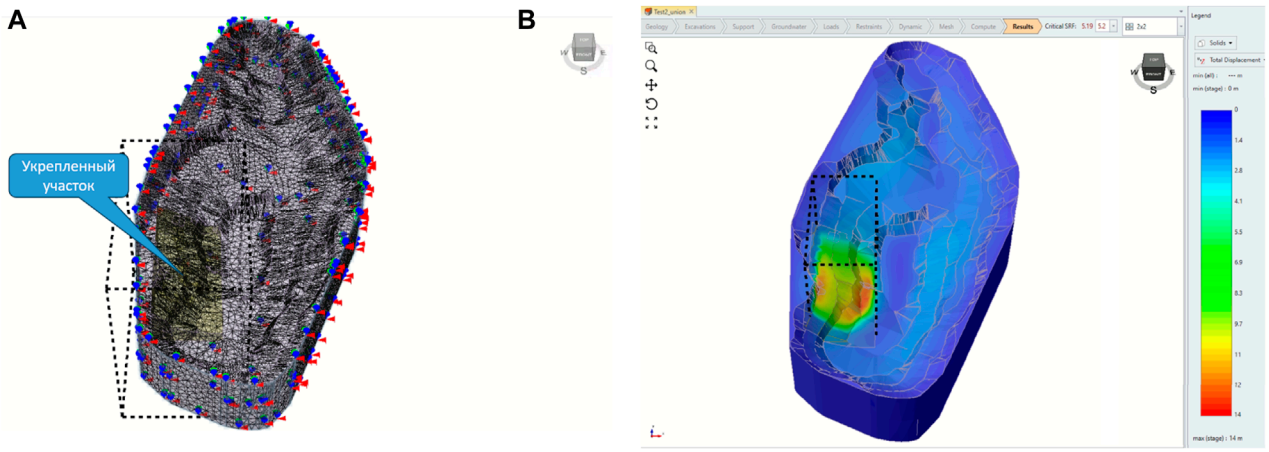

FIGURE 18
Strengthened slope modeling: **(A)**–calculation scheme of finite element analysis on a quarry-scale with a strengthened area; **(B)**–potential displacements.

The methodology is unique in that it combines social and economic significance. Social significance is primarily related to the prevention of technogenic disasters associated with the development of negative geomechanical processes. Strengthening unstable quarry slopes, placed in a limiting position, will prevent large deformations, thereby saving the lives of workers, engineers and technicians mining minerals at great depths. Economic significance–timely issued prediction on unfavorable geomechanical situation of quarry slopes and its timely strengthening will save enormous material costs for handling the consequences of technogenic disasters in subsoil use.

Taking into account the stress state of rocks in the near-wall mass, it is possible to obtain more objective information on the formation of a possible sliding wedge in different periods of quarry operation. This approach allows, even at the design stage, to model geomechanical processes and their possible negative manifestations in the form of landslides and to determine the stability parameters of quarry slopes, taking into account its service life.

The main principal difference of the performed scientific research is the modeling of rock mass SSS to assess and predict the deformation processes of quarry slopes, based on geospatial data, namely, high-precision measurements, terrestrial laser scanning, unmanned aerial vehicle for making managerial decisions to ensure industrial reliability in subsoil mining.

As a result of the research performed, in the future it is planned to study the dynamics of change in geotechnical processes on the basis of geospatial data obtained during subsoil mining with the development of a methodology for observing geotechnical and geodynamic processes, taking into account the patterns of manifestation of the measured values. This will improve the accuracy, reliability and efficiency of determining the rate of development of the rock mass deformation process. It is planned to develop an integrated method that will make it possible to monitor the stability of mine workings and improve subsoil mining safety and mining efficiency.

4 Conclusion

To determine the rock mass SSS and the main characteristic determining the stability of the quarry walls–the safety factor (SF), a well-tested numerical finite element method is used, implemented in the licensed RS3 software (Rocscience, Canada).

Research conducted on a homogeneous macro-level model has shown that, taking into account only the quarry geometry factor and the averaged physical-mechanical properties of the rock mass at the current stage of mining operations, the south-western area of the Vostochny quarry is potentially hazardous. In this case, it is possible to speak only of a “potential” hazard, as the safety factor is 3.53.

The safety factor decreases to the value of SF = 3.39 when the problem is solved in two-dimensional formulation and physical-mechanical properties of rock layers are taken into account. It is this value that should be taken into account when developing methods for quarry wall protection.

After identifying weakened Vostochny quarry areas by means of SSS modeling, a method for strengthening stationary quarry slopes has been developed and patented. On the one hand, it can provide the necessary bench slope stability for the non-working quarry walls and, in some cases, prevent possible rock failures in weakened areas. On the other hand, it can significantly reduce the volume of stripping operations. The analysis of modeling results has shown that the overall effectiveness of the new slope strengthening method is 20%–25% of the increase in SF, while the lower the rock cohesion, the higher the proposed method effectiveness.

Our study not only enhances the understanding of quarry slope stability, but also provides actionable insights to improve the safety and efficiency of mining operations. By integrating advanced geodetic, geological, and geophysical technologies, our methodology offers a systematic approach to identifying and mitigating risks associated with weakened quarry areas. Moreover, the development and patenting of a novel methodology for strengthening stationary quarry slopes underscore the significance of the research. Ultimately, our research contributes to the advancement of sustainable mining practices, minimizing

environmental impact while ensuring the long-term viability of mining operations.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

PS: Conceptualization, Funding acquisition, Investigation, Project administration, Writing–original draft. KR: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing–original draft. K-KK: Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Writing–original draft. VL: Funding acquisition, Investigation, Validation, Writing–original draft, Writing–review and editing. GK: Software, Validation, Visualization, Writing–review and editing. SM: Formal Analysis, Resources, Validation, Writing–review and editing. DB: Data curation, Software, Visualization, Writing–review and editing. AS: Data curation, Formal Analysis, Resources, Writing–review and editing.

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Conflict of interest

Author AS was employed by LLP NPK "Algeorithm".

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Simulation research on blasting of an open pit mine slope considering elevation conditions and slope shape factors

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This study established a numerical model that considers elevation conditions and slope shape factors by the modified Sadovsky formula to analyze the vibration attenuation law of open-pit slopes under blasting vibration conditions. The blasting excavation of a slope in a certain open-pit mine in Yunfu, Guangdong, is selected as an example. Using a numerical model that considers elevation conditions and slope shape factors by the modified Sadovsky formula, a triangular pulse load was utilized to approximate the time-history characteristics of explosion vibration with FLAC^{3D} software. The simulation results showed the radiation range of the blasting vibration seismic wave. By comparison with field monitoring data, the numerical model that considers the slope shape factor had a relative error of ~10%, while the numerical model that disregards the slope shape factor had a relative error of ~15%. The relative accuracy of the calculation results of the new numerical model is higher and closer to the actual attenuation law of blasting particle vibration speed, providing more reliable results for slope stability assessment. The peak particle velocities obtained from the numerical simulation results were generally higher than the field monitoring data. These discrepancies might be attributed to the use of simplified models that disregard the discontinuous structural planes within the rock mass. This study provides an important reference for the stability assessment of open-pit slopes under blasting vibration conditions, offering guidance for improving slope stability assessment and related engineering practices.

KEYWORDS

numerical simulation, vibration attenuation law, Sadovsky formula, blasting vibration, elevation condition, slope factor

1 Introduction

The blasting of open pit mine slopes can lead to slope deformation and damage, potentially resulting in safety hazards in some nonmining areas that should be kept stable. Blast-induced vibrations are the phenomenon where energy released from explosions causes vibrations in rock mass or slopes, causing instability and alteration of the rock structure. Furthermore, this phenomenon can cause slope instability and rock mass collapse. Inside the rock mass, the discontinuity in the surface rock mass is common and its distribution is complex (Wang et al., 2023; An et al., 2024; Yong et al., 2024), which is one of the important

factors affecting the blast vibration velocity. Outside the rock mass, the topography also affects the propagation of the blast vibration velocity. Therefore, in the context of open-pit mining, reliable blasting design is crucial to avoid generating excessive vibrations and shock waves that could cause irreversible damage to slopes and rock masses in some nonmining areas.

The effects of blast vibration on slope stability are classified into three methods: one is to predict the blast vibration rate by field monitoring using the traditional Sadowski correction formula (Singh and Roy, 2008; Dindarloo, 2015); some other scientists use machine learning techniques to predict blast vibration to overcome the limitations of the traditional formula (Nguyen et al., 2019; Bui et al., 2021; Zhang et al., 2021; Xu and Wang, 2023); In recent years, numerical simulation methods have been widely employed in conjunction with vibration attenuation principles to investigate slope stability, providing crucial insights for engineering construction. These studies encompass methods such as the Janbu limit equilibrium method and pseudostatic methods to assess the impact of blasting loads on slope stability (Ma et al., 2016). Based on the monitoring results and the propagation and attenuation patterns of blasting-induced vibrations, these studies offer guidance for mine safety production (Li et al., 2017). The effects of blast vibration velocity on the slope surface, offering practical value for blast vibration prediction and regional protection, are explored (Yan et al., 2022). Certain scholars have employed laboratory methods to calibrate numerical models for the influence of different fault rock structures on rock slope stability (Azarfar et al., 2019; Kang et al., 2020; Dehghan and Khodaei, 2022). The three-dimensional dynamic stability of high slopes due to blast vibrations using a combination of engineering geological surveys, field blasting tests, vibration monitoring, and numerical simulations is explored, providing technical support and theoretical guidance for mining blasts (Li et al., 2022). By comparing the impact of seismic events and blasting on slope stability, scaling seismic acceleration spectra have been proposed to obtain more reliable dynamic slope stability results (Jiang et al., 2018; Shafiei Ganjeh et al., 2019). Through the study of different blasting techniques, predictions of blasting vibration attenuation and propagation patterns have been made, and mathematical models for cumulative rock damage due to blasting have been established (Wang et al., 2021; 2022; Cao et al., 2023). Other researchers have examined the optimization of blasting parameters, vibration effect predictions, and stability analysis of steep slopes under deep bench blasting vibrations and have proposed effective solutions for open-pit mining blasting issues, offering significant references for engineering practice (Soren, 2014; Cao et al., 2018; Yin et al., 2021; Su and Ma, 2022; Yang et al., 2022; Bai et al., 2023). Through experiments and numerical simulations, the damage patterns of slopes due to blasting vibrations have been investigated, leading to the development of slope blasting vibration damage functions and the identification of the most critical areas (Liu et al., 2023).

In summary, extensive research on slope stability is conducted by combining numerical simulation methods with vibration attenuation principles. This research has predominantly focused on factors such as blasting loads, vibration propagation, and geological characteristics but have given relatively limited consideration to the influence of slope geometry factors. Slope geometry factors are critical parameters affecting slope stability and have a significant impact under different blasting conditions. Therefore, we aim to integrate relevant vibration attenuation theories and introduce the Sadowski modified formula, which incorporates elevation conditions and slope geometry factors into numerical simulations. Through a combined approach of field measurements and numerical simulations, this study analyzes the patterns of blasting-induced vibrations and predicts the displacement of slopes under blast conditions. This study also provides an important theoretical basis and technical support for the safe production of the Guangdong Yunfu Sulfur-Iron Mine.

2 Materials and methods

Elevation conditions and the slope shape factor are considered. FLAC^{3D} software is selected to establish the numerical model of the slope to simulate the blasting vibration propagation process and analyze the vibration velocity attenuation law of rock mass particles inside the slope. By comparing and verifying the measured data and simulation results, the accuracy of the numerical simulation and the reliability of the evaluation results are discussed. An in-depth understanding of the dynamic response characteristics of the slope provides a valuable reference for engineering stability evaluation. The technical route adopted in this paper is shown in Figure 1.

2.1 Elevation conditions and slope shape factor

When an explosive explodes in rock, the generated pressure shock forms a shock stress wave. With an increase in the explosion center distance, the shock wave gradually decays into a stress wave. Presently, an empirical formula proposed by Sadovsky is often utilized to analyze the attenuation law of particle vibration velocity. Regression analysis is carried out according to the Sadovsky formula, which is denoted Formula 1, and then the magnitude of the blasting vibration velocity is predicted based on the Sadovsky formula obtained by regression.

$$V = K\left(\frac{Q^{\frac{1}{3}}}{R}\right)^{\alpha} \tag{1}$$

where K is the coefficient related to rock properties, blasting site conditions and other factors; Q is the maximum amount of explosive charge (kg) in blasting; R is the blasting center distance, that is, the distance (m) from the measuring point to the center of the explosion source; and α is the blasting vibration attenuation coefficient.

However, with an increase in the height difference and topographic complexity of the mine slope, the applicability of the Sadowski formula is limited. The monitoring data show that the peak vibration velocity V of the blasting particle decreases with increasing elevation but that the vibration velocity still increases when it reaches a certain elevation. The formula only considers the influence of the vibration velocity V with the blasting center distance R and has high accuracy under the condition of levelling the terrain. However, the formula does not reflect the influence of elevation. Therefore, some scholars have proposed improved formulas based on this understanding. Li et al. (1997) investigated the amplification

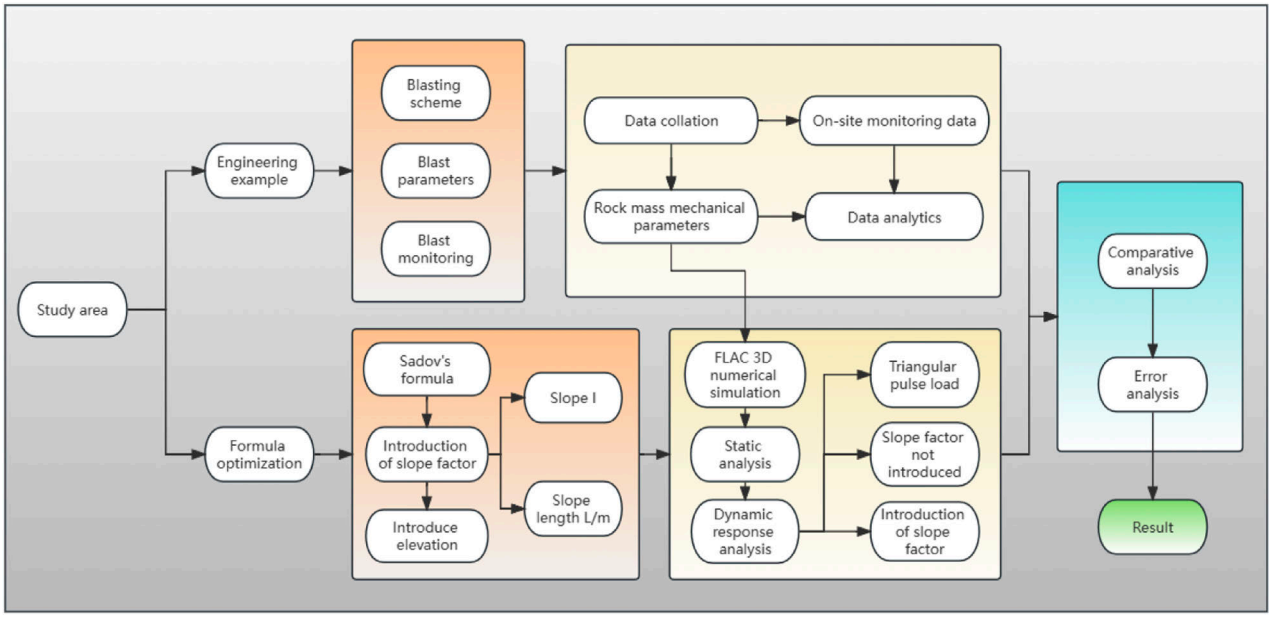

FIGURE 1
Technology route.

effect of blasting vibration on high slopes. Hu and Wu (2004) added a height difference factor on the basis of the Sadovsky formula and modified the vibration velocity formula to Eq. 2:

$$V = K\left(\frac{Q^{\frac{1}{3}}}{R}\right)^{\alpha}\left(\frac{R}{S}\right)^{\beta} \tag{2}$$

where S is the horizontal distance (m) between the measuring point and the explosion center and β is the elevation influence coefficient.

Wang and Lu (1994) then enter the dimensionless treatment of the influence coefficient of elevation H on the vibration speed and suggest that the vibration speed has an amplification effect along the elevation. Thus the calculation formula should be Eq. 3:

$$V = K\left(\frac{Q^{\frac{1}{3}}}{R}\right)^{\alpha}\left(\frac{Q^{\frac{1}{3}}}{H}\right)^{\beta} \tag{3}$$

where H is the relative height difference between the measuring point and the explosion center.

Chen et al. (2011) suggest that during the blasting process, the open-air multilevel slope will substantially vibrate near the free suspended surface, and some rocks on the open-air slope steps will produce a whiplash effect, resulting in a more obvious rock mass amplification effect of the slope steps. There is an amplification effect in the blasting vibration process of the slope step and introduced elevation parameters, but a slope factor is not introduced to analyze its influence on the amplification effect. Our study introduces elevation conditions and slope factors and establishes a blasting vibration amplification effect formula considering these factors as follows Eq. 4:

$$V = K\left(\frac{Q^{\frac{1}{3}}}{R}\right)^{\alpha}\left(\frac{Q^{\frac{1}{3}}}{H}\right)^{\beta}\frac{cI+d}{eL+f} \tag{4}$$

where I is the slope of the stepped slope, L is the slope length of the stepped slope, and c, d, e, and f are the relevant influence coefficients.

In the study, slope I is usually expressed as the percentage value of the tangent function of the foot γ of the slope, while slope length L represents the length from the foot of the slope to the top of the slope. When considering the impact of slope shape on blasting, a larger slope angle results in greater vibration velocity, while increased slope length leads to the gradual attenuation of the vibration wave and a corresponding decrease in velocity. Because the height of each step in the study area is much larger than the width of the step, it is possible to connect the end point of the slope foot of the blasting horizontal plane with the end point of the slope top of the horizontal plane of each step and to construct a new slope as a multilevel slope with different steps.

2.2 Principle of dynamic calculations in FLAC^{3D}

FLAC^{3D} uses a linear explicit Lagrangian finite difference method and a mixed discrete technique to solve the motion equations. The specified computational domain is divided into several elements, with nodes connecting these elements. When a load is applied to a particular node, the node's motion equation is expressed in the form of finite differences over a small time increment. The load applied to a node within a small time step only affects adjacent nodes. Based on the stress state at a given time t and the strain increments over the time step Δt, the stress state at $t+\Delta t$ is determined. According to Gauss's law, the strain increment of an element is calculated based on the node's velocities. Then, the stress-strain relationship, i.e., the constitutive equations, and the element stresses are computed and integrated to obtain the stress vectors acting on the nodes.

By combining the equilibrium equations, the node velocities and displacements are further solved from the node forces. This iterative process continues with a time step advancing throughout the entire computational domain until convergence is achieved, simulating the plastic deformation and flow of rock masses and other materials.

In the dynamic calculations of velocity and displacement, FLAC3D focuses on nodes as the computational entities. Mass and forces are concentrated at the nodes, and the motion equations are solved in the time domain. The node motion equation is expressed as follows Eq. 5:

$$\frac{\partial v_i^l}{\partial t} = \frac{F_i^l(t)}{m^l} \tag{5}$$

In the equation, $F_i^l(t)$ represents the equilibrium force component in the i -direction for node l at time t, which can be derived from the principle of virtual work, and m^l is the concentrated mass of node l.

By approximating the left side of Eq. 5 using central differencing, the node's velocity is obtained Eq. 6:

$$v_i^l\left(t+\frac{\Delta t}{2}\right)+\frac{F_i^l}{m^l} = v_i^l\left(t-\frac{\Delta t}{2}\right)+\frac{F_i^l(t)}{m^l}\Delta t \tag{6}$$

2.3 Strength reduction

In FLAC^{3D}, the numerical analysis method that utilizes the strength reduction technique is employed to analyze engineering problems related to slope stability. When performing stability analysis of slopes, the safety factor needs to be redefined. It is assumed that all parameters, with the exception of the shear strength of the rock or soil (comprising cohesion and internal friction angle), remain negligibly unchanged. The shear strength of the rock or soil is continuously reduced until the critical sliding state of the slope is reached. The final reduction factor (ratio of the ultimate shear strength to the initial shear strength) is then considered as the safety factor, which is expressed by the following Eqs 7, 8:

$$F_S = \frac{\int_0^l \tau_f dl}{\int_0^l \tau dl} = \frac{\int_0^l (c+\sigma tan\varphi) dl}{\int_0^l \tau dl} \tag{7}$$

$$F_S \frac{\int_0^l \left(\frac{c}{F_S}+\sigma\frac{tan\varphi}{F_S}\right) dl}{\int_0^l \tau dl} = \frac{\int_0^l (c'+\sigma tan\varphi') dl}{\int_0^l \tau dl} \tag{8}$$

Here, $c' = c/F_s$ and $\varphi' = arctan(tan\varphi/F_S)$, with c, φ, c', and φ', are used to represent the cohesion coefficient and internal friction angle of the soil, respectively, before and after applying the strength reduction method. l represents the length of the sliding surface.

3 Simulation research

3.1 Introduction of engineering case

This study case is the Guangdong Yunfu Open-pit Mining Project, which is located in Yunfu City, Guangdong Province. The project involves large-scale blasting operations, and these blasting vibrations can have a significant impact on slope stability in some nonmining areas. Therefore, accurate assessment and prediction of slope stability is essential to ensure the safe operation of the project. The Guangdong Yunfu Pyrite Open-pit is the largest pyrite mine in China, with an annual output of three million tons. The Yunfu pyrite mine started large-scale construction in 1979 and was completed and put into operation in January 1988. The long axis with 1,800 m of the open pit is due north–south. The short axis is positive east–west, and the width is approximately 800 m. The geographical location of Yunfu open pit mine is shown in Figure 2.

The length of the open stope is approximately 1,800 m from north to south and 800 m wide from east to west. The height of the steps in the mining area is 10 m above 370 m and 12 m below 370 m, and the slope angle of the working steps is 70°. The maximum height of the designed slope exceeds 800 m. Because the mining area is a metamorphic rock area, there are discontinuities that are not conducive to slope stability, and shallow landslides have occurred many times. Therefore, conducting blasting vibration tests and stability research on the open-pit slope of the Yunfu Pyrite Mine is not only essential but also important.

3.2 Blasting scheme

The ore rock of the Yunfu Pyrite Mine is difficult and cannot be directly shoveled by excavators, so the horizontal step mining and stripping method of loose blasting is adopted. To ensure the normal operation of mechanical equipment, detonators are used to realize hole-by-hole initiation, control the blasting scale, and reduce the impact of vibration and flying stones on the surrounding environment. The step height is 12 m, and the minimum working platform width is 40 m. The blasting adopts vertical drilling and a triangular arrangement. The hole spacing is 7–8 m, and the row spacing is 6–7 m. By balancing the blasting scale and adhering to safety requirements through such a blasting scheme, the efficiency and safety of blasting operations are improved.

3.3 Open-pit mine blasting vibration monitoring

3.3.1 Purpose of blasting vibration monitoring

Through blasting vibration monitoring, information on blasting vibration waves, such as vibration speed and frequency, can be obtained, and the blasting attenuation propagation law can be linearly analyzed by regression according to measured blasting vibration data. The accuracy of the numerical simulation is simultaneously verified by comparison with the numerical simulation results and analysis of the measured data. The test results will provide a scientific basis for formulating a reasonable blasting

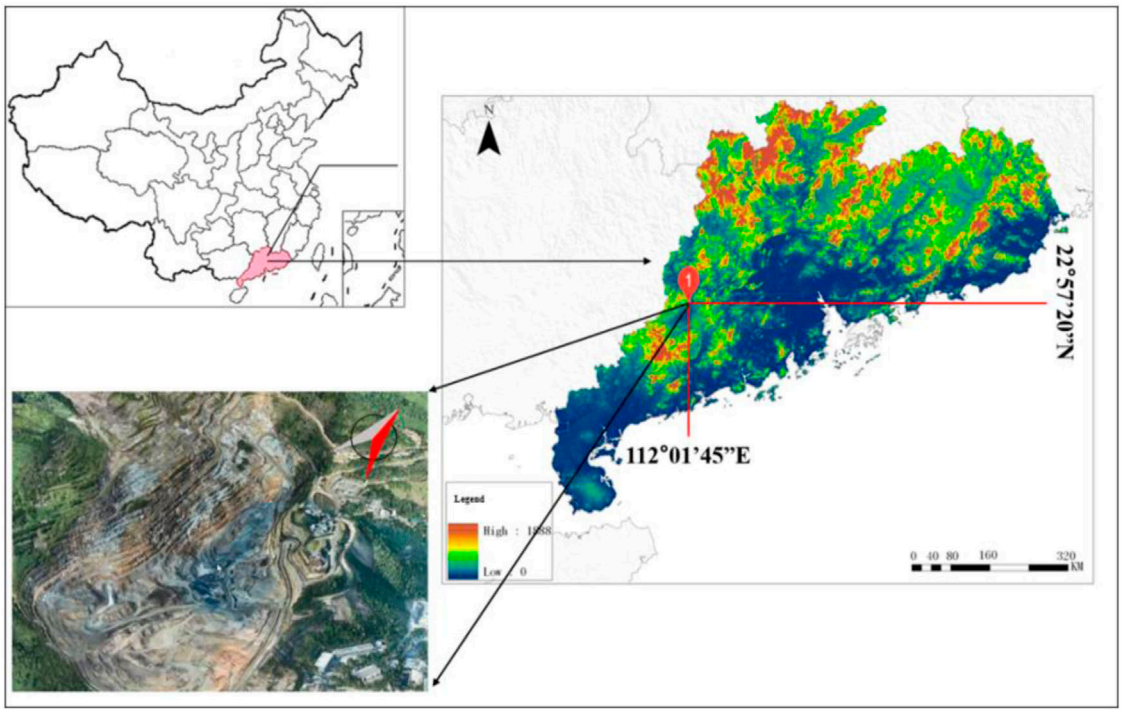

FIGURE 2
Geographical location of the Yunfu open-pit mine.

plan, controlling blasting vibration and taking disaster prevention and mitigation measures.

3.3.2 Blasting vibration monitoring

Because the blasting vibration monitoring of open-pit mines is real-time monitoring work, it is necessary to survey the topography and formulate a detailed monitoring plan before monitoring. Sensors are installed before blasting, each sensor is connected to the collector, and the parameters are configured. During the blasting process, if the vibration exceeds the established threshold, the vibrometer starts to record the blasting vibration signal. After blasting, we can obtain data such as vibration speed and frequency. The data are utilized for the K value and α value of the mining area.

The main factors of the seismic effect of blasting are the blasting charge and blasting center distance. The increase in the charge will cause more energy to be converted to seismic waves, resulting in more violent ground vibration. The farther from the explosion center, the more obvious the vibration attenuation and ground vibration. According to the site conditions, measurement points are arranged at different elevations of the slope measurement line, and TCS-B3 triaxial vibration velocity sensors are arranged at each measurement point to test the blasting vibration speed value of each point of the slope. The slope section and the arrangement of measurement points are shown in Figure 3.

In this blasting monitoring, the blasting vibration self-recording instrument TC-4850 is employed for monitoring. The instrument can set various collection parameters on site and can display the waveform, peak value, and frequency in real time. Numerical analysis is performed using the TC-4850 blasting vibration self-recording instrument supporting software and the Vib'SYS numerical vibration signal acquisition and analysis system. To make the blasting vibration data more accurate, the sensor is bonded to the surface with gypsum, and the sensor forms a whole with the surface to facilitate the collection of vibration waves and other data. The layout of the monitoring points for a part of the monitoring site is shown in Figure 4.

3.3.3 Blasting vibration monitoring data

The blasting parameters used in the blasting vibration monitoring were statistically analyzed, and detailed vibration data were obtained. Table 1 shows the blasting monitoring data.

3.4 Numerical simulation

In this study, FLAC^{3D} numerical analysis and simulation software is selected to numerically simulate the slope of the Guangdong Yunfu open-pit mine under blasting vibration. The numerical analysis and calculation model of this time appropriately simplifies the original project. According to the profile geological generalization model, the geometric shape of the slope is transformed into a three-dimensional, finite difference mesh model via RHINO software and imported into FLAC^{3D} software to establish a numerical model. The slope shape factor is introduced into the FISH language for numerical calculation and analysis. The results of the numerical model development can be seen in Figure 5.

According to the actual geological survey and experimental test data, key parameters such as the elastic modulus, Poisson's ratio, and strength parameters of the slope material are determined. The physical and mechanical parameters of the rock mass needed in this model are shown in Table 2.

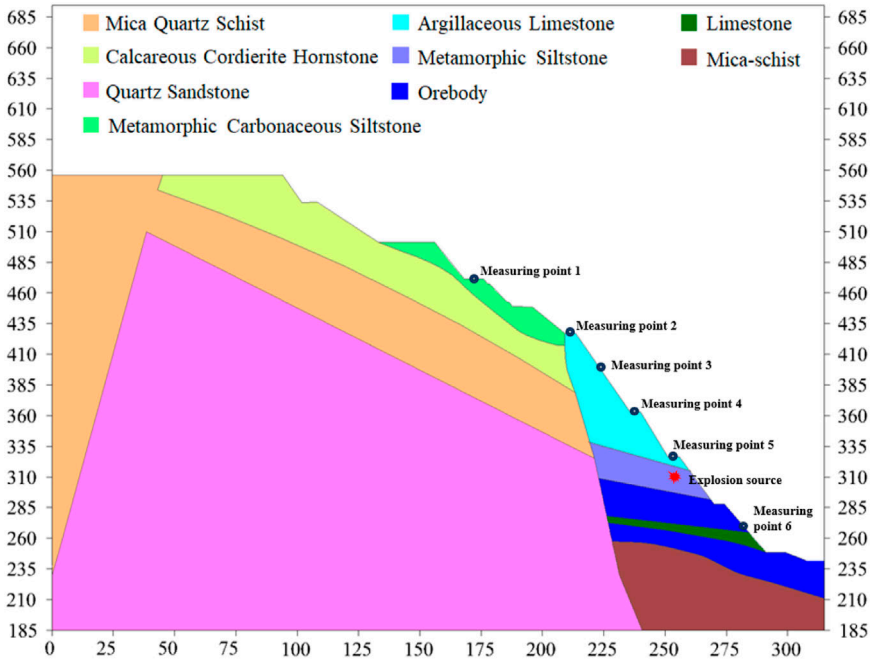

FIGURE 3
Profile geological generalization model and measurement point arrangement.



FIGURE 4
Placement of site monitoring points.

3.4.1 Static analysis of open pit slope

The blasting vibration was simulated by a numerical simulation method and analyzed by comparison with the measured data. The static analysis part is a key step in evaluating the stability of the open-pit slope, and it plays an important role in blasting simulation research. A reliable basis for blasting simulation research is provided by comprehensively considering factors such as geological characteristics, slope geometric parameters and material properties. The static analysis part of this time adopts the Mohr–Coulomb constitutive model, and the slope model formed from the survey data generates the initial *in situ* stress field under the action of gravity in Figure 6A. The initial vertical *in situ* stress is distributed in layers. The maximum value is 8.42 MPa at the bottom of the slope, and the minimum value is 0.52 MPa at the surface of the slope.

After the initial *in situ* stress field of the slope is generated, the stability of the slope in the preblasting stage is calculated and analyzed. The initial displacement cloud diagram of the slope under static conditions is shown in Figure 6B. The largest area of slope displacement is in the middle of the high and steep slope, and there is no obvious plastic area distribution of the slope. The increment of the slope shear strain is shown in Figure 6C. There is a significant shear strain increment at the top and bottom regions of the slope, while in other areas, the shear strain increment is relatively small, indicating

TABLE 1 Blasting monitoring data.

Explosion source elevation (m)	Measuring point number	Measuring point elevation (m)	Burst distance (m)	Peak value of explosion vibration velocity (cm/s)		
				Radial *L*	Tangential *T*	Vertical *V*
310.775	#1	466.0	585.44	0.159	0.148	0.293
	#2	433.4	548.05	0.215	0.069	0.308
	#3	399.7	504.31	0.160	0.274	0.456
	#4	370.3	498.68	0.177	0.286	0.432
	#5	334.4	509.24	0.173	0.123	0.435
	#6	274.8	481.47	0.230	0.216	0.234

Remarks: The total dosage is 11,265 kg, and the maximum dosage is 515 kg.

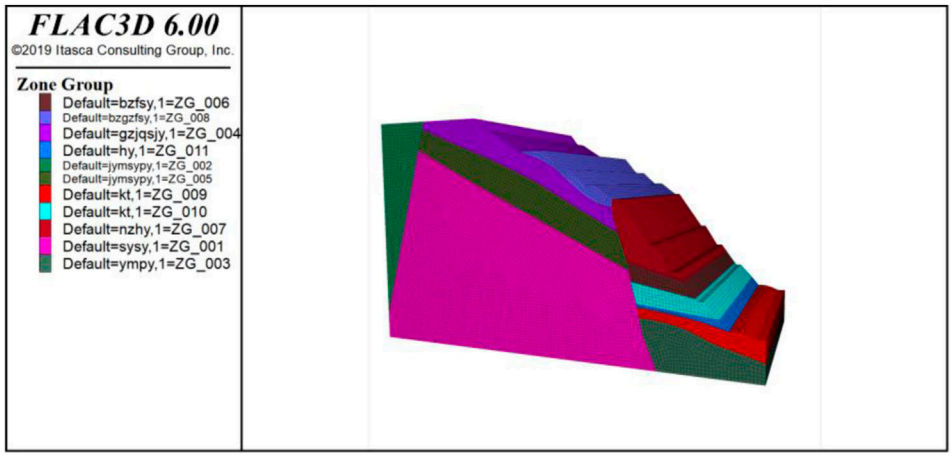

FIGURE 5
FLAC^{3D} numerical analysis mesh model.

no substantial tensile and shear failures. The particle velocity of the slope is shown in Figure 6D. The slope has no large movement speed, the velocity change area is distributed mainly at the top and bottom, and the overall stability of the slope is good.

3.4.2 Dynamic analysis of an open pit mine slope

Due to the complexity of the explosion process and the limitation of the actual measurement, every detail of the explosion vibration cannot be directly obtained and can only be equivalently treated by an empirical formula. The triangular pulse load is adopted in this study to approximate the time-history characteristics of the explosion vibration. In the numerical simulation, the determined triangular pulse load is applied to the slope model using FLAC^{3D} software. By defining the load function in FLAC^{3D} and using it as an external loading condition, the deformation and stress distribution of the slope under the action of explosion vibration are simulated. The determination of the triangular pulse load involves two fundamentals: the load amplitude and load time history (Kuhlemeyer and John, 1973; Moszynski, 1983; Chen et al., 2000; Xia et al., 2005).

The determination of the load amplitude determines the peak compressive stress of the detonation gas generated during the explosion of the explosive on the gun hole wall. According to the C-J theory of detonation waves, the average bombardment pressure of the explosive acting on the gun hole wall is Eq. 9:

$$p_j = \frac{\rho_e D_j^2}{2(\gamma+1)} \tag{9}$$

In the formula, p_j is the average initial detonation pressure of the instantaneous explosive, ρ_e is the explosive density, D_j is the detonation velocity of the explosive, γ is the isentropic coefficient of the explosive, and the value of γ is related to the charge density. Research shows that when $\rho_e < 1.2$ g/cm^3, γ is 2.1, and when $\rho_e \geq 1.2$ g/cm^3, γ is 3.

Under the condition of coupled charge, the initial explosion pressure P0 after the explosion of the explosive is Eq. 10:

$$P_0 = P_j \tag{10}$$

Under the condition of uncoupled loading, according to the diameter d_b of the blast hole and the diameter d_e of the charge

TABLE 2 Rock mass mechanical parameters.

Rock mass name	Elastic modulus (GPa)	Poisson's ratio	Cohesion (MPa)	Internal friction angle (°)	Density ($kg \cdot m^{-3}$)	Tensile strength (MPa)
Mica Quartz Schist	3.65	0.32	0.45	35.22	2,790	2.16
Calcareous Cordierite Homstone	5.07	0.31	0.60	36.61	2,760	2.32
Quartz Sandstone	7.68	0.29	0.8	40.32	2,700	3.31
Metamorphic Carbonaceous Siltstone	0.59	0.38	0.09	30.60	2,680	0.32
Argillaceous Limestone	1.65	0.36	0.22	29.84	2,710	0.97
Metamorphic Siltstone	4.18	0.32	0.51	32.17	2,760	2.27
Limestone	4.34	0.32	0.52	36.90	2,670	2.61
Mica-schist	3.65	0.32	0.45	35.22	2,790	2.16
Orebody	10.98	0.27	0.98	38.06	3,510	5.03

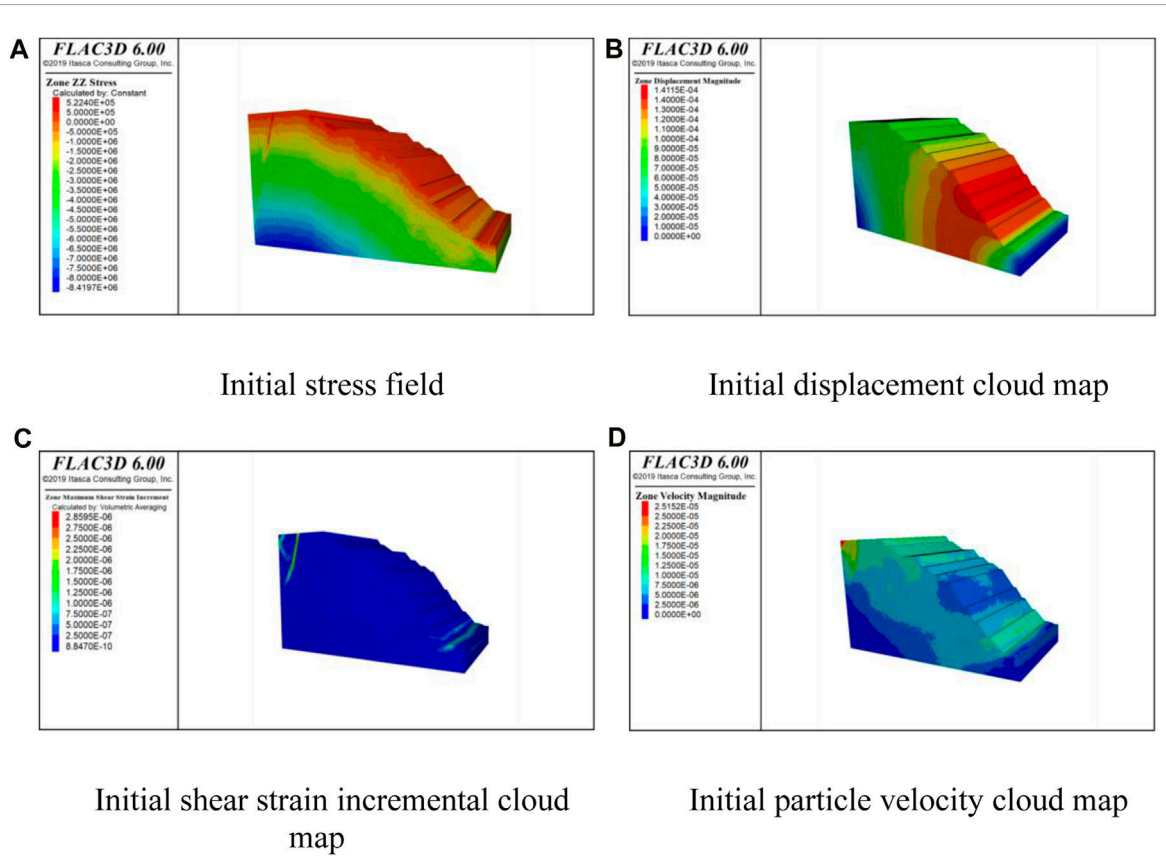

FIGURE 6
Static analysis of open pit slope. **(A)** Initial stress field **(B)** Initial displacement cloud map **(C)** Initial shear strain incremental cloud map **(D)** Initial particle velocity cloud map.

TABLE 3 Blasting load peak calculation-related parameters.

Explosive density (kg·m^{-3})	Blast velocity (m/s)	Charge diameter (mm)	Blast hole diameter (mm)
1,300	4,500	72	80

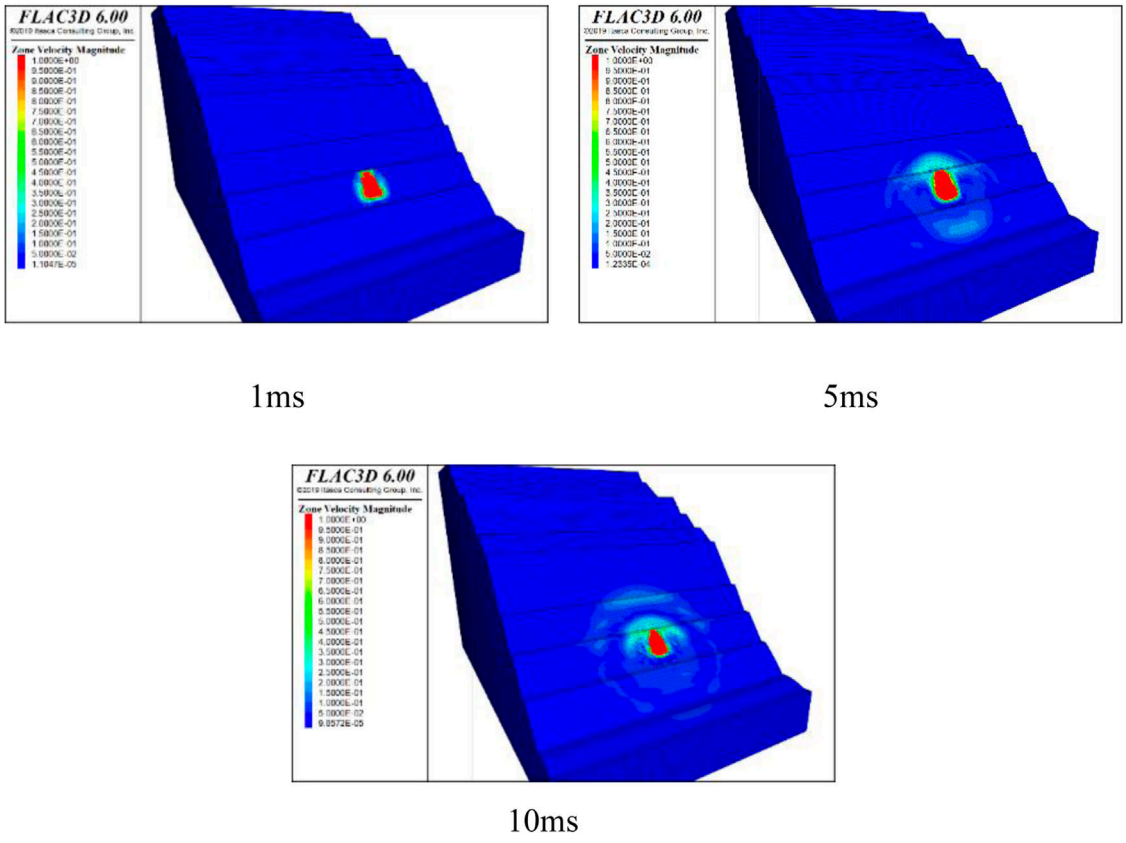

FIGURE 7
Cloud diagram of the particle vibration velocity at different times after blasting.

coil, the initial blasting pressure after the modified explosive explosion is Eq. 11

$$P_0 = n\frac{\rho_e D_j^2}{2(\gamma+1)}\left(\frac{d_b}{d_e}\right)^{-2\gamma} \tag{11}$$

In the formula, n is the pressure increase coefficient when the explosion product expands on the hole wall, n = 8–10, and 10 is used in this study.

The specific blasting peak calculation parameters are shown in Table 3:

During the action time of the blasting load, the shock wave and the pressure of the detonation gas generated by the explosion of the explosive will instantly act on the mine slope or rock formation, resulting in its rupture and fragmentation. Therefore, reasonable control of the action time of the blasting load and the time of pressure rise and fall can effectively control the blasting effect. The action time of the blasting load is very short. In this study, the load rises by 1 ms and falls by 7 ms. The total action time is 8 ms.

In this blasting simulation calculation, the radiation range of the blasting seismic wave is shown in Figure 6. Because blasting vibration seismic waves exhibit distinct directionality, when blasting occurs on high and steep slopes, although the rock mass below also slightly responds, over time, the propagation direction of the blasting vibration seismic wave is predominantly concentrated on the upper slope where the load is applied. Figure 7 shows the distribution of the model particle velocity between 1, 5, and 10 ms after blasting.

4 Analysis of the results

This study establishes pertinent monitoring points and explosive load parameters within the model, ensuring that the imposition of loads in numerical computations closely aligns with monitored outcomes and real-world conditions. The numerical calculation results are improved by introducing elevation conditions and slope factors and compared with the on-site monitoring data in Figure 8.

The results with and without the introduction of the slope factor at each measuring point are compared, and the error analysis is

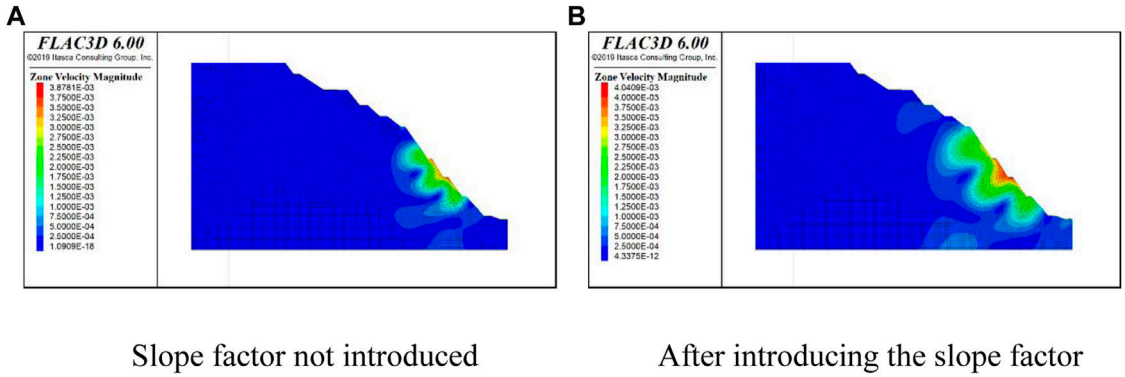

FIGURE 8
Particle vibration velocity cloud diagram. **(A)**Slope factor not introduced **(B)**After introducing the slope factor.

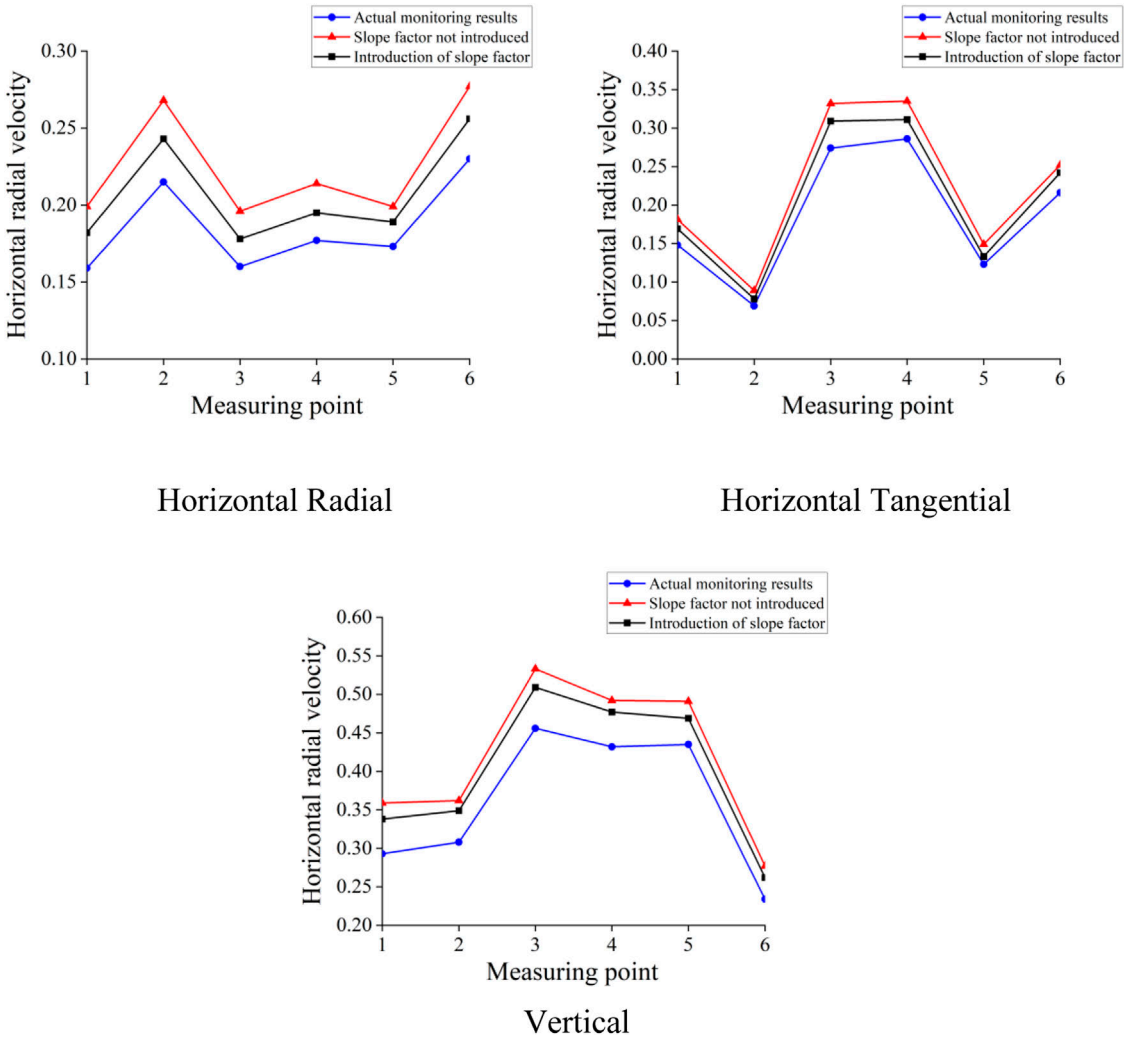

FIGURE 9
Comparison of monitoring data and calculation results.

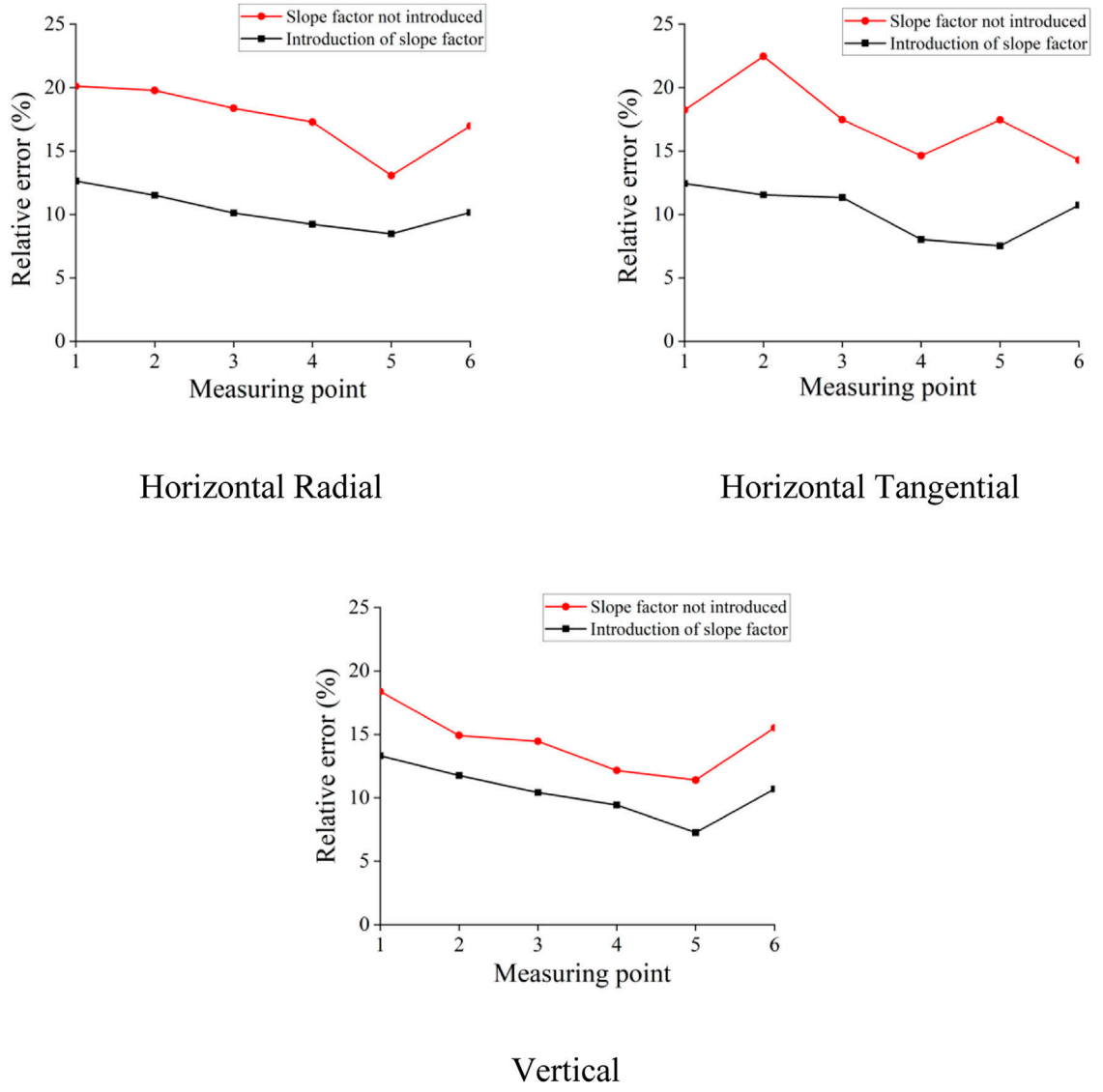

FIGURE 10
Comparison of relative errors.

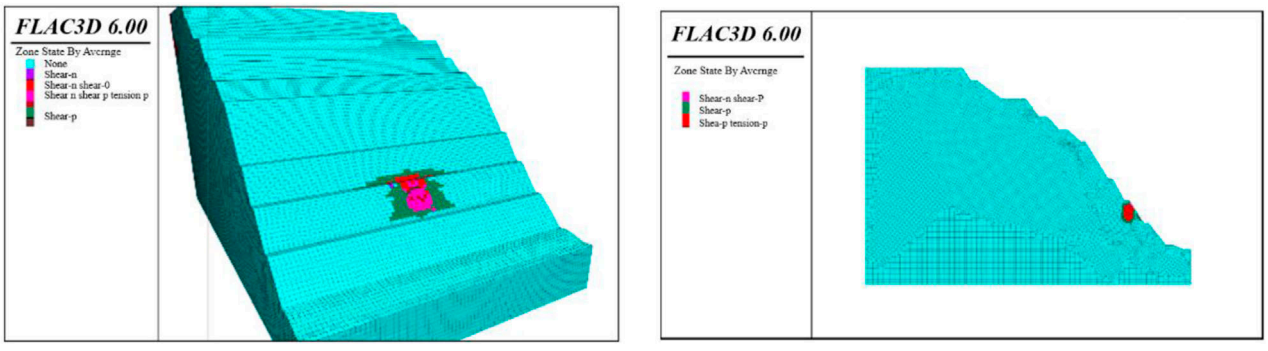

FIGURE 11
Distribution of plastic zones after blasting.

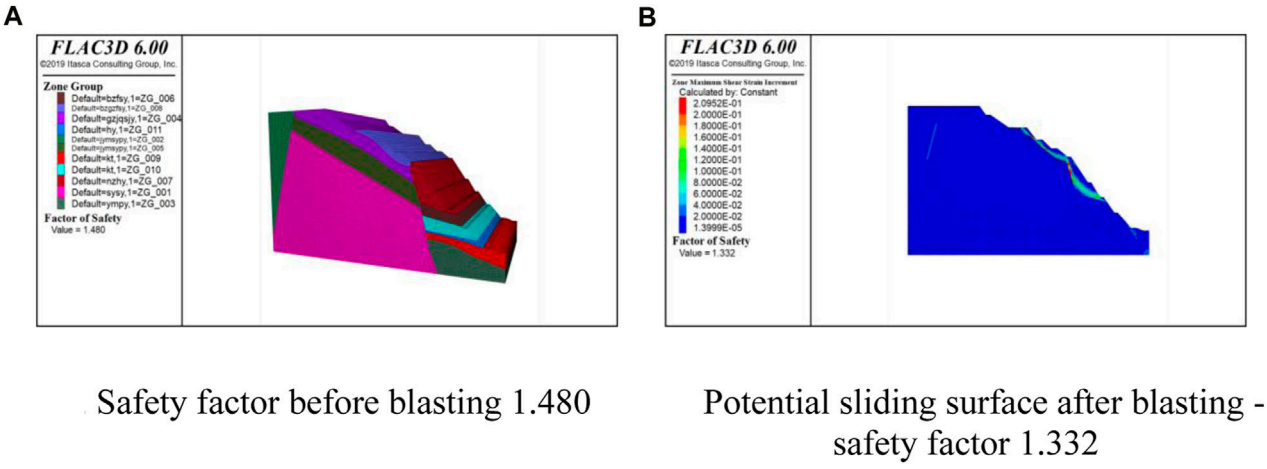

FIGURE 12
Safety factor before and after blasting. **(A)**Safety factor before blasting 1.480 **(B)**Potential sliding surface after blasting—safety factor 1.332.

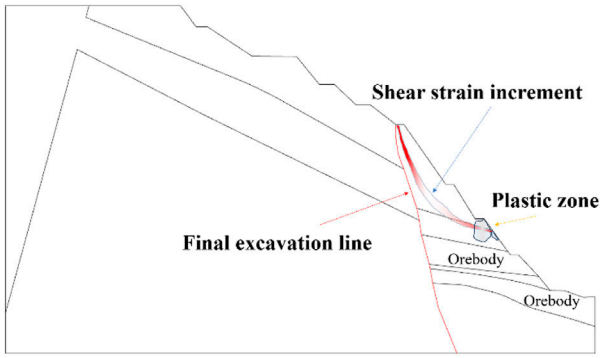

FIGURE 13
Schematic of the slope state after blasting Additional Requirements.

carried out in Figure 9. The relative error was calculated according to Eq. 8, which is given in Eq. 12, and the line graph is shown in Figure 9.

$$\left|\frac{V_1}{V_2} - 1\right| \times 100\% \tag{12}$$

In the formula, V_1 is the vibration velocity of the particle monitored on site, and V_2 is the numerical simulation calculation result.

When incorporating the slope shape factor into numerical simulations, it is observed that there is a relative error of approximately 10% in the peak vibration velocity compared to the field monitoring data as shown in Figure 10. However, when the slope shape factor is not considered in the numerical simulation, the relative error between the simulation results and field monitoring data for the peak vibration velocity is approximately 15%. For multitiered slopes in the Yunfu open-pit mine in Guangdong, analyzing the slope shape factor leads to an overall velocity attenuation pattern that is closer to the measured data and has a higher accuracy. Notably, the peak vibration velocities from both sets of numerical simulation results are generally higher than the field monitoring data. This discrepancy could be attributed to the simplified model employed in the numerical simulation, where the rock mass is treated as a uniform and continuous medium, disregarding discontinuities such as joints and fractures within the actual rock mass. This simplification may lead to a slightly slower attenuation of the blasting-induced seismic wave, causing differences from real-world engineering scenarios. Despite these deviations, overall, the accuracy of numerical calculation results remains within an acceptable range.

Observed by the vibration velocity in all directions, when the value of α is large, the vibration velocity of the particle will rapidly decrease with increasing horizontal distance. In addition, the more negative the value of β is and the smaller the value is, the more obvious the amplification effect. The calculation results show that the improved formula considers the elevation factor and slope factor, and its error is smaller than that of the original model, which is closer to the actual situation. In a multilevel slope, in addition to considering the influence of factors such as rock properties, blast center distance, explosive quantity and elevation on the blasting mining results, the slope shape of different steps would also have a certain degree of influence on the blasting results. Therefore, before blasting mining, we need to more accurately assess the blasting strength of the explosive for a blasting method.

In Figure 11, the numerical simulation results after multiple strength reductions on the model indicate that the surface of the slope exhibits a potential sliding surface in the form of arc-shaped failure. The simulation results are shown in Figure 12, with a safety factor of 1.332, a reduction of approximately 10% compared to the pre-sandblasting period. The reduction in the safety factor signifies a weakening of slope stability. However, the slope's safety factor remains above 1.2, meeting the needed safety margin. The plastic zone is distributed mainly around the blast source, and no continuous plastic zone appears above the slope. This finding suggests an overall stabilizing trend in the slope's condition. The numerical simulation results after slope blasting provide crucial insights for assessing slope stability.

The blasting simulation results indicate the formation of plastic zones and potential sliding surfaces predominantly within the excavation and stripping area needed for this project. In Figure 13,

the red solid line represents the final slope excavation line, with ore bodies and other features located to the right of the excavation line, i.e., in the construction-ready area. The distribution of sliding surfaces and plastic zones is centered in the construction-ready area, positively impacting the project plan and suggesting that a moderate level of geological disturbance has occurred in the excavation zone. This phenomenon creates more favorable geological conditions for construction in the subsequent excavation and stripping processes. In contrast, no potential distribution of sliding surfaces and plastic zones has been observed on the left and upper slopes of the excavation line. This result indicates that the geological conditions in these areas are relatively stable, with no signs of moderate disruption, providing a more controlled environment for the project. Overall, the observed moderate geological disturbance in the construction-ready area lays a solid foundation for subsequent construction, ensuring stability during the excavation and stripping processes and contributing to the planning and execution of the subsequent construction phases.

5 Conclusion

Based on the numerical simulation results and analysis of this study, the following conclusion can be drawn.

1) By introducing the slope influence factor, there is only a relative error of approximately 10% between the calculation results and the peak vibration speed of the on-site monitoring data. Compared with the calculation results without the introduction of the slope influence factor, it is closer to the particle vibration speed attenuation law of the on-site monitoring data.
2) The time-history characteristics of blasting vibration simulated by triangular pulse load can approximate the actual explosion vibration. Numerical simulation results show that the action range of blasting vibration seismic waves is concentrated on the upper slope where the load is applied and has obvious directionality.
3) The numerical simulation results show some deviation from the field monitoring data in terms of peak vibration velocity. However, the overall accuracy still falls within an acceptable range, providing a significant reference for slope stability assessment. The presence of a potential sliding surface in the slope after the blasting simulation is observed. Nevertheless, the safety factor of the slope remains above 1.2, satisfying the safety factor requirement. The plastic zones are concentrated in the excavation and stripping area needed for this project, while no continuous plastic zone is observed above the slope.

In conclusion, the numerical simulation results of this study validate the accuracy of incorporating the slope factor, which is significant for assessing the stability of open pit mine slopes under blasting-induced vibrations. Future research can consider integrating more field monitoring data and complex vibration propagation models, considering the influence of internal joints and fractures in the rock mass, and embedding the discontinuous nature of the rock mass in the numerical simulations, in order to optimise the blast design and ensure the stability of the slope and the safety of the engineering project.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

XW: Investigation, Methodology, Writing–original draft, Writing–review and editing. DZ: Writing–review and editing. HL: Data curation, Writing–original draft. LL: Data curation, Writing–original draft.

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Conflict of interest

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The disaster-causing factors of the flash floods for the July 20th extreme rainstorm in Henan, China

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Global warming has accelerated the frequency and intensity of extreme rainfall events in mountainous areas. Coupled with their vulnerable environment and the impact of intensive human activities, along with the complex and variable causes of flash floods, this exacerbates casualties and property losses. Therefore, this article investigates the triggering mechanisms and potential disaster-causing factors of the extreme "720"flood in the WZD-HGZ basin of Henan. The research results indicate that the flash floods in the WZD-HGZ basin were primarily caused by prolonged heavy rainfall, combined with the complex terrain, obstructive backwater, and human activities. The amplification of the flood mainly occurred in three stages: concentrated runoff from multiple channels, water obstruction caused by the successive collapse of roadbeds and bridges, and the generation of backwater. Besides, due to the lack of basic flood prevention awareness, unclear warnings, and inadequate guidance, the transition chain from issuing warnings to taking action was disrupted. The aforementioned research findings provide references for current flash flood disaster prevention efforts.

KEYWORDS

flash flood, disaster-causing factors, mechanism, Henan, extreme rainstormFlash flood

1 Introduction

Flash flood is usually defined as a rapid rise of water level along a stream gully or in a small catchment associated with short-duration but high-intensity rainstorms (Burrell and Eve, 2002; Martin et al., 2013). As such, it is characterized by sudden occurrence, short response time, high flow velocity and sometimes carrying debris and rocks, which has become one of the most devastating disasters all over the world (Mehdi et al., 2018). World Meteorological Organization (WMO) reported more than 5,000 deaths worldwide annually due to flash floods, which exceeds any other flood-related events. Paprotny et al. (2018) studied flood losses from 1,564 flood events in Europe during the last 150 years, of which more than half are flash floods. There are 1,075 fatalities due to flash flood recorded from 1996 to 2014 across the United States, with approximately 100 casualties each year (Ashley and Ashley, 2008; Terti et al., 2017). In China, the total number of casualties caused by flood-related events is around 0.28 million since 1950, and nearly

80% of losses during 2010–2016 were due to flash floods (He et al., 2018; Liu et al., 2022a).

To achieve a better understanding of flash floods, many researches have focused on studying its mechanism (Meral, 2016; Mónica et al., 2017; Yang et al., 2023; Qiu et al., 2024) and identifying meteorological and hydrological factors that have the potential to trigger the disasters, e.g., complex topography with terrain gradients, land use and soil type, land cover, antecedent heavy rainfall, human activities, etc. These factors can determine the hydrological response of watersheds to the rainfall which most flash floods are associated with (Liu et al., 2024). For example, Zhang et al. (2021) and Zhang et al. (2019) investigated the changes in future flash floods due to climate change. They found that extreme rainfall would lead to an increase in inundation depth, thereby increasing the risk of flash floods. However, in the decades, climate change has dramatically altered the extreme weather patterns by which flash floods are generated more likely, the formation mechanisms of flash floods induced by frequent extreme rainfall under climate change have not been thoroughly studied. Meantime, with the rapid social and economic development, the frequent and unpredictable impacts of human activities have increased the risk of flash floods (Billi et al., 2015; Gan et al., 2018; Papagiannaki et al., 2017; Liu et al., 2020; Ye et al., 2024). Especially in China, although the data monitoring network has been developed and implemented at the national level, monitoring facilities in mountain areas need further improvement. Direct measurement equipment is particularly prone to damage under extreme conditions. Therefore, it is essential to develop a decent post-disaster review strategy based on limited data, which can provide a reasonable detection to the hidden factors that induce disasters. One of the greatest challenges is that regions prone to flash floods often lack the limited historical records during such extreme events.

This article focuses on the record-breaking rainfall that occurred in Henan Province, China, on 20 July 2021 (so-called "720 rainstorm"), which reached up to 624 mm/day (Wang and Xuan, 2022; Xu et al., 2022); the motivation is to propose a post-disaster assessment strategy, that leverages limited data to uncover the factors inducing flash floods. This strategy involves comprehensive data collection, including victim accounts and post-disaster surveys, field investigations, and the use of drones for disaster identification. Scenario assumptions and modeling are then employed to rapidly simulate and explore contributing factors to the disaster."720 rainstorm" triggered devastating flash floods in many cities in Henan Province, particularly in the provincial capital, Zhengzhou, causing casualties and significant economic losses. The severe flooding disaster occurred in two villages in the southwestern mountainous area of Zhengzhou, named Wangzongdian (WZD) and Haigouzai (HGZ). The watershed controlled by the two villages experienced the highest number of deaths due to flash floods in 2021. However, due to limited data and the complexity of the situation, it has been challenging to quickly determine the causes that triggered the disaster. Additionally, given the small scale of the WZD-HGZ watershed, it is difficult to explain why the number of casualties in this area was significantly higher than in other flood-affected regions, and what the main factors triggering the flash floods in this watershed?Furthermore, despite issuing a public warning 14 h in advance, why the evacuation process did not proceed effectively remains a question?

To address the aforementioned issues, the study proposes a post-disaster review strategy. Firstly, data collection is emphasized. Given the susceptibility of actual measurement instruments to damage and the difficulty in collecting data, information from various sources such as victim descriptions and post-disaster survey data is considered. Disaster identification primarily relies on field investigations and the use of drones to assist. Subsequently, through scenario assumptions and modeling, the aim is to rapidly simulate and explore the potential factors contributing to the losses. Building upon this foundation, the strategy is applied and validated through practical case studies, specifically considering the characteristics of the flash floods in the WZD-HGZ watershed. The aim is to provide valuable insights for mountain flood disaster defense strategies. The article is organized as follows: Section 2 describes the details of the study area, data collection and process, geographic analysis to extract topographic features and the simulation model; Section 3 shows the simulation results including the rainfall characteristics, flood simulation in the upstream and downstream watersheds and the mechanism and factors driven the disaster; the impact of human behavior is then discussed in Section 4 and the conclusion is given in Section 5.

2 Study area and methods

2.1 Study area

The study area, i.e., WZD-HGZ watershed, presented in Figure 1, with the size of 42 km^2 is a sub-catchment controlled by the Suohe River which is a tributary of the Jialu River in the Huai river basin situated in northern China between the Yellow river and the Yangtze river (the two longest rivers in China). According to the on-site survey, the land of the WZD-HGZ watershed is mainly covered by woodland and agricultural crops together with several quarries where the soil mainly composes of sandy clay. According to the historical record, the annual average rainfall of the WZD-HGZ watershed is 608.8 mm with an uneven temporal distribution throughout the year. The rainfall recorded in the period of June-September accounts for 66% of the annual amount. Village WZD controlling the upstream watershed is surrounded by mountains with a total mountain area of 5.3 km^2 on all sides. The watershed can be subdivided into two small watersheds that are bounded by WZD Group, the most north part of village WZD, where the boundary is presented as a yellow dash line and marked as "Upstream (WZD)" in Figure 1B. The upstream watershed is located in the south of WZD Community (marked as red circle), partly under the jurisdiction of Xinmi City, with the size of around 22 km^2 and the length of the main ditch in the area is about 13.9 km which three ditches (west, middle, east) concentrate into. The downstream watershed is located in the north between Village WZD and HGZ (marked as "Downstream (HGZ)" in Figure 1B) where another three tributaries converge to the main ditch and a Railway "Mami Line" (marked as red dash line) passes through. The outlet of the WZD-HGZ watershed is a reservoir called "Zhidingdian" that is designed for preventing a one-in-100-year return level with the check flood level of a one-in-2000-year return period. The reservoir has a total storage capacity of 60.65 million m^3. As the reservoir had just been reinforced and kept empty storage, it undertook the main flood

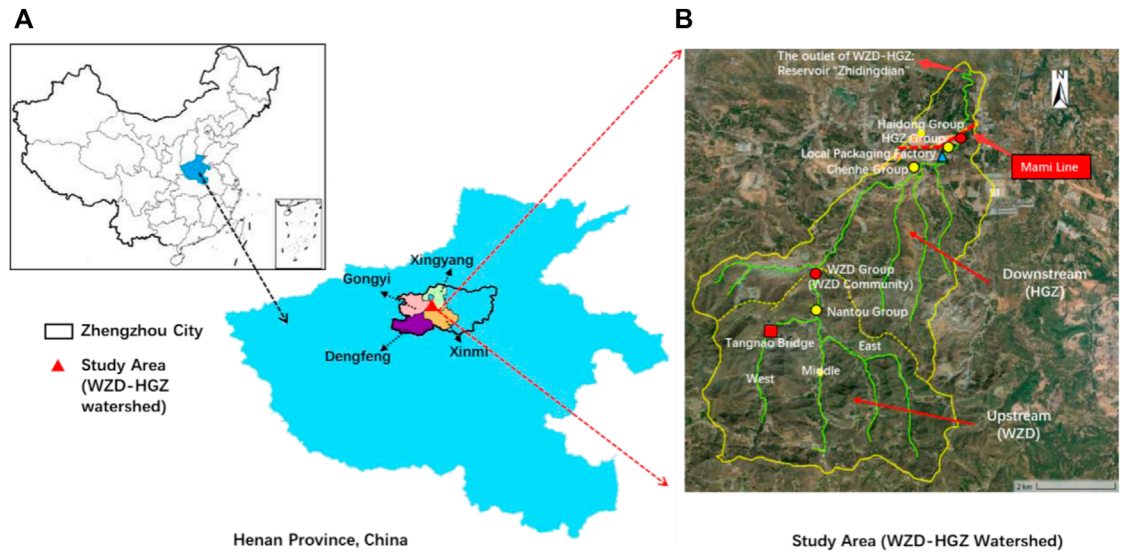


FIGURE 1
Geographical location **(A)**, ditches and important landmarks **(B)** of WZD-HGZ watershed.

during the occurrence of the "7.20" rainstorm event. There are 12 local communities including WZD Group, Nantou Group, etc., 442 households and 1,472 residents living in Village WZD while 24 communities including Village Cuimiao, Haixi Group, Hainan Group, Haidong Group and Chenhe Group, 1938 households and 7,047 people in HGZ.

The rainstorm occurring on 20 July 2021 in Zhengzhou City, Henan Province, China, has been recognized as one of the rarest and most extraordinary events since 1951, which causes hundreds of casualties and serious financial losses, especially in the watershed located in two mountainous villages named "Wangzongdian" (WZD) and "Haigouzhai" (HGZ). During the event, many direct measurement facilities were destroyed, which leads to great difficulties in supporting flood simulation and disaster analysis (Chen et al., 2022; Liu et al., 2022b). The flash flood accompanied by various topographical disasters such as landslides and debris flow destroyed more than 40,000 houses and caused 251 deaths in total in the four most-affected cities. The worst hit identified according to the casualties and property losses is located in a watershed controlled by the villages of Wang Zong Dian (WZD, upstream) and Hai Gou Zhai (HGZ, downstream) with 49 casualties which are the maximum fatalities due to flash flood disasters and landslides in 2021 (China, 2021). Figure 2 demonstrates one of the most damaged places. Thus, this area is selected to demonstrate the strategy and analyze the flood risk and the underlying reasons leading to the huge lost.

2.2 Data collection

The onsite investigation was carried out after the "720" rainstorm event. The unmanned aerial vehicle (UAV) was employed to depict the topographic features and identify the post-disaster situation and finally selected two representative cross-sections at both upstream and downstream watersheds. The spatial distribution of nine gauges is presented in Figure 3 and marked as red circles. The basic attribute information of the watersheds and Extracted features used in this study is shown in Table 1.

The rainfall data were collected from automatic rain gauges where some were uploaded directly to the local flash flood early warning and response platforms, Then the inverse distance weighting method (Han and Bray, 2006) was employed to convert the observed point rainfall to hourly areal average. Based on the National flash flood disaster investigation and assessment database and onsite investigation, the basic attribute information of the watersheds was extracted, i.e., land use (Table 1 a), soil type (Table 1 b), river network and elevation (Table 1 c), casualty locations (Table 1 d), and generated the precious digital elevation model (DEM) with the resolution of 30 m and a series of orthophoto maps. These maps were processed in ArcGIS to convert into GIS-compatible format and the details of upstream and downstream watersheds and river networks including nodes were then extracted for generating the model environment.

In addition, the local official departments also provided some investigation data. One is located at the WZD community shown in Figure 2, which is based on the flood trace survey and onsite measurements carried out by Henan Provincial Bureau of hydrology and water resources. They found the values of water surface slope (0.006), the cross-sectional area (200 m^2), the hydraulic radius (3.9 m) and riverbed roughness (0.05). Then the peak flow can be roughly calculated by using the Manning formula (Yen, 1992) as 768 m^3/s. However, it should be noted that during such event, the flow conditions are highly turbulent and supercritical and the application of the calculation can only be a reference value with on-site investigation because many gauges for measuring water levels were destroyed. Henan Provincial Bureau of hydrology and



FIGURE 2
The comparison of the situation before and after 720 rainstorm in one of the most damaged areas, i.e., WZD community.

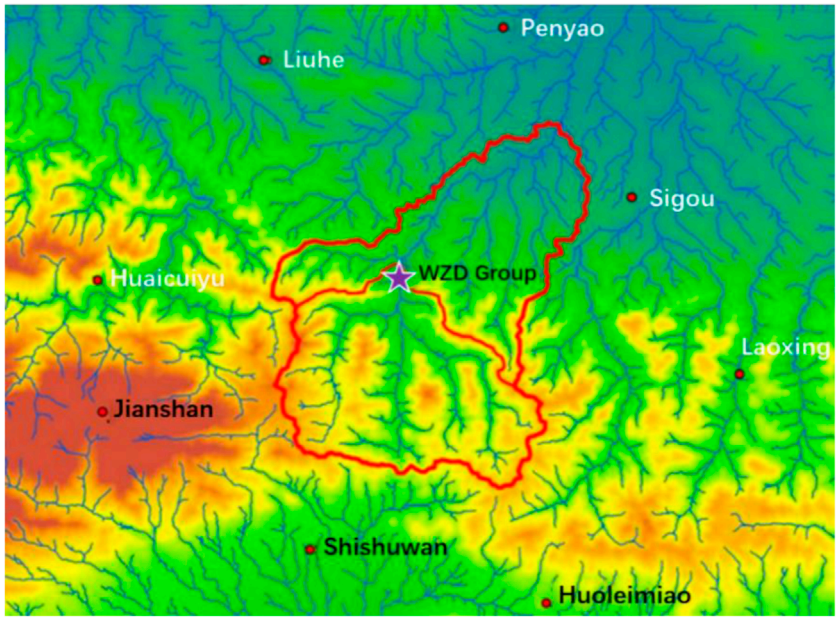


FIGURE 3
The surrounding rain gauges for calculating areal rainfall.

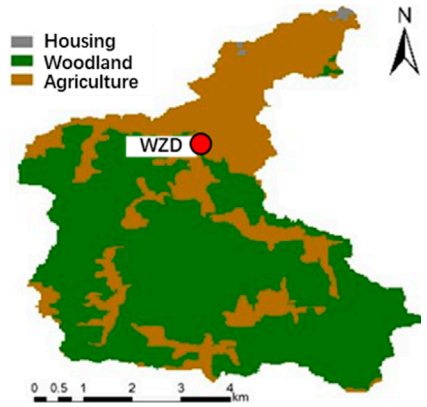
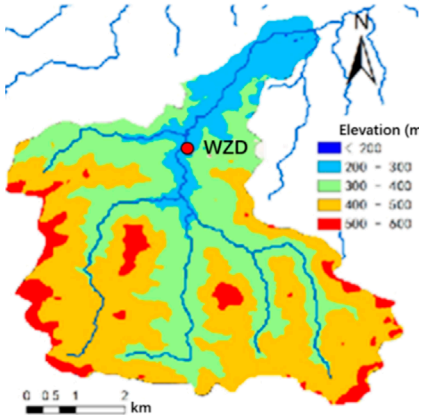
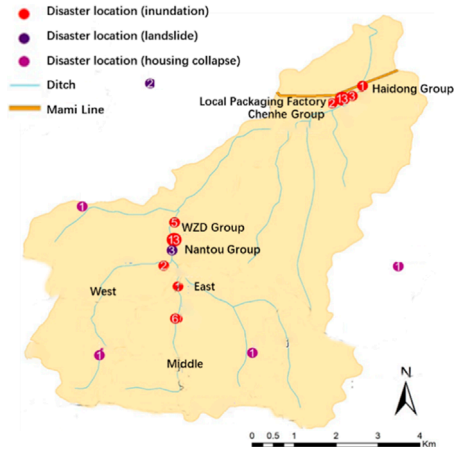
water resources also carried out a survey in HGZ where the cross-section is located at the entrance of Chenhe Group about 1 km far away from Haidong Group. The ditch cross is almost straight where the riverbed is covered by a hard clay layer while both sides are very steep and made of soil, and the investigated discharge is 905 m^3/s.

2.3 Methods

In this article, the model simulation was implemented by following a two-phase model strategy proposed by Hao et al. (2023). The first stage of the model strategy involves utilizing a distributed mountainous flood hydrological model to analyze the

TABLE 1 Description and characterization of basic watershed attribute data.

Source	Automatic rain gauges	Measurement stations	The local official departments
Data type	Rainfall	Water level	Water surface slope, the cross-sectional area…
Processing	Convert the observed point rainfall to hourly areal average	Export by time series	Using the Manning formula (Yen, 1992) calculate the peak flow

Source	the National flash flood disaster investigation and assessment database and onsite investigation	
Data type	Land use (a)	Soil type (b)
Processing		
Data type	River network and elevation (c)	Casualty locations (d)
Processing		

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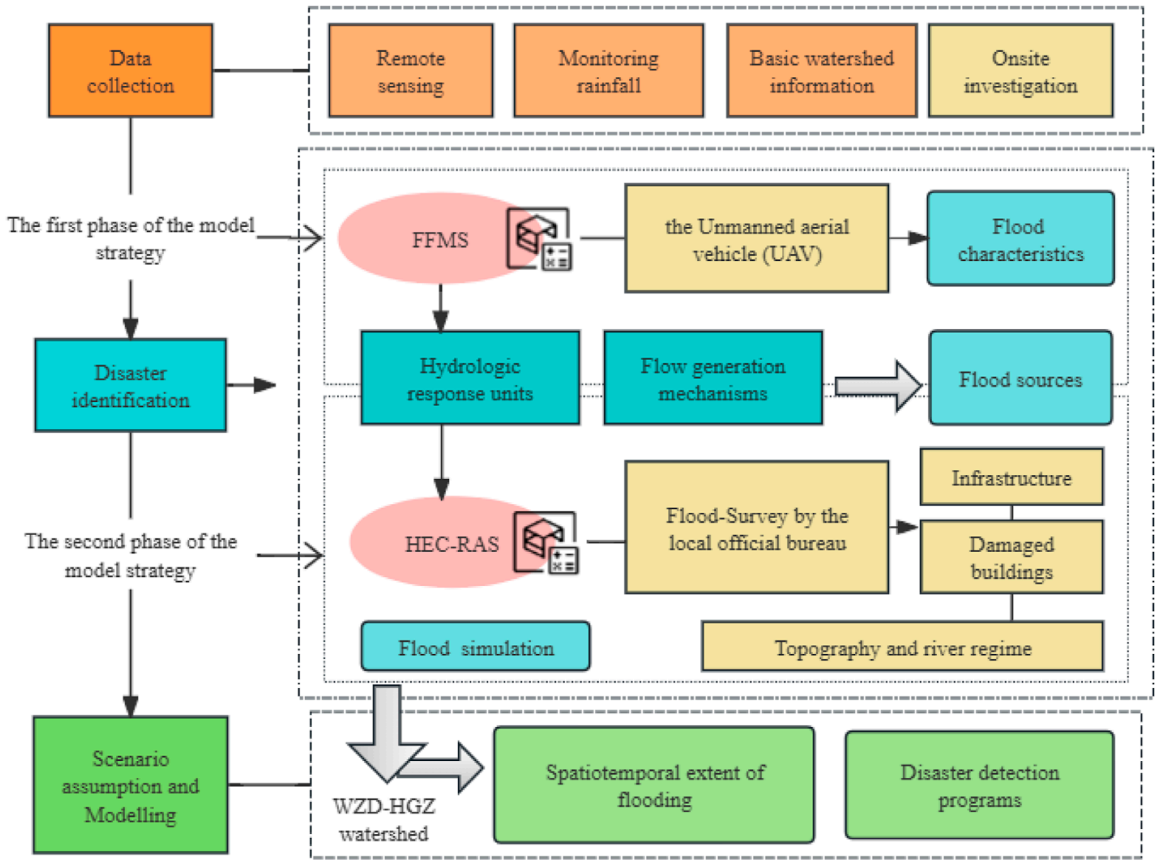

FIGURE 4
Research framework of post-disaster review strategy.

flood characteristics that triggered the disaster and to identify their sources. The second stage entails establishing a refined hydraulic model to simulate the flood process. The specific methodology is described in Figure 4.

The hydrological model in first stage is the spatiotemporal variable-source hybrid flow model, which is a distributed model Flash Flood Modelling System (FFMS). The FFMS model's flow generation model employs a spatiotemporal variable-source hybrid flow model, with the calculation process divided into four parts: super-permeable flow, full-storage flow, preferential flow, and base flow, where the slope-channel flow concentration model uses the kinematic wave method. The model calculations are conducted in both daily and hourly modes, with individual flood events calculated in hourly mode. Initially, hydrological response units are delineated based on the topographical and geomorphological characteristics of small and medium-sized basins, and the corresponding flow generation mechanisms are determined according to these units; through two major modules of spatiotemporal variable source and hybrid flow production, a planar, vertical, and temporal mixed flow production model is constructed, achieving the spatiotemporal transformation of super-permeable/full-storage flow in each geomorphological hydrological response unit. More details about the parameters of hydrological model and setup can be found in Hao et al. (2023).

The main parameters involved in this paper include flow production, variables in millimeters (precipitation, evaporation, upper soil moisture content, lower soil moisture content), calculation time step in seconds, evaporation coefficient (interception capacity in millimeters, average water storage in depressions in millimeters), infiltration coefficient, and soil water dynamic equilibrium parameters (such as soil leakage to the groundwater system m/d, linear coefficient of preferential outflow, etc.). This paper applies the FFMS model to the analysis of the spatiotemporal characteristics of floods. The spatiotemporal variable-source hybrid flow model judges the area changes of super-permeable and full-storage flow within the target unit based on the calculated values of water content and cumulative infiltration of different hydrological response units. It also discerns the relationship between the intensity of rainfall in the basin and the infiltration and storage capacity of the underlying surface, achieving the spatiotemporal transformation of super-permeable/full-storage flow in each geomorphological hydrological response unit.

In second stage, an open-source HEC-RAS model (Rangari et al., 2019; Kumar et al., 2020; Ongdas et al., 2020) was then largely built using the parameters proposed by the first stage hydrological model (Hao et al., 2023) and the flood survey of the local official bureau, i.e., Henan Provincial Bureau of Hydrology and Water Resources. The general process is as follows: According to

the characteristics of the small watershed area, the flow production adopts the initial loss stable infiltration rate method, with required parameters being calibrated or calculated based on empirical values or reference values. The flow concentration method uses the Snyder unit hydrograph method in the parametric unit line method, determining the suitable unit line for the basin by calculating the characteristic values of the unit line through the Bernoulli equation. The base flow impact is not considered during the calculation process, and the river flow concentration calculation uses the kinematic wave method. Combined the disaster locations based on onsite investigation, several scenarios were proposed and setup for detecting the possible factors that can lead to the deaths. More details are described in Section 3.2 and 3.3 with the discussion of the results.

3 Results and discussion

3.1 Spatiotemporal change at WZD community

3.1.1 Rainfall and water level

The results of transforming the rainfall at observation points in the WZD watershed (upper) during the "720 storm" event to hourly averages are shown in Figure 5A. It can be observed that the rainfall system during the period of 19 July 08:00 to 21 July 08:00 contributed the majority amount of rainfall where several peaks can be easily recognized. The maximum peak is observed to occur at 14:00 on 20 July, which exceeds 60 mm. And the 24-h accumulated maximum rainfall breaks local historical records and is around 500 mm. Figure 5B presents the hourly areal rainfall in HGZ (downstream). The rainfall system is similar to that in the upstream while the 24-h maximum is around 30 mm higher but the maxima of 6-h, 3-h and 1-h are slightly less than the upstream watershed.

Beside the rainfall, two measurement stations survived and are able to provide the record of water level during the event. One is located at the WZD community and it can be observed that the first peak occurred at 8:30, 20 July and just inundated the road surface in front of the building of the community (see Figure 5C), and the second peak reached a very high level of 263.3 m rapidly (only took about 1 h) and maintained the high for around 1 h. The other locates near the Haidong group in the HGZ watershed (see Figure 5D). Different from the situation in the upstream, the downstream flood only has one peak but with the same rapidly increasing rate as the second peak presented upstream. The flood began to increase at noon of 20 July with a very steep gradient and it took only two and half hours for the water level to rise from the bottom of the main ditch (184.3 m) to the peak (195.5 m) inundating Mami Line and the local bureau of land resources near Haidong group but locate relatively high in the area. The flood receded also fast in the first one and half hours and then gradually decreased to 186 m when the second rainfall event ceased.

3.1.2 Rainstorm characteristics

The "720" rainstorm in Henan Province, China is observed to start from 8:00 on July 17 to 8:00 on 23 August 2021. The average rainfall in Zhengzhou city, the capital of Henan Province,

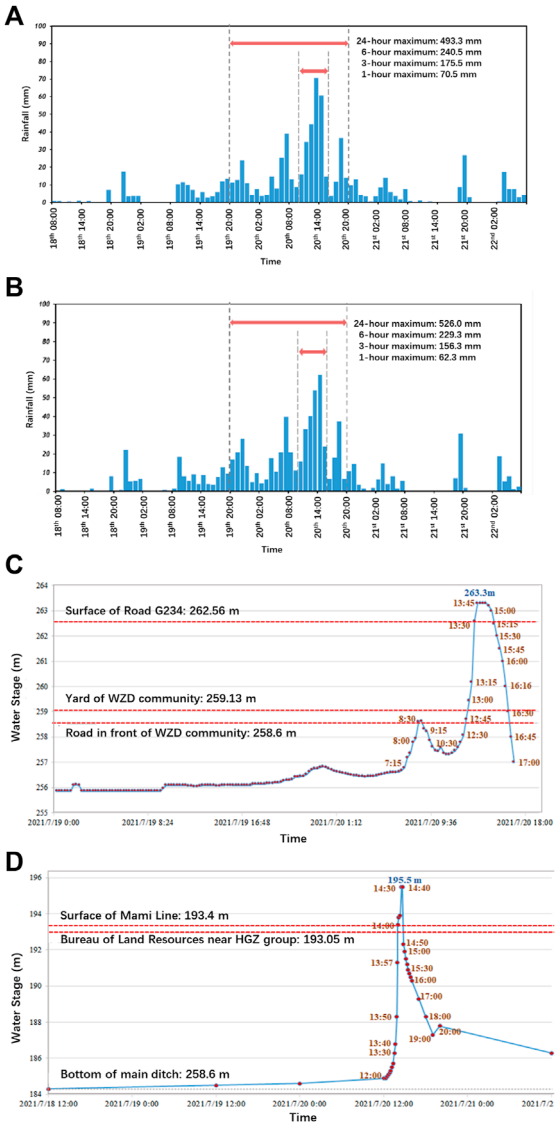

FIGURE 5
The rainfall during the event in WZD watershed **(A)** and HGZ watershed **(B)** and Temporal change of water level recorded at WZD community **(C)** and Haidong group **(D)**.

is 534 mm with a total volume of around four billion m^3, which is the highest observation since the local historical precipitation record was available. The average rainfall from 8 a.m. on July 17 to 8 a.m. on July 22 in Xingyang city is 574 mm, where the WZD-HGZ watershed suffered the most intensive rainfall. In order to reveal the rainfall characteristics, we extracted the 6-h accumulated rainfall before the first disaster event has been observed and presents in Figure 6. It can be seen that the highest accumulation is in the upstream watershed with the average of 190 mm while the downstream is relatively low, which is 165 mm in average.

Table 2 presents the comparison results of rainfall in the WZD watershed with historical records. In the upstream watershed controlled by WZD, the maximum rainfall intensities for 1 h, 6 h, and 24 h are 70.5 m, 240.5 m, and 493.3 m, respectively. In the

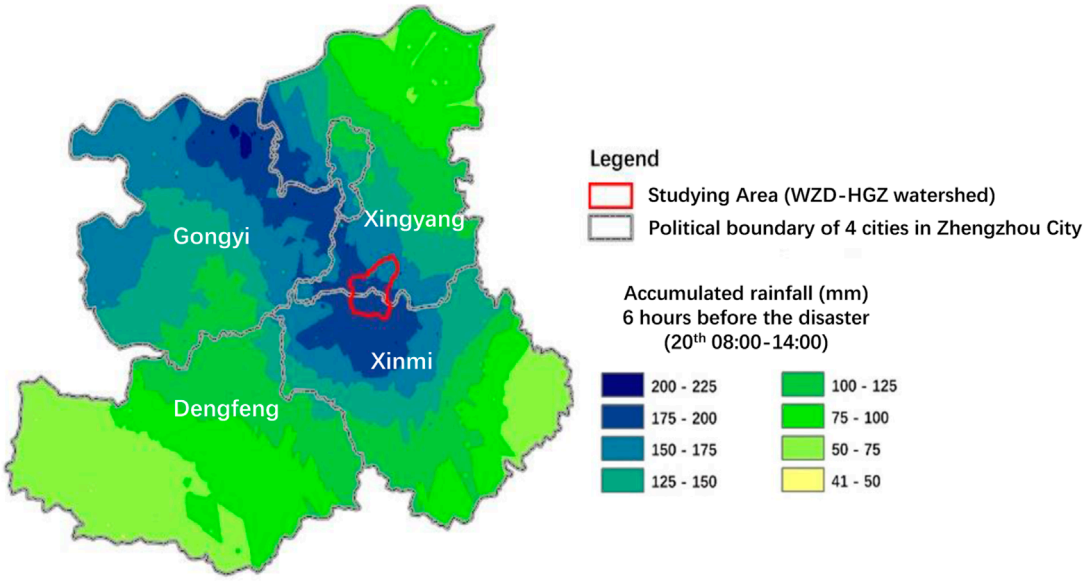

FIGURE 6
6-h accumulative rainfall observed in the western mountainous area of Zhengzhou City (8:00–14:00 on July 20) where the studying area, i.e., the WZD-HGZ watershed, is marked within the red boundary.

TABLE 2 Areal average rainfall analysis of the WZD-HGZ watershed.

Watershed	River	Location of controlled cross-section	Area (km^2)	Areal average rainfall				
				Number of representative rain gauges	Observation (mm)		Return period (years)	
					1-h	6-h	1-h	6-h
Upstream	Souhe River	WZD community	22	3	70.5	240.5	10–20	More than 500
Downstream	Souhe River	HGZ group	43	5	62.3	229.3	10	500

downstream watershed controlled by HGZ, the maximum average rainfall intensities for 1 h, 6 h, and 24 h are 62.3 m, 229.3 m, and 526 m, respectively. Meanwhile, the measured maximum rainfall intensity for 1 h corresponds to a return period of approximately 20 years, while the 6-h maximum rainfall intensity corresponds to a return period of approximately 1,000 years. In the downstream area, the maximum 1-h rainfall intensity approaches a return period of approximately 10 years, while the 6-h rainfall intensity corresponds to a return period of approximately 500 years (Bureau, 2021).

Therefore, Combined the results with the onsite investigation (see Table 1; Figure 4), the rainfall characteristics in the WZD-HGZ watershed are as follows: Firstly, there is a large cumulative amount throughout the event, with a total rainfall of 764.5 mm, which is 4.9 times the annual average rainfall (156.5 mm). Secondly, the rainfall duration was long, spanning four to 5 days. Additionally, the rainfall intensity was high, with the maximum rainfall in a 6-h period on July 20 exceeding a 500-year return period event.

3.2 Flood simulation in the WZD-HGZ watershed

3.2.1 WZD watershed flood process analysis

Based on the records from the water level station located near the WZD community (which was destroyed at 13:00 on July 20), and combined with relevant information from victim interviews, a hydrograph of the upstream WZD watershed was generated. This hydrograph is depicted in Figure 3C.The water levels before 13:00 are measured by the station while after 13:00 are estimated by the on-site survey. From 13:15 to 13:30, the flood depth at the cross-section increased by 7.15 m, with a maximum flow velocity of 2.4 m/15 m. At around 13:00, the flood inundated Road G234 with a maximum depth of 263.3 m. To identify the factors leading to the sudden increase in flood depth, combined with on-site investigations, it was found that in the WZD watershed, there are three concentrated drainage channels, with two casualty locations. One is located near Tangnao

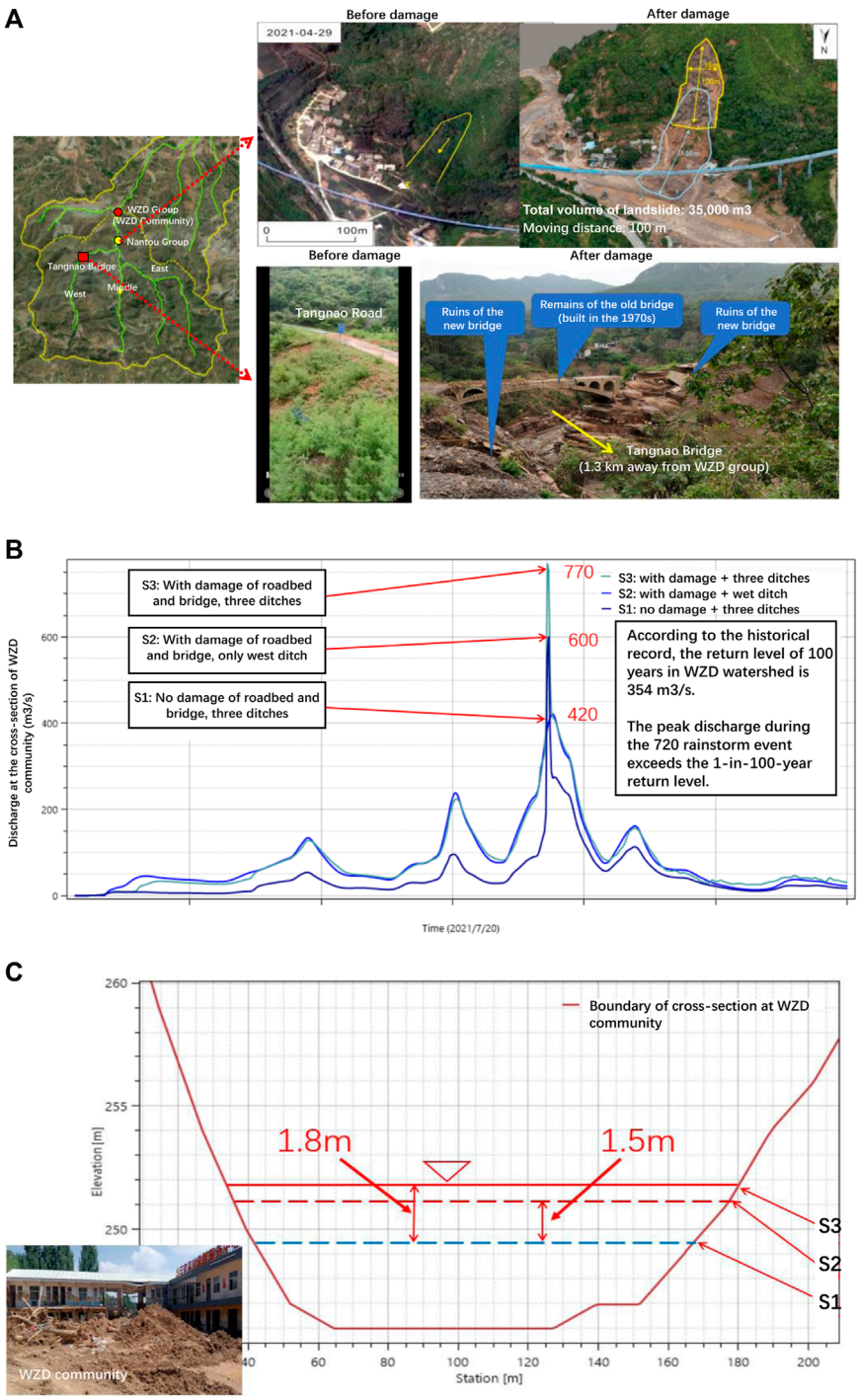

FIGURE 7
Onsite investigation: water block due to landslide, roadbed and bridge damage **(A)**; discharge simulated at the cross-section of WZD community (upstream watershed) under three scenarios **(B)**; water level corresponding to the peak discharge of three scenarios at the cross-section of WZD community **(C)**.

Bridge, where the embankment of the bridge suffered severe damage during the event. The other is near Nantou Cluster, where a landslide damaged the drainage channel (see Figure 7A). Therefore, to identify triggering factors, three different flood simulation scenarios were generated using the HEC-RAS model, as shown in Figure 7B:

The first scenario only considers the natural flow process of the three drainage channels, with a peak flow of 420 m^3/s (as shown by the blue curve in Figure 7B), which matches well with the measured flow at the same cross-section. The second scenario accounts for water resistance caused by embankments, bridges, and landslides, assuming that only the West Channel triggers floods

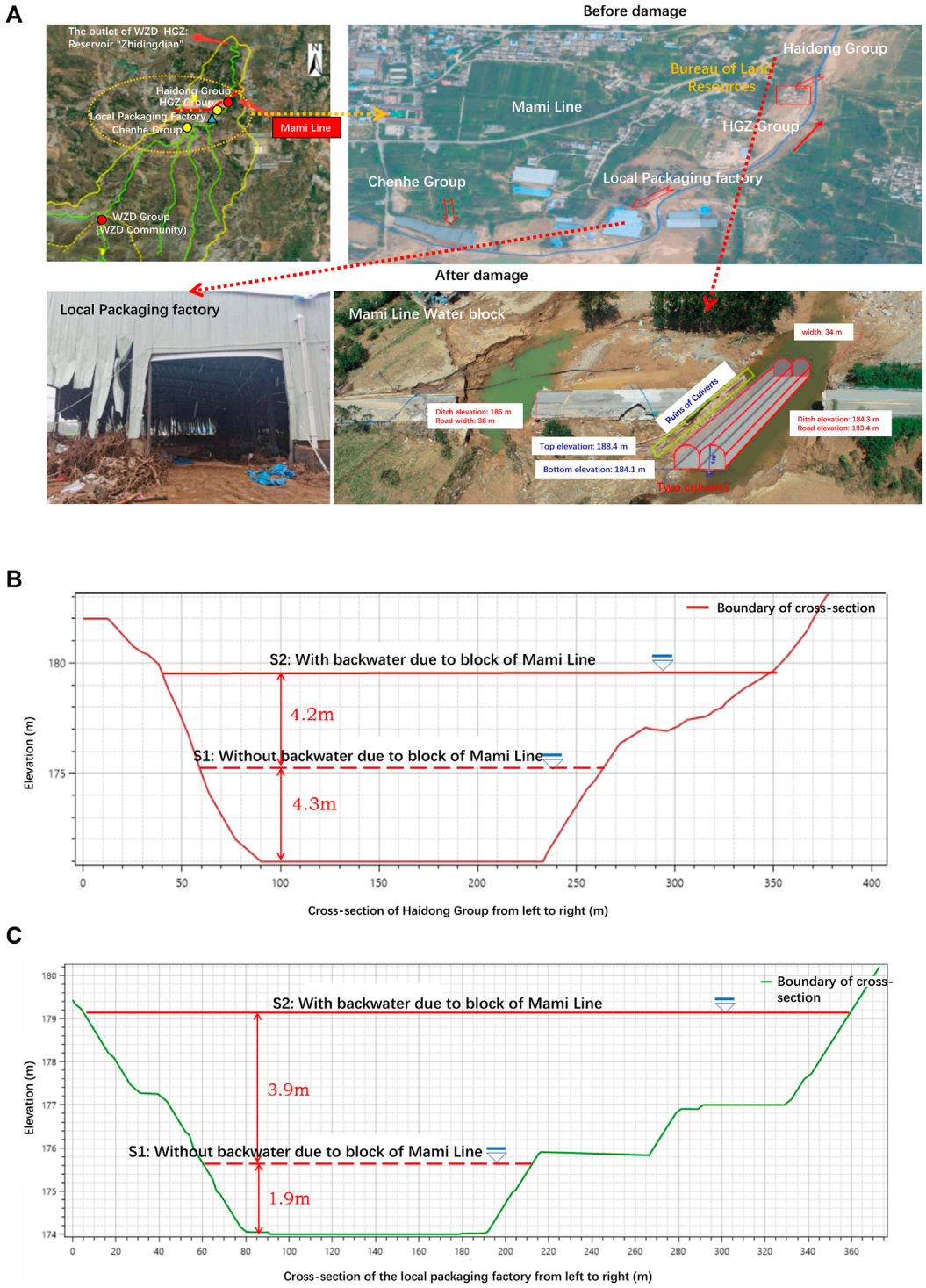

FIGURE 8
Onsite investigation: water block due to damage of factory and Mami Line **(A)**; water level corresponding to the peak discharge at the cross-section of Haidong group (downstream watershed, **(B)** and local packaging factory **(C)** under two scenarios.

while the other two channels remain dry; with a peak flow of 600 m^3/s (marked as the dark blue curve in Figure 7B). The third scenario considers both water resistance and concentration in the three drainage channels, with a peak flow of 770 m^3/s (marked as the green curve in Figure 7B).

Comparing the simulation results of the three scenarios with the measured peak flow, it was found that the third scenario exhibited excellent consistency. Approximately 60% of the flow can be attributed to the higher peak flow caused by the convergence of the three drainage channels, while the remaining 40% can be

attributed to the accumulation of debris blockages resulting from multiple damaged embankments, bridges, and landslides. Clearly, there is a noticeable spike in the peak flow rate once these drainage areas are cleared, as illustrated in Figure 7C. In contrast to the flood events typically triggered by intense precipitation, the water level at the WZD section saw an elevation of 1.8 m. Considering historical records and isohyet maps of heavy rainfall in Henan Province, the simulated peak flow corresponds to a return period of 200–300 years.

3.2.2 HGZ watershed flood process analysis

The results for the downstream watershed are as shown in Table 1c, Figure 8. The water level at Haidong Group rose by 11.2 m, with a maximum rising velocity of 2.1 m/3 m (from 13:57 to 14:00 on July 20). The highest water level reached 195.5 m, which is 2.1 m above the road surface of the Mami Line. The investigation revealed that, in addition to the substantial rainfall, the collapse of a nearby packaging plant also obstructed the river's drainage. This blockage notably reduced the flow capacity of the two culverts located beneath the Mami Line, leading to a worsening of the disaster through the creation of a backflow effect. In the HGZ watershed, two scenarios are considered: one where the obstruction of the Mami Line causes backflow and one where it does not. Using the hydrological model, water levels were simulated for both scenarios with and without backflow at Haidong Group and the local packaging factory. It can be observed that the water levels at the two cross-sections increased by 4.2 m and 3.9 m, respectively. However, based on the measured value of 908 m^3/s, the impact of backflow is limited. Meanwhile, at Chenhe Group, approximately 1 km away from Haidong Group, flooding is minimally or not affected by backflow due to the damage to the Mami Line. Furthermore, the first scenario captured the measured values: at Chenhe Group, a flow similar to that of a broad-crested weir was obtained, with a headwater level of 2.83 m, an average river width of 113.83 m, and a weir width of 70 m.

3.3 Mechanism analysis for leading to disaster

Based on on-site investigations, interviews with victims, and model simulations, the following explores the factors leading to the massive casualties in the WZD-HGZ watershed, summarized primarily into four aspects, as shown in Figure 9.

3.3.1 Special topography and river regime

Village WZD is located close to the confluence of the three ditches (East, Middle and West presented in Figure 1), with a short distance to the headwaters of these ditches. The special topography results in the simultaneous flooding in the single ditch and the soil slopes on both sides of the ditches. Besides, The flood flow velocity at the confluence is extremely high, reaching 6 m/s. Such landforms and fluvial dynamics complicate the precise functioning of flood surveillance, alert systems, and emergency responses, presenting considerable difficulties for evacuation initiatives in the area. In particular, the Nantou Group community in WZD village, located on the convex bank of the channel, was severely affected by the high-flow, high-speed flood, resulting in the destruction of many houses, with casualties accounting for over half of the villagers.

3.3.2 Continuous disruption of infrastructure

In WZD village, there are 31 embankments and silt dams of various sizes, among which only two have flood discharge capabilities, while eight silt dams and small reservoirs with a capacity of less than 100,000 m^3 are unable to control floods. These infrastructures were damaged, severely blocking the upstream water sources. Due to heavy rainfall, 27 embankments, small reservoirs, and silt dams were continuously washed away, especially the embankment of the Tangnao Road, which is only 1.3 km away from the WZD group. Although the embankment height is 16 m, which is 50 m lower in elevation than the WZD group, the blocked water volume is 103,200 m^3, resulting in a nearly 2-m increase in downstream flood depth and maintaining a high-water level on the road surface for about 3 h, greatly exacerbating the disaster in WZD village. To quantify the impact of damaged infrastructure, based on the on-site investigation on 5 September 2021, the simulation of the flood process in WZD, as shown in Figure 7, was conducted. It confirmed that the collapse of the Tangnao Road caused blockage, which is the main factor exacerbating the flood disaster in WZD village.

In the WZD community, the water level increase due to the damage to these infrastructures is 1.8 m compared to the normal rainfall runoff process, reaching a maximum of 7.5 m. Taking into account the natural convergence time of the three channels, the flood is expected to overflow the embankment of the Tangnao Road around 11 a.m., with the road collapsing completely by 1 p.m. The flood level begins to rise between 12:30 and 1 p.m., while the maximum rainfall intensity (58.5 mm/h) occurs between 2 p.m. and 3 p.m. In other words, the flood peak caused by the embankment damage occurs earlier than the flood peak caused by the rainfall-runoff response. Therefore, the sustained high-water level is not caused by intense rainfall.

3.3.3 Damaged buildings accelerated backflow

Another factor is that buildings, roads, and bridges constructed along the channel were destroyed, leading to debris accumulation, which exacerbated the disaster by causing backflow. The buildings located in WZD Group were damaged seriously, which narrows the ditch by 21%. Several local factories are situated in the alluvial area of the ditch, which narrows the cross-section of the overflow by 71%. Besides, WZD village has three bridges, with small openings that severely limit the flow. These bridge openings are blocked by a large amount of sediment and floating debris carried by the water flow, such as branches, vehicles, and debris from buildings. Therefore, When a large amount of water is retained, if a blocked bridge collapses, the speed and depth of the released floodwaters rapidly increase, leading to downstream disasters.

According to the investigation, the railway line, Mami Line, crosses the Su River, standing 9.1 m above the downstream watershed channel. Below the railway surface, there are two culverts with the size of 4 × 4 m, which are designed for releasing water. However, during the rainstorm event, one culvert was blocked, which totally reduces the cross-section for passing flow by more than 90% and the discharge capacity is only 80 m^3/s. Therefore, the peak flow rate (i.e., 908 m^3/s) is trapped at the Mami Line, causing

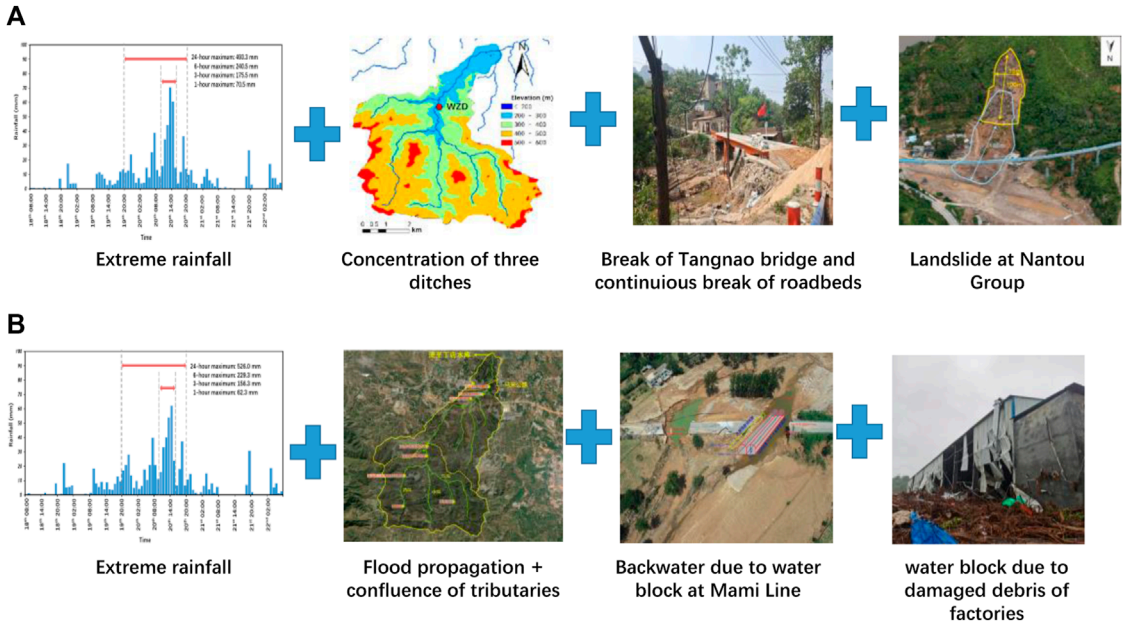

FIGURE 9
Underlying reasons identified in WZD watershed **(A)** and HGZ watershed **(B)**.

the water level to rise by approximately 4 m upstream, resulting in 4 deaths in the Haidong Group and 13 deaths in the factory. To quantify the impact of backflow, the cross-section with the highest number of casualties was chosen, and water levels were simulated considering both the blocked and unblocked scenarios of the Mami Line. Compared to the response of runoff to rainfall and flow rates, the flooding levels in the Haidong Group increased by 4.2 m due to backflow, while the flooding levels in the local materials factory increased by 3.9 m.

3.3.4 Low-effective evacuation for flash floods

This disaster causing such serious consequences can be also attributed to the lack of public awareness of flash flood risk prevention. The local government did not realize that during heavy rainfall, infrastructure damage could block floodwaters, causing a sharp increase in flow and raising potential flood risk. Besides, the local management of flash flood risks was improperly implemented. During the revision of the management plan in 2021, several areas that could be affected by river flooding were even removed, increasing the number of residents facing risk. The flood risk management officials did not take timely action upon receiving the "immediate evacuation" warning, mainly evidenced by: (1) no warning was issued to the public near ditches and rivers in WZD Village; (2) residents in low-lying areas of Cuimiao Village were not forcibly evacuated, and local factories were only instructed to temporarily shut down without evacuating their employees. Therefore, the lack of disaster awareness, coupled with the slow response to warning information, should a congested bridge succumb to the pressure of the retained water volume, the consequent release results in a swift upsurge in both the velocity and depth of the floodwaters, exacerbated the scale of the disaster.

3.4 Recommendations of early warning information

One automatic rain gauge recorded a 24-h rainfall of over 120 m in Xingyang City, reaching the "immediate evacuation" warning level, while the rainfall recorded by two other rain gauges did not reach the warning level. Thus, the Xingyang City Water Resources Bureau issued a warning to the public at 22:28 on 19 July 2021.

Although the Bureau issued a peer-to-peer warning of "immediate evacuation" 14 h in advance, the information did not convert into effective action, which leads to great casualties and economic loss. It is important not only to identify triggering factors as outlined in Section 3.3 but also to analyze the public's attitude upon receiving the warning. In recent decades, many studies have explored the underlying reasons why the flood early warning system runs less effectively. For example, the World Meteorological Organization (WMO) released the "Flood Forecasting and Warning Manual" in 2014, which found that the local perspective and attitudes of people have a greater influence on outcomes than the technical aspects of flood forecasting and response systems. Ling and He (2020) applied social psychology theories, particularly persuasion psychology, to find that flood defense knowledge dissemination typically follows persuasive theories in conveying information to the public.

Flash flood warnings are an "end-to-end" operation, demanding high timeliness, which means a successful warning relies on the public's awareness of defense measures. In the progress from issuing a warning to taking action, there are five psychological barriers needing to be removed, i.e., noticing the warning, understanding the warning, believing in the warning, remembering the warning and taking precautions or evacuation (see Figure 10). During

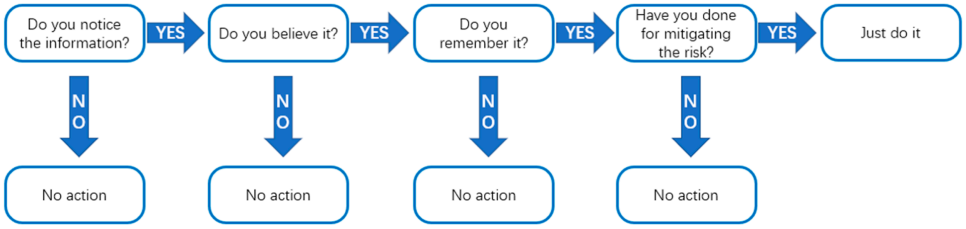

FIGURE 10
The chain of the transition from issuing a warning to taking precautionary or evacuation actions.

on-site investigations, it was found that after the warning was issued, local officials and residents generally harbored doubts, primarily attributing this to the absence of severe floods in recent years. People lack basic knowledge about flash floods and how to prevent them, including preventative measures, with a particular shortfall in recognizing imminent local hazards and their specific locales. Besides, although many departments issued warnings, local personnel found it difficult to understand professional terms such as "implementing level three response" and "issuing level two warning," increasing the difficulty of filtering the most valuable warning information. The aforementioned issues could potentially interrupt the chain illustrated in Figure 10, resulting in evacuation failure.

In addition, since the WZD-HGZ watershed locates in part of regions of Xingyang City and Xinmi City, where three locations (i.e., Village Wenzhuang of Xinmi City, Village WZD and Cuimiao of Xingyang City) along ditches observed serious casualties, it reveals that defending flood should be implemented in the unit of watershed rather than administrative region. To be detailed, firstly, the actual rainfall measurements in Xinmi City serve as real-time indicators for issuing alerts to neighboring cities, but the Xingyang City flood warning system struggles to capture this data. Additionally, the system can provide effective rainfall monitoring information from rain gauges in Xinmi City, which could enhance the rainfall data in the WZD-HGZ watershed. Secondly, there is no communication between administrative districts along the same river. In such a case, the flood propagation time in the WZD-HGZ watershed is approximately 40 min; evidently, information needs to be effectively transmitted between upstream and downstream areas.

4 Conclusion

The article focuses on the extraordinary heavy rainfall that occurred in Henan Province in 2021. Through on-site investigations, interviews with victims, remote sensing image analysis, hydrological model simulations, etc., it analyzes the characteristics of extreme rainfall and corresponding floods in the severely affected WZD-HGZ watershed. The study aims to explore the fundamental reasons for the severe casualties, and the specific conclusions are as follows.

1) The "720″heavy rainfall and flash flood in Henan were primarily caused by prolonged intense rainfall, which was exacerbated by the complex terrain, steep slopes, and human activities. The flood magnified in three main stages: runoff generation and concentration-induced flooding, continuous damage to the roadbed, and backwater effects caused by blockages of roads and bridges.
2) The reasons for the severe casualties and the difficulty in effective evacuation can be attributed to the confluence of floodwaters from three ditches, the rupture of the Tangnao Road roadbed in the west ditch, and water blockage caused by the Mami Line downstream in HGZ. The water blockage occurred before the peak rainfall arrived, causing the water level to remain high for an extended period. The rupture of Tangnao Road elevated the water level to around 2 m, and the rupture of the Mami Line raised the water level at local factories and the Haidong Group to about 4 m.
3) Considering both social psychology and watershed flood control, the article analyzes the evacuation and warning issuance mechanisms. It finds that the main reasons for the disruption in the chain from issuing a warning to taking preventive or evacuation actions are a lack of basic knowledge about flash flood risk prevention, unclear warnings, and insufficient guidance.

In conclusion, for ungauged basins, establishing an appropriate data monitoring network and developing a data quality assessment plan are crucial for enhancing flash flood risk management. Moreover, warnings must be conveyed in a manner that is both explicit and directive, enabling the public to respond effectively. Different departments should strengthen communication to ensure the continuity of the chain from issuing warnings to taking preventive measures or evacuation actions. Additionally, data quality should be further examined to improve simulation accuracy.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding authors.

Author contributions

BH: Data curation, Funding acquisition, Methodology, Writing–original draft, Writing–review and editing. CL: Methodology, Validation, Writing–original draft, Writing–review

and editing. QY: Formal Analysis, Software, Writing–original draft, Writing–review and editing. HW: Project administration, Visualization, Writing–original draft, Writing–review and editing. LL: Writing–review and editing. MM: Funding acquisition, Methodology, Project administration, Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Monitoring and disaster prevention of high and steep sandstone slopes along highways under construction

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High and steep sandstone slopes along highway line are at high risk of disasters such as landslides, cracking of support structures, and so on. The monitoring, early warning, and emergency response of such slope disaster face enormous challenges, especially during the rainy season. In this paper, intelligent monitoring, early warning and forecasting system were carried out for the high steep sandstone slope with a transmission line tower at the slope crest along the highway under construction in Guangxi, China. The automatic monitoring data, emergency rescue program and rescue effect were analyzed, and emergency rescue measures for high steep slope protection were taken. The research results show that timely access to disaster warning information can effectively support the analysis of disaster causes and the evaluation of disposal programs. Deep-hole monitoring of deformation characteristics can determine the stable state of slopes, and the tangent angle warning criterion can be used for early warning and prediction of high steep slope landslides. By analyzing the location of the sliding surface and taking timely emergency disposal measures such as layered counterpressure method and micropipes, the landslide activities can be effectively controlled to prevent further acceleration of slope collapse. This study can provide an important reference for the monitoring, early warning, forecasting and emergency rescue of sandstone slopes along highways under construction.

KEYWORDS

high-steep slope, monitoring and early warning, tangential angle, emergency rescue, solpe deformation

1 Introduction

With the increased traffic density and infrastructures constructed in mountainous areas of southwest China, slopes are gradually common along the expressway and high-speed railway (Li et al., 2020). In the meanwhile, Some rock masses such as siltstone shows obvious water sensitivity and disintegration due to disparity in material compositions and pore structures (Vivoda Prodan et al., 2017). Thus, it can increase the susceptibility of sliding and collapsing of slopes, resulting in cracking and failure of supporting structures (Taalab et al., 2018). The impact of rainfall on these processes has been critically analyzed, showing how different rainfall conditions exacerbate slope instability (Li et al., 2022; Li et al., 2023). In recent years, the engineering failures and disasters have a significant increase in quantitative terms and pose

a serious threat to the safety of construction personnel and equipment (Wang et al., 2015; Yang et al., 2022). Research into the dynamic response characteristics of these slopes under seismic influences also highlights an increased risk in regions prone to earthquakes (Shi et al., 2024).

The effective monitoring and early warning of the slope-related disasters are important means to reduce the loss of life and property caused by landslides (Gariano and Guzzetti, 2016). Currently, traditional monitoring technology is relatively mature and has achieved good results in practical engineering applications. However, it did not get wide-spread popularity due to its intrinsic disadvantages, such as large field workload, poor monitoring timeliness and small monitoring area (Yang et al., 2020). With the rapid development of optoelectronics, big data and communication technology, the research and development about monitoring equipment and systems for geotechnical and geological disasters have been greatly promoted (Xu, 2020a; Zhu et al., 2024). In terms of the monitoring means, the advanced detection devices and means have been developed, such as 3S technology integrating Global Positioning System (GPS), Geographic Information System (GIS) and Remote Sensing (RS) (Yong et al., 2022). Besides, Time Domain Reflection (TDR) technology, 3D Laser Scanning technology (Xie et al., 2013), Interferometric Synthetic Aperture Radar (InSAR) technology (Xu, 2020b), Close Range Photogrammetry (Scaioni et al., 2015), Distributed Fiber Optic Strain Sensor (DFOSS) (Wang and Shi, 2010; Zhang et al., 2018), Interface Newtonian Force (INF) and Shape Acceleration Array (SAA) technology are also applied to monitor deformation popularly (Uhlemann et al., 2016). The innovative use of UAV nap-of-the-object photogrammetry has further enhanced our ability to identify potential rockfalls (Wang et al., 2022; Yan et al., 2023). Furthermore, sophisticated models for assessing the risk of unstable rock masses have been developed to improve safety measures on such slopes (Tao et al., 2021). The multi-level and multi-angle monitoring data can be achieved through these techniques from point to surface, from slope surface to interior of rock and soil body and from macrocosm to microcosmic based on different spatial dimensions of monitoring through "space-sky-earth-depth," significantly promoting the intelligence and information about the potential disasters, and improving the efficiency and reliability of the potential disasters monitoring (Dai et al., 2020).

The monitoring and early warning means and systems are important tools for identifying and forecasting potential geological disasters (Xu, 2020a; Dai et al., 2020). Since the landslide forecasting model was established based on soil creep characteristics, the study on early warning models for landslide has gained significant attention from many researchers (Guzzetti et al., 2020). There are many early warning models and discrimination methods put forward for applications in forecasting landslide (Xu, 2020b; Liu, 2021; Qin et al., 2021). In addition, quite a few forecasting models are established based on the displacement or deformation data. For instance, Xu et al. (2008) optimized the "Saito model" and further divided the accelerated deformation stage into initial acceleration stage, middle acceleration stage and critical-sliding stage, pointing out that the time-space evolution of landslide in the model should be comprehensively considered in landslide early warning and forecasting (Xu et al., 2008; Xu, 2020a; Xu et al., 2024). Moreover, a series of early warning methods selected the tangent angle as the landslide criterion are also proposed. Chen et al. (2015) proposed a method for analyzing the evolution law and predicting the early warning time of landslide based on the kinetic energy-time and kinetic energy change rate-time relation curves. In-depth analysis of deformation characteristics in high-steep slopes provides crucial insights into the interaction between geotechnical structures and bridge substructures, which is fundamental in designing more resilient infrastructural elements (Zhang et al., 2022).

In this paper, automatic monitoring, early warning, and forecasting are carried out on typical high-steep slopes along the highways under construction. The engineering measures taken during the slope rescue process and their effects to the causes of instability, early warning and forecasting methods are analyzed and discussed. The engineering rescue measures for the high-steep sandstone slopes have important theoretical and practical significance for guiding the design and construction, and also for decision-making and implementing emergency disposal measures.

2 Engineering conditions and monitoring arrangement

2.1 Geological conditions

The Naliang slope along the Tian'e-Beihai expressway under construction from Bama town to Pingguo town were considered as the study area. The tunnel area is located within Dahua Yao Autonomous County, on the northern edge of the South Asian subtropical monsoon climate zone, characterized by mild climate and rain heat occurring in the same season. The average annual temperature is between 18.2°C and 21.7°C, with annual rainfall ranging from 1,249 to 1,673 mm, making it suitable for outdoor work most of the year. The tunnel area has an erosive low mountain landscape with significant topographical undulations. The proposed tunnel will traverse the same mountain body, with surface elevations ranging approximately from 219.33 to 276.50m, a relative height difference of about 57 m, and the maximum burial depth of the tunnel is about 57.9 m. The natural slope angles of the entrance and exit sections of the mountain range from 20° to 50°. The Quaternary cover layer in the tunnel area is locally thick, with well-developed surface vegetation mainly consisting of shrubs, eucalyptus, pine, etc.

Based on drilling and engineering geological surveys, the strata are primarily composed of Quaternary colluvial layers (Qel+dl) and Middle Triassic BaiFeng Group (T2b), detailed as follows.

(1) Silty Clay: Hard plastic; brownish-yellow, uniform soil quality, mainly silty particles, smooth cut surface, core shows columnar soil structure, with a large amount of plant roots between 0 and 0.4 m, representing the hillside topsoil, drilling reveals a thickness of 3.0 m.
(2) Gravel: Semi-dense to dense; reddish-brown, slightly moist, mainly composed of highly weathered sandstone and muddy sandstone, with particle sizes of 2–8 cm, angular to sub-angular, about 60% content, filled with sticky soil and gravel. Drilling reveals a thickness of 1.6–4.0 m.
(3) Highly Weathered Sandstone: Grayish-yellow, sandy structure, thin to moderately thick layering, developed joint fissures, iron-manganese staining visible on fracture surfaces,

approximately 45°–50° orientation, interlayered with thin sandy shale layers, slightly soft and brittle rock, generally 10–40 cm thick, unevenly distributed with no regular pattern. Core integrity is poor, very fragmented, core pieces are blocky, fragmentary, and partially short-columnar, drilling reveals a thickness of 13.3–15.0 m.

(4) Moderately Weathered Sandstone: Dark gray, sand-mud structure, thin to moderately thick layering, interlayered with thin sandy shale layers, rock layer inclination about 65°–70°, with developed joint fissures in the 14.9–20.9 m segment, commonly filled with iron, steep inclination, core mainly columnar, node lengths 7–32 cm, secondary in block and pie shapes, harder rock quality, RQD = 48. Only revealed by drilling SS438-2, thickness is 15.1 m.

According to the regional geology and on-site geological survey, there is a regional fault near the river gorge about 800 m northwest of the tunnel site intersecting with the line, with a strike of about 300–340°. The fault has been stabilized at present, and the impact of the fault on the tunnel site area is relatively small. The tunnel site is mainly a monoclinic structure with extremely developed joints and fissures, which has a greater impact on tunnel excavation. The measured rock formation at the tunnel site is 332°/SW∠51°.

2.2 Supporting scheme of the slope

The engineering section changed from the original Naliang tunnel to an open-cut slope expansion scheme, with a high slope of about 75 m formed on the left side of the expressway. There were six-stage supporting schemes used for the slope. The first stage was a single row of anti-slide piles with a diameter of 2 m, the second stage was anchor-pile support with lattice beams at a slope rate of 1:0.75, and the third to sixth stages were anchor-pile support with lattice beams at a slope rate of 1:1 (Figure 1).

2.3 Monitoring arrangement

The displacement, deformation, stress, environmental impact, and other factors for the Naliang slope were monitored in real-time with various monitoring methods. The monitoring data can guide the on-site construction and provide an accurate basis for the treatment design, thus realizing information utilization and dynamic design. In terms of the development of the slope and the need for on-site monitoring, different monitoring arrangement and content are carried out into two stages. The first stage is the monitoring of Nanliang slope before instability. The monitoring type is displacement monitoring, including surface displacement, deep displacement, settlement of tower foundation, horizontal displacement of tower foundation and tower tilt. The monitoring methods used include GNSS displacement monitoring, micro-variation radar, in-place inclinometer, hydrostatic level and total station. The second stage is the monitoring of Nanliang slope after rescuing and applying counterpressure. The monitoring type is displacement monitoring and environmental monitoring, including surface displacement, deep displacement and rainfall. The monitoring methods used include total station and in-place inclinometer. The monitoring location layout of these two stages can be obtained in Figure 1.

During the construction stage (first stage), different targeted points were arranged for monitoring the artificial surface displacement, deep displacement and axial force of anchor cable respectively. One settlement observation point was arranged at the bottom of the tower. Based on the original monitoring points, including a deep displacement monitoring point, 16 artificial surface displacement monitoring points within a total station and two anchor pile stress measuring points, an environmental meteorological monitoring station was added.

3 Development of slope deformation and sliding

3.1 Initiation of sliding

The excavation and construction of Naliang slope started from March 2021. The monitoring for the slope was carried out simultaneously. On April 3, the deep displacement inclinometer borehole, namely, CX2-1 showed an obvious turning point at the depth of 18 m. From April 3 to 5, the differential settlement of the hydrostatic leveling measuring point on the top of the slope for the 620# tower base was 1.91 mm and 0.29 mm, respectively. The tower showed a tilting tendency towards the main subgrade line. On April 26, the deformation rate of the deep displacement inclinometer borehole, namely, CX2-1 reached 2.3 mm/d at the position of 15 m, with an accumulated displacement value of 5.5 mm. The peak speed was 6.5 mm/d at the depth of 5 m, with a peak accumulated displacement of 15.8 mm. The horizontal displacement rate and the vertical displacement rate were 3.14–8.84 mm/d and −0.89–6.11 mm/d, respectively. Besides, the horizontal and vertical accumulated displacements were 8.17–23.17 mm and −2.84–15.96 mm/d, respectively. Then, the slope entered the state of moderately accelerated deformation. Subsequently, the supporting scheme was adjusted, and the reinforcement measures of arranging three rows of steel piles on the third stage platform and three rows of anchor piles on the sixth stage platform were adopted (Figure 1).

3.2 Sliding development and rescue

On 14 June 2021, the deformation rates of the deep displacement inclinometer boreholes, namely, 2-CX1, 2-CX2, and 2-CX3 in the main monitoring section of the slope increased to 12.84 mm/d, 14.80 mm/d, and 19.60 mm/d respectively. After that, the slope entered the high-speed deformation stage, and the tangent angle of the deep accumulated displacement-time curve reached 83°, triggering the critical-sliding. The maximum accumulated deformation of the slope reached 51 mm from 21:00 on June 17 to 15:00 on June 18. As to the maximum deformation period, the converted daily rate was 144 mm/d. The slope continued deformation until 15:50 on June 19, and local failure occurred on the slope surface during the first to second grade. The damage and crest cracks are shown in Figure 2 and Figure 3.

After the critical-sliding triggered, counter pressure was applied to the toe of the slope. The counter pressure was applied on

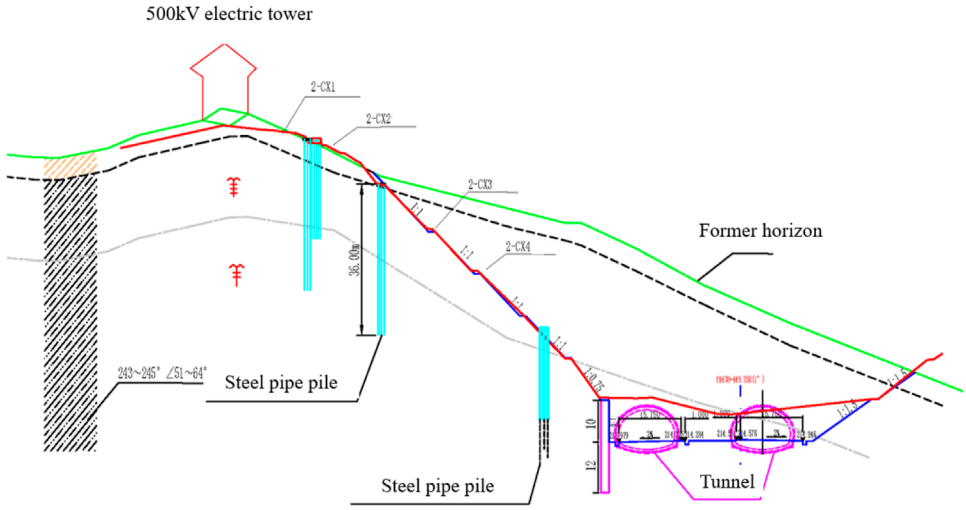

FIGURE 1
Deformation result before the Naliang landslide.



FIGURE 2
Local engineering failure in the field.



FIGURE 3
Crest cracks appearing in the slope failure process field.

the first to third stage platforms with a height of 37 m. In addition, three rows of anchor piles were set on the slope crest for reinforcement and matched with the concrete anchorage and tensioned steel cables to confine the deformation of the pile top and power tower seen from Figure 4. As of June 26, after the first-stage rescue construction, the development trend of the horizontal displacement rate of surface monitoring points and that of deep horizontal displacement showed a downward convergence trend. The axial force of the slope anchor cable was maintained within the allowable range.

3.3 Tangent angle theory

In general, the relationship between the slope deformation curve and the tangent angle over time, as shown in Figure 5, can be divided into three stages. The first stage is the initial deformation stage, where the slope is in a decelerating deformation state, the deformation rate gradually decreases, and the displacement gradually increases. The displacement-time curve flattens, which is reflected in the geometry of the curve where the tangent angle increases from small to large. The second stage is the steady-state stage, where the deformation rate tends to a constant value. The displacement-time curve is approximately linear, with the tangent angle and rate being nearly constant, indicating a constant-rate deformation state. The third stage is the accelerated deformation stage, where the deformation rate gradually increases, and the displacement-time curve becomes steeper. Thus, the curve reflects



FIGURE 4
Rescue construction for the Naliang slope.

an accelerated deformation state, and the tangent angle increases with the rate. It can be observed that the increase or decrease in the tangent angle of the displacement-time curve can reflect changes in the deformation rate. If the tangent angle continuously increases, it indicates that the deformation rate is also continuously increasing, meaning the deformation is in the accelerated stage. Conversely, if the tangent angle decreases, it indicates a decelerating deformation stage. If the tangent angle remains constant, it means the deformation rate remains unchanged, indicating a constant-rate deformation state. Based on this characteristic, the deformation state of the slope can be determined.

4 Early warning and rescue measure

4.1 Analysis of monitoring data

4.1.1 Analysis of the deep displacement monitoring data

From June 9 to 18, 2021, within 10 days before the rescue for the collapse, the cumulative displacement-rate curves of each deep inclinometer borehole generally developed at a certain slope with time. On June 14, the deformation rate of each borehole increased to 12.84–19.60 mm/d, and the slope was in a state of high-speed deformation, triggering the first red critical-sliding alarm. The average displacement rate at the peak depth during this period was 5.08–6.20 mm/d, with a cumulative displacement of 45.72–55.81 mm in this stage. The maximum rate reached 19.90–30.26 mm/d, with the deformation developing till June 18. On June 18, the peak displacement accounted for 37%–54% of the cumulative displacement in stages. The deep displacement of the slope was in the critical-sliding acceleration stage (Table 1). Sliding surface depths and peak depths mentioned in the text are relative to the surface after excavation as a reference.

The impact period of the failure was from June 19, 2021, on which local failure occurred during the first to second-grade slope surface at the small mileage end of the slope. On June 21, 2021, the rescue construction began. Within 3 days, the average displacement rate of the peak depth was 18.27–60.13 mm/d, and the cumulative displacement in different stages was 164.46–541.20 mm. The displacement rate reached the maximum value of 102.24–440.03 mm/d on June 19 on which the slope collapsed, and the displacement on that day accounted for 62.2%–81.3% of the cumulative displacement in this stage (Table 2). The cumulative displacement curve of each borehole for the slope increased sharply, the tangent angle corresponding to different points were more than 80°, and the slope was in the sliding-failure stage. The rule of "large front, small back" in the previous period was amplified by the displacement rate and cumulative displacement of each inclinometer borehole. The ratio of the displacement rate to cumulative displacement from 2-CX3 to 2-CX1 at the top of the slope was about 3.3:1.6:1. From 2-CX3 to 2-CX2 and then to 2-CX1, the slope showed an obvious staged pattern, confirming that the failure of the slope belongs to a traction landslide (Table 2).

From June 22 to 2 July 2021, it was the construction period for the failure rescue. The average displacement rate at the peak depth of each inclinometer borehole during this period was 4.84–15.00 mm/d, 25%–28% of that in the previous sliding destruction period. The maximum rate was 21.06–30.03 mm/d, which decreased to 7%–21% of that in the sliding destruction period. The cumulative displacement during the 10 days was 48.41–149.98 mm, which decreased to 28%–31% of the cumulative displacement during the previous 3-day sliding destruction period. All monitoring data showed that the rate of deep displacement during this period was significantly lower than that in the previous periods. After the rescue construction began on June 21, the cumulative displacement-time curve rapidly transformed from the approximate vertical development in the previous period to the small-angle development. The displacement rate-time curve suddenly dropped from the peak point of the previous stage to the level before the slope collapsed and decreased continuously with time. It was shown that the rescue construction measures with counter pressure at the slope bottom and anchor piles under the power tower (on the top of the slope) had significant prevention effects on the deep displacement of the slope. With the increase of the completion degree, the anchor pile structure gradually restrained the sliding destruction trend. With the increase of the counterpressure height, the counterpressure body resisted the extrusion failure of the slope mass at the shear outlet (Table 3).

The observation period for the prevention of the slope was from July 3 to 13 August 2021. On July 2, the slope bottom was backfilled and counter-pressured to the third-stage platform at the height of 37 m. By August 13, the 620 # high-voltage transmission line tower on the top of the slope was successfully removed. The high-risk hidden dangers were eliminated, indicating that the rescue engineering for Naliang slope was completed successfully. The average displacement rate at the peak depth of each borehole during this period was 0.49–2.86 mm/d, which was 10%–33% of that in the previous construction period. The maximum rate was 6.33–11.65 mm/d, which was 29%–55% of that in the previous periods. After the completion of prevention construction, the deep displacement rate was further reduced. The accumulated displacement was 20.11–117.07 mm lasted about 40 days, with the low-speed deformation maintained. The cumulative displacement curve and displacement rate curve during this period presented approximately horizontal development tendency. At the end of July, a slight reaction occurred to the deep slope displacement caused

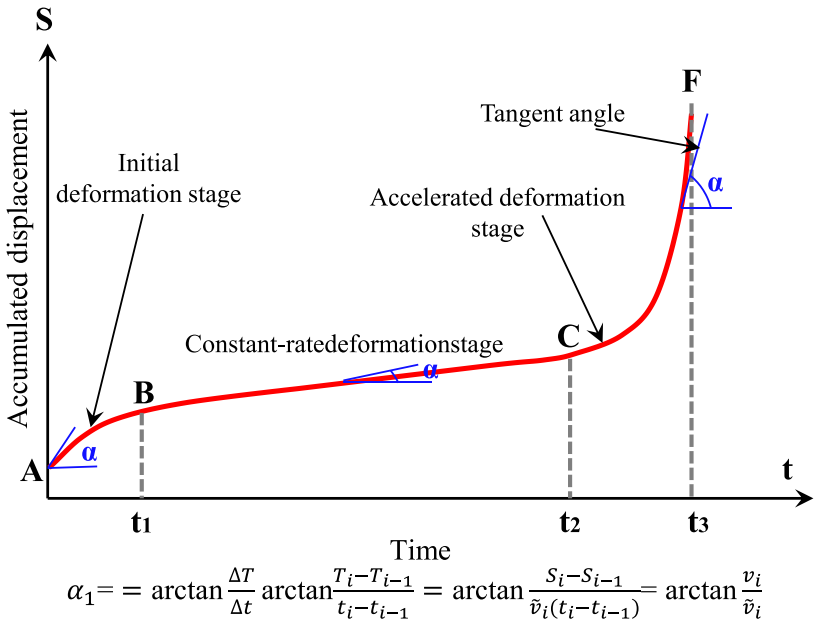

FIGURE 5
Different deformation stage in terms of tangent angle theory.

TABLE 1 Statistical table of deep displacement data from June 9–18, 2021.

No. Of inclinometer borehole	Sliding surface depth	Peak depth	Average displacement rate	Maximum displacement rate	Accumulated displacement in stages
	m	m	mm/d	mm/d	mm
2-CX1	−20.0	−0.5	5.08	21.19	−20.0
2-CX2	−21.0	−2.0	5.97	19.90	−21.0
2-CX3	−14.0	−2.0	6.20	30.26	−14.0

TABLE 2 Statistical table of deep displacement data from June 19–21, 2021.

No. Of inclinometer borehole	Sliding surface depth	Peak depth	Average displacement rate	Maximum displacement rate	Accumulated displacement in stages
	m	m	mm/d	mm/d	mm
2-CX1	−20.0	−0.5	18.27	102.24	164.46
2-CX2	−21.0	−2.0	29.74	200.65	267.65
2-CX3	−14.0	−2.0	60.13	440.03	541.20

by rainfall and the curve rose slightly. Combined with the rainfall monitoring data, the total rainfall did not reach 5 mm for more than half a month before heavy rainfall occurred at the end of July. A large loose deposit remained on the slope surface after the slope collapsed, and smaller displacement of the unstable soil layers occurred due to the infiltration of a large amount of rainfall. The emergency rescue measures with counter pressure on the bottom of the slope and anchor piles under the power tower on the top were treatment measures, which were not designed as permanent prevention means. Therefore, during this period, the deep displacement of the slope fell

TABLE 3 Statistical table of deep displacement data from June 22 to 2 July, 2021.

No. Of inclinometer borehole	Sliding surface depth	Peak depth	Average displacement rate	Maximum displacement rate	Accumulated displacement in stages
	m	m	mm/d	mm/d	mm
2-CX1	−20.0	−0.5	4.84	21.82	48.41
2-CX2	−21.0	−2.0	8.20	21.06	81.99
2-CX3	−14.0	−2.0	15.00	30.03	149.98

TABLE 4 Statistical table of deep displacement data from July 3 to August 13, 2021.

No. Of inclinometer borehole	Sliding surface depth	Peak depth	Average displacement rate	Maximum displacement rate	Accumulated displacement in stages
	m	m	mm/d	mm/d	mm
2-CX1	−20.0	−0.5	4.84	21.82	48.41
2-CX2	−21.0	−2.0	8.20	21.06	81.99
2-CX3	−14.0	−2.0	15.00	30.03	149.98
2-CX4	−10.0	−8.5	1.28	6.56	43.49

to the state of low-speed deformation, but it did not converge to zero completely (Table 4).

According to the monitoring data of each deep displacement inclinometer borehole, the cumulative displacement-depth curves (Figure 6; Figure 7) were drawn. Then, the analysis of the deep inclinometer displacement curve of the main monitoring section was obtained (Figure 8). It can effectively guide the rescue construction by accurately inferring the depth and change trend of the sliding surface.

4.1.2 Analyzing monitoring data of surface displacement

The surface displacement was mainly monitored by GNSS. Meanwhile, the surface displacement and displacement change rate distribution were obtained with microvariation monitoring. During the rescue period, artificial surface displacement monitoring points were added. A total of a datum point and six monitoring points were set up before and after the construction and rescue period, and 17 artificial surface displacement monitoring points were added from 28 June 2021. The surface displacement monitoring was carried out to measure horizontal and vertical displacement, respectively.

From June 9 to 18 June 2021 (during the period before the failure occurred), the horizontal displacement rate of the measuring points, namely, 4-GNSS1 was relatively small (1.85 mm/d), while that of other measuring points were relatively large (6.19–22.48 mm/d). The cumulative displacement in stages was 55.74–89.92 mm, reaching the high-speed deformation state. The average vertical displacement rate of each measuring point was less than −2.00 mm/d, indicating that the slope surface was dominated by the horizontal displacement. The cumulative displacement curve of each measuring point rose significantly in the later period, which was consistent with the deep displacement. The surface displacement of the slope also entered the critical-sliding acceleration stage. In addition, the average and maximum rates of 1-GNSS2 were about 2–3 times than that of other measuring points. According to the distribution location of measuring points, the area near the small mileage end of the third stage platform had shown obvious potential failure signs before the slope collapsed.

From June 19 to 21 June 2021, except for the 4-GNSS1, the horizontal displacement rate of the other monitoring points increased rapidly to the super-high values of 47.22–681.56 mm/d, which was 763%–3,032% of that in the previous monitoring period. Within 3 days, the accumulated displacement in the horizontal stage was 141.65–2044.69 mm, showing that the displacement in the horizontal direction was still much greater than that in the vertical direction. The surface displacement took precedence over the deep displacement in the case of the collapse of the shallow slope suddenly. The horizontal and vertical cumulative displacement curves suddenly rose and fell from June 19, with the corresponding tangent angle greater than 80°. Thus, the surface displacement of the slope was in the sliding failure stage. In addition, the displacement rate of 1-GNSS2 and 2-GNSS3 were far greater than those of the other measuring points, i.e., the deformation from the small mileage end to the middle area of the third-level platform was the most serious, which was consistent with the case in the local collapse area. Combined with the location of measuring points, the rule of “large front, small back,” the displacement of the area near the bottom of the slope was much greater than that of the area near

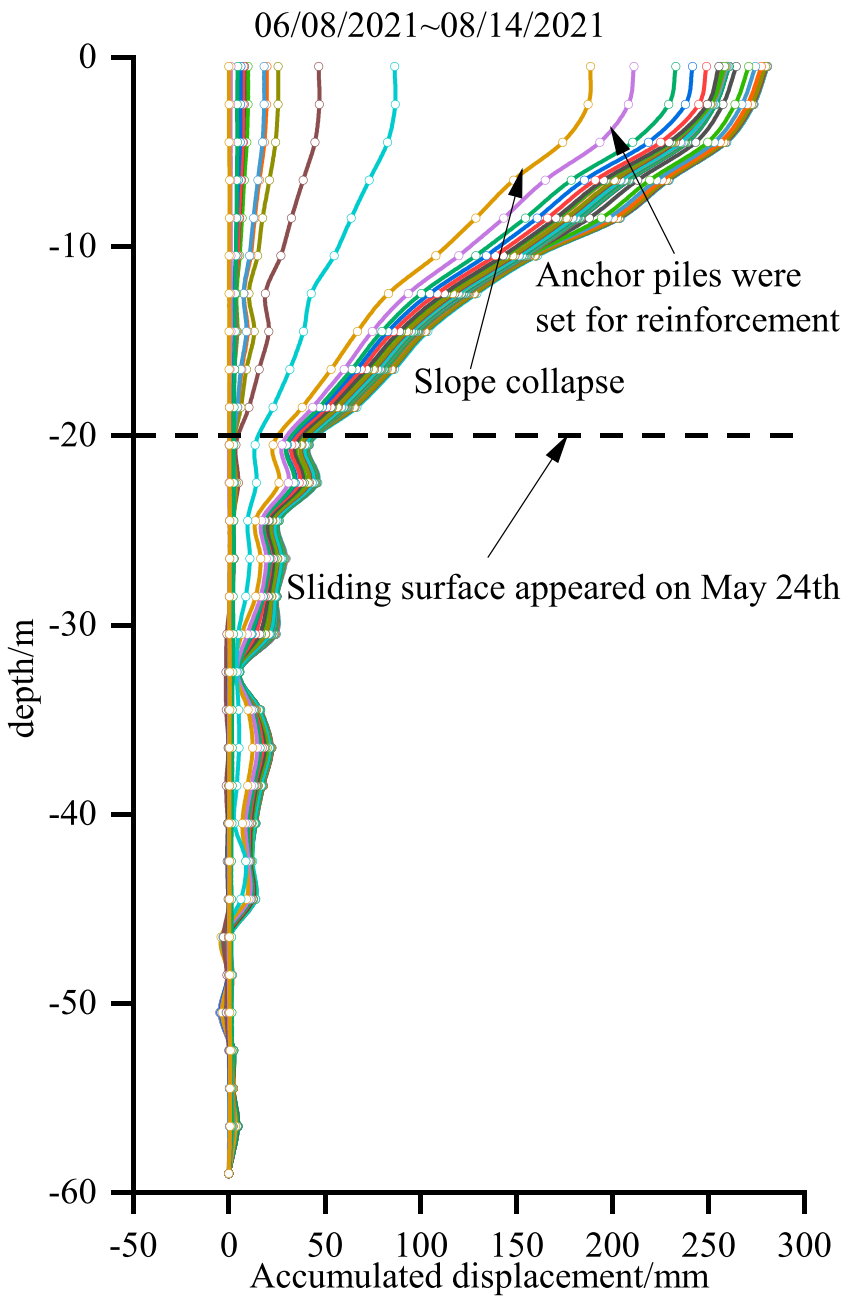

FIGURE 6
The variation law of deformation with depth at 2-CX1.

the top of the slope, was presented. Therefore, the displacement of the measuring points on the surface conformed to the deformation characteristics of the tractive landslide and was consistent with the deep displacement.

The micro-variation monitoring could obtain an intuitive cloud map about the surface displacement distribution, showing the areas with larger surface displacement (Figure 9). In addition, the surface displacement and displacement rate-time curves of each characteristic point in micro-variation monitoring could also be obtained. The results of typical feature points in the area with larger displacement were selected, as shown in Figure 10. The displacement rate of the characteristic points decreased to a relatively safe level, the surface displacement-time curve gradually became gentle, and the slope showed no tendency of further failure. The overall results were consistent with the GNSS displacement monitoring results (Figure 10).

From June 22 to 2 July 2021, the average horizontal rate of each measuring point was 0.63–36.65 mm/d, which decreased to 5%–22% of that during the collapse period. The vertical rate was −0.13–4.84 mm/d, which decreased to 13%–59% of that during the collapse period. Compared with the previous period, the cumulative displacement curve significantly transformed to slow development

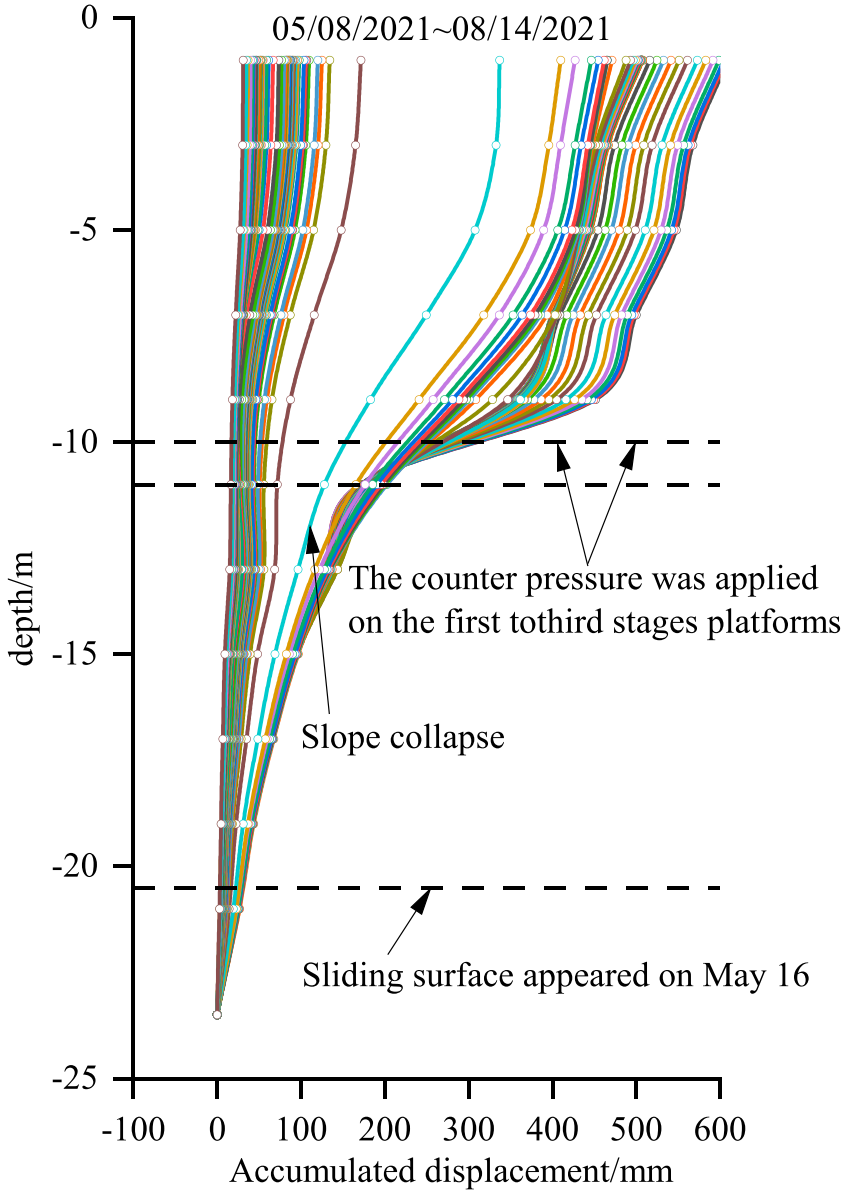

FIGURE 7
The variation law of deformation with depth at 2-CX2.

with a small angle, indicating the positive regulating effect of the emergency rescue measures (counter pressure at the bottom of the slope and anchor pile at the top of the slope) on the slope. The gradual filling of the counter-pressure body effectively prevented the shear destruction of the first to third-slope platforms, greatly reducing the displacement rate of 1-GNSS1 and 2-GNSS3. The construction of anchored piles restrained the internal deformation of the upper slope, thus reducing the displacement rate of 1-GNSS1 and 3-GNSS1. During this period, the slope was in the stage with deceleration deformation.

From July 3 to August 13, 2021, the displacement rate of all surface measuring points further decreased comparing with that in the previous period. The horizontal displacement rate was 1.63–3.16 mm/d, which decreased to 47%–65% of that in the previous monitoring period. Besides, the vertical displacement rate was −0.97–2.11 mm/d, which was the same with the previous period. The horizontal and vertical displacement curves tended to develop horizontally. Affected by the heavy rainfall at the end of July, the slope had a small increase in displacement compared with that before the rainfall. Overall, a low-speed deformation state was presented during this period. The emergency rescue measures positively improved the surface displacement of the slope (Figures 11, 12).

The artificial surface displacement monitoring started from the initial completion of rescue work on June 28 and ended with the full completion on August 13. From June 28 to July 31, the horizontal displacement rate of each measuring point on the slope surface was 0.57–2.20 mm/d, the vertical displacement rate was

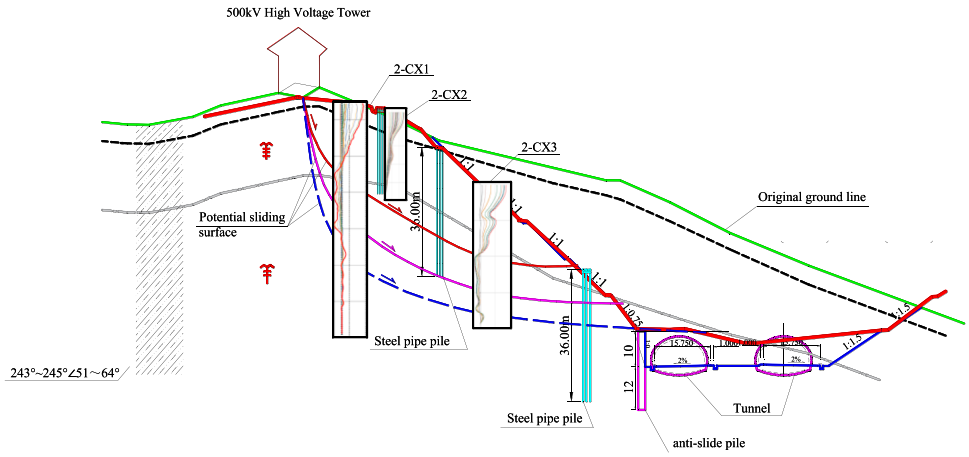

FIGURE 8
Analysis diagram of the inclinometer displacement curve for monitoring the deep layer of the main section.

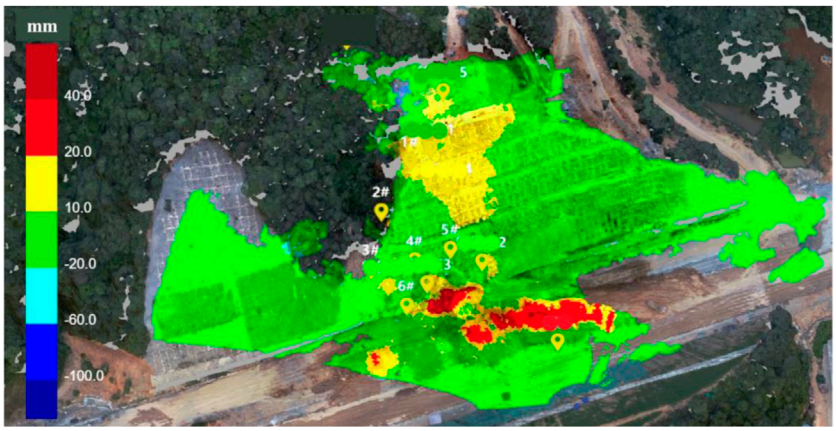

FIGURE 9
Thumbnail of surface displacement distribution in micro-variation monitoring.

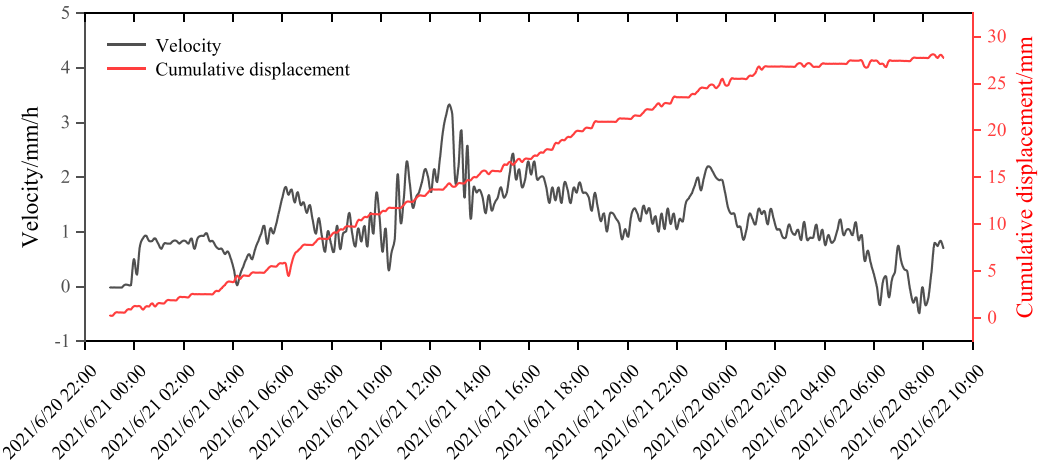

FIGURE 10
Surface displacement and displacement rate-time curves in micro-variation monitoring.

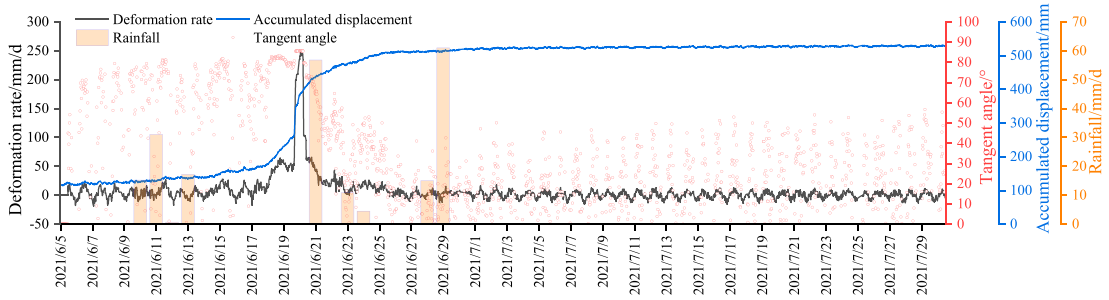

FIGURE 11
Cumulative displacement-time curve of 1-GNSS1.

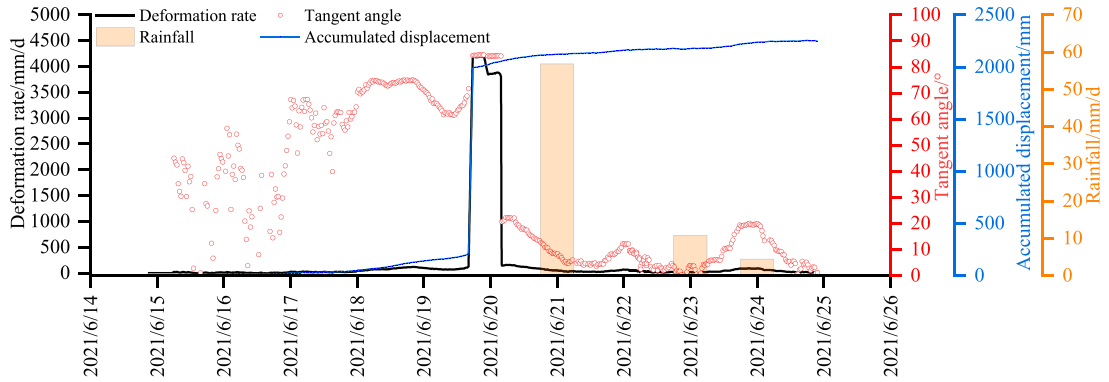

FIGURE 12
Cumulative surface displacement-time curve at 2-GNSS1.

−0.08–0.7 mm/d, and the displacement curve gently developed at a small angle, maintaining an overall low-rate displacement state. From August 1 to 13, the rescue work was completed, the horizontal displacement rate of each measuring point was 2.96–6.42 mm/d, and the vertical displacement rate was −2.62–14.20 mm/d. The displacement curve for the slope increased, with the displacement increasing more obviously than the one in previous period, which may be attributed to a large amount of precipitation seeping into the slope. By the comparison, the development trend of the artificial surface displacement was consistent with those of deep slope displacement and GNSS surface displacement, and the stability of the slope and the effectiveness of monitoring data were corroborated.

4.1.3 Monitoring and analyzing the settlement of tower foundation with hydrostatic level

From the implementation of the time before the local failure of the slope, the average settlement rate of each measuring point of the tower foundation at the slope top was less than 1 mm/d. In the process of slope collapse, the tower foundation suffered obvious settlement. The average settlement measuring point of the tower foundation at the toprate of each measuring point was −3.59–12.88 mm/d, 9.74–19.94 times than the value before the collapse, indicating that the tower foundation settlement was significantly affected by the slope displacement. Since the tower foundation settlement was aggravated due to the rescue construction, the settlement rate of each measuring point was less than −0.30 mm/d. At the same time, the settlement curve had slowed to develop horizontally, indicating that the emergency rescue construction on the slope could effectively prevent the rapid settlement of the tower. Among the four settlement measuring points of the tower, the settlement at JL-03, the farthest from the slope surface, was the smallest, and the settlement at JL-02, the closest to the slope surface, was the largest. That was, the settlement difference between JL-02 and JL-03 was the largest. In combination with the location and distribution of the measuring points, it showed that the tower was mainly inclined towards the subgrade (Figure 13).

4.2 Early warning of the slope

4.2.1 Criteria for early warning

The criteria for graded monitoring and early warning were given in Table 5. According to the displacement and deformation rate, the early warning level was divided into blue-attention level, yellow-caution level I, yellow-caution level II, orange-guard level, and red-alarm level.

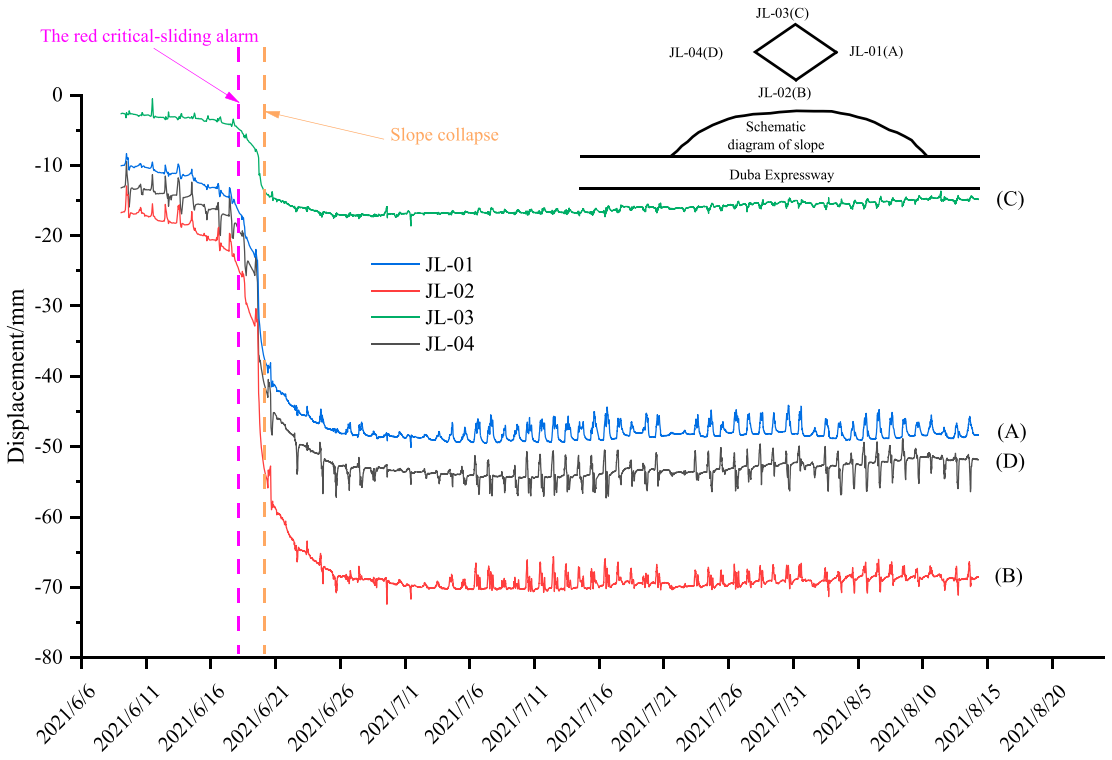

FIGURE 13
Accumulated surface settlement-time curve for the tower foundation.

TABLE 5 Criteria for graded monitoring and early warning.

Early warning level	Blue-attention level	Yellow-caution level I	Yellow-caution level II	Orange-guard level	Red-alarm level
Deformation stage	Peristaltic deformation	Isokinetic deformation	Preliminarily accelerated deformation	Moderately accelerated deformation	Sharp slide

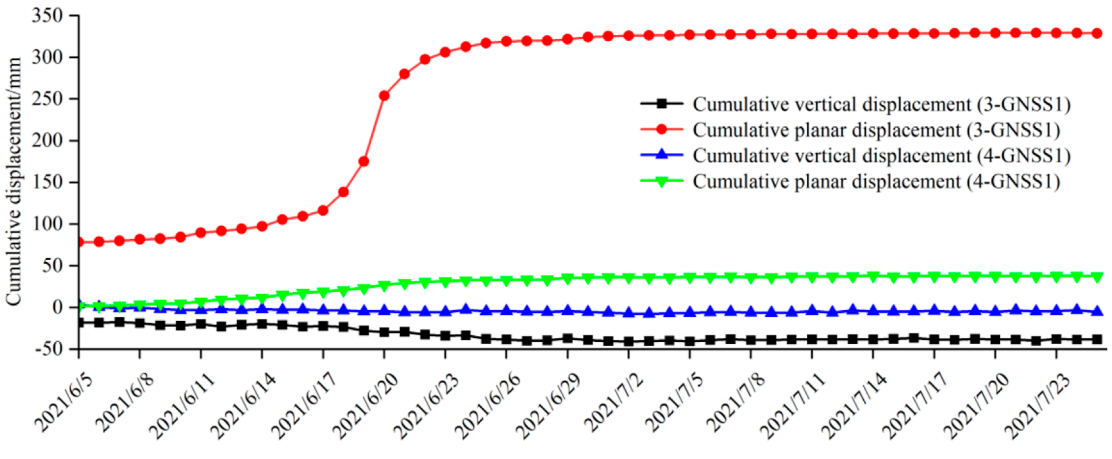

FIGURE 14
Cumulative surface displacement-time curves at 3-GNSS1 and 4-GNSS1.

4.2.2 Early warning methods

The early warning system employed for the Naliang slope integrates various monitoring technologies and data analysis techniques to assess the risk of slope failure dynamically. This system leverages the tangent angle and displacement rate as primary indicators, which are crucial for assessing the stability and predicting potential landslide events. Key aspects of the early warning method include:

Real-Time Monitoring: Continuous monitoring using deep displacement inclinometers and surface displacement sensors provides a comprehensive understanding of the slope's behavior under varying environmental conditions.

Data Integration: The system integrates data from multiple sources, including rainfall gauges, soil moisture sensors, and seismic activity monitors, to enhance the predictive accuracy of the early warning system.

Tangent Angle Analysis: This technique involves calculating the tangent angle of the cumulative displacement-time curve to identify acceleration phases that may precede a landslide. A critical threshold of 83° has been established as an indicator of imminent slope failure.

Automated Alerts: The system is configured to automatically categorize risk levels and issue alerts ranging from blue (attention) to red (critical alarm), based on pre-defined thresholds of displacement and deformation rates.

4.2.3 Examples

With the multiple monitoring means and according to the reasonable analysis of various monitoring data, five early warnings were issued during the construction and rescue process of Naliang slope and described as follows.

From April 3 to 5, 2021, the deep displacement inclinometer borehole, namely, CX2-1 showed a significant inflection point at the depth of 18 m. The differential settlement of the static leveling point of the tower foundation support on the top of the slope was 1.91 mm and 0.29 mm. The tower showed a tilt towards the main subgrade line. The first orange warning was issued on April 6.

On April 26, the monitoring data from the surface and deep displacement measuring points showed that the slope experienced a moderately accelerated deformation state, which triggered the orange alert again and issued the second orange warning.

On June 14, the deformation rates of the three deep displacement inclinometer boreholes in the main monitoring section increased to 12.84 mm/d, 14.80 mm/d, and 19.60 mm/d, respectively. The slope entered the high-speed deformation stage, and the tangent angle of the deep cumulative displacement-time curve reached 83°, activating the red critical-sliding alarm. On June 15, the early warning level was adjusted from the orange guard to red critical-sliding alarm.

The maximum cumulative displacement at the deep slope reached 51 mm from 21:00 on June 17 to 15:00 on June 18, which could be converted to a daily rate of 144 mm/d. The second red critical-sliding alarm was issued on June 18.

The first stage of rescue work for the local collapse of Naliang slope ended on June 26. The horizontal displacement rate of all surface and deep monitoring points showed a downward convergence trend. The axial force of anchor cables remained within the allowable range, and the early warning level for the slope was lowered to an orange-guard level.

4.3 Rescue measures for Naliang slope

On the afternoon of 19 June 2021, the Naliang slope suffered local instability and failure, presenting the trend of further development to the overall instability. The rescue construction was carried out immediately by counter pressure with piled soil and reinforcement with anchor piles.

4.3.1 Counterpressure with piled soil

The designed height of on-site counterpressure was 37 m, and the initial volume of counterpressure earthwork was 150,000 m^3. The concrete pump was used to pump concrete to block the mountain cracks at the collapse site further to prevent rainwater from pouring down. The earth surface and slope surface in the exposed slope area was covered with colored strip cloth to further prevent rainwater from seeping into the soil layer and aggravating the slip. After the preliminary counterpressure, the final earthwork was continuously counter-pressed to the third-level platform (30 m), and the actual counter-pressure backfill volume was 249,000 m^3 in total. The area from the third-level platform to 37 m was counter-pressed using the lifted geotextile bag filled with soil.

4.3.2 Construction of anchor piles

The anchor piles were used to reinforce the slope, and the pile top and power tower deformation was confined with the concrete anchorage and tensioned steel cables. The power tower at the front and rear ends of the slope body was strengthened by cable pulling. Three rows of anchor piles were set along the range of 26 m in front of the tower with a spacing of 1 × 1 m, and 74 anchor reinforcement piles were completed. To limit the top displacement of the pile, three anchorages were added at the rear of the high-voltage transmission line tower to form a pair of tension with the anchor piles, ensuring the temporary stability of the tower.

4.3.3 Rescue effect

The first stage of rescue work for the local collapse of Naliang slope was completed on June 26, 2021 After the rescue construction, as of 8:00 a.m. on July 5, the tilt rate of the tower foundation was 4.675%, while the tilt rate of the tower tip was 4.225%. The total tilt rate of the tower remained constant for 288 consecutive hours. The cumulative settlement and horizontal displacement fluctuated steadily, whereas the deformation rate slowed down significantly. The curve converged, while the slope and power tower were in a stable state.

There was no significant change after the heavy rain from June 28 to 30, 2021. The data from two surface displacement monitoring points, 3-GNSS1 and 4-GNSS1, showed that the trend of further deformation and failure of the slope was effectively controlled after the rescue measures were carried out (Figure 14). Therefore, the early warning level of the main slope was reduced from red to orange, and the safety level of the power tower was reduced from red to yellow.

5 Conclusion

Taking the high and steep slopes along highways in the distribution area of high-voltage transmission line towers as the engineering background, the intelligent monitoring, early warning, forecasting and emergency disposal work for Naliang slope were carried out, and the conclusions are as follows.

(1) Similar to the deformation characteristics of natural slopes, the deformation of engineering slopes composed of sandstone and mudstone with protective measures is often characterized by creep, and the whole deformation process of slopes can be divided into initial deformation, isovelocity deformation and accelerated deformation of three deformation stages. Once the deformation of slopes enters into the stage of near-slip, which signifies that the evolution of the slopes has entered into the critical state, overall destabilization of damage and landslides are about to occur.

(2) According to the deformation rate, the deformation state of the slope can be judged, which is convenient for taking measures in time. In the early stage of slope collapse, the cumulative displacement and rate curves of each deep inclinometer holes are generally developed with time at a certain slope rate, and the deformation rate when the slope is in the state of high-speed deformation is 12.84–19.60 mm/d, the average displacement rate is 5.08–6.20 mm/d, and the cumulative displacement in the stage is 45.72–55.81 mm, and the displacement of the deep part of the slope in the stage of pro-slip acceleration reaches the maximum rate of 19.90–30.26 mm/d, and the displacement in the stage of pro-slip acceleration reaches the maximum rate of 19.90–30.26 mm/d.

(3) The tangent angle landslide early warning criterion can be applied to the landslide early warning and forecasting of high steep engineering slopes in sandstone and mudstone. When the slope is in the stage of sliding failure, the slope of the cumulative displacement curve of each hole increases sharply, and the corresponding tangent angle of the data point is greater than 80°.

(4) Due to the high voltage transmission line tower being located within the influence range of the slope, when the use of automated monitoring means to carry out monitoring work, special attention should be paid to strengthening the geotechnical body deep displacement monitoring work. Deep displacement monitoring data is an important basis for determining the later engineering plan.

(5) On the basis of analyzing and determining the location of the slope slip surface, the use of timely layered counter-pressure, anchor bar piles and other micro-pile emergency measures can effectively control the deformation scope of the steep slope, and prevent further deterioration slope and subsequent landslide.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

XiL: Conceptualization, Data curation, Formal Analysis, Project administration, Software, Visualization, Writing–original draft. XL: Formal Analysis, Funding acquisition, Methodology, Resources, Writing–review and editing. YS: Investigation, Methodology, Software, Writing–review and editing. CC: Resources, Visualization, Writing–review and editing. GL: Investigation, Validation, Writing–review and editing. YL: Data curation, Methodology, Writing–review and editing. ML: Validation, Visualization, Writing–review and editing. XW: Validation, Writing–original draft, Investigation. YC: Validation, Writing–review and editing, Software, Visualization.

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Conflict of interest

Authors XL, YS, CC, GL, YL, ML, and XW were employed by Guangxi Communications Design Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Investigating the internal erosion behavior and microscopic mechanisms of chemically stabilized soil: an experimental study

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Introduction: Internal erosion triggered by water pipeline leaks seriously threatens the stability of the urban ground. Hangzhou, a city in Zhejiang Province, China, is facing critical challenges due to urban ground collapse (UGC) caused by internal erosion. However, there is a lack of research on the prevention of UGC by improving the internal erodibility of underground soil. Addressing this issue is of utmost importance to ensure the city's stability and safety. This paper proposes to improve the internal erodibility of typical sandy silt soils with chemical stabilisers.

Methods: The effects of three chemical stabilisers, lignosulphonate (LS), lime (LI), and lignin fibre (LF), on the critical shear stress (τ_c) and erosion coefficient (k_d) of sandy silt soils were investigated, which from Hangzhou, Zhejiang, China, by the hole erosion test (HET) at different mixing amounts and at different conservation times.

Results: The findings indicate that LF mainly improves the erosion resistance of sandy silt by increasing τ_c, and the maximum increase is 2.38 times; LI mainly improves the erosion resistance by decreasing k_d, and the maximum decrease is 2.18 times. After adding LS, τ_c and k_d did not change significantly. The scanning electron microscope (SEM) test revealed that the inclusion of LF led to the formation of larger agglomerates in the sandy silt soil. The microstructure of sandy silt soil remained dispersed even after adding LS. Various chemical stabilisers used to improve sandy silt soils exhibited distinct erosion mechanisms. Sandy silt soils improved with LF exfoliated into agglomerates, displaying high resistance to erosion. On the other hand, the sandy silt treated with LF still lacks a protective layer and shows minimal improvements in its ability to withstand erosion. In contrast, the LS-amended sandy silt remains stripped with individual soil particles with insignificant changes in erosion resistance.

Discussion: This study can provide a conceptual framework for choosing foundation treatment techniques in future urban development projects.

KEYWORDS

sandy silt, chemical stabilisers, internal erosion, hole erosion test (HET), urban ground collapse (UGC)

1 Introduction

With the warming of climate and the intensification of human activities, natural disasters such as landslide, debris flow and ground collapse occur frequently (Qiu et al., 2024; Wei et al., 2024; Ye et al., 2024). Ground subsidence is a common geological hazard worldwide. It is a dynamic geological phenomenon in which rock and soil bodies on the ground fall downwards under the action of natural or man-made factors and form a subsidence pit (hole) on the ground (Cheng et al., 2020; Dastpak et al., 2023). Urban ground collapse (UGC) is a specific type of ground collapse that occurs mainly on urban pavements (Zhang et al., 2023a). In recent years, UGC accidents have occurred frequently in Chinese cities, posing a serious threat to the safety of traffic facilities, passing vehicles, and pedestrians (Cheng et al., 2020; Tan and Long, 2021; Wang and Xu, 2022). According to statistics, the frequency of UGC accidents in China's eastern coastal areas accounts for 38%, making it the region in China where UGC occurs most frequently (Cheng et al., 2020). Hangzhou City in Zhejiang Province, located on China's eastern coast, suffered 16 UGC during 2018–2020 alone, causing severe economic losses (Wang and Xu, 2022). On 15 November 2008, a UGC occurred at the site of Hangzhou Metro Line 1, resulting in 21 deaths and 24 injuries, making it the most serious UGC in Hangzhou in recent years (Tan and Long, 2021). Therefore, it is urgent to conduct research on new technology for UGC prevention and control.

Internal soil erosion due to pipeline leaks is one of the major causes of UGC (Dastpak et al., 2023). According to statistics, the proportion of UGC accidents caused by pipeline leaks in China is as high as 40.87% (Cheng et al., 2020; Wang and Xu, 2022). Currently, the prevention and control of internal soil erosion caused by pipeline leakage, which in turn induces UGC, is still facing serious challenges. Internal soil erosion occurs when water picks up fine particles and flows through soil pores (Dastpak et al., 2023). The water flow generated by the leakage of the pipeline continuously erodes the soil around the pipeline, leading to the formation of voids around the pipeline, and with the gradual expansion of the size of the voids, the overhanging ground surface eventually collapses under the action of self-weight or external loads (Dave and Juneja, 2023a; Zhang et al., 2023a; Dave and Juneja, 2023b; Guo et al., 2023). Internal soil erosion is influenced by factors such as hydraulic loading, soil material composition, and microstructural characteristics (Dastpak et al., 2023). There have been many research results presenting test methods for erodibility within soils, such as the flume test, the submerged jet erosion test (JET), and the hole erosion test (HET) (Wan and Fell, 2004a; Benahmed and Bonelli, 2012; Haghighi et al., 2013). HET is the most widely used method for quantitative testing of erodibility thresholds within soils (Liang et al., 2021; Cai et al., 2022). The critical shear stress (τ_c) and the erodibility coefficient (k_d) can be obtained by HET to quantitatively evaluate the internal erodibility of the soil (Wan and Fell, 2004a). HET has the advantages of economic, low-carbon, and quantitative testing, and it is currently being used to test the internal erodibility of modified soils (Liang et al., 2021; Banu and Attom, 2023).

Soil improvement techniques can increase soil strength and erosion resistance, thereby limiting the expansion of erosion cavities in the soil, and are generally categorised into physical and chemical methods (Banu and Attom, 2023). Based on the basic principles of chemical soil improvement (Firoozi et al., 2017), adding chemical stabilisers to the soil to change the composition of soil materials and enhance the cementation between soil particles can reduce soil porosity and increase soil compactness, which in turn improves soil resistance to erosion (Firoozi et al., 2017; Liang et al., 2021). Using chemical stabilisers to improve the erosion resistance of peripipe soils has a promising application in preventing future UGC accidents. In recent years, many scholars have explored research into green stabilisers that can improve soil erosion resistance while being low carbon and environmentally friendly (Liang et al., 2021; Konstadinou et al., 2023; Kwon et al., 2023). Multiple research findings show that lignin and cement can reduce the soil k_d and significantly increase τ_c (Indraratna et al., 2008; Khabbaz, 2008; Vinod et al., 2010; Indraratna et al., 2013). Mehenni et al., 2016, found that addition of cement and lime can also increase τ_c of silt soils. In 2018, Vakili et al. (2018) showed that the combination of calcium lignosulphonate and polypropylene fibres can improve the erosion resistance and mechanical strength of dispersed clays. Scientists investigated the effect of three chemical stabilisers, water glass solution, calcium lignosulphonate, and sodium polyacrylate, on the erosion resistance of sandy soil (Liang et al., 2021). It has been shown that increasing the amount of chemical stabiliser added and prolonging the curing time can reduce the amount of erosion and particle loss (Liang et al., 2021). As the lignosulfonate content increased, τ_c of the treated soil samples increased, and k_d decreased significantly (Vinod et al., 2010; Indraratna et al., 2013; Rasika et al., 2013). However, conventional chemical stabilisers effectively improve soil erosion resistance (Vinod et al., 2010; Herrier et al., 2018; Konstadinou et al., 2023). Human society is currently facing the trend of global warming, and the production of existing chemical stabilisers such as cement consumes a large number of natural resources and causes environmental pollution, which is a growing concern for many people (Liang et al., 2021). Therefore, it is increasingly important to use new environmentally friendly modifiers that are environmentally friendly, economical, and have better erosion resistance than traditional stabiliser such as cement.

In this study, the effects of calcium lignosulfonate, lignin fiber and lime on the critical shear stress and corrodibility coefficient of typical sandy silt in pavement collapse-prone area were investigated. First, the cylindrical samples were prepared under different dosage

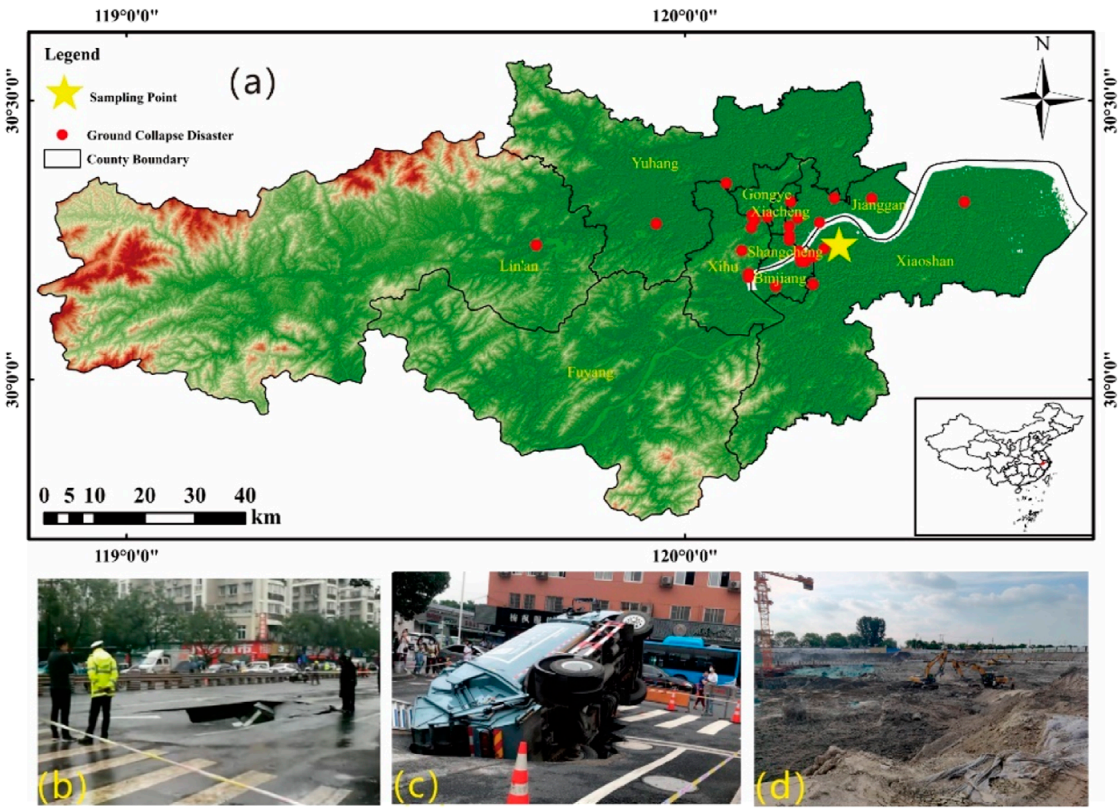

FIGURE 1
Historical UGC cases and sampling locations **(A)** Historical UGC and sampling locations; **(B)** Pavement collapse due to sewerage pipe breakage (Photo from Hangzhou Planning and Natural Resources Bureau); **(C)** Pavement collapse due to stormwater pipe leakage [Photo from Qianjiang Evening Post (newspaper)]; **(D)** Sampling location.

and curing time. Secondly, the internal erosion of sandy silty soil improved by chemical stabilizer is tested by the improved HET. Finally, the microscopic mechanism of chemical stabilizers improving soil internal erosion was analyzed based on SEM images. This research has a high engineering practical value for the prevention and control of UGC disasters in Hangzhou and its neighboring areas.

2 Materials and methods

2.1 Material properties

Hangzhou, located in Zhejiang Province, is a city in the southeast coastal area of China that experiences a significant number of UGC. Despite climate change and the ongoing development and use of urban underground spaces, Hangzhou continues to face a substantial risk of future UGC accidents (Wang and Xu, 2022; Zhang et al., 2023b; Zhou et al., 2024).

Figure 1A displays the dense distribution of historical occurrences of UGC in the eastern region of Hangzhou, with a particular focus on Xihu District. Upon examining a typical instance of UGC caused by a pipeline leaking in the city, it was noted that the formation of hollow spaces beneath the pavement primarily took place inside the sandy silt layer.

The sandy silt has a loose structure and very low erosion resistance, which is very easy to be hollowed out by leaking water pipeline, forming empty spaces under the road surface, leading to UGC accidents (Figures 1B, C). Therefore, a typical sandy silt soil was selected as the test soil sample in this study, and the sampling location is shown in Figure 1A, D. Sandy silt soil was used for the test at a sampling depth of about 12 m. The basic physical parameters of the soil samples obtained from the laboratory test are shown in Table 1. The maximum dry density of the soil sample was 1.55 g/cm^3 and the optimum water content was 20.2%. LS has a broad application prospect as a chemical stabiliser for erodible soil. In this study, LS is produced by Qiangxing Chemical Company (Figure 2A). LF can form a three-dimensional mesh structure after being added to the soil, linking the individual soil particles together and increasing the stability of the soil in the flow of water, so it has a broad application in soil erosion enhancement, the lignin fibre used in this study is the white lignin fibre produced by China's Shandong Yusuo Chemical Science and Technology Company (Figure 2C). LI has demonstrated effective performance in improving the erodibility of soils and in recent years more and more water conservation engineers are interested in this technology. The lime raw material used in this study was sourced from Fuchen (Tianjin) Chemical Reagent Company in China (Figure 2B).

This study used three chemical stabilisers, LS, LF, and LI, to treat the soil samples. The additional amounts (*m*) of the three

TABLE 1 Indicators of physical properties of soil samples used in the test.

W (%)	G_S	Clay (%)	Silt (%)	Sand (%)	ρ_d (g/cm^3)	W_O (%)	Classification
26.9	**2.69**	**8.4**	**72**	**16.3**	**1.55**	**20.2**	Sandy silt

W, Natural moisture content (%); G_s, Specific gravity; Clay, Clay content (%); Silt, Silt content (%); Sand, Silt content (%); ρ_d, Maximum dry density (g/cm^3); W_o, Optimal water content (%).



FIGURE 2
Chemical stabilisers **(A)** Calcium Lignosulphonate (LS); **(B)** Lignin Fibre (LF); **(C)** Lime (LI).

chemical stabilisers was calculated according to the following equations:

$$m = a \cdot m_1 \tag{1}$$

$$m_1 = (1 + 0.01w_0)\rho_d V \tag{2}$$

$$m_w = 0.01(w` - w_0)\rho_d V \tag{3}$$

a = 0%, 2%, 4%, 6%, 8%, m is the mass of chemical stabiliser, g; m_1 is the mass of dry soil required to prepare a specimen, g; w_0 is the moisture content of air-dried soil, w_0 = 0.68%; ρ_d is the maximum dry density, g·cm^{-3}, V is the cylindrical sample volume, cm^3, m_w is the amount of water to be added to prepare a cylindrical soil sample, g; w is the moisture content of the sample, $w = W_0$ = 20.2%.

This study explores the effect of maintenance time (T = 1 day, 3 days, 7 days, and 14 days) on the internal erodibility of improved soils at 8% dosing, considering the chronological nature of each of the three chemical stabilisers separately. The maintenance time in this study refers to the preparation of cylindrical samples with chemical stabilizers and preservation for 1–14 days under the same environmental conditions. The purpose of this is to make the chemical stabilizer in full contact with the soil particles, and at the same time, to explore the early change of the corrosion resistance of the soil modified by the chemical stabilizer. Table 2 provides an overview of the test conditions employed in the study.

2.2 Sample preparation

Following their retrieval, the soil samples were dried at 105°C and sieved using a regular 2 mm sieve to remove any remaining pebbles or debris. According to Equations 1–3, the calculations were carried out using the "Geotechnical Test Method Standard GB/T 50123–2019" to determine the dry soil mass (m_1), water content (m_w), and corresponding mass of the chemical stabiliser (m) required for the various working conditions shown in Table 2.

The dry soil was first mixed thoroughly with the weighed chemical stabiliser, then water was added, mixed thoroughly, and placed in a sealed bag for 24 h to allow for uniform water migration from the soil sample. The specimens used in the current study for the HET were cylindrical samples measuring 6 cm in diameter and 10 cm in height. Several procedures were followed to get the compacted soil samples ready for the HET. The initial step involved calculating the amount of soil samples required for each layer of the landfill and determining the intended height of the landfill. These calculations were based on the preparation procedure specified in the Standard GB/T 50123–2019 Geotechnical Test procedure. This calculation ensured precise measurements for the following processes. After that, soil samples were formed in layers (Figures 3A, B). The loose soil was carefully measured using an electronic scale and then put into the mould to create samples. A customised compactor was utilised to compress the dirt to get the appropriate height for each layer. The compacted soil sample's upper surface was scraped and treated to execute layered interface shaving (Figure 3C). The process was repeated five times, following steps (1) and (2), until the sample-making mould was filled (Figure 3D). This ensured the soil samples were layered and compacted correctly. Following the preparation of the specimens, they entered a maintenance phase. The specimens were enclosed in airtight bags, marked for identification, and stored at room temperature for a duration ranging from 0 to 14 days. This provided an ample amount of time for the stabilisation and conditioning of the specimen. Every well-maintained cylindrical specimen was drilled before conducting the HET (Figure 3E). To minimise moisture leakage along the soil sample and the chamber wall, a coating of petroleum jelly was applied to the wall of the specimen chamber. Next, the cylindrical specimen was inserted into the specimen chamber, and a hole with a diameter of 6 mm was drilled along its central axis. The drilling method produced uniform conditions

TABLE 2 Overview of employed test conditions.

Chemical stabilizers	w` (%)	ρ_d (g/cm3)	m (%)	T (d)
—	20.2	1.55	0	1
LS	20.2	1.55	2	1
	20.2	1.55	4	1
	20.2	1.55	6	1
	20.2	1.55	8	1
	20.2	1.55	8	3
	20.2	1.55	8	7
	20.2	1.55	8	14
LF	20.2	1.55	2	1
	20.2	1.55	4	1
	20.2	1.55	6	1
	20.2	1.55	8	1
	20.2	1.55	8	3
	20.2	1.55	8	7
	20.2	1.55	8	14
LI	20.2	1.55	2	1
	20.2	1.55	4	1
	20.2	1.55	6	1
	20.2	1.55	8	1
	20.2	1.55	8	3
	20.2	1.55	8	7
	20.2	1.55	8	14

for subsequent experiments. Preparing and installing various HET specimens was conducted multiple times, following the specific circumstances outlined in Table 2.

2.3 Hole erosion test (HET)

2.3.1 HET steps

The modified HET setup used in this study is shown in Figure 4 (Wan and Fell, 2004b). The HET setup consists of an upstream water supply tank, a sample box, a downstream water supply tank, and associated linked valves and pipework. By adjusting the height of the upstream tank, it was possible to create 1–3 distinct hydraulic gradient test conditions in this study, considering a head difference of 10 cm (equivalent to a hydraulic gradient of 1). The upstream and downstream water supply tank volumes were 25 cm^3. The water pipeline used for the experiments had an inner diameter of 25 mm. The test initiation and termination were controlled using a valve. The upstream pressure gauge position is set with a 3 cm thick gravel buffer layer to prevent erosion damage to the specimen surface, and the upstream and downstream pressure gauge range is 0–10 kPa, with a resolution of 0.001 kPa. The testing apparatus employed in this study can carry out a variety of conditions under the evaluation of fine-grained soil internal erosion characteristics.

The HET procedure is as follows: 1) Place the prepared mould containing round holes on the bracket and open the upstream and downstream pressure gauges; 2) Adjust the water supply device to the height required by the design; firstly, fill up the downstream of the mould with water so that the water fills up the holes until the air in the holes is excluded; 3) Open the valves of the water supply device, and at the same time, turn on the video camera and the timer, and start the experiment; 4) Pay attention to the erosion and collapse of the side wall of the specimen in the course of the experiment, and make timely Adjustment; 5) When the erosion to the side wall of the specimen box when the end of the experiment or the flow rate increased to the water supply valve and water flow at the same time when the end of the experiment; 6) Immediately after the end of the experiment, remove the specimen box, take a picture of the two ends of the specimen, and then melt the paraffin wax filled into the final hole, to be cooled down, the launch of the specimen, the direction of the axial dissection, the use of vernier calipers several times to measure the diameter of the final paraffin wax model, and seek the average value, to determine the final hole diameter; 7) Remove the waste soil in the test box, clean the specimen box, and then repeat the above steps to carry out the next test.

2.3.2 Erosivity threshold prediction

This paper adopts the basic assumptions of Wan and Fell for HET (Wan and Fell, 2004a). By analyzing the experimental data, shear stress τ_t (Pa) and erosion rate $\varepsilon_t\,(kg\cdot m^{-2}\cdot s^{-1})$ were obtained from Equations 4, 5:

$$\tau_t = \rho_w g s_t \frac{\phi_t}{4} \tag{4}$$

$$\varepsilon_t = \frac{\rho_d}{2}\frac{d\phi_t}{dt} \tag{5}$$

where ρ_w is the density of water, 1000 kg/m^3; g is the gravitational acceleration, $9.8m\cdot s^{-2}$; S_t represents a hydraulic gradient, ϕ_t is the diameter of the specimen at time t, ρ_d is the dry density of the sample. The runoff shear stress and erosion rate calculated in Equations 4, 5 are substituted into Equation 6, which is the most widely used soil erosion model. The slope of Equation 6 corresponds to the erodibility coefficient denoted as, k_d, with the unit $m\cdot s^{-1}$. The advantage of the overshear stress equation is that it can simply express the quantitative relationship between the runoff shear stress and the erodibility coefficient. This equation is applicable to soil with linear relationship between runoff shear stress and erodibility coefficient.

$$\varepsilon_t = k_d(\tau - \tau_c) \tag{6}$$

The internal erosion stability of the *in situ* loess was then evaluated based on the grading method of internal erosion stability

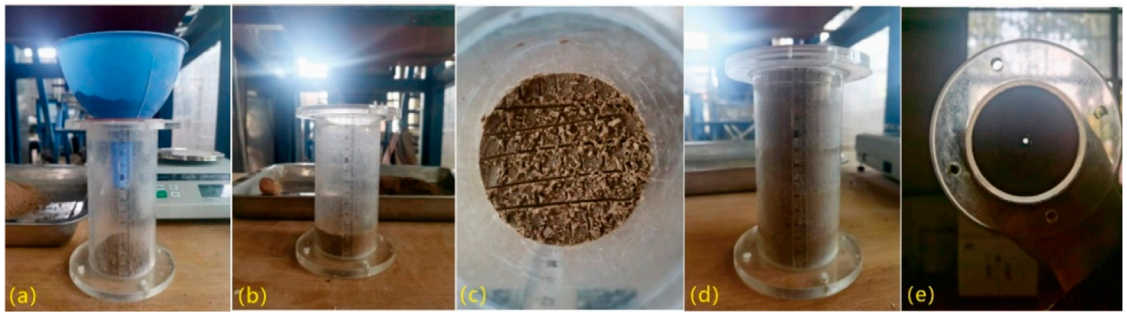

FIGURE 3
Specimen preparation process **(A)** Soil sample filling; **(B)** Layered compaction; **(C)** Interfacial scraping; **(D)** Columnar specimen; **(E)** Hole in the specimen.

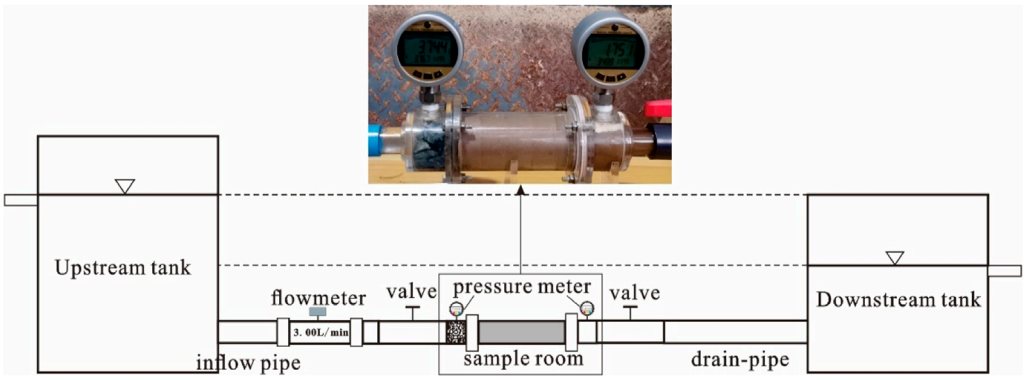

FIGURE 4
Schematic diagram of the HET setup.

of soils proposed by (Wan and Fell, 2004a). Where Pin and Pout are the water pressure at the entrance and exit of the hole in kPa, and L is the length of the specimen in *m* as shown in the Equation 7.

$$S_t = \frac{P_{in} - P_{out}}{\rho_w g L} \tag{7}$$

2.4 SEM test

This study studied the microscopic mechanism of three chemical stabilisers in enhancing soil's internal erosion resistance. To do this, specimens were taken from the middle of the final pore wall after conducting a HET. These specimens were then subjected to scanning electron microscope (SEM) using a Phenom Pure-type microscope. An ion-sputtering device was used to apply gold to the test area in order to obtain a higher-resolution scanning electron microscope (SEM) image. A representative soil block, measuring approximately 1 cm × 1 cm × 1 cm, was chipped on the soil block, and the specimen was broken along the middle before the test to ensure that the specimen possessed a fresh section. The specimen containing the fresh section was then placed into a vacuum cold dryer to be cold-dried for 8 h. Two typical viewpoints were selected for picture taking in order to lessen the effect that differences in soil samples could have on the test results. Next, images captured with a scanning electron microscope (SEM) were obtained at magnifications of ×200, ×500, ×800, ×1,000, and ×2,000.

3 Results

3.1 Final hole diameter

The internal erosion test was conducted on 22 specimens, following the HET protocol described in the previous section. After preparing for the test, the upstream water supply valve was opened, and the water flowed through the prefabricated holes under the effect of the head difference. The holes eroded under the impact of runoff shear stress, and the diameter of the internal holes in the specimens increased gradually as the erosion proceeded. Figures 5A–C shows the morphological characteristics of the cross-section of the holes in different states. As can be seen from Figure 5B, the final pore morphology of the untreated specimen is elliptical, and the inner wall of the pore is smooth, indicating that the untreated specimen has a low frictional resistance to water flow. The most kind of morphology of the treated specimen is nearly circular, and the inner wall of the hole is rougher in terms of the hole opening, which results in a higher frictional resistance to the

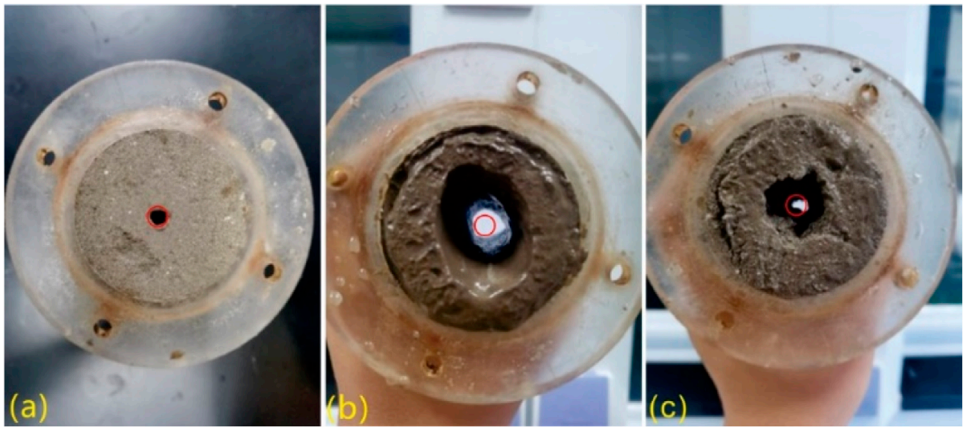

FIGURE 5
Morphological characteristics of final holes: **(A)** initial state; **(B)** untreated soil sample; **(C)** treated soil sample, whereas the red circles represent initial holes.

runoff. In addition, Figure 5 also shows that the final hole diameter of the treated specimen is reduced compared to the untreated specimen.

At the end of the test, the melted paraffin was poured into the final hole, and a three-dimensional paraffin model of the final hole was obtained. The diameter of the paraffin model was measured several times using electronic vernier callipers and averaged, and this average was taken as the diameter of the hole. Under the same hydraulic conditions, the size of the final hole diameter (*D)* in the sample after the HET reflects the ability of the improved soil sample to resist erosion by concentrated runoff, and the smaller *D* is, the stronger the ability to resist erosion.

The *D* of the specimens treated with different chemical stabilisers were counted as shown in Figure 6. *D* were reduced to varying degrees with the increase of the stabiliser dosage (*m)* as illustrated in Figure 6A. *D* of the specimens treated with different chemical stabilizers are shown in Figure 6A. Among them, the addition of 8% LS had the smallest final hole diameter of 2.2 cm. The addition of 2% LF specimens had the largest *D* of 3.8 cm. With the dosage increase from 2% to 8%, *D* of specimens treated with three kinds of stabilizers, namely, LS, LF, and LI, decreased by 0.7 cm, 1.2 cm, and 1.31 cm, respectively. *D* of the test, with the addition of 8% LI, had the most considerable reduction. The relationship between the maintenance time (*T*) and *D* of the soil samples treated with the three chemical stabilisers are shown in Figure 6B. From this, it can be seen that under the same dosage (8%), *D* of LS-treated specimens increased and then decreased, *D* of LI-treated specimens slowly reduced with the curing time, *D* ranged from 2.53 cm to 2.88 cm, and the average *D* was 2.74 cm. The LF demonstrated the most sensitive to the duration of the curing process. As the curing time increased, the final hole sizes also increased, ranging from 2.6 cm at 1 day to 1.46 cm at 14 days, resulting in a decrease of 1.14 cm. *D* is visual evidence of the phenomenological interpretation of chemical stabilisers to improve the internal erodibility of the soil and to evaluate the amelioration effect of the three chemical stabilisers quantitatively. Further quantitative analysis and evaluation are required.

3.2 Hole wall characteristics

After the test concluded, melted paraffin was put into the final hole. Once the paraffin solidified, it was divided into two equal parts along the centre of the specimen. This allowed us to observe the final pipe wall's morphological characteristics after erosion (Figure 7). Comparison of the morphological characteristics of the final pore wall reveals that one type of pore wall is particularly rough, with many small holes distributed in beads of depressions (Figure 7A), which corresponds to the unevenness of the outer surface of the paraffin model. Figure 7B shows a typical representation of the smooth wall, and it can be seen that the outer surface of the paraffin model corresponds to the inner wall of the cut-open model, which are both relatively smooth. The specimen with a clear outlet water flow during the test has a rougher final wall (Figure 7A), while the turbid liquid containing sediment at the outlet location of the water flow for a long time during the test has a smoother final wall (Figure 7B). The roughness of the wall after erosion reflects some extent the pattern of pipe wall denudation under the action of concentrated runoff scour, which will be elaborated in the analysis of the improvement mechanism below.

3.3 Critical shear stress

According to Equation 6, with τ_t as the horizontal coordinate and ε_t as the vertical coordinate to do the scatter plot, fitted to obtain the overshear stress equation of the modified specimen, as shown in Figure 8 (6% LS, conservation 1 day). In Figure 8, the intersection coordinate of the straight line and the horizontal axis is τ_c, and the slope of the straight line is k_d.

As τ_c increases, the soil's ability to withstand erosion increases. The erosion resistance of the soil body rises as k_d decreases. According to this method, τ_c and k_d under different working conditions are shown in Figures 9, 10, respectively.

The histogram of τ_c of the modified sandy silt soil is in Figure 9. The effect of ameliorant dosage on τ_c is demonstrated in Figure 9;

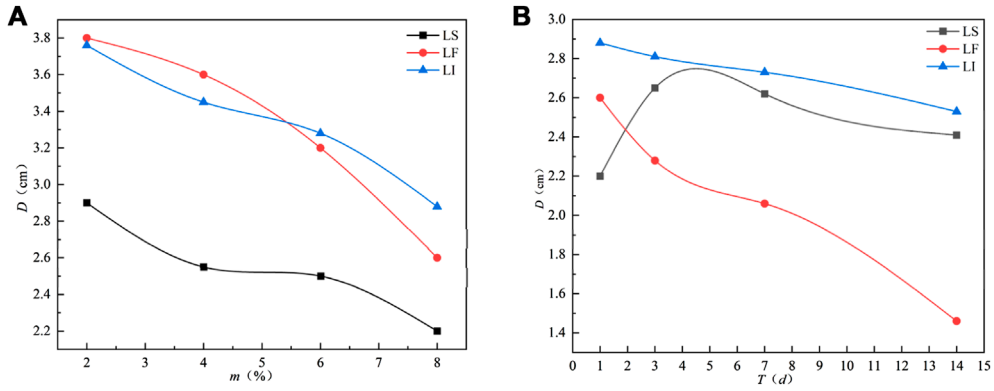

FIGURE 6
Final diameter **(A)** different addition amount; **(B)** different curing time.

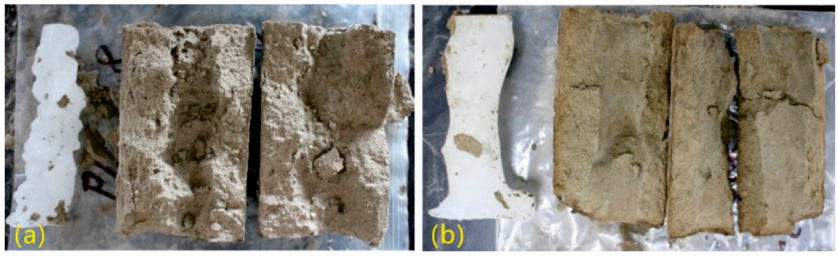

FIGURE 7
Morphological characteristics of the inner wall of the hole: **(A)** 8% LF-treated specimen; **(B)** 8% LS-treated specimen.

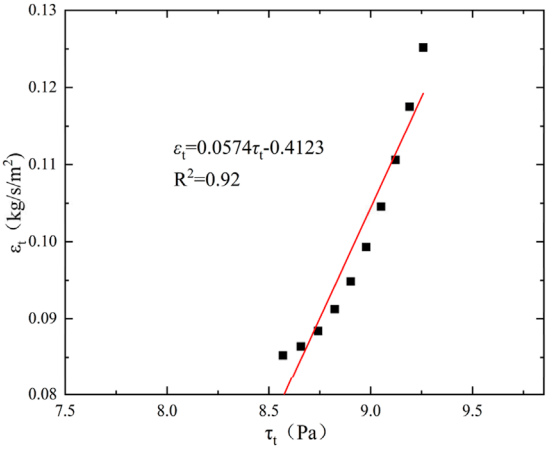

FIGURE 8
Typical τ_t-ε_t curve.

it can be seen that τ_c of the powdered soil before amelioration is the smallest, which is only 5.19 Pa. Adding LS leads to an increase in LS dosage and a gradual decrease in the value of τ_c. Among different dosages, the highest τ_c is observed at a 2% LS dosage, measuring 8.72 Pa τ_c is similar for the 4% and 6% dosages, while the lowest value is observed at an 8% dosage, measuring 6.33 Pa. This value is 1.14 Pa higher than τ_c without adding ameliorant. The minimal τ_c is 6.33 Pa, representing an increase of 1.14 Pa compared to powdered soil without any additional stimulant. The growth trend of τ_c of powdered soil after adding LI is more noticeable; τ_c of powdered soil with 2% added reaches 10.38 Pa, which is twice as much as that of powdered soil without any addition of improver, and that of powdered soil with 8% added LI reaches 11.44 Pa, which is 1.06 Pa higher than that of powdered soil with 2% added LI. τ_c of LI-amended pulverised soil doped with 6% and 8% in the middle position increases by 3.987 Pa and 4.67 Pa, respectively, compared to the unmodified soil. It can also be seen that Figure 9A demonstrates that as the amount of LF doping increases, τ_c gradually increases. Notably, τ_c of LI doped with 2% LF is 2.05 times higher than that of the untreated LI, and τ_c of LI doped with 8% LF is 2.38 times higher than that of the non-doped LI. τ_c rose by a factor of 2.38 compared to the unadded condition.

The influence of an 8% dosage and various curing times on τ_c is shown in Figure 9B. For LS with an 8% dosage, τ_c gradually increased as the curing time extended. It was 6.33 Pa at 1-day curing, 3.71 Pa at 3-day curing (compared to 1-day curing), 9.99 Pa at 7-day curing (compared to 1-day curing), and 9.01 Pa at 14-day curing (compared to 1-day curing). On the other hand, for LF with an 8% dosage, τ_c did not exhibit significant changes at 1-day and 3-day curing. The difference was only 0.123 Pa at 7-day and 14-day curing compared to 1-day curing. With the addition of LI at an 8% dosage,

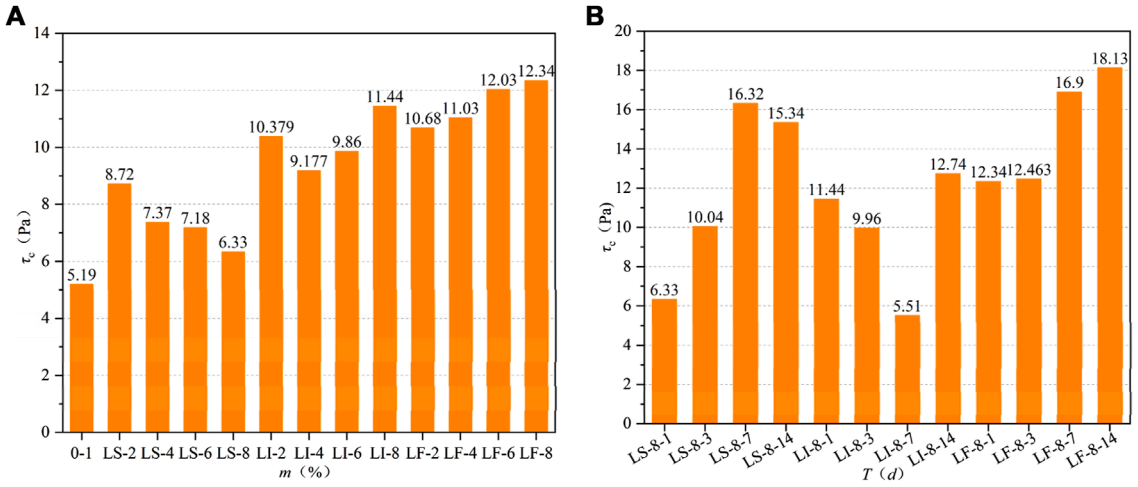

FIGURE 9
Critical shear stress of stabilised soil; **(A)** different dosage; **(B)** maintenance time.

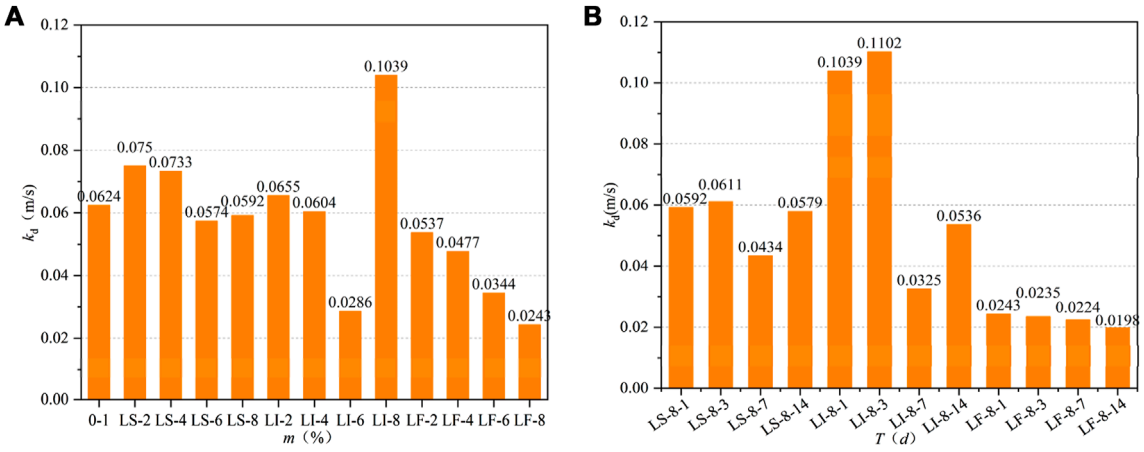

FIGURE 10
Erodibility coefficient of modified soil **(A)** Different dosage **(B)** Maintenance time.

τ_c initially decreased and then increased with the prolongation of curing time. The difference in τ_c between 14-day and 1-day curing was 1.3 Pa.

The influence of chemical stabiliser dose and maintenance time on τ_c is highly significant. Choosing the correct dosage and maintenance time can effectively enhance the soil's resistance to erosion shear stress.

3.4 Coefficient of erodibility

k_d is an important indicator in assessing the internal erodibility of soil. A smaller k_d indicates a higher level of erosion resistance in the soil. Figure 10A displays the histogram depicting k_d at various levels of chemical stabiliser doses. From the detailed analysis of Figure 10A, it can be seen that k_d of pulverised soil without chemical stabiliser is 0.0624 m/s, and with the increase of LF doping, k_d decreases significantly when 2% doping of LF is added, k_d is 0.0537 m/s, and the minimum k_d is 0.0243 m/s for 8% doping, which is 0.0381 m/s less than that of the un-added chemical stabiliser. The addition of a 6% dosage of LI also significantly reduced the corrosivity to 0.0286 m/s. It was observed that there was no significant pattern in k_d with the addition of LS. The impact of maintenance time on k_d of the modified chalk is depicted in Figure 10B. Analyzing the last four bars of the figure, it is evident that k_d ranges between 0.0243 m/s and 0.0198 m/s when an 8% dosage of LF is added. This range represents a significant reduction in erodibility as compared to samples that did not include the chemical stabilizer. In comparison to samples without a stabilizer, there was a minor decrease in k_d following the addition of 8% LS. At 7 days of maintenance, k_d measured 0.0434 m/s. On the other hand, when 8% LI was added, an increase in k_d was observed at 3 days and 7 days of maintenance, reaching values of 0.1039 m/s

and 0.1102 m/s, respectively. These observations indicate that the relationship between k_d of the pulverized soil and the dosage and maintenance time becomes more complex after the addition of a chemical stabilizer. Furthermore, it was noted that the relationship between k_d and the dosage and maintenance time becomes more complicated after introducing a chemical stabilizer. Therefore, it is deemed more appropriate to select τ_c as the evaluation parameter for assessing the effectiveness of improvement.

4 Discussions

4.1 Improvement effect

Internal erosion presents a significant risk to the sustainable operation of structures such as dams and urban highways (Zhang et al., 2023a). To solve this problem, chemical stabilisers incorporated into the interior of erosion-prone soils can significantly improve the erosion resistance of soils (Banu and Attom, 2023). In this study, three chemical stabilisers, LS, LI, and LF, were selected to consider the effects of chemical stabiliser dosage (0%–8%) and maintenance time (1 day–14 days) after completion of specimen preparation on the internal erodibility of the soil (Liang et al., 2021). The most commonly used HET was used to obtain the parameters for evaluating the internal erodibility of the modified sandy silt: τ_c, k_d, and ε_t (Wan and Fell, 2004a). The test results show that after adding chemical stabiliser, the internal erodibility of sandy silt soil will change significantly, and the overall trend will reduce (Liang et al., 2021). Still, the improvement effect is more sensitive to the type of chemical stabiliser, the amount of chemical stabiliser added, the maintenance time, and other factors (Vakili et al., 2018). By applying τ_c as a measure, it was observed that τ_c of LF increased consistently as the dosage increased. The maximum increase was 2.38 times compared to the specimen without a chemical stabiliser. Additionally, τ_c of LI was slightly lower than that of LS, with a maximum increase of 2.2 times (Ta'negonbadi and Noorzad, 2017). τ_c increased by 1.68 times when the amount of LS was added at 2% and gradually decreased when the amount of LS was higher than 2% (Liang et al., 2021). With the increase in maintenance time, τ_c of LF with 8% addition increases steadily, which aligns with the actual engineering requirements (Liang et al., 2021). Based on the economic benefits and improvement impact, using τ_c as the evaluation index, adding a 2% chemical stabiliser results in LF having the most significant improvement effect, followed by LI and LS having the least improvement effect. Using the k_d as the assessment index, adding 6% of LI and 8% of LF and maintaining for 1 day lowers the k_d by 2.18 times and 2.57 times, respectively (Rasika et al., 2013). The k_d of the LF specimens fell significantly as the curing period increased, mainly when the additional amount was 8%. Thus, when k_d is employed as the assessment criterion, LF exhibits the most significant improvement effect, followed by LI, and LS demonstrates the least improvement. Hence, based on τ_c and k_d analysis, it is advisable to prioritise LF>LI>LS in practical applications.

4.2 Stabilisation mechanism

4.2.1 Microstructural characteristics

The structure of soil is the spatial arrangement of particles, aggregates, and pores in soil, and the development of the theory of microstructural mechanics has linked microstructure to the macroscopic behaviour of soils (Duan et al., 2024). Microstructure and macrostructure together determine soil's mechanical behaviour and water stability (Duan et al., 2023). Soils with different structures have different internal erosion behaviour (Lefebvre et al., 1986). Therefore, by comparing the microstructural characteristics of pulverised soils before and after improvement, the mechanism of chemical stabiliser improvement of pulverised soils can be revealed (Hassan et al., 2023). Figure 11 displays scanning electron microscope (SEM) pictures of the pulverised soil in various conditions, observed at a magnification of ×1,000. Figure 11A displays the microstructure of the sandy silt soil in its natural state, without chemical stabilisers. The image reveals distinct particle boundaries, with particles primarily in direct contact with one another. There is evidence of microcementation, and no clumps or agglomerates are observed. Additionally, the soil exhibits well-developed pores (Cheng et al., 2021). Consequently, the natural sandy silt soil possesses minimal resistance to erosion (Lefebvre et al., 1986).

With the addition of 8% content of LI, the maintenance time is 14 days, it can be seen that the pores in this specimen are all filled by LI, LI covers the particles around the particles, the particles form a microcementation between the particles, which enhances the erosion resistance as illustrated in Figure 11B (Shourijeh et al., 2020). The microstructure of pulverised soil after adding 8% content of LS and maintenance for 14 days is shown in Figure 11C. It can be seen that the microstructure of soil body did not change significantly, and insignificant cementation was formed between some particles, the pore space was still relatively developed, and the point-point contact still dominated the contact between the particles, and thus the stability was poor, which was also an intrinsic factor of the poor effect of the LS in improving the pulverised soil (Indraratna et al., 2009). The SEM image of 8% addition and 14 days maintenance, as shown in Figure 11D, can be seen that the picture is covered with a fibrous material, which tightly entangles the soil particles together, the number of pores is substantially less, distributed along the fibres, and the shape is elongated, which indicates that the LF-improved chalky soil is dense, and thus has the best amelioration effect (Liu et al., 2018).

4.2.2 Microscopic parameters

The software "Image-Pro Plus" (IPP) is one of the most commonly used tools for quantitative analysis of soil microstructure (Huo et al., 2023). Soil particles and pores can be quantitatively analyzed by using IPP software (Xu et al., 2021). The distribution characteristics of pore diameter have significant influence on soil erosivity (Khabbaz, 2008). The ×500 SEM image was used as the data source to analyze the pore distribution of the sample. There are four types of pores in the samples strengthened by different chemical stabilizers: macropore (Pore diameter >32 μm), mesopore (16–32 μm), small pore (8–16 μm) and micropore (<8 μm) (Figure 12). As shown in Figure 12, the addition of different chemical stabilizers had significant effects on soil pore distribution.

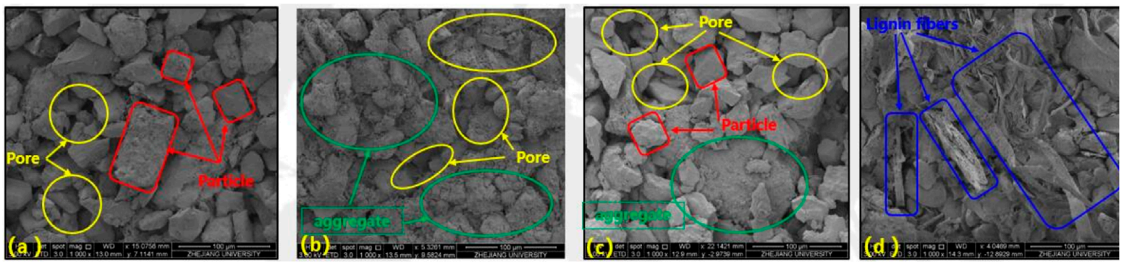

FIGURE 11
Microstructure images of powdered soil before and after modification; **(A)** 0%; **(B)** LI 8% 14 days; **(C)** LS 8% 14 days; **(D)** LF 8% 14 days.

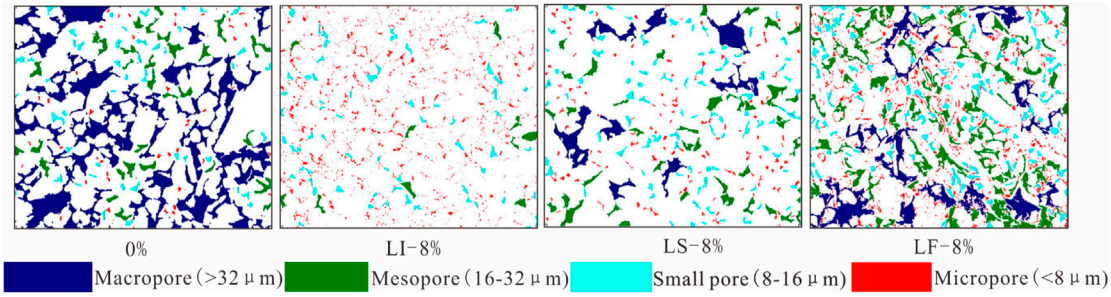

FIGURE 12
Pore distribution under different chemical stabilizers.

The samples without any chemical stabilizer were dominated by macropores (>32 μm), and the number of macropores (>32 μm) was significantly reduced after the addition of chemical stabilizer, among which the addition of 8% LI could significantly reduce the number of macropores (>32 μm). This shows that the chemical stabilizer can fill the macropores (>32 μm) of the soil, so that the contact between the soil particles becomes tight, thereby improving the connection between the particles, and therefore, the erosion resistance is improved.

Figure 13 reveals the quantitative changes of various pore distribution characteristics after the addition of different chemical stabilizers. It can be seen from Figure 13 that the addition of chemical stabilizer will greatly increase the number of micropore (<8 μm) in the soil. For example, after adding 8% LI, the micropore (<8 μm) increased by 29.89%. Small pore (8–16 μm) percentage is not sensitive to chemical stabilizer. Figure 13 also shows that the percentage of mesopore (16–32 μm) and macropores (>32 μm) in the soil is greatly reduced after the addition of chemical stabilizer. In summary, the addition of chemical stabilizers can make the soil structure more dense, thus enhancing the critical shear stress and reducing the erodibility coefficient.

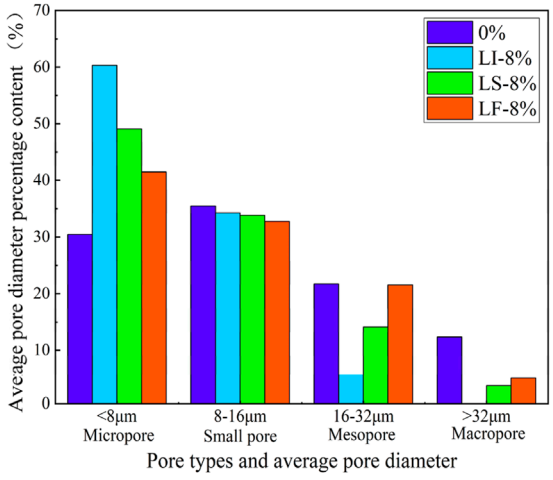

FIGURE 13
Percentage of mean pore diameter under different chemical stabilizers.

4.2.3 Internal erosion mechanisms in stabilised soils

The internal erosion mechanisms vary significantly depending on the soil structure (Lefebvre et al., 1986). The microstructure of the sandy silt soils changed substantially after the addition of different chemical stabilisation (Figure 11) (Reddy et al., 2020), resulting in a differentiated internal erosion behaviour (Figure 7) (Vakili et al., 2018). In fact, the variability in the internal erosion behaviour of the soil is an outward indicator of the difference in the internal erosion mechanism (Lefebvre et al., 1986). The addition of chemical stabilisers alters the microstructure of the natural sandy silt soil, leading to significant changes in the contact relationships between particles

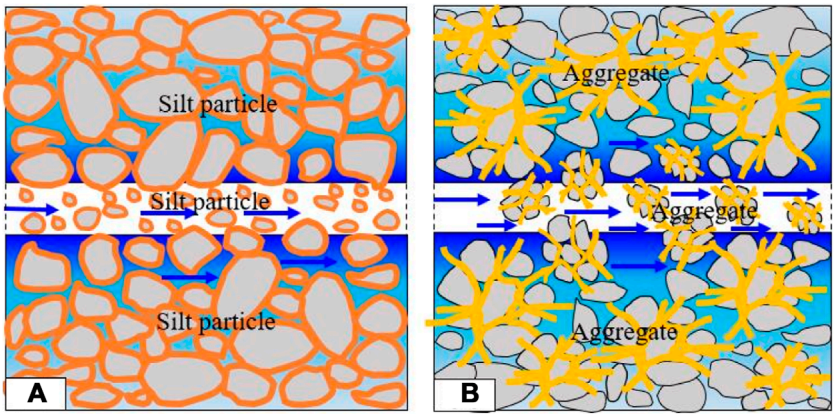

FIGURE 14
Schematic diagram of two typical exfoliation mechanisms for modified sandy silt soil: **(A)** particle exfoliation and **(B)** agglomerate exfoliation.

(Elandaloussi et al., 2018). There are two common ways in which runoff removes material when it comes into contact with the surface of the silt particles (as shown in Figure 14). As depicted in Figure 14A, the addition of chemical stabilisers resulted in the formation of a thin cover layer on the particle surface (Ta'negonbadi and Noorzad, 2017). However, this did not effectively enhance the contact relationship between the silt particles.

Consequently, the cementation between the particles was weak, and the silt particles remained separate (Khabbaz, 2008). Concentrated runoff scouring results in a remarkably high erosion rate, causing the swift displacement of soil particles. The fragmented soil particles are evenly carried away during this procedure, leading to a level surface after erosion, as depicted in Figure 7A. Under the conditions of soil being stripped and transformed, the ability to resist erosion is very low, as evidenced by the case of LS. Figure 14B shows another improved powder soil stripping mechanism; as can be seen in Figure 14B, a large number of agglomerates are formed within this improved soil body, and under the action of the runoff, the smaller, smaller agglomerates are peeled off in the form of agglomerates. Small pits are formed in the wall after peeling off in the form of agglomerates (Figure 7B). Due to the incorporation of amendments such as fibres, the initially dispersed and distributed particles are bonded together, the soil body is more holistic, and the agglomerates have a stronger resistance to erosive scouring than the dispersed individual soil particles. Therefore, the improvement effect is better than that of the LF.

5 Conclusion

This study investigated the stabilizing effects of three chemical stabilizers on sandy silt soil, and the following conclusions were drawn:

1) LF mainly improves the erosion resistance of sandy silt soil by increasing the critical shear stress (τ_c), and the maximum increase is 2.38 times; LI mainly improves the erosion resistance by decreasing the erodibility coefficient (k_d), and the maximum decrease is 2.18 times. The critical shear stress (τ_c) and erodibility coefficient (k_d) did not change significantly after adding LS; the improvement effect is general.
2) LF mainly enhances the erosion resistance through fibre entanglement of silt particles to improve the integrity of the soil body, while LI mainly enhances the erosion resistance through the formation of weak cementation between the particles;
3) The variability of morphological characteristics of the pore wall at the end of erosion reflects the differences in stripping patterns. The better modified LF was stripped in the form of larger agglomerates, which weighed more than the individual soil particles and thus had a higher erosion resistance; the modified soil samples stripped with individual soil particles, such as the LS modified soil samples, did not differ much from the natural silt microstructure, and thus did not have a significant improvement in erosion resistance.

This study conducted HET on three different chemical stabilisers to enhance the quality of sandy silt soil. The study additionally investigated the impact of dosage and maintenance time on the effectiveness of soil improvement. In the future, conducting HET will be essential for determining the ideal dosage of various chemical stabilisers. Furthermore, it is imperative to integrate the principles of pipeline hydrodynamics and soil chemistry in forthcoming research to understand the internal erosion mechanism of chemical stabilizer-treated soils completely.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

BZ: Data curation, Investigation, Writing–original draft. XZ: Conceptualization, Methodology, Supervision, Writing–original draft, Writing–review and editing. XT: Funding acquisition, Investigation, Resources, Writing–review and editing. MW: Formal

Analysis, Validation, Visualization, Writing–review and editing. AA: Formal Analysis, Supervision, Validation, Writing–review and editing. GM: Data curation, Investigation, Resources, Writing–review and editing.

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Conflict of interest

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Triaxial mechanical behaviours of Ili loess after freeze–thaw

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Loess is strongly sensitive to water, and its properties are substantially affected by weathering and other factors. Loess landslides, which are widely distributed in Ili, are closely related to seasonal freeze–thaw effects. In this study, multiple freeze–thaw cycle tests were conducted on loess samples with different moisture contents from the Ili region, and triaxial shear tests were conducted to study mechanical characteristics of the loess. Variations in the microstructure of the loess samples were analysed using scanning electron microscopy images to reveal the underlying mechanisms. The results showed that the freeze–thaw cycles significantly influence failure mode of the stress–strain curve of loess samples with a lower moisture content of 10%, which transitioned from strain softening to strain hardening with six cycles as the turning point, whereas the stress–strain curve transitioned from strong to weak hardening for the loess samples with higher moisture content of 18%. As the number of freeze–thaw cycles increased, failure strength and shear strength parameters of loess gradually decreased, and tended to stabilize after the 10th cycle. In addition, strength parameters deterioration is most significant after the first cycle, and the degree of cohesion deterioration was much greater than that of internal friction angle. Cohesion and internal friction angle showed attenuation exponential function and polynomial function relationship, respectively, with the number of freeze–thaw cycles, and their fitting parameters underwent a sudden change with increasing moisture content, with 14% as the turning point. Microscopic SEM revealed that the number of overhead pores increased, and point–to–point contact between particles increased after freeze–thaw, which was consistent with increase in of loess porosity. This revealed the fundamental reason for the significant deterioration in loess strength caused by freeze–thaw cycles.

KEYWORDS

Ili loess, freeze-thaw cycle, failure mode, shear strength parameters, deterioration degree, Microstructure

1 Introduction

Loess is a special type of loose sediment formed during the Quaternary with porous pores and weak cementation. Its composition is mainly dominated by silty particles with unique microstructural characteristics (Hu et al., 2021). It is strongly sensitive to water and its properties are substantially affected by weathering and other factors. Loess is widely distributed in the northwestern region of China, Ili located the Tianshan Mountains, is the westernmost part of China's loess distribution area and is a typical seasonally frozen soil region (Zhuang et al., 2021). The rising temperature in spring leads to thawing of frozen loess, resulting in frequent occurrences of loess landslides, such as the super large Gallente,

the Yining Kizilesai, and the Zeketai landslides in the Ili Valley which mainly occur in spring and summer. (Wang and Yao, 2003). highlighted that seasonal freeze–thaw cycles are the main factor causing loess landslides. Under the cyclic action of climate change, the soil is in a state of repeated freezing and melting with its strength gradually deteriorating, easily leading to the occurrence of geological disasters (Zhou et al., 2018; Kong et al., 2023; Liu et al., 2020; Ismeik and Shaqour, 2020; Nguyen et al., 2019; Xu et al., 2018; Bragar et al., 2022; Liu et al., 2023; Jing et al., 2022; Zhou et al., 2023). Zhuang et al. (2021) highlighted that loess landslides in the Ili Basin are strongly affected by seasonal freeze–thaw cycles. Therefore, in the context of construction of "the Belt and Road," studying on the mechanical properties of the Ili loess under the freeze–thaw effect in the seasonal freezing area is particularly important.

With increase in engineering construction in western China, studying mechanical properties of loess under freeze–thaw conditions has become an important issue in the cold regions. Through laboratory experiments in recent years, most researchers have found that repeated freeze–thaw cycles weaken the strength of loess, and the variation law of loess shear strength is affected by many factors, such as moisture content, porosity, dry density, plasticity index, stress, freeze–thaw cycles, and temperature (Xu et al., 2018; Wang et al., 2018; Xu et al., 2018; Liu et al., 2021; Wang et al., 2024). Similar conclusions have been reached for variation of cohesion (one of the shear strength parameters) with the number of freeze–thaw cycles, and the cohesion of loess is strongly deteriorated by the effect of freeze–thaw cycles, which decreases to the lowest value after a certain number of freeze–thaw cycles (Wang et al., 2024; Ni and Shi, 2014; Ye et al., 2018). However, results of the freeze–thaw effect on the internal friction angle (the other shear strength parameter) were different. Some researchers have found that there is no significant change in internal friction angle (Xu et al., 2018; Song et al., 2008; Dong et al., 2010), while some researchers have obtained that internal friction angle slightly increases with the total number of freeze–thaw cycles (Song et al., 2008; Wang et al., 2024; Ye et al., 2018; Liu et al., 2021). Some scholars have also found that freeze–thaw cycles have a significant weakening effect on cohesion of highly saturated loess (Qian, 2018). For experimental studies on shear strength parameters, from previous simple direct shear tests to current more realistic triaxial shear tests, triaxial shear tests have been increasingly applied due to various advantages (Zhou et al., 2018; Kong et al., 2023; Wang et al., 2018; Li et al., 2018; Ren and Vanapalli, 2020; Yin et al., 2022; Zhang et al., 2024).

Macroscopic engineering properties of soil are significantly influenced its microstructural state and variation laws (Hong and Liu, 2010). Therefore, increasing number of scholars focus on revealing the mechanism of mechanical properties variation of loess under various weathering effects and loadings from microstructure perspective (Gao, 2013; Mu et al., 2011; Wang et al., 2016; Wei and Li, 2019; Zhang et al., 2020; Liang et al., 2023; Ye and Li, 2019; Hu et al., 2022; Nie et al., 2023). Several studies have found that freeze–thaw cycles cause changes in the micro–structure of loess, such as particle size distribution, roundness, contact mode, cementation, pore area, size, and type, etc. After freeze–thaw, large particles in loess are decomposed into several small particles, the fine particles increase, angularity of the particle surface is continuously rounded, and cementation of soil deteriorated (Xu et al., 2018; Ye et al., 2018; Qian, 2018). Ni and Shi (2014) illustrated through scanning electron microscopy (SEM) experiments that continuous decrease in cohesion was caused by repeated freeze–thaw, which gradually weakened the original inherent cementation between loess particles. Ye and Li (2019) analysed changes in the structure of loess under freeze–thaw cycles, and highlighted that with increase in the number of freeze–thaw cycles, contact between particles changes from surface–plane contact to point–plane and point–point contact, and porosity ratio of the cross–section increases with the increase in freeze–thaw cycles (Ye et al., 2020; Li et al., 2020; Liu et al., 2021).

In recent years, there has been more research on Ili loess, with most studies focusing on collapsibility, water retention, the influence of soluble salt content on mechanical properties, and the tensile properties (An et al., 2018; Liu et al., 2021; Wang et al., 2019; Niu et al., 2021; Zheng et al., 2022). With the continuous increase of loess landslides in Ili region, through on–site investigations, remote sensing and other methods, many scholars have conducted study on movement process and formation mechanism of landslides and found that these are closely related to seasonal freeze–thaw effects and rainfall (Zhuang et al., 2021; Li et al., 2020; Liu et al., 2021; Yu et al., 2022). Actually, the decrease in soil strength is the core factor causing landslides, which has been confirmed by many scholars (Zhuang et al., 2021; Zhang et al., 2022; Bragar et al., 2022; Liu et al., 2023; Wang et al., 2024). However, there is little attention paid to the study on effect of freeze–thaw on Ili loess deterioration, which is an important factor contributing to the formation of loess landslides. Therefore, further research focusing on the deterioration of mechanical properties and micro–mechanisms of Ili loess under freeze–thaw action is needed to better study the mechanism of landslides formation in seasonally frozen soil region from both macro and micro perspectives.

Here, we aimed to study on the macroscopic characteristics including the failure mode and the variation law of loess strength under freeze–thaw cycles, and explore the deterioration mechanism of loess strength under freeze–thaw cycles through microstructure testing. We took the loess in the Ili landslide in the seasonally frozen region as the research object. Different initial moisture contents and different freeze–thaw cycles were considered as influencing factors for a comparative analysis, of the evolution laws of the stress–strain relationship, failure strength, and shear strength parameters of loess samples. Qualitative and quantitative evaluations were conducted through SEM images to reveal the deterioration mechanism of Ili loess strength under freeze–thaw. Analyzing the evolution of mechanical properties of loess in freeze–thaw environments from both macro and micro perspectives is beneficial for improving the research of loess mechanics theory. More importantly, this work can not only provide important calculation parameters for evaluating the stability of foundation and engineering slopes, ensuring the safe of engineering in cold regions, but also can provide a theoretical basis for future disaster prevention and mitigation in the Ili region, which is of great significance in promoting the construction of the core area of the Silk Road Economic Belt.

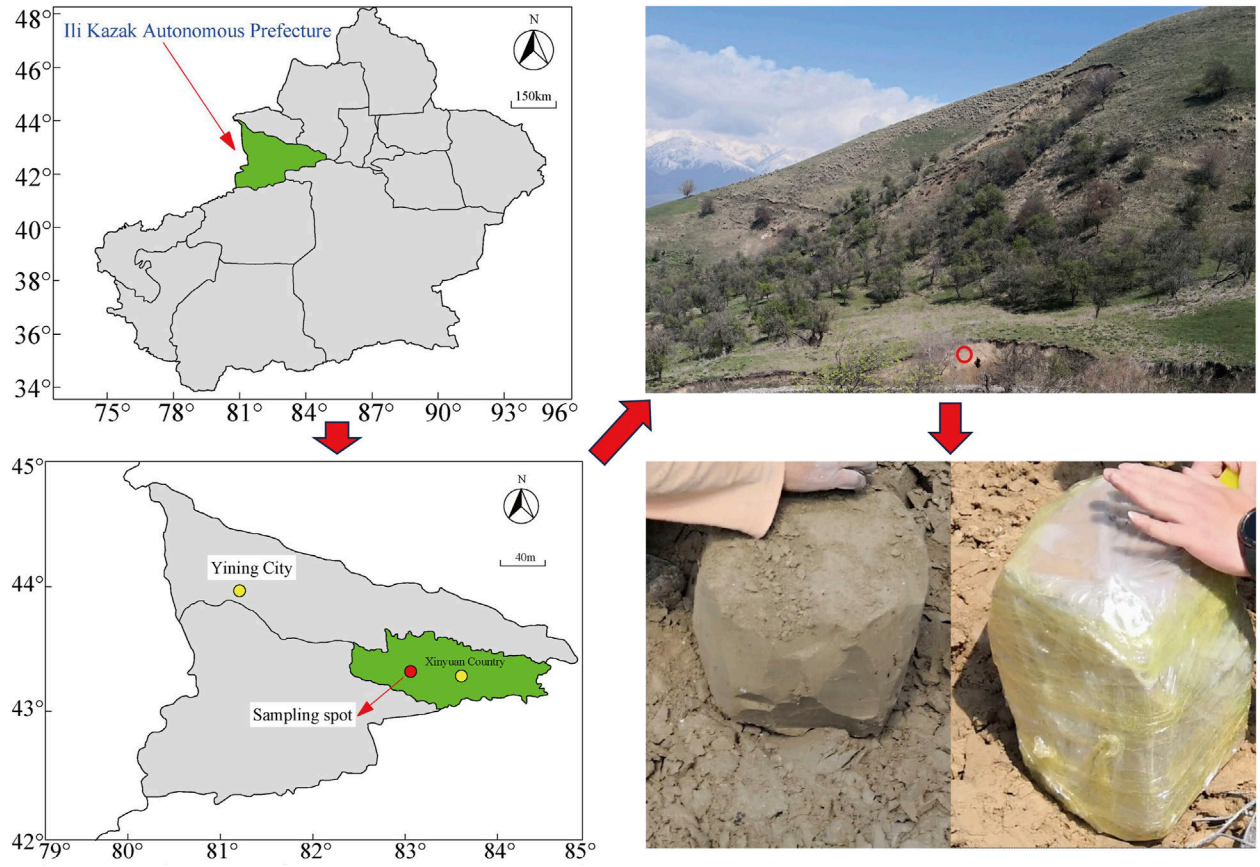

FIGURE 1
Sampling spot at Xinyuan Country.

2 Materials and methods

2.1 Materials

To study the mechanical properties of the Ili loess under freeze–thaw conditions, samples were taken from the Haindesayi Gully loess landslide in Almaler Town, Xinyuan County (as shown in Figure 1), with a sampling depth of 2 m and classified as Q_4 loess. Six sets of undisturbed samples were obtained using a cutting ring to determine the natural density of the loess. Many disturbed soil samples were collected for the physical and mechanical tests.

The physical properties of the Ili loess are listed in Table 1. Through X–ray, mineral composition was determined to be quartz, albite, calcite, lepidolite, and chlorite, with percentages of 21.53, 50.66, 11.22, 12.02, and 4.57, respectively, as shown in Figure 2. Particle size distribution curve obtained by a laser particle size analys is shown in Figure 3, with particles dominated by 20–50 μm and followed by 5–20 μm, contributing a total of 75.2%. According to the soil classification standard, Ili loess is classified as low–liquid–limit clay, with coefficient of nonuniformity (C_u) 18.14 and coefficient of curvature (C_c) 0.50, indicating that uneven, poorly graded particle size, and uneven porosity distribution.

2.2 Sample preparation

Previous studies have shown that freeze–thaw has different effects on soil with different initial moisture contents (Xu et al., 2018; Wang et al., 2010; Ye et al., 2018; Qian, 2018). Remolded samples were used in this experiment to ensure uniformity of each group of samples, First, loose soil samples taken from the field were thoroughly air–dried and their dry moisture content is measured. Five sets of moisture contents were set at 6%, 10%, 14%, 18% and 22% based on the plastic limit of the Ili loess, which are consistent with the dry density of the original soil on site, with a dry density of 1.4 g/cm^3. Masses of dry soil samples and water required for each group were calculated. Distilled water was sprayed multiple times into the soil, and the soil samples were wrapped with preservative film and placed in moisturising container for 48 h to be fully moistened, while controlling the moisture content error to within 1%. Those samples were prepared for triaxial shear and microstructural tests. Next, according to the "Standard for Soil Test Methods GB/T5023–2019," 120 cylindrical samples with a diameter of 39.1 mm and a height of 80 mm were prepared using the tapping method and compacted in 4 layers (Figure 4B). Finally, the samples were wrapped and sealed with plastic film for the freeze–thaw test to avoid water evaporation.

TABLE 1 Basic physical parameters of loess in ili.

Specific gravity (*Gs*)	Natural density (ρ)	Dry density (ρ_d)	Natural water content (w)	Void ratio (e)	Plastic limit (w_p)	Liquid limit (w_L)	Plastic Index (I_p)
2.74	1.70	1.40	18.9%	1.0	21.80%	29.40%	7.60

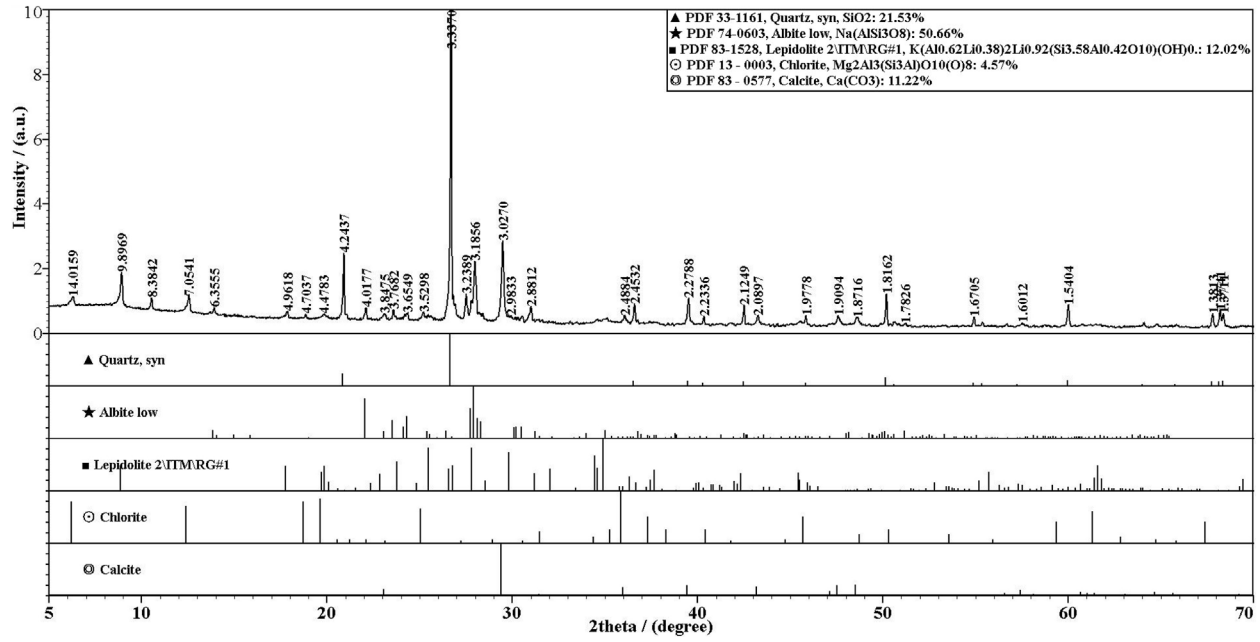

FIGURE 2
The X–ray diffraction patterns of samples.

2.3 Test method

2.3.1 Freeze–thaw test

A programmable high/low–temperature test device with constant temperature and humidity (Figure 4C) was used for the freeze–thaw test in this study. Based on local meteorological data of Xinyuan County, freezing and thawing temperature for this experiment were set at −20°C and 20°C, respectively, and freeze–thaw procedure lasted 16 h (8 h for freezing and 8 h for thawing), completing one freeze–thaw process. According to previous experimental research (Ye et al., 2018; Qian, 2018), after the 15th freeze–thaw cycle, the physical and mechanical properties of the soil mass reached stability. Therefore, the number of freeze–thaw cycles in this experiment was considered as 0, 1, 3, 6, 10, and 20. After the freeze–thaw process, the samples are were removed for subsequent microscopic structure and triaxial shear tests.

2.3.2 Triaxial shear test

To understand the characteristics of the triaxial shear strength and stress–strain relationship curve of the Ili loess after freeze–thaw cycles, TFB–1 unsaturated soil stress–strain triaxial apparatus (Nanjing Soil Instrument Co., Ltd.). (Figure 4D). was used for the triaxial shear test. Considering the influence of consolidation on the mechanical properties of soil, undrained consolidation method was adopted in this experiment, with confining pressure of 50, 100, and 200 kPa, and equal strain rate of 0.1 mm/min. According to the Chinese geotechnical testing method standards, the test was terminated when the axial strain reaches 15%.

2.3.3 Microstructure test

Firstly, after undergoing a specified number of freeze–thaw cycles, the samples were dried naturally. Following this, they were cut into cuboids of 10 × 10 × 20 mm by using a blade, and then the middle section in the height direction was broken to form a fresh section, and the floating soil was blown away with a rubber suction bulb. After that, a gold–sputtering process, which was crucial for obtaining clear and high–quality SEM images, was carried out to enhance the conductivity for electron microscopy. Lastly, the samples were placed on a Quanta 250 FEG SEM (FEI Company; Hillsboro, OR, United States) (Figure 4D). The four corner points and the middle point on the horizontal plane of the cube sample were selected as representative observation points to obtain SEM images at different magnifications, avoiding positions with large holes, impurities, and unevenness.

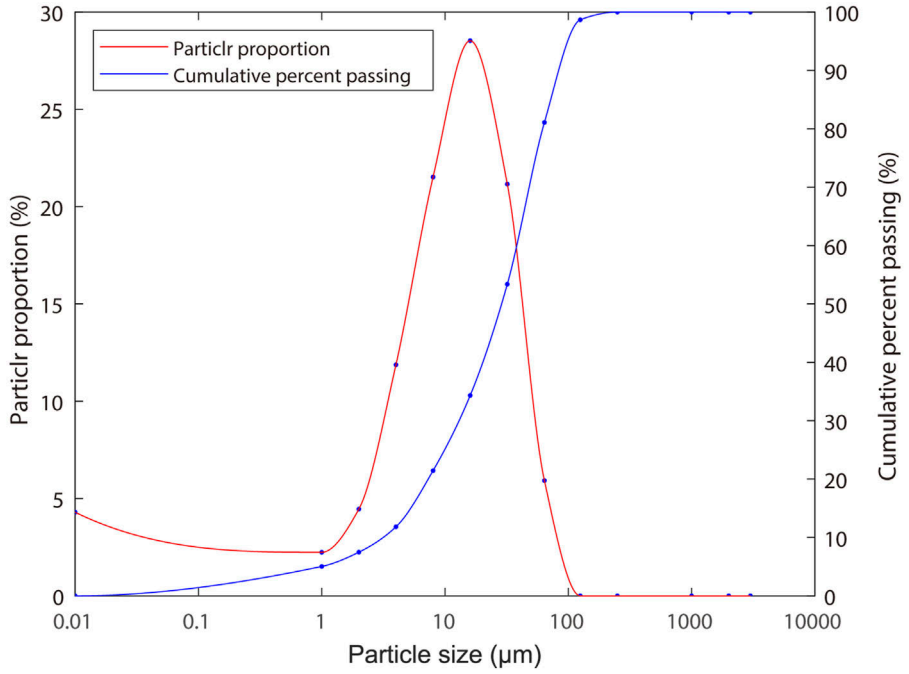

FIGURE 3
Soil particle size distribution curve.

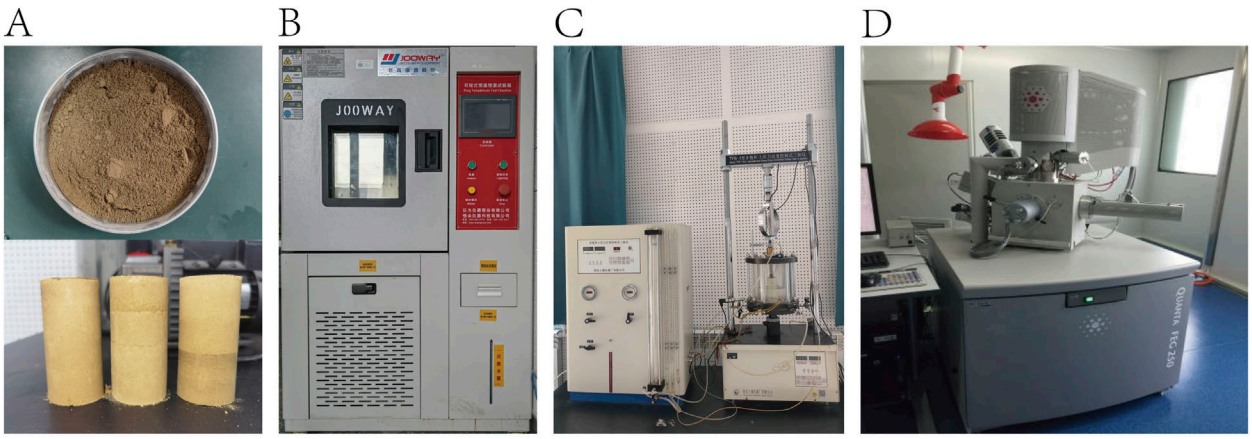

FIGURE 4
Test process: **(A)** Remolded loess, **(B)** High/low–temperature test device used for freeze–thaw test **(C)** Strain–control triaxial instrument, **(D)** The SEM used for Microstructure test.

To explore microscopic mechanism of freeze–thaw effects on loess samples, the microstructure characteristics of loess were analyzed in depth from SEM images. Firstly, the SEM images were qualitatively identified, including particle characteristics and pore characteristics. Then, the computer image processing technology IPP6.0 was used to extract microstructure parameters (including particle size and pore distribution area), and the quantitative analysis of the variation law of loess microstructure with the number of freeze–thaw cycles was carried out.

3 Results and analysis

3.1 Macroscopic characteristics of loess sample under freeze–thaw cycles

3.1.1 Stress–strain curves

Figure 4 shows the stress–strain curves of the loess samples subjected to freeze–thaw cycles. Owing to space limitations, only the results of the loess samples with initial moisture contents of 10% and 18% are presented in this paper. The more the number

of cycles, the lower the corresponding curve position, and with different failure modes of the low and high–water–content curves (Figure 5). For loess samples with an initial moisture content of 10%, under the confining pressure of 50 kPa and 100 kPa, with the increase in freeze–thaw cycles, the peak point of the curve gradually disappears, and the failure mode transitioned from strain softening to strain hardening, with six cycles as the critical value. When the loess samples were subjected to a confining pressure of 200 kPa, peak point was not observed in the stress–strain curves, and the failure mode of the sample was mainly strain hardening, which is consistent with the general law that loess exhibits strain softening behavior under low confining pressure and strain hardening behaviour under high confining pressure (Li et al., 2019). For loess samples with a moisture content of 18%, peak point was not observed in the stress–strain curve, and the type of stress–strain curve changed from strong to weak hardening with increasing cycle number. Figure 6 presents the failure modes of the loess samples with moisture contents of 10% and 18%. Evidently, the loess with moisture content of 10% mainly exhibits brittle failure when the confining pressure was less than or equal to 100 kPa, and plastic failure when the confining pressure reached 200 kPa. Loess samples with a moisture content of 18% exhibited plastic failure, which is consistent with the shape of the curve in Figure 5.

We found that moisture content, cycle number, and confining pressure all have a certain influence on the stress–strain curve and failure mode of loess samples after freeze–thaw cycles. Pan et al. (2023), and Liu et al. (2023) also highlighted that the stress–strain curve is mainly affected by the number of freeze–thaw cycles, initial moisture content of the sample, and confining pressure. Among them, moisture content has the greatest influence on the stress–strain curve and failure mode (Liu et al., 2021), when the deviatoric stress was small, the stress–strain relationship was close to linear in the initial stage.

3.1.2 Failure strength

Figure 5 shows that that the lower the position of the stress–strain curve, the smaller the principal stress difference. To further study the deterioration effect of freeze–thaw cycles on loess, the peak point of the stress–strain curve or the principal stress difference corresponding to a strain of 15% was considered as the failure strength (PRC, 2019). Variation law of loess failure strength with the number of freeze–thaw cycles and moisture content was analyzed. Figures 7A, C shows the relationship between failure strength of loess samples and different moisture contents and the number of freeze–thaw cycles. Under different confining pressures, variation law of the failure strength of loess samples with the number of freeze–thaw cycles was generally the same. Failure strength of loess samples increased with confining pressure. Under the same confining pressure, the maximum amplitude of failure strength deterioration occurred after one cycle. In addition, the deterioration amplitude gradually decreased with increase in cycle number, and even tended to be stabilise. Loess samples with low moisture content (≤14%), reached stability easier, and the curves showed that moisture content increased from top to bottom. Moreover, failure strength of loess samples with moisture content ≥14% decreased significantly, and the maximum deterioration amplitude occurred after one cycle from the moisture content 10%–14%, and the corresponding deterioration amplitude values under confining pressures of 50, 100, and 200 kPa were 134.9, 202.4, and 152.7 kPa, respectively.

Failure strength curves of loess samples with varying moisture content under a confining pressure of 100 kPa are shown in Figure 7D. Under the same confining pressure, failure strength of the loess samples gradually decreased with increasing moisture content, and the trend for every curve was similar, and could be divided into three stages: slow, steep, and steady decline. The steep decline stage indicates, that the maximum decrease in failure strength occurred when the initial moisture content of the samples ranged from 10% to 14%, and the loess amplitude values corresponding to 0, 1, 3, 6, 10, and 20 cycles were 194.9, 202.4, 187.9, 179.6, 169.6, and 168.2 kPa, respectively.

3.1.3 Shear strength parameters

Shear strength parameters of the soil can be easily calculated based on the Mohr–Coulomb strength theory of soil, (Figure 8). Loess samples cohesion gradually decreased with increase in freeze–thaw cycles, and eventually stabilize (Figure 8A). For samples with lower initial moisture content (≤10%), the slope of the curve was larger before the 6th cycle of freeze–thaw, while for samples with higher initial moisture content (≥14%), the slope of the curve was larger before the 3rd cycle. However, sample loss rate between each cycle was mostly 20%–30%. Figure 8B shows the loss of cohesion was greatest when the initial moisture content increased from 10% to 14%. The corresponding loss amplitude values for 0, 1, 3, 6, 10, and 20 cycles were 50.7, 45.0, 31.6, 20.3 kPa, 19.8, and 21.8 kPa, respectively, and the loss amplitude value relatively decreased as the number of freeze–thaw cycles increased, indicating that loeess strength cohesion decreases rapidly from the unfrozen to the frozen–thawed state.

Variation law of the internal friction angle of loess with the number of freeze–thaw cycles and moisture content is shown in Figures 8C, D. The internal friction angle slowly decreased with the increase in the number of freeze–thaw cycles. When the initial moisture content were 6% and 10%, the variation in the internal friction angle of the loess is very small. When the initial moisture content was ≥14%, the internal friction angle of loess decreased with increase in the number of freeze–thaw cycles, but the maximum decrease was 2.8°. Internal friction angle of the loess showed a decreasing trend with an increase in moisture content, and the trend was the same at different cycles. Before the 6th cycle, the maximum reduction amplitude in the internal friction angle occurred between moisture contents of 14% and 18%.

Overall, shear strength parameters of loess samples decreased with increase in freeze–thaw cycles and then tended to stabilise, which is similar to the result obtained by (Zhao et al., 2023) through triaxial undrained tests. The freeze–thaw cycle had the greatest influence on the cohesion of loess, and the influence trend is similar to the failure strength, which is consistent with previous research findings (Song et al., 2008; Dong et al., 2010; Wang et al., 2010; Ni and Shi, 2014; Ye et al., 2018).

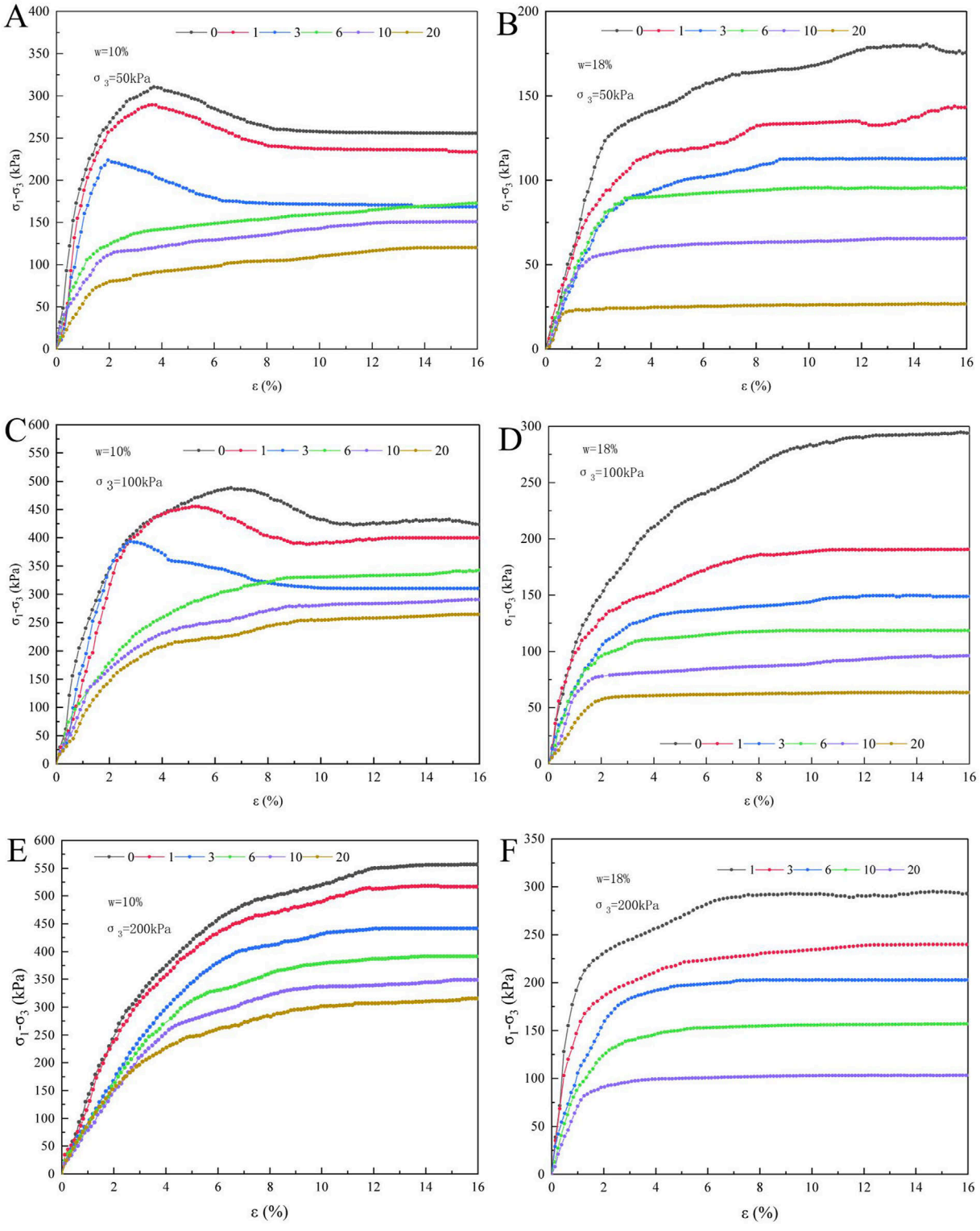

FIGURE 5
Stress–strain curves of samples under freeze–thaw cycles: **(A)** Initial moisture content 10%, confining pressure 50 kPa, **(B)** Initial moisture content 18%, confining pressure 50 kPa, **(C)** Initial moisture content of 10%, confining pressure of 100 kPa, **(D)** Initial moisture content of 18%, confining pressure of 100 kPa, **(E)** Initial moisture content 10%, confining pressure of 200 kPa, **(F)** Initial moisture content of 18%, confining pressure of 200 kPa.

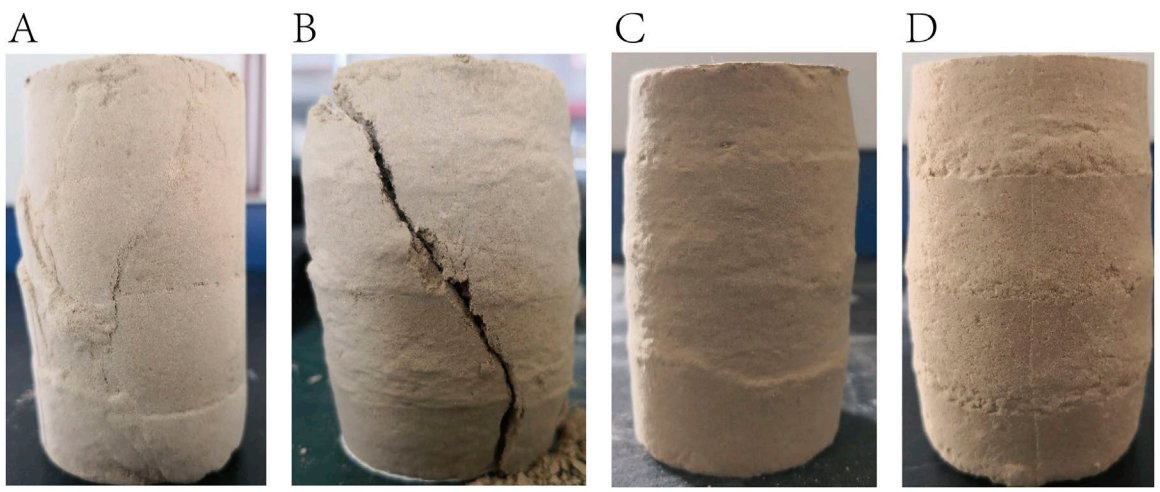

FIGURE 6
Loess samples failure mode under freeze–thaw cycles: **(A)** 10% (100 kPa, 3 times), **(B)** 10% (100 kPa, 6 times), **(C)** 10% (200 kPa, 6 times), **(D)** 18% (200 kPa, 20 times).

3.2 Macroscopic analysis of the loess strength

3.2.1 Fitting of strength parameters

To accurately predict the change law of loess strength subjected to freeze–thaw cycles, further quantitative analysis is required. Therefore, the strength parameters were fitted with the number of freeze–thaw cycles as the independent variable, and the fitting formulas were obtained (Table2). Through fitting, it was found that cohesion is an attenuation exponential function with the number of freeze–thaw cycles as single variable (as shown in Equation 1), which is similar to the power function obtained by Liu et al. in the experiment, but the function expression is different. Furthermore, the change law of the cohesion is a polynomial function (as shown in Equation 2). Fitting parameters A, B, C, D, E, and F for samples with different moisture contents were obtained, and the correlation coefficient R_2 of each fitting equation was almost greater than 0.95, indicating a good fitting degree.

$$y = Ae^{-\frac{x}{B}} + C \tag{1}$$

$$y = D + Ex^2 + Fx \tag{2}$$

where x and y in the formula represent the number of freeze–thaw cycles and strength parameter (cohesion or internal friction angle), which are the independent and dependent variables, respectively.

A sudden change in fitting parameters for cohesion and internal friction angle occurred (Table 2; Figure 9). This can be explained by analysing changes in the fitting parameters. The decrease amplitudes in fitting parameters A and C were 25.228 and 25.828 respectively, with moisture content increasing from 6% to 14%, When the moisture content increased from 14% to 22%, the decrease in fitting parameters A and C was 6.717 and 7.311, respectively. In addition, when moisture content increased from 10% to 14%, parameter D for internal friction angle decreased from 62.445 to 24.511, with a decrease in the amplitude of 37.934. Therefore, moisture content of 14% can be used as the critical moisture content for the variation in the shear strength parameters of the loess. After the moisture content exceeded 14%, parameter D changed slowly, and as the moisture content increased, parameter cohesion B gradually increased, whereas the internal friction angles E and F changed minimally, indicating that changes in moisture content mainly affected parameters A, C, D, and B.

3.2.2 Strength deterioration

To further analyse deterioration degree of triaxial shear strength parameters of loess samples with different moisture contents under freeze–thaw cycles, this study proposes a strength deterioration index L, defined as the degree of strength reduction of loess under freeze–thaw compared to that without freeze–thaw, as shown in Equations 3, 4, to characterise the effect of freeze–thaw cycles on shear strength parameters c and φ of loess.

$$L_c = \frac{c_0 - c_N}{c_0} \times 100\% \tag{3}$$

$$L_\varphi = \frac{\varphi_0 - \varphi_N}{\varphi_0} \times 100\% \tag{4}$$

where L_c and L_φ represent the deterioration of cohesion and internal friction angle, respectively, with the lower subscripts 0 and N representing the number of freeze–thaw cycles of 0 and N, respectively. The value of L is between 0 and 1, with L = 0 indicating no deterioration of the strength indicators, and a higher value of L indicating a higher degree of deterioration.

The deterioration of loess strength parameters was positively correlated with the number of freeze–thaw cycles, and showed an increasing trend with increase in moisture content (Figure 10). The curves of soil samples with moisture content below 14% showed an increasing trend before stabilising, whereas the curves of soil samples with moisture content above 14% showed an increasing trend, but the amplitude of the increase decreased. A comparison deterioration degree of cohesion and internal friction angle revealed that the deterioration degree of cohesion was much greater than that

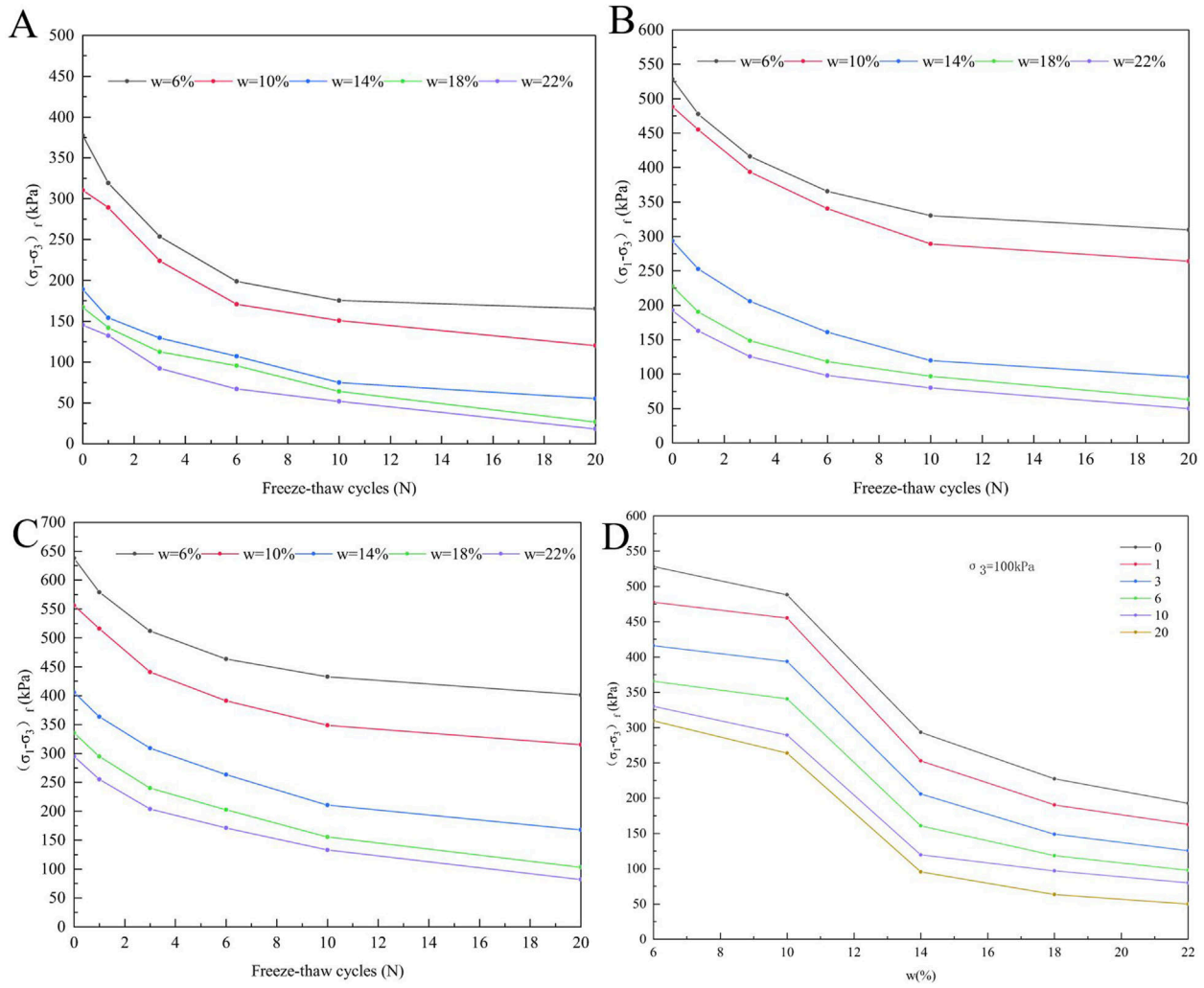

FIGURE 7
Variation law of loess failure strength with the number of freeze–thaw cycles and moisture content: **(A)** Failure strength under confining pressure of 50 kPa, **(B)** Failure strength under confining pressure of 100 kPa, **(C)** Failure strength under confining pressure of 200 kPa, **(D)** Variation of failure strength with moisture content under confining pressure of 100 kPa.

of internal friction angle, which explains why the decrease in the shear strength of loess under a freeze–thaw environment is mainly due to the weakening of cohesion.

3.3 Microscopic characteristics of loess samples under freeze–thaw cycles

3.3.1 Qualitative analysis

Magnifications used for the SEM test were 500, 1,000, 1,500, 2000, and 3,000. After comparison, the ×1,000 magnification image be used to observe overall morphology and complete microstructure (including the shape of particles, contact relationship between particles, particle arrangement, morphology and structure of pores). Although overall morphology was observed at a ×500 magnification, the complete structure could not be distinguished. A higher magnification (over 1,000 magnification) image was exactly the opposite of the lower magnification, therefore, SEM images (magnified 1,000 times) were selected or comparative analysis. Soil samples with initial moisture contents of 10% and 18% were selected, and SEM images (Figure 11) after 0, 3, 6, and 10 freeze–thaw cycles were analysed.

The loess samples without freeze–thaw action (i.e. 0 cycles) contained a relatively high distribution of angular particles, with only a small amount of aggregates in the loess with a moisture content of 18%. Surfaces of the coarse particles were coated with many clay particles, and contact between particles is mostly in the formed of surface–to–surface contact, with a small amount of point–to–surface and point–to–point contact. A large number of medium–sized particles form a mosaic pore structure, whereas some large particles formed an overhead pore structure. As the number of freeze–thaw cycles increased, the number of rounded particles and aggregates begin to increase, and large particles were filled with many small particles. Contact between particles gradually shifted to point–to–point and point–to–surface contacts, and the overhead pore structure gradually became dominant.

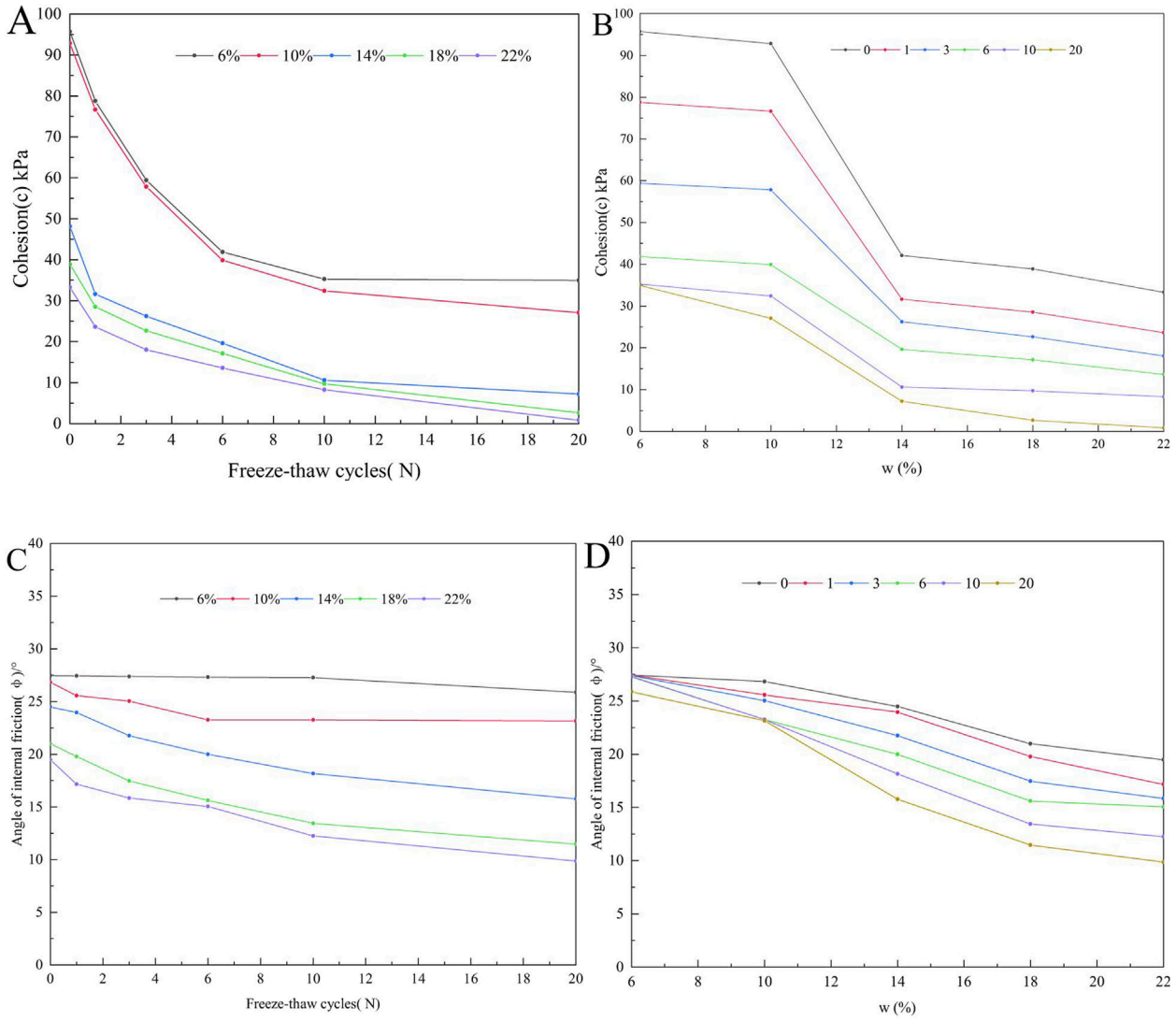

FIGURE 8
Variation of shear strength parameters with the number of freeze–thaw cycles and moisture content: **(A)** The change of cohesion with the number of freeze–thaw cycles, **(B)** The change of cohesion with moisture content, **(C)** The variation of internal friction angle with the number of freeze–thaw cycles, **(D)** Variation of internal friction angle with moisture content.

Evidently, the pore area increased and the particle arrangement was relatively loose. Many small pores were observed inside the aggregates. A comparison of loess samples with initial moisture contents of 10% and 18% revealed that the particles in the samples after 10 freeze–thaw cycles were significantly different, As shown in the SEM images, samples with an initial moisture content of 10% mainly consisted of single detrital grains, with both mosaic and overhead pores, while the particle composition in the soil samples with an initial moisture content of 18% mainly consisted of aggregates with few small particles. The number of freeze–thaw cycles for N = 10 is a critical value, after which the pore area decreases.

3.3.2 Quantitative analysis

According to Gao (2013), loess grain unit is divided into five intervals, d < 2 μm for fine clay particles and colloidal particles, d = 2–5 μm for coarse clay particles, d = 5–10 μm for fine silt particles, d = 10–50 μm for coarse silt particles, d = 50–100 μm for micro–sand particles, and d > 100 μm for sand particles. The particles of remolded loess were mainly <2 μm, followed by 2–5 μm, and the sum of the two could reach about 80%. The distribution of particles >100 μm was the least.

After freeze–thaw cycles, an increasing trend was observed in the content of particles <2 μm in the remolded loess, while a decrease was observed in the content of particles 2–5 μm (Figure 12). A comparion of the remolded loess with initial moisture contents of 10% and 18% revealed that the higher the initial moisture content, the more obvious the trend of increased in the content of particles <2 μm and 10–50 μm with the increase of freeze–thaw cycles, and both exceed the average values under different moisture contents. The percentage content of

TABLE 2 Fitting formula for shear strength parameters.

Parameter	Initial water content (%)	Equation	Correlation Coefficient (R^2)
Cohesion(c) (kPa)	6	$c = 62.226e^{\frac{-N}{3.192}} + 33.601$	0.997
	10	$c = 65.539e^{\frac{-N}{3.843}} + 26.925$	0.999
	14	$c = 36.988e^{\frac{-N}{4.192}} + 7.773$	0.956
	18	$c = 34.738e^{\frac{-N}{6.512}} + 1.696$	0.978
	22	$c = 30.281e^{\frac{-N}{6.432}} + 0.462$	0.998
Angle of internal friction(φ) (°)	6	$\varphi = 27.3905 - 0.0053N^2 + 0.03N$	0.986
	10	$\varphi = 62.445 + 0.021N^2 - 0.0561N$	0.936
	14	$\varphi = 24.5111 + 0.022N^2 - 0.0872N$	0.996
	18	$\varphi = 20.760 + 0.029N^2 - 1.0376N$	0.996
	22	$\varphi = 18.701 + 0.019N^2 - 0.8291N$	0.969

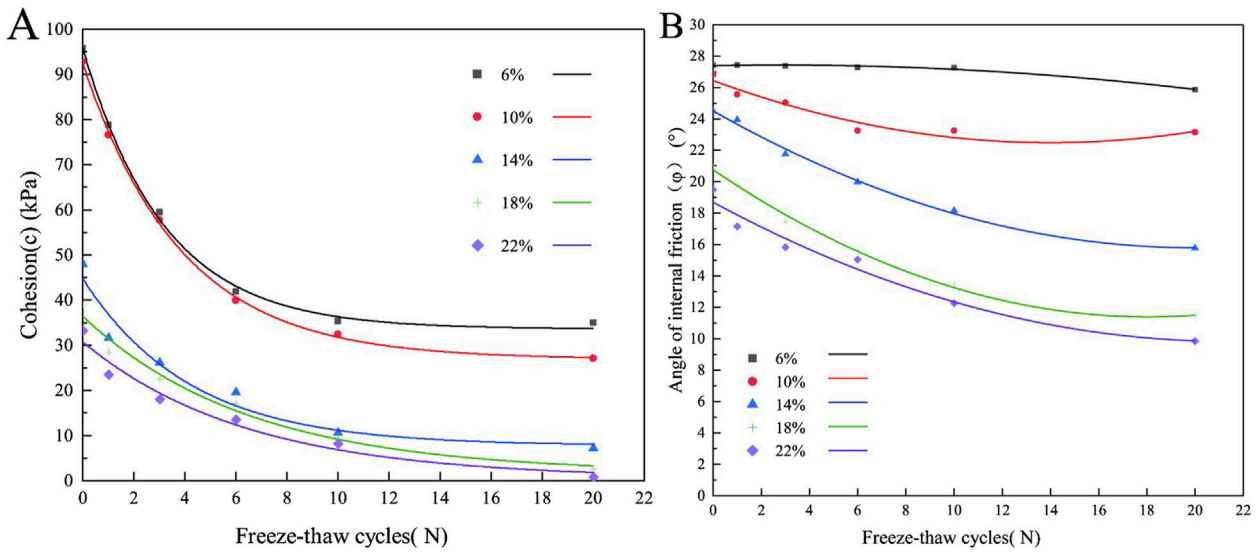

FIGURE 9
Fitting curve of shear strength parameters under freeze–thaw: **(A)** Cohesion, **(B)** Angle of internal friction.

particles <2 μm increases from 55.574% to 69.23%, with a growth percentage of 27.04%, while the trend of decreased in the content of particles 2–5 μm and 5–10 μm became more obvious, and both were lower than the average values under different initial moisture contents.

These findings indicates that the freeze–thaw cycle has a minimal influence on particle distribution of loess with a low moisture content of 10%, and the content of each particle group is relatively concentrated. However, the freeze–thaw cycle had a significant influence on particle distribution of loess with a high moisture content of 18%. It can be concluded that the expansion force of ice crystals formed during freeze–thaw action on loess with high moisture content and the transformation effect on loess particles after thawing are very strong (Xu et al., 2018, Wang et al., 2010).

Figure 13 shows variation in porosity of loess with different initial moisture contents after the freeze–thaw cycles. It can be observed that porosity of loess generally increased first and then decreased with increase in freeze–thaw cycles, reaching a peak. For low moisture content (6% ~ 14%) loess, the peak point occurred at 10 freeze–thaw cycles, whereas for high moisture content (18% ~ 22%) loess, the required number of freeze–thaw cycles for the peak point was relatively small. The freeze–thaw cycle

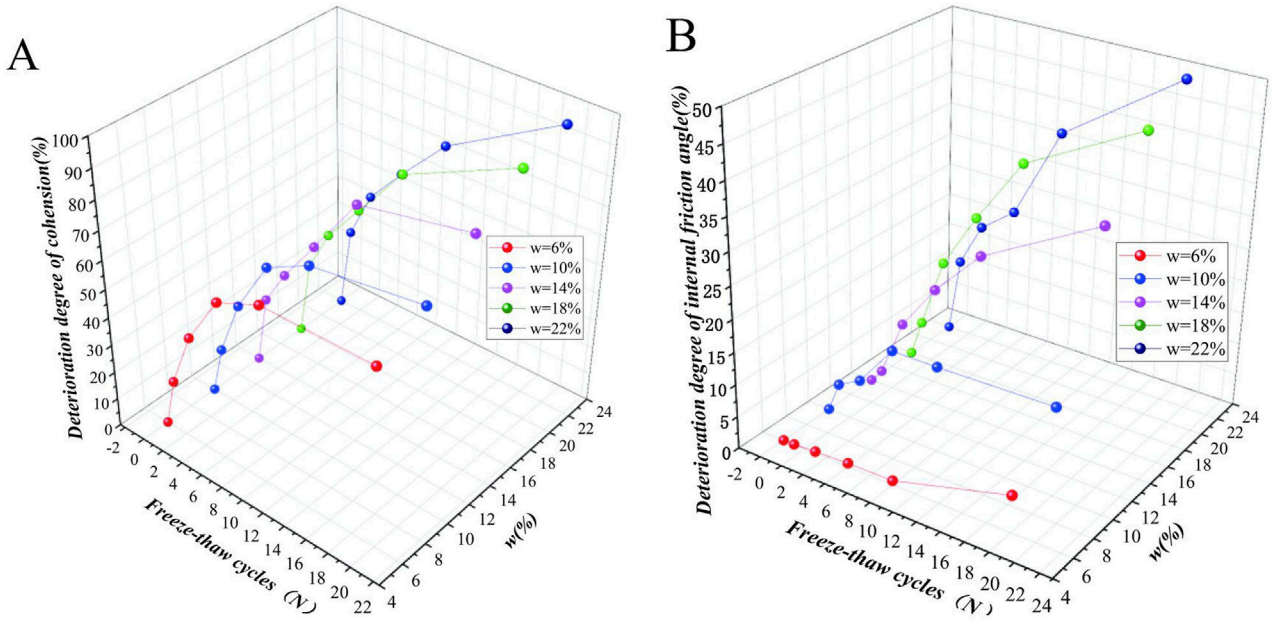

FIGURE 10
Degree of deterioration of loess strength parameters: **(A)** Cohesion, **(B)** Angle of internal friction.

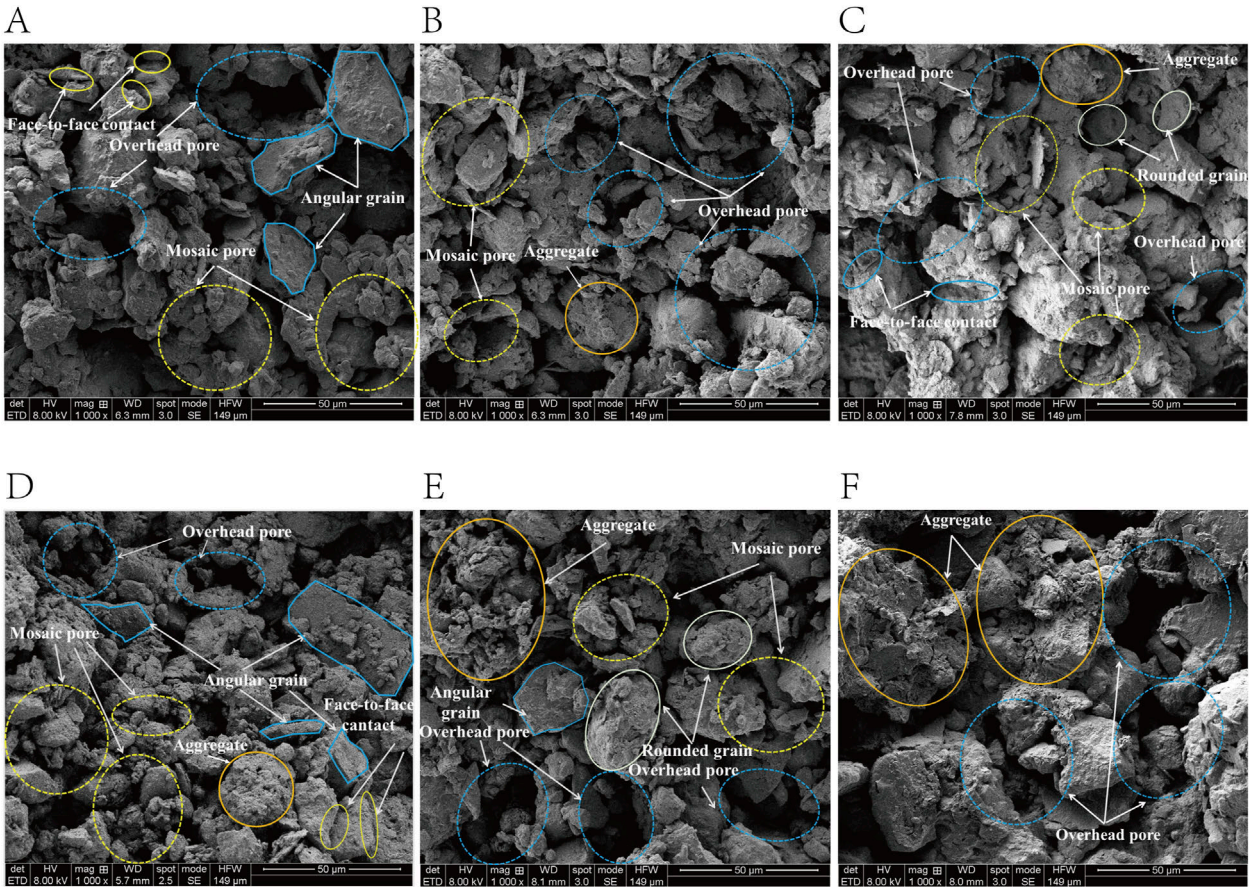

FIGURE 11
SEM images of loess samples after freeze–thaw cycles: **(A)** 10%, 0 time, **(B)** 10%, 6 times, **(C)** 10%,10 times, **(D)** 18%, 0 time, **(E)** 18%, 6 times, **(F)** 18%, 10 times.

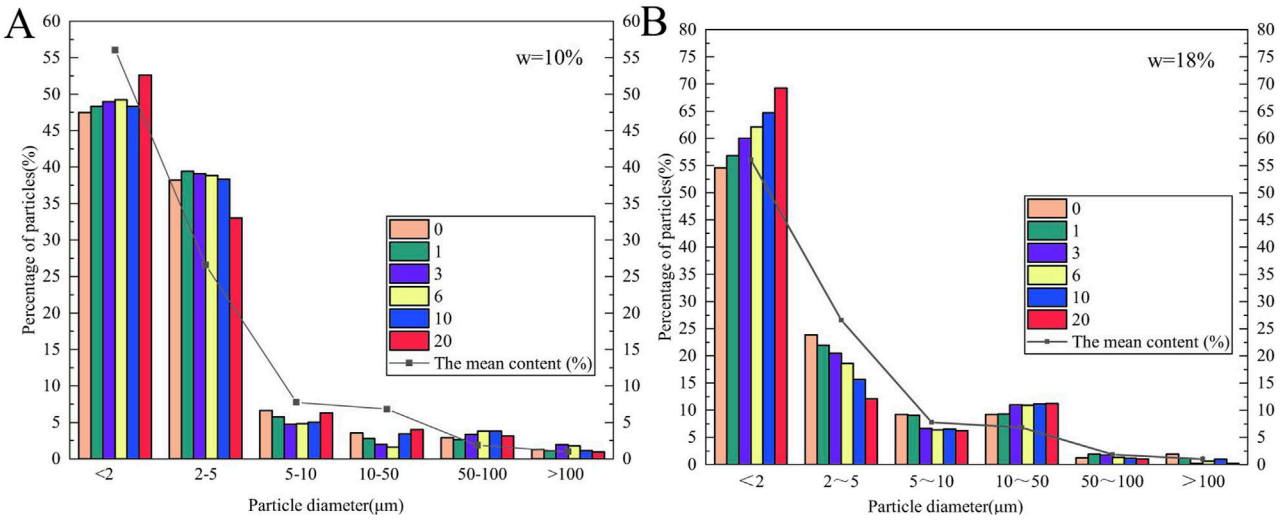

FIGURE 12
Column graph of the percentage content of particle groups after freeze–thaw cycles: **(A)** Initial moisture content 10%, **(B)** Initial moisture content 18%.

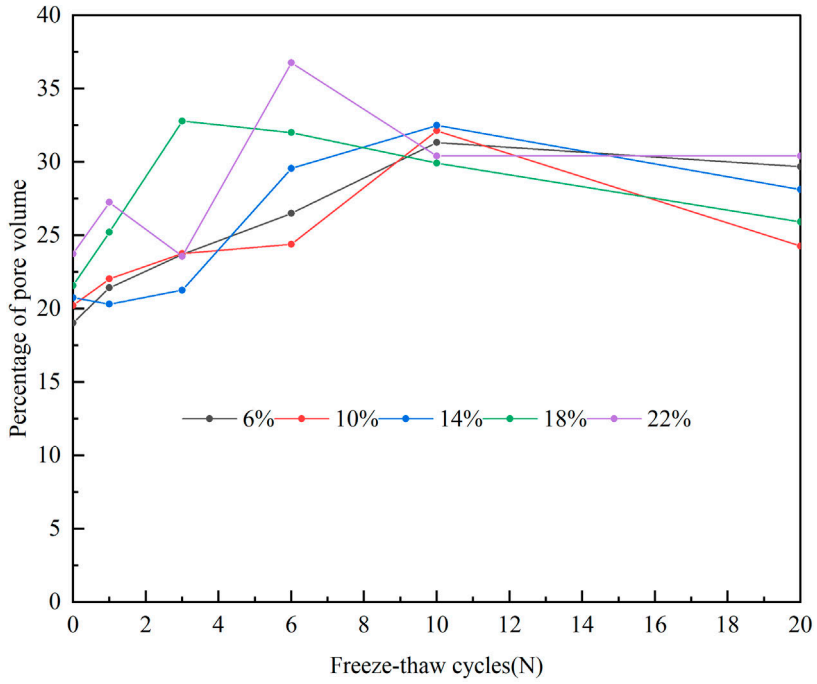

FIGURE 13
Variation curve of porosity after freeze–thaw cycles of loess with different initial moisture contents.

had a significant influence on the porosity of loess with high moisture content, indicating that when the moisture content is high, the frost heaving effect was more pronounced, and the formation of ice crystals caused the loess pores to expand, resulting in the penetration of small pores to form large and medium pores (Mu et al., 2011).

4 Discussion

Loess is a highly water-sensitive and special type of soil. Repeated decrease and increase in temperature in seasonally frozen regions cause changes in the morphology of water in the pores of loess, exhibiting mutual transformation between

liquid and solid phases, and continuous migration of internal water molecules. Ultimately, macroscopic deterioration of loess mechanical properties caused by freeze–thaw cycles is the external manifestation of damage to the internal microstructure.

The microscopic mechanism of loess under freeze–thaw action is illustrated in Figure 14. The loess skeleton is mainly composed of granular units with direct contact between the particles and a small amount of cementation at the contact point. The strength of the contact point p_s (i.e., intergranular pressure, as shown in Figure 14) is mainly composed of the effective stress p_1 transmitted by the overlying load, bonding force p_2 generated by the cementation at the contact point, normal stress p_3 generated by the curved liquid surface between the particles, and the p_4 comprised of the double layer suction and frictional resistance formed by high concentration of dielectric and extremely thin hydration viscous film at the contact point respectively (Gao, 2013). Cohesion value of loess depends on the strength of the contact point between the particles. After freeze–thaw cycles, the structure of loess is damaged owing to the significant extrusion stress caused by the expansion of ice crystals during freezing. As the temperature rises, the soil melts, the arrangement of soil particles becomes loose, and bonding force p_2 between particles decreases (Wang et al., 2010; Li et al., 2018; Ye and Li, 2019; Ye et al., 2020; Liu et al., 2021). From the SEM image as shown in Figure 11, after multiple freeze–thaw cycles, the number of mosaic pores inside the sample decreased and the number of overhead pores increased, resulting in a metastable soil structure. This also indicated that the pore volume of the entire sample increased, which weakened the particle density and cohesion. Therefore, compared with that of the specimens that did not undergo freeze–thaw cycles, the strength of the specimens after freeze–thaw cycles significantly deteriorated, which also indicates that the maximum loss of cohesion occurs in the first cycle (Figure 8). Ye and Li (2019) indicated that irreversible medium and large pores were formed because the large volume of ice crystals exceeded the range of the bonding force of cementation, resulting in a large number of overhead pores. Some scholars have also highlighted reciprocating movement of water causes continuous dissolution of cementation between particles under multiple freeze–thaw cycles, directly weakening the solidification cohesion between structures (Liu et al., 2021; Zhao et al., 2023). However, when the moisture content is high, the bonded water film thickens, extrusion stress formed by ice crystals increases, and structural destruction of the soil intensifies (Xu et al., 2018). Therefore, through experiments, we found that the initial moisture content had a significant influence on the strength parameters of loess in freeze–thaw environments. As the initial moisture content increased, both the cohesion and failure strength decreased. The initial water content of the soil reflects the magnitude of the capillary force (surface) tension p_3 between the particles. The higher the water content, the smaller the capillary force and contact force between the particles, and the lower the cohesion. When the initial moisture content of the sample is high, electrolyte content in the aqueous solution, interparticle attraction p_4 decreases, and bonding force decrease (Li et al., 2018; Gao, 2013).

Owing to the low content of clay particles in loess, insufficient colloids are formed between the soil skeletons, making it a highly dispersed material. The freeze–thaw effect strongly breaks the structure of the soil, not only changing the arrangement, connection, and pore structure of soil particles, but also significantly impacting on the contact mode and shape of the particles. After freeze–thaw cycles, the contact mode between particles gradually changed from face–to–face to point–to–point contact. Compared with those in the face–to–face contact, the connection points between the particles formed by point–to–point contact decreased, resulting in a decrease in the internal friction angle (Zhao et al., 2023). Change in particle shape significantly contribut to the internal friction angle, mainly manifested in the increase in roundness of particles after freeze–thaw, which makes the contact surface smoother and reduces contact points, and interlocking force between particles. The interlocking force between the particles was the strongest when the particles were mainly angular. Compared with that of rounded particles, their movement or rolling needs to overcome a longer path, resulting in a larger internal friction angle. Figure 11 showed that when the number of freeze–thaw cycles was low, the particles were mainly subangular, and as the number of freeze–thaw cycles increases, they are mainly rounded. Therefore, the freeze–thaw effect weakens the friction angle of the loess.

The above analyses indicate that the deterioration mechanism of loess strength parameters under freeze–thaw action is complex and influenced by multiple factors. Both the moisture content and dry density have a significant impact on loess cohesion (Xu et al., 2018). Expansion force generated by ice crystal formation can cause the formation of cracks within the soil during the low–temperature freezing process. In addition, original loess is characterized as the distribution of discontinuous surfaces with various origins and morphologies. Therefore, focusing on analysis of crack initiation under various factor is also crucial for understanding the evolution of mechanical properties and the failure mode (Bi et al., 2016; Zhou et al., 2019; Zhao et al., 2020; Zhao et al., 2021; Zhao et al., 2023). However, no obvious cracks were observed in the SEM images of this study, which may be related to the fact that loess samples in this study were remolded with a low dry density, and ware relatively loose. The influence of crack initiation on the mechanical properties of loess in freeze–thaw environments should also be considered in future study. Moreover, attention should be paid to the original samples to better study the mechanical evolution of Ili loess under freeze–thaw conditions from the analyzing crack initiation perspectives.

Loess landslides are widely distributed in the Ili region, and previous studies have shown that their formation mechanism is closely related to seasonal freeze–thaw effects. Freezing and thawing, as strong weathering effects in seasonally frozen regions, break the soil structure, and frost heave effect intensifies the expansion of cracks in loess slopes, providing a good seepage channel for snow melt and rainfall infiltration. Under this repeated freeze–thaw action, mechanical properties of the surface soil substantially deteriorated, promoting the occurrence of landslides. With the promotion of 'the Belt and Road', various engineering constructions have increased, and landslide hazards in the Ili area have intensified. To reduce the harm caused by such disasters, improving the monitoring technology for landslide disasters and monitoring key landslides and regional disasters is necessary. Currently, high–precision global navigation satellite system technology (Nikolakopoulos et al., 2023; Wang et al., 2023; Huang et al., 2023) is being used globally. Through this technology, an automatic deformation monitoring system has been established, and data on rainfall, snowfall, temperature, moisture content,

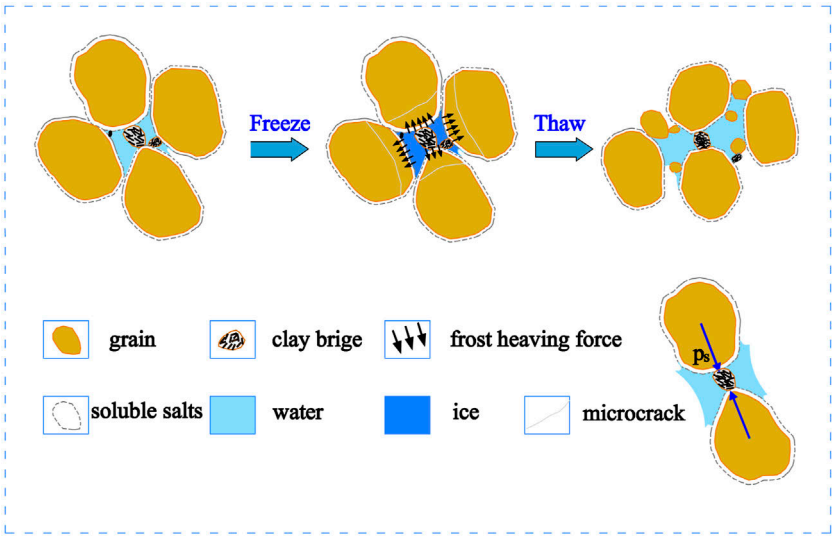

FIGURE 14
Schematic diagram of microstructure evolution of loess under freeze–thaw action.

surface deformation, and cracks are obtained based on the characteristics of landslide mechanisms in the Ili region, establishing early–warning models and combineing 3D image recognition technology to achieve dynamic monitoring of geological hazards (Gu et al., 2023; Li et al., 2023).

5 Conclusion

To study the characteristics and deterioration mechanism of freeze–thaw action on the shear strength of Ili loess, indoor triaxial shear tests and microstructural tests were conducted on 30 sets of loess samples with different freeze–thaw cycles and moisture contents. The following conclusions were drawn:

(1) With the increase in the number of freeze–thaw cycles, the failure mode of the stress–strain curve of low–moisture loess samples (≤10%) changes from strain softening to strain hardening, with the critical point 6 freeze–thaw cycles. Failure mode of the stress-strain curve follows a similar pattern with the increase of confining pressure. However, for loess samples with moisture content of 18%, as the number of cycles increased, the stress–strain curve changed from strong softening to weak hardening.

(2) Freeze–thaw cycle have a significant weakening effect on the failure and shear strength parameters of loess. The curve of the failure strength with the number of freeze–thaw cycles presents three stages of development: slow, steep decline, and steady decline, and the trend of decreasing cohesion values is similar to that of the strength of failure. Simultaneously, comparison of the shear strength parameters of loess revealed that freeze–thaw action has the greatest effect on the cohesion of loess. The degradation is strong after the first freeze–thaw cycle. In addition, after the 10th cycle, the weakening effect gradually slowed down. However, the internal friction angle decreased slowly with an increase in number of freeze–thaw cycles. The initial moisture content also has a significant influence on cohesion, manifested as a significant deterioration of cohesion with fewer freeze–thaw cycles when moisture content is high. Similar patterns were observed on degree of deterioration.

(3) By fitting, it was found that the cohesion and internal friction angle exhibit an attenuation exponential function and a polynomial function relationship with the number of freeze–thaw cycles, respectively. The main fitting parameters showed a sudden change with an increase in moisture content, with a turning point of 14%. This function provides a theoretical basis for disaster prevention and mitigation of loess landslides.

(4) Qualitative and quantitative analysis of SEM images indicate that the content of particle groups changes significantly with the number of freeze–thaw cycles; with an increase in freeze–thaw cycles, the number of overhead pores increases and number of mosaic pores decreases, contact mode of particles changes from point–to–plane to point–to–point. Overall, the porosity of loess shows a an increasing trend first and then decreasing with an increase in freeze–thaw cycles, the freeze–thaw cycle has a strong influence on the porosity of loess with high moisture content, indicating that freeze–thaw has a stronger effect on transformation of loess particles when moisture content is high. The above microstructural changes fully explain the deterioration of the shear strength parameters of the loess samples under freeze–thaw action.

(5) Analyses of the changes in the microstructure after freeze–thaw action, which led to a decrease in the strength p_s between the contact points and an increase in moisture content weakening p_s, demonstrated the deterioration of the shear strength parameters of loess samples under freeze–thaw action. Furthermore, the degradation

mechanism of the microstructure under freeze–thaw action was revealed.

(6) In this study, soil samples were remolded, which can ensure uniformity of each group of samples. However, structures of the remolded samples were not identical to those of the original samples. To better understand the degradation of the freeze–thaw effect on original samples, analyzing crack initiation is necessary to strengthen research on the samples and test their mechanical degradation evolution under freeze–thaw conditions in the future.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

CC: Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Supervision, Writing–original draft, Writing–review and editing. LY: Formal Analysis, Investigation, Supervision, Writing–review and editing. WC: Data curation, Formal Analysis, Methodology, Writing–review and editing. JW: Formal Analysis, Software, Writing–original draft. XW: Software, Writing–original draft.

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Conflict of interest

Author LY was employed by Wuhan Design & Research Institute Co., Ltd. of China Coal Technology and Engineering Group.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Remote sensing identification of shallow landslide based on improved otsu algorithm and multi feature threshold

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In low-resolution remote sensing images under complex lighting conditions, there is a similarity in spectral characteristics between non-landslide areas and landslide bodies, which increases the probability of misjudgment in the identification process of shallow landslide bodies. In order to further improve the accuracy of landslide identification, a shallow landslide remote sensing identification method based on an improved Otsu algorithm and multi-feature threshold is proposed for the temporary treatment project of the Yangjunba disaster site in Leshan City. Using Retinex theory, remote sensing images are enhanced with local linear models and guided filtering; then, multi-feature scales and sliding window calculations of opening and closing transformations identify potential landslide areas, which are finally segmented using the Otsu algorithm. Through experimental verification, the method proposed in this article can clearly segment the target object and background after binary segmentation of remote sensing images. The recognition rate of shallow landslide bodies is not less than 95%, indicating that the method proposed in this article is relatively accurate in identifying shallow landslide bodies in the research area and has good application effects.

KEYWORDS

otsu algorithm, multi feature threshold, remote sensing images, landslide mass, image segmentation

1 Introduction

Global climate change has led to a significant increase in the number and scale of rainfall landslides, posing greater threats to human activity areas such as roads, houses, farmland, and residential areas (Amarasinghe et al., 2024). The initial stage of a rainfall landslide is a shallow landslide that occurs on the surface or in shallow soil (Su et al., 2024). Therefore, how to effectively identify and monitor shallow landslide bodies has become an important issue that urgently needs to be addressed in the field of geological disaster prevention and control (Wang et al., 2024). Remote sensing technology has demonstrated unique advantages in identifying and monitoring geological hazards (Liang and Sun, 2023). Through the interpretation of remote sensing images, rapid identification and dynamic monitoring of landslide bodies can be achieved, involving the accuracy of landslide disaster identification and monitoring efficiency and providing strong technical support for geological disaster prevention and control.

In the face of increasingly severe environmental changes and geological disasters, it is particularly important to study remote sensing identification methods for shallow landslide bodies.

Jiang W et al. (2023) proposed a landslide disaster remote sensing image recognition method based on AED Net (Attention combined with Encoder De der Network). Optimizing the multi-scale feature extraction capability of deep neural networks using shallow feature extraction networks and combining the feature restoration ability of the encoder-decoder structure to restore the boundary information of landslide disaster remote sensing images, an AED Net model is constructed to complete landslide disaster identification. This method does not consider the close spectral characteristics between non-landslide areas and landslide bodies, significantly increasing the probability of misjudgment in identifying landslide bodies under background interference.

Du et al. (2023) proposed a high-resolution remote sensing image landslide identification and detection method based on DETR. Using the Transformer as the primary research method and combining the advantages of convolutional neural networks, a DETR network was constructed to augment the remote sensing images dataset through offline data augmentation algorithms. By leveraging the structural advantages of the encoder-decoder, the DETR network was trained and predicted to identify landslide changes in remote sensing images (Liu et al., 2024). However, when the landslide mass is small, or the remote sensing image resolution is low, DETR may have difficulty accurately segmenting the shallow landslide mass from the background, resulting in poor detection performance.

Xin et al. (2023) proposed combining image recognition technology with computer vision technology to extract local deformation features of landslides and monitor the entire slope. At the same time, time series image data was combined with machine vision data for analysis, and a landslide model was used to simulate the deformation and displacement during the landslide process. The deformation and displacement of the landslide were verified by combining drone orthophoto data (Qiu et al., 2024). However, landslide monitoring often faces complex and variable environmental conditions, such as changes in lighting, weather influences (such as rain, fog, snow, etc.), and vegetation coverage. These factors may lead to a decrease in image quality, thereby affecting the accuracy of recognition and monitoring.

Zheng et al. (2024) used LiDAR data to extract geomorphic features and analyzed the deformation characteristics of landslide locations using InSAR technology. The deformation rate and range were determined through time-series deformation information, and the landslide boundary was identified using unmanned aerial vehicle radar (Wei et al., 2024). The principle of geometric distortion was used to correct remote sensing images, achieving real-time monitoring of landslide deformation. However, in complex lighting environments, using only geometric distortion correction as a method is difficult to effectively enhance the clarity of remote sensing images, which affects the subsequent recognition of shallow landslide targets that are difficult to detect.

In response to the problem that existing research methods are difficult to accurately identify small shallow landslide bodies in low-resolution remote sensing images under complex lighting environments, this paper proposes a shallow landslide body remote sensing identification method based on the improved Otsu algorithm and multi-feature threshold 1 (He et al., 2024a). Innovatively combining Retinex enhancement and guided filtering methods to enhance the clarity of remote sensing images in complex lighting scenarios. Due to the complex terrain information contained in remote sensing images, in order to segment small shallow landslide targets in complex backgrounds and distinguish various spectral features between non-landslide areas and landslide bodies, this paper uses multiple feature thresholds to remove invalid or redundant background features, thereby improving the accuracy of image segmentation. The traditional Otsu algorithm can perform image segmentation by automatically selecting a threshold in image processing. However, it is easy to ignore the spatial relationship of pixels and reduce the segmentation effect. Therefore, this paper innovatively uses the Monte Carlo iteration strategy to improve it, optimize the flexibility and applicability of landslide remote sensing identification, and improve the accuracy and efficiency of identification.

2 Data and method

2.1 Data

2.1.1 Overview data of the experimental area

This article takes the temporary remediation project of the Yangjunba disaster site in Suji Town, Yanlong Village, Shizhong District, Leshan City, as the research object and conducts remote sensing identification research on shallow landslide bodies. The geographical coordinates of this area are E: 103°39′0.49″, N: 29°34′20.81″, and the elevation range of the exploration area is roughly between 400 and 500 m. The geomorphic features are hills with significant undulations and steep slopes in some areas. There are also rural roads leading directly to the landslide area, providing convenient transportation conditions. The landslide body is located in an “m” - shaped micro gully area on a hill slope, with a rear edge elevation of 455 m and a front edge elevation of 407 m, with a height difference of 48 m. The landslide body is tongue-shaped and has a regular shape. It extends from the north side to the exposed bedrock, from the south side to the deformation boundary of the landslide, from the east side (front edge of the landslide) to the houses and village roads of the villagers, and from the west side (rear edge of the landslide) to the exposed bedrock. The landslide mass in this area has been deformed since July 2018, with transverse tensile cracks appearing in the middle of the slope and signs of forward movement of the retaining walls of some houses at the front edge. On 6 August 2019, Leshan was hit by an extremely heavy rainstorm once in 50 years, with a maximum daily rainfall of 380 mm. After the heavy rainfall, the landslide mass in this area was deformed again, and a downward dislocation crack appeared at the rear edge. The deformation of the retaining wall behind the house was aggravated, and the soil mass of the steep slope collapsed. In August 2020, the central district of Leshan City experienced another general rainstorm, with continuous rainfall from the 15th to the 17th, and the maximum rainfall intensity from 11:00 on the 17th to 2:00 on the 18th, exceeding 50 mm/h, leading to the aggravation of mountain deformation. At present, the landslide is about 110 m long and 55 m wide along the slope, with an area of about 6,050 square meters. The main sliding direction of the landslide is 115°, and there



FIGURE 1
Local landslide cracks.

are tensile cracks of varying widths at the rear and middle of the landslide. Among them, the deformation of the central tensile crack is the most significant, with a width of about 30–40 cm, a north-south direction, and an extension length of about 27 m. On the right boundary, there is a sunken crack deformation with a width of about 5–15 cm, running nearly east-west and extending for about 110 m. On the right side of the retaining wall behind Xie Renzhong's house at the front edge of the landslide, perennial clear water can be seen flowing out between the bedrock layers, while on the back edge of the landslide, brick red sandstone bedrock is exposed, with a rock attitude of 310°∠ 4°. The middle crack L1 and the north crack L2 of the landslide in this area are shown in Figure 1.

The landslide stability is poor, and large-scale collapse and damage are possible. Therefore, it is necessary to conduct remote sensing image recognition of shallow landslide bodies in this area to identify the geological hazard characteristics of the landslide, which is representative of the experimental target.

2.1.2 Experimental remote sensing data

In response to the on-site landslide case, five wide-swath panchromatic remote sensing images were captured using the Gaofen-1 satellite, and landslide recognition experiments were conducted based on the image data. The remote sensing image of the research area is shown in Figure 2.

The width size of these images is 8,192×2048 pixels, with a pixel width of 8 bits, and the data volume of a single image reaches 128 Mbit. In order to improve recognition accuracy, images with significant differences in grayscale values were selected, where the ground area contains interference factors such as vegetation with higher grayscale values. Divide satellite image data and digital elevation model data based on spectral characteristics and spatial resolution. The digital elevation model of the region is shown in Figure 3, and the data parameter information is shown in Table 1.

2.2 Method

Figure 4 shows the shallow landslide remote sensing identification process based on the improved Otsu algorithm and multi-feature threshold studied in this article.

According to the process shown in Figure 4, firstly, the remote sensing image is enhanced and smoothed based on the Retinex theory and the local linear model. Then, multi-scale feature values of the remote sensing image background and landslide targets are extracted. Finally, the Otsu algorithm is used to segment the remote-sensing images of landslide bodies. Improve the binary threshold processing of the Otsu algorithm, use the optimal threshold to segment the image into foreground and background, and achieve remote sensing recognition of shallow landslide bodies.

2.2.1 Image preprocessing replace

Remote sensing images may be affected by various factors, such as atmospheric disturbances, cloud cover, sensor noise, etc., during transmission and acquisition (Tao et al., 2022). Therefore, the accuracy of recognition can be improved by enhancing remote-sensing images (Lin et al., 2023). However, using a single enhancement method alone may not achieve the desired effect (Ye et al., 2024). Therefore, this article innovatively combines the Retinex enhancement and guided filtering methods to adapt to this complex lighting scene, improving the processing effect and practicality of remote sensing images.

The Retinex theory emphasizes color constancy, which means that the color perception on the surface of an object should remain consistent under changing lighting conditions (Yang et al., 2024). It can effectively handle highlight and shadow areas in the image, making the brightness distribution of the image more uniform and also restoring color information lost due to lighting changes in the image (Li et al., 2023). Guided filtering uses a guided image

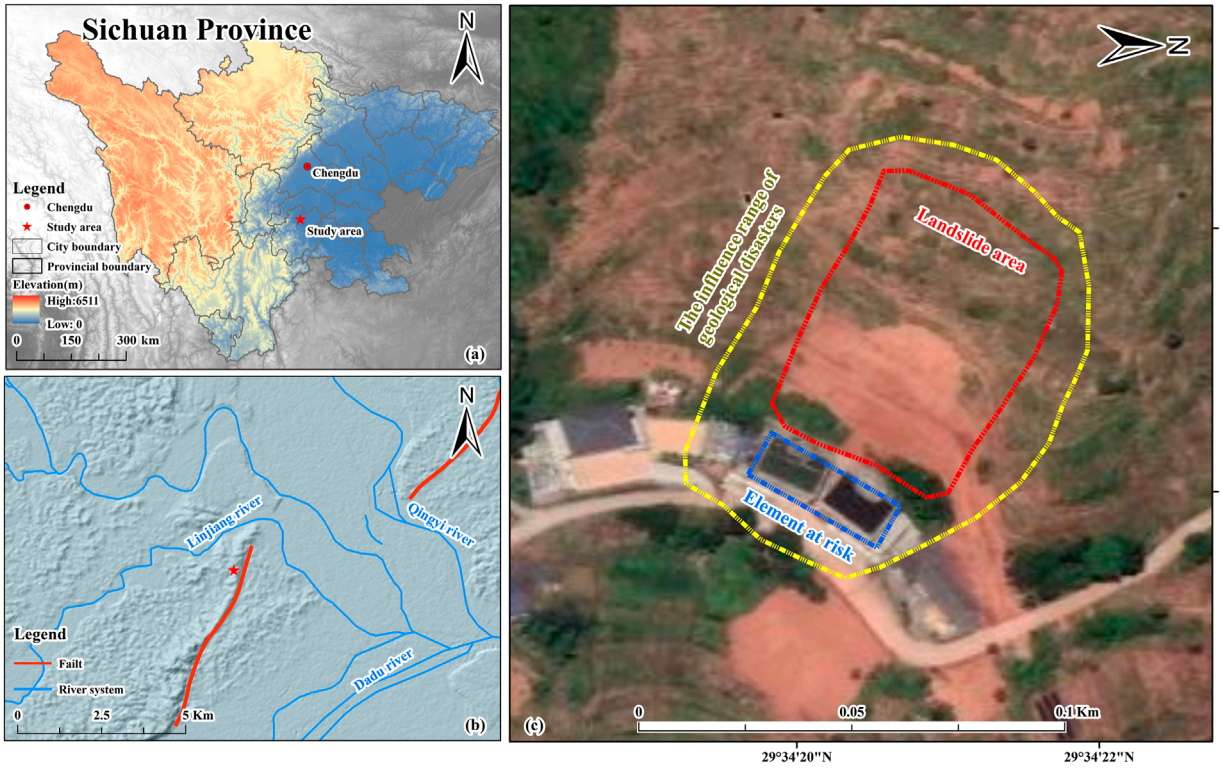

FIGURE 2
Location of the study area and the general situation of the landslide.

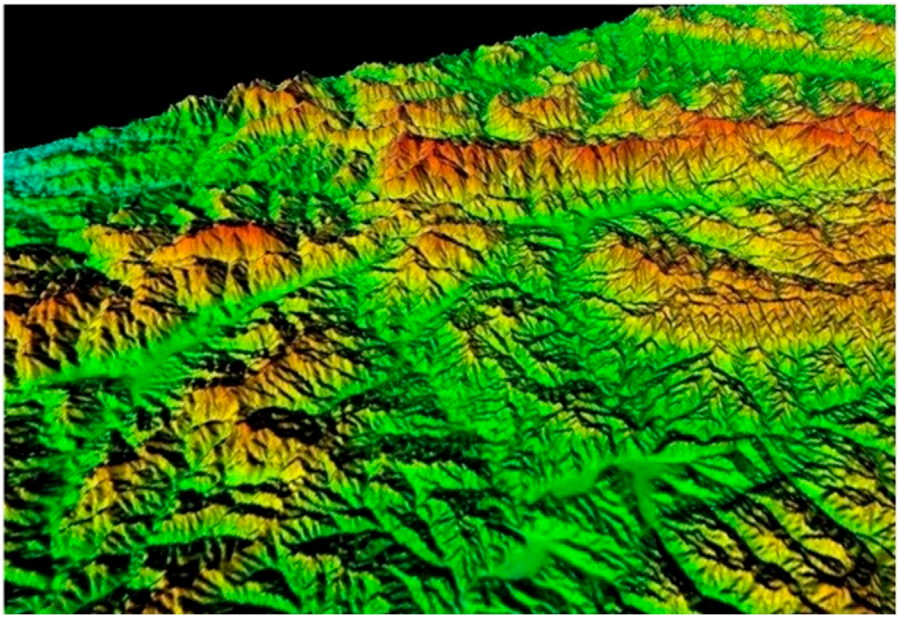

FIGURE 3
DEM model.

TABLE 1 Raw data parameter information.

Raw data	Spectral range/μm	Spatial resolution/m
Gaofen-1 (GF-1) Satellite imagery data	0.45~0.90	2.00
	0.45~0.52	8.00
	0.52~0.59	
	0.63~0.69	
	0.77~0.89	
Digital Elevation Model (DEM)	—	30.00

Input the DEM, model and remote sensing data of working conditions into the Revit2020 database. Divide the database data into training and testing sets in a 3:1 ratio. The training set data is input into the TensorFlow model training and learning framework for training processing, while the test set data is used for testing.

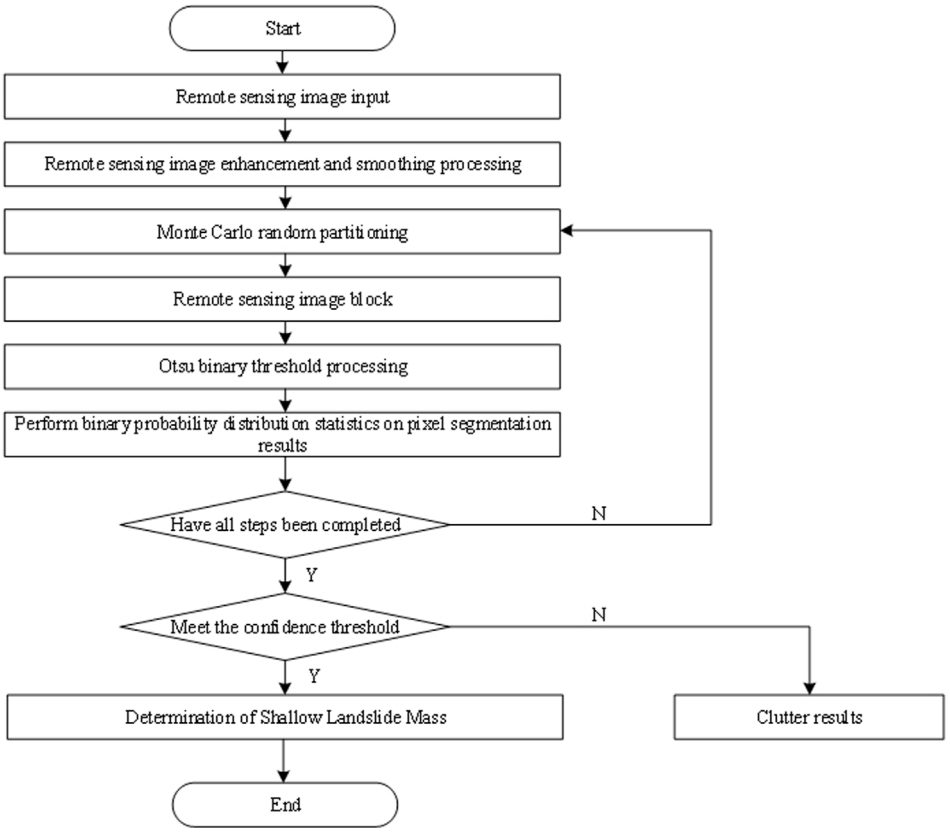

FIGURE 4
Remote sensing image segmentation and recognition process.

to guide the filtering process. Compared to other edge-preserving filtering methods, such as bilateral filtering, guided filtering has lower computational complexity. It can process large-scale images faster, making it suitable for preprocessing high-resolution remote-sensing images. However, it has disadvantages in color enhancement of low-resolution images. The Retinex enhancement performs well in dynamic range compression, edge enhancement, and color restoration but may have shortcomings in smoothing processing. Guided filtering is adept at achieving smoothing while preserving edge information (Panigrahi and Gupta, 2022). The combination of the two can compensate for their respective shortcomings and achieve a more comprehensive image enhancement effect by starting from image enhancement and image smoothing (He et al., 2024b). Therefore, this article combines the Retinex enhancement algorithm and guided filtering algorithm to preprocess remote sensing images.

2.2.1.1 Remote sensing image enhancement processing based on retinex

The Retinex enhancement method can effectively handle the quality loss caused by uneven lighting on shallow landslide remote sensing images, improve the brightness, contrast, and color expression of the images, and enhance the clarity of remote sensing images. In the Retinex algorithm, shallow landslide remote sensing images can be represented as:

$$S(i,j) = L(i,j) \times R(i,j) \tag{1}$$

In the formula, $S(i,j)$ represents the original shallow landslide remote sensing image; (i,j) represents the pixel points of shallow landslide remote sensing images; $L(i,j)$ and $R(i,j)$ represent the illumination component and reflection component, respectively.

The irradiation component mainly involves light source conditions, including factors such as solar position, angle, and atmospheric conditions. These factors can affect the brightness distribution and contrast of ground objects in remote sensing images, thereby affecting the identification and analysis of landslide bodies. The reflection component is related to the physical properties and geometric shape of surface objects, including the material, humidity, roughness, etc., of landslide bodies (He et al., 2023). These factors will affect the reflection characteristics of the landslide body to light, and to some extent, affect the characteristics of the landslide body in remote sensing images. Multi-Scale Retinex (MSR) can adjust the contrast and brightness of an image while preserving its detailed information. In order to highlight the characteristics of the landslide body and improve the readability of the image, it is necessary to process the illumination $L(i,j)$ by removing or reducing the influence of the illumination component, thereby highlighting the reflection component that reflects the surface characteristics of the object. The calculation formula for MSR is:

$$\lg R(i,j) = \lg S(i,j) - \lg [G * L(i,j)] \tag{2}$$

In the formula, $*$ is the convolution operation; G stands for Gaussian filter scale, and its calculation formula is:

$$G = u \exp\left[\frac{-(i^2 - j^2)}{\sigma^2}\right] \tag{3}$$

In the formula, u represents Gaussian filter; σ stands for Gaussian kernel.

After filtering through multiple Gaussian kernels, the reflection components at this scale can be extracted to enhance the color and detail of shallow landslide remote sensing images and obtain Retinex-enhanced remote sensing images $I(i,j)$. The calculation formula is:

$$I(i,j) = \sum_{m=1}^{N} W_m \{\lg S(i,j) - \lg R(i,j) + g[G * S(i,j)]\} \tag{4}$$

In the formula, W_m represents the fusion weight in the m-th number field.

After completing color detail enhancement, the edges of low-resolution remote sensing images in complex lighting scenes are prone to blurring, so smooth filtering is required.

2.2.1.2 Smooth processing of remote sensing images based on guided filtering

To further enhance the edge details of shallow landslide remote sensing images, a local linear model guided by filtering is used to apply smoothing filtering to the obtained enhanced remote sensing image $I(i,j)$, improving the edge details of the image. The calculation formula is:

$$q_i = a_h C_i + b_h, \quad \forall i \in h \tag{5}$$

In the formula, q_i represents the output image of the guided filtering algorithm after filtering pixel i in remote sensing image $I(i,j)$; a_h and b_h represent the linear coefficients of remote sensing images during filtering processing; h represents the window used in the smoothing filtering process; C_i represents the radius of the window for pixel i during the smoothing filtering process. Using q_i as the guiding image, substitute remote sensing image $I(i,j)$ and apply the minimum cost function to constrain its implementation. The calculation formula is:

$$E(q_i) = \sum_{i \in h} \left[(a_h C_i + b_h - p_i)^2 + \varepsilon a_h^2\right] \tag{6}$$

In the formula, p_i represents the number of pixels; ε stands for regularization parameter.

Using linear regression analysis method, the remote sensing images under guided filtering are smoothed to obtain the smoothed shallow landslide remote sensing image $J(i,j)$. The calculation formula is:

$$J(i,j) = \frac{1}{\sigma_h^2 + \varepsilon} \frac{1}{|h| E(q_i)} \sum_{i \in h} C_i p_i - u p_h \tag{7}$$

In the formula, u represents the number of iterations of the local linear model smoothing filtering process; p_h stands for pixel mean.

Based on Formulas 1–7, complete remote sensing image preprocessing using the Retinex enhancement algorithm and guided filtering algorithm, providing clear image data for subsequent landslide identification.

2.2.2 Landslide feature extraction replace

Remote sensing images typically contain complex terrain information, such as water bodies, vegetation, buildings, etc., which exhibit different features in the image, such as color, texture, shape, etc. Multi-feature thresholds can be used to screen for features that have a significant impact on the segmentation results of the target, removing invalid or redundant features (Deng et al., 2024; Senogles et al., 2023). By setting reasonable threshold conditions, the most representative subset of landslide target features can be selected to more finely distinguish between these terrain backgrounds and landslide targets, thereby improving the accuracy of image segmentation.

In the task of landslide segmentation and recognition, traditional recognition models often rely on the spectral information features of a single pixel target to classify and determine landslide bodies. However, current hyperspectral remote sensing images reveal that even within potential landslide areas, differences in spectral information between different regions may be significant, while spectral features between certain non-landslide areas and landslide bodies may be closer (Niu et al., 2023; Peters et al., 2024). This phenomenon greatly increases the noise interference

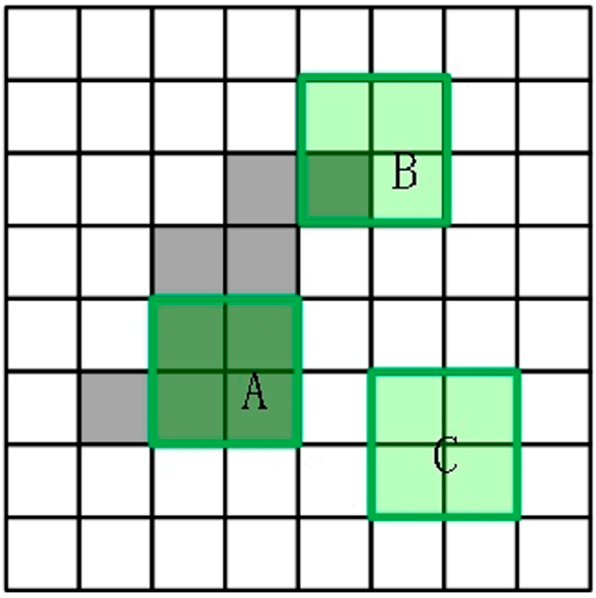

FIGURE 5
The process of extracting morphological features from remote sensing images.

in the landslide identification process, which can easily lead to misjudgment, such as misclassifying non-landslide areas as landslide bodies or omitting landslide bodies. Therefore, this article delves into and integrates multiple spectral features in remote-sensing images based on traditional single-pixel spectral features. These features can capture subtle spatial changes in the landslide body and its surrounding environment, such as abnormal changes in surface morphology, specific patterns of vegetation coverage, etc., providing richer information for accurate identification of landslide bodies. By comprehensively utilizing these features, it is possible to better depict the spatial details of landslide bodies and improve the accuracy and reliability of landslide body identification. Therefore, in the process of multi-feature extraction for landslide identification, special attention is paid to the extraction of spatial features, which contain geographical information about the landslide and its surrounding environment and are crucial for accurate identification of the landslide. Spatial features can be further subdivided into morphological features and attribute features (Rajan et al., 2024).

In the extraction of morphological features, a fixed-sized window is used to slide scan remote sensing images. By operating this switch window, the connected pixel regions in the remote sensing image are identified and connected, which often reflect key spatial features such as the shape contour and edge changes of the landslide body, effectively highlighting the spatial distribution characteristics of the landslide body. The entire extraction process can be visually demonstrated through a diagram, as shown in Figure 5:

In Figure 5, the green box represents the ABC window range, and the gray block refers to the target area. The white block is the background area. The annotated sliding window is considered a key structural unit for landslide identification, where A, B, and C represent three typical situations that the window may encounter when scanning landslide remote sensing images. Window A simulates an idealized scenario where the feature values (such as spectral reflectance, texture features, etc.) of all pixels within the window are almost equal. This is rare in actual landslide recognition and may indicate uniform regions or specific backgrounds in the image. Window B reflects a more common situation in landslide identification, where at least one pixel in the area covered by the window has a feature value that is not equal to other points. This difference may be caused by changes in geological features at the edge of the landslide body, different parts of the landslide body, or differences in vegetation coverage, which are crucial for identifying the morphology, scale, and boundaries of the landslide body. Window C describes an extreme situation where all expected pixel feature values within the window are significantly different from those outside the window boundary. This situation may indicate a strong contrast between the landslide body and the surrounding environment, such as the contrast between the exposed rocks of the landslide body and the dense vegetation around it, which is of great significance for quickly locating the location of the landslide body. However, in practical applications, the situation of window C is relatively rare and requires careful handling to avoid misjudgment. The transformation function for opening and closing the above window is as follows:

$$\begin{cases} s(f_1(J(i,j))) = (f \odot s) \oplus s \\ s(f_0(J(i,j))) = (f \oplus s) \odot s \end{cases} \tag{8}$$

In the formula, $s(f)_1$ represents the transformation function under the window opening operation; $s(f)_0$ represents the transformation function under window closure operation; s stands for sliding window; f represents the area covered by the window; The $\oplus$ symbol represents the characteristic changes of expansion; $\odot$ represents the characteristic changes of corrosion.

After extracting morphological features using the above formula, it is also necessary to extract attribute features from remote-sensing images for landslide recognition. Extract feature vectors of length 2n from each pixel for images of different resolutions. By using dimensionality reduction techniques, these high-dimensional data are effectively compressed while preserving key information and arranging feature values in an orderly manner to reflect their importance. The core of the attribute feature extraction process for landslide identification lies in the use of carefully designed attribute filters, which calculate the feature values of the potential coverage area of the landslide based on specific attribute sets such as terrain slope, vegetation index, soil moisture, etc. (Kusunose et al., 2022). During this process, the selection and definition of attributes are highly flexible and can be customized according to the specific characteristics and recognition needs of the landslide mass. For a given detection area and threshold conditions, due to the complexity and diversity of landslide bodies, direct feature mapping in low-dimensional space often fails to fully reflect their characteristics. Therefore, this article extends the low dimensional spatial attribute features in the high-dimensional feature space to capture more subtle information that is helpful for landslide identification:

$$E = T\{A_1(P_1), A_2(P_2), ..., A_n(P_m)\} \tag{9}$$

In the formula, E represents the attribute characteristic values of the potential coverage area of the landslide mass; T stands

for attribute set; $A_1 \sim A_n$ represents feature value ranking; $P_1 \sim P_m$ represents attribute feature categories, such as terrain slope, vegetation index, soil moisture, etc.

Formulas 8, 9 can be used to extract features from landslide remote-sensing images based on multiple feature thresholds. The extracted features can be used to segment the background and identify landslide targets.

2.2.3 Landslide segmentation replace

In the field of image processing and remote sensing recognition, the Otsu algorithm is widely used for its ability to automatically select the optimal threshold for image segmentation, which can effectively distinguish landslide bodies (i.e., target foreground) from the surrounding environment (i.e., background) (Neogi et al., 2024). Therefore, after completing the feature extraction of landslide remote sensing images based on multiple feature thresholds, the Otsu algorithm was selected to segment the landslide remote sensing images. However, the traditional Otsu algorithm needs to traverse all possible gray levels and calculate their corresponding inter-class variances when searching for the optimal threshold. This process requires a huge amount of computation when processing high-resolution or large data images, resulting in low algorithm efficiency and difficulty meeting real-time requirements. To overcome this limitation, this article innovatively uses the Monte Carlo iterative method to optimize the remote sensing identification effect of landslide bodies. As the sample size increases, the results of the Monte Carlo method will become closer to the true solution, with high flexibility and applicability.

Firstly, by applying the Otsu algorithm, the pixels in the local image are divided into two categories: one represents the high brightness or specific grayscale value range of the landslide body, and the other represents the low brightness or different grayscale value range of the background (König et al., 2022; Zhu et al., 2024). Assuming that the shallow landslide remote sensing image $J(i,j)$ processed by smoothing enhancement in section 2.1 can be divided into $\{0,1,\cdots,F\}$ gray levels, where the total number of pixels corresponding to gray level F is F_b and its proportion is $B_b = F_b / \sum_{b=0}^{F} F_b$, then $\sum_{b=0}^{F} B_b = 1$. Using grayscale value d as the threshold for segmenting landslide mass and background in remote sensing images, the pixels in interval $[0,d]$ can be regarded as background D_0, and the pixels in interval $[d,F]$ can be regarded as landslide mass target D_1. Then, the proportion η_0 of background pixels and the average grayscale value μ_0 in the remote sensing image are calculated as follows (Equation 10):

$$\begin{cases} \eta_0 = \sum_{b=0}^{d} B_b s(f_1(J(i,j))) \\ \mu_0 = \frac{1}{\eta_0} \sum_{b=0}^{d} B_b s(f_0(J(i,j))) \end{cases} \tag{10}$$

The proportion η_1 and gray value mean μ_1 of landslide target pixels in landslide remote sensing images are as follows (Equation 11):

$$\begin{cases} \eta_1 = \sum_{b=d}^{d} B_b E \\ \mu_1 = \frac{1}{\eta_1} \sum_{b=d}^{d} B_b E \end{cases} \tag{11}$$

The calculation formula for the average grayscale value μ of landslide remote sensing images is as follows (Equation 12):

$$\mu = \eta_0 \mu_0 + \eta_1 \mu_1 \tag{12}$$

Then, the Monte Carlo iterative strategy is used to optimize the remote sensing image of the landslide body. Firstly, the large remote sensing image is segmented into multiple smaller local image regions using random partitioning techniques (Jiang et al., 2023). This process aims to reduce the computational complexity of directly processing the entire image and allow for a more refined analysis of each local region. Evaluate the confidence level of the binarization effect within each block based on the random samples generated by the Monte Carlo iteration process and their processing results. The calculation of confidence can be based on factors such as the stable appearance of feature patterns in multiple iterations, the consistency of classification results, and the degree of conformity with other known information. High-confidence segmentation means that the landslide identification results are more reliable, while low-confidence segmentation may require further analysis or validation (Shen et al., 2023). Based on the above block processing and binary recognition results, combined with the fusion technology of panchromatic images and terrain data, the accuracy and comprehensiveness of landslide identification can be further improved. Full-color images provide rich texture and detail information, which helps to more accurately depict the morphology and boundaries of landslide bodies. Terrain data (such as DEM) provides key information about surface morphology, slope changes, etc., which are crucial for understanding the causes, development trends, and potential risks of landslide bodies. The specific operational approach is as follows:

(1) Based on the ratio of the number of morphological features $s(f_1(J(i,j)))$ and attribute features E extracted from the remote sensing image in Section 2.2, the size of the Monte Carlo random block of the remote sensing image is set to $H \times W$, and the Monte Carlo calculation steps are N steps. Monte Carlo random block is performed according to this setting.

(2) Using Monte Carlo to perform Otsu binary thresholding on remote sensing images. Determine the optimal threshold d through inter class variance, so that the image can be divided into foreground (target object, i.e., landslide) and background parts based on this threshold. The inter class variance θ^2 between D_0 and D_1 can be obtained as follows (Equation 13):

$$\theta^2 = \mu(D_0 - D_1) = \eta_0(\mu_0 - \mu)^2 + \eta_1(\mu_1 - \mu)^2 = \eta_0\eta_1(\mu_0 - \mu_1)^2 \tag{13}$$

The inter class variance θ^2 can be used to determine the optimal threshold of the Otsu algorithm. When the θ^2 takes its maximum value, the difference between D_0 and D_1 is the largest, and the corresponding gray value threshold d of the landslide remote sensing image is the optimal threshold.

(3) Monte Carlo iteration itself is based on random sampling and does not directly correspond to a mathematical formula. But the sampling process can be based on a random number generation algorithm to calculate the binary probability distribution $P(i,j)$ as follows (Equation 14):

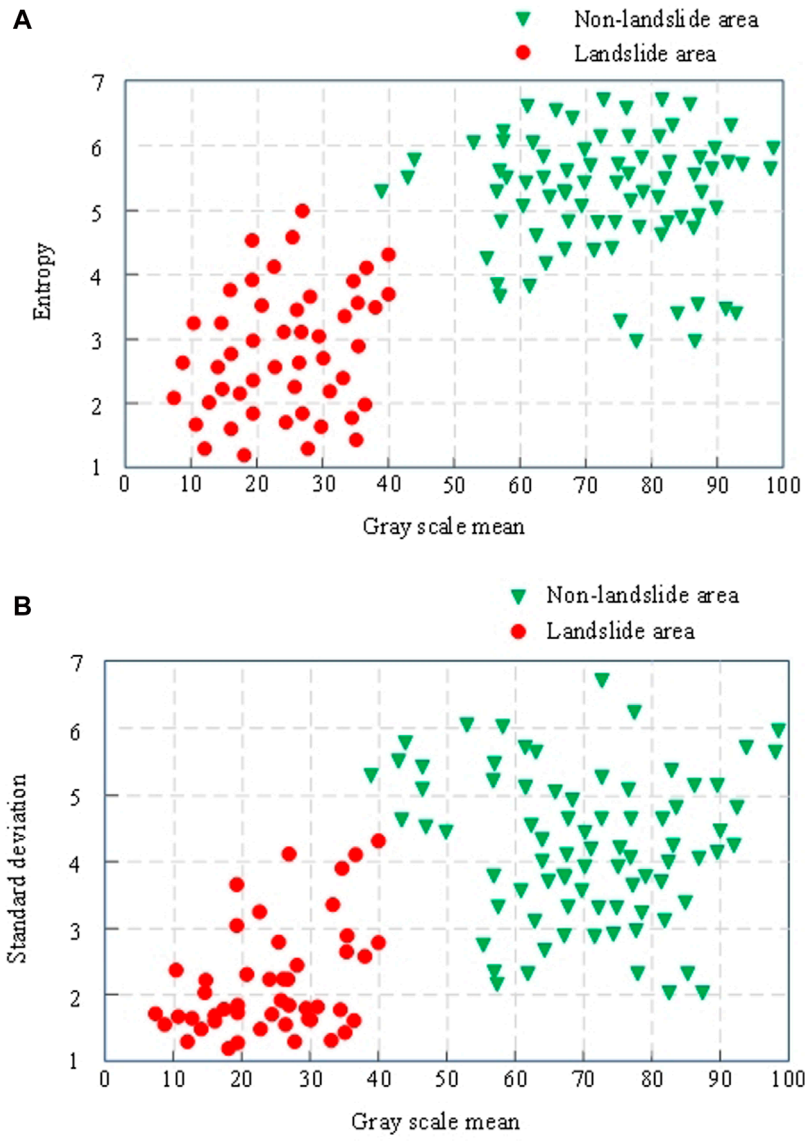

FIGURE 6
(A) Comparison of local window entropy and grayscale mean **(B)** Comparison of local window standard deviation and grayscale mean.

$$P(i,j) = \frac{1}{N}\sum_{k=1}^{N} \theta^2 O_k(i,j) \tag{14}$$

In the formula, O_k represents obtaining the binary segmentation result for each pixel, where $k \in N$.

(4) Set the confidence level T_P as the probability threshold, with a value greater than T_P used as the foreground for landslide remote sensing image segmentation (target object, i.e., landslide), and a value less than T_P used as the background clutter for segmentation. Assuming that in Monte Carlo iterative calculation, a pixel is identified as a target foreground above this probability threshold, then this pixel is identified as a shallow landslide mass in the final result, achieving remote sensing recognition of shallow landslide mass.

3 Results and discussions

3.1 Experimental environment and preparation

3.1.1 Experimental environment settings

The above data and DEM model require the construction of an experimental platform environment before they can be applied.

Set the experimental environment as follows: Hardware environment: Intel Core Ultra 9 285K processor, NVIDIA GeForce GTX1070 graphics card, 10 TB Seagate ST10000NM017B mechanical hard drive, 260G-SSD solid state drive.

Software environment used: Windows 11 operating system, Python programming language, MATLAB with SIMULINK simulation platform, TensorFlow model training and learning framework. Based on the above experimental environment,

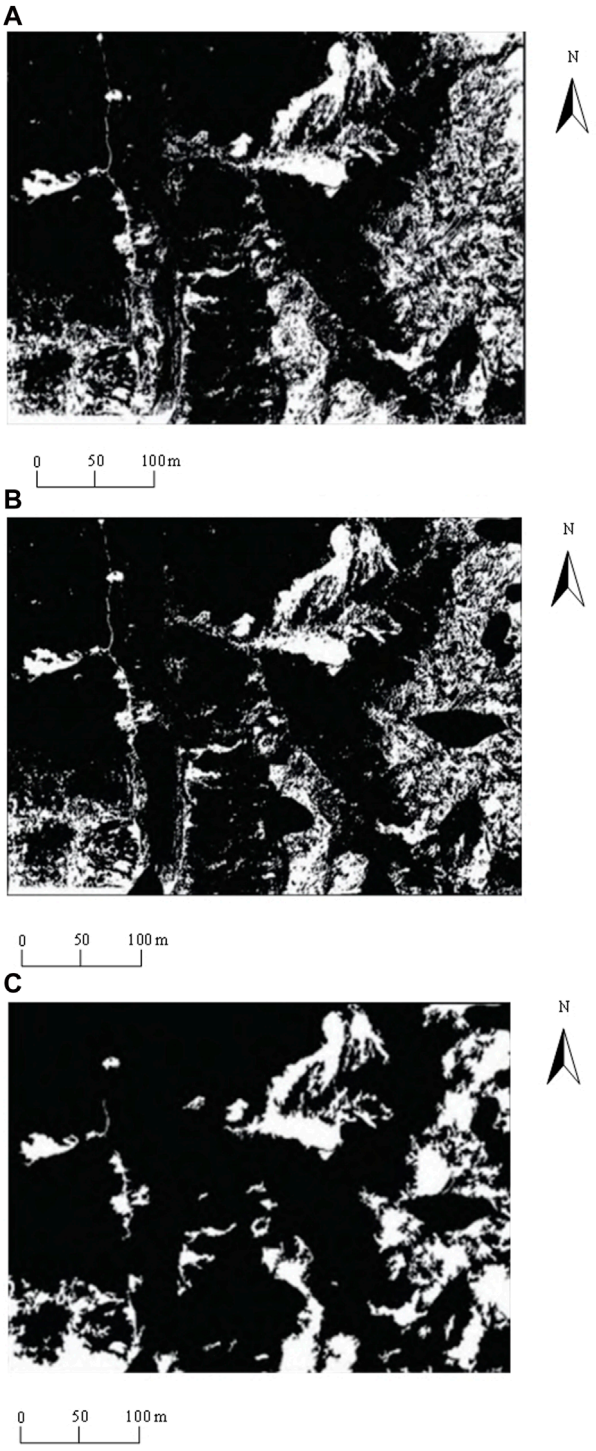

FIGURE 7
(A) Proposed method **(B)** High-resolution sensing image recognition method based on DETR **(C)** Methods based on image recognition technology and computer vision technology.

input the DEM model and data into the Revit2020 database for experimental testing.

3.1.2 Selection of local feature threshold

In order to verify the effectiveness of the shallow landslide remote sensing identification method based on the improved Otsu algorithm and multi-feature threshold proposed in this paper, the local feature threshold is first selected. When smoothing remote sensing images, a 64 × 64 pixel local window was set, and 100 local window images of landslide areas and surface types affected by geological disasters were selected for analysis. An appropriate threshold can be determined by analyzing the distribution of these images on two indicators: grayscale mean entropy and grayscale mean standard deviation. The result is shown in Figure 6. When smoothing remote sensing images, a 64 × 64 pixel local window was set, and 100 local window images of landslide areas and surface types affected by geological disasters were selected for analysis.

(a) Comparison of local window entropy and grayscale mean
(b) Comparison of local window standard deviation and grayscale mean

Figure 6 shows that the one-dimensional entropy, grayscale mean, and standard deviation values of normal ground types in non-landslide areas are lower. In contrast, the local characteristics of ground types in landslide areas exhibit higher numerical distributions. Based on the observation of Figure 6, the following thresholds can be set: the threshold for one-dimensional entropy is 4.2, the threshold for grayscale mean is 50, and the threshold for grayscale standard deviation is 20. When the eigenvalues of a local window are all less than or equal to these three thresholds, the window is classified as a normal ground type. If these conditions are not met, it is identified as a landslide type.

3.2 Analysis of identification comparison experiment results

To further verify the application effect of the shallow landslide remote sensing recognition method based on the improved Otsu algorithm and multi-feature threshold proposed in this paper, the high-resolution remote sensing image landslide recognition method based on DETR proposed in reference (Du et al., 2023) and the landslide recognition method based on image recognition technology and computer vision technology proposed in reference (Xin et al., 2023) were compared and tested together with the method proposed in this study. The binary segmentation effect of remote sensing images and the accuracy of landslide recognition will be used as experimental indicators to verify the effectiveness of different methods.

3.2.1 Binary segmentation effect

In this study, binary segmentation was performed on the target object (landslide) and background in remote sensing images. Therefore, the binary segmentation effect of different methods on remote sensing images in complex lighting environments with environmental noise interference is shown in Figure 7.

(a) Proposed method
(b) High resolution remote sensing image recognition method based on DETR
(c) Methods based on image recognition technology and computer vision technology

Figure 7 shows that although all three methods can segment the target object from the background, there is still a significant

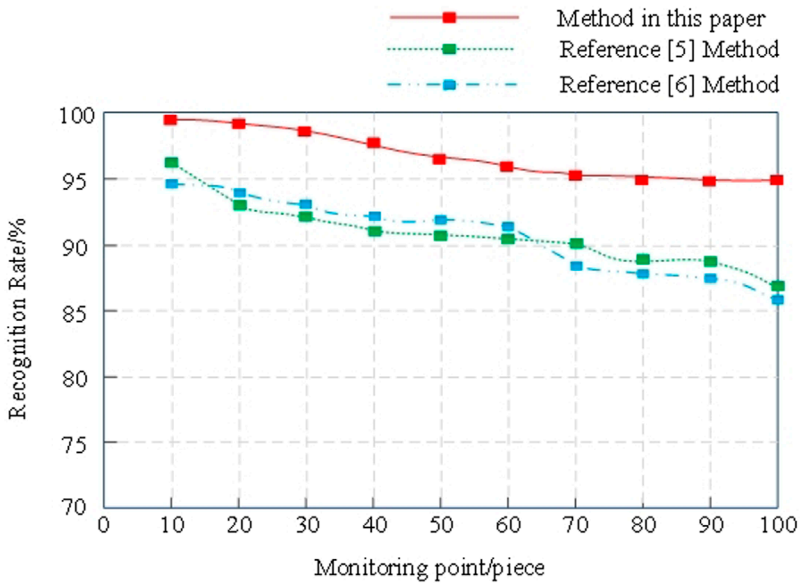

FIGURE 8
Identification rates of shallow landslide bodies using different methods.

gap in the binary segmentation effect of different methods in terms of details. Among them, the high-resolution remote sensing image landslide body recognition method based on DETR can effectively segment ordinary ground and landslide bodies. However, some areas containing vegetation have missing details, which may reduce the accuracy of shallow landslide body recognition. After binary segmentation of remote sensing images based on image recognition technology and computer vision recognition methods, some areas have high noise, blurriness, and low edge features, making it difficult to accurately segment the target object and background, which is not conducive to shallow landslide recognition. In contrast, the shallow landslide remote sensing recognition method based on the improved Otsu algorithm and multi-feature threshold proposed in this article can clearly segment the target object and background in complex lighting environments after binary segmentation of remote sensing images, with clear edges and good binary segmentation effect, which can effectively improve the accuracy of shallow landslide remote sensing recognition.

3.2.2 Accuracy of landslide identification

The accuracy of landslide identification refers to the ability to correctly identify landslide bodies (including their location, shape, size, and other information) after processing remote sensing images through specific methods. The recognition rate is a key indicator for measuring the effectiveness of landslide identification methods, which is the ratio of the number of correctly identified landslide bodies to the actual number of landslide bodies. The higher the recognition rate, the stronger the recognition ability of the method and the better the actual application effect. Arrange 150 monitoring points in the research area to monitor landslide displacement, randomly select 100 monitoring points for experimental testing, and verify the recognition rate of different methods on shallow landslide bodies in the research area. The comparison results of identification rates of shallow landslide bodies in the study area using different methods are shown in Figure 8.

Figure 8 shows that as the number of monitoring points increases, the identification rate of shallow landslide bodies using different methods shows a decreasing trend. Among them, the recognition rate of landslide bodies based on the DETR high-resolution remote sensing image recognition method decreased from 96% to 87%, with a decrease of 9 percentage points; The recognition rate based on image recognition technology and computer vision technology has decreased from 95% to 86%, a decrease of 9 percentage points. The shallow landslide remote sensing recognition method based on the improved Otsu algorithm and multi-feature threshold proposed in this article has reduced the recognition rate of shallow landslides in the study area from 99% to 95%, with a decrease of only 4 percentage points and a recognition rate of not less than 95%. This indicates that the method proposed in this article is more accurate in identifying shallow landslides in the study area and has good application effects.

4 Conclusion

This article proposes a shallow landslide remote sensing identification method based on the improved Otsu algorithm and multi-feature threshold. By conducting detailed analysis and processing of remote sensing images, the traditional Otsu algorithm has been optimized, and a multi-feature threshold strategy has been introduced to improve the accuracy and reliability of landslide identification. The experimental results show that this method can effectively distinguish landslide bodies from complex backgrounds in complex remote sensing images, accurately identify shallow landslide bodies, and provide strong technical support for early warning and prevention of geological disasters. With the continuous

advancement of remote sensing technology and the increasing richness of data sources, there is still room for further optimization of research methods, such as combining higher-resolution image data or introducing machine learning algorithms to improve recognition performance. Future research will focus on these directions to achieve higher recognition accuracy and provide more comprehensive and in-depth solutions for monitoring and managing landslide disasters.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

JR: Conceptualization, Project administration, Resources, Writing–original draft. JW: Data curation, Formal Analysis, Funding acquisition, Investigation, Writing–original draft, Writing–review and editing. RC: Conceptualization, Writing–original draft. HL: Supervision, Writing–original draft. DX: Formal Analysis, Investigation, Writing–original draft. LY: Validation, Visualization, Writing–review and editing. JS: Conceptualization, Writing–original draft.

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Conflict of interest

Authors JR, JW, RC, HL, DX, LY, and JS were employed by Sichuan Leshan Geological Engineering Survey Institute Group Co., Ltd.

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Review on the research progress of earth pressure on slope retaining structure

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The earth pressure of slope retaining structure is one of the problems that are often encountered in geotechnical engineering but have not yet been fully understood and well solved. At present, there are still a lot of problems that need to be solved. For complex conditions such as stratified soil or containing ground water, the distribution law of earth pressure and the displacement mode of retaining structure need to be further studied. This paper summarizes the existing research on earth pressure of slope retain structures. According to the research methods, it is divided into three categories: research on the theoretical calculation method of earth pressure, research on earth pressure by model test, and research on earth pressure by numerical simulation. Focused discussions are carried out respectively, and the previous research results are summarized. At present, there are still a lot of problems that need to be solved in the research of earth pressure of slope retaining structure, and the calculation formula of earth pressure and the assumed fracture surface of earth are lack of experimental verification and engineering measurement.

KEYWORDS

slope, retaining structure, earth pressure, numerical simulation, model test

1 Introduction

With the development of engineering construction, the problems encountered in geotechnical engineering are becoming more and more complex, which poses a challenge to classical soil mechanics and also a great test to geotechnical engineers. Earth pressure on retaining structures is a classical subject in soil mechanics. The traditional Rankine earth pressure theory and Coulomb earth pressure theory sometimes have large calculation errors due to too many assumptions and the limitation of applicable conditions. Many experts and scholars have carried out more in-depth research on the earth pressure on various forms of retaining structures. In this paper, the existing research on the earth pressure on retaining structures is summarized. And put forward some suggestions aim at that deficiency of the existing research. In theoretical investigations of earth pressure, and the simplified assumptions of the model should be as reasonable as possible, such as the form of soil sliding surface, the angle of soil fracture, and whether the rigidity of the assumed retaining structure meets the needs of the project. Numerical simulation of earth pressure can directly observe the distribution form of earth pressure, but there are certain requirements for grid division, and numerical simulation results are usually used to verify the test or theoretical results. The model test method can obtain the actual observation of displacement, stress and other data, and can intuitively study the displacement pattern of retaining wall, but the reasons for the different displacement patterns need to be further studied.

2 Study on theoretical calculation method of earth pressure

The derivation of earth pressure calculation method is an important way to study earth pressure. Many scholars have studied it and put forward a variety of calculation methods. This paper summarizes the existing calculation methods of earth pressure of slope retaining structure.

Based on the ultimate equilibrium theory and the assumption of plane sliding surface, Ma et al. (2008) deduced the Formula 1 for calculating the active earth pressure of the finite soil between two walls and the expression of the failure angle of the sliding surface of the soil by assuming that the soil is a rigid-plastic body, not considering the friction between the soil and the retaining structures, and considering the cohesion of the soil. The formula shows that the failure angle of sliding surface of finite soil is not a constant value 45° + φ/2, but a variable related to the calculation depth, soil internal friction angle, soil cohesion and finite soil width. It also points out that the active earth pressure of finite soil is less than Rankine active earth pressure, the Rankine earth pressure causes the calculated earth pressure to be greater than the actual value, resulting in unnecessary waste. The strength of active earth pressure of finite soil has a nonlinear distribution with depth.

$$E = \left[\gamma b\left(z - \frac{b}{2}\tan\theta\right) - bc\tan\theta\right] - \tan(\theta - \varphi) - bc \tag{1}$$

Based on the equilibrium theory of sliding wedge, Li and Guo (2008) established a formula (Formula 2) for calculating the earth pressure of the finite soil between two walls, assuming that the soil is cohesive soil, considering the friction between the wall and the soil, considering the adhesion force behind the wall, and considering the uniform load on the top of the soil. The assumption that the soil is treated as a rigid body and the interaction between piles and soil is not taken into account can lead to biased calculation results and waste of materials in engineering design.

$$E_a = \left[\left(\frac{1}{2}\gamma b - k\right)(2H - b\tan\theta) + qb\right]\frac{\sin(\theta - \varphi)}{\cos(\theta - \delta - \varphi)} - \frac{cb}{\cos\delta}\left(1 + \frac{\sin(\theta - \delta)\sin(\theta - \varphi)}{\cos\theta\cos(\theta - \varphi - \delta)}\right) \tag{2}$$

When the width of the finite soil is less than or equal to 0.5–0.75 times of the depth of the pit, the calculation model of the earth pressure of the finite soil should be considered. In addition, the author also noticed that when the depth of the foundation pit is greater than the depth of the basement of the adjacent building, the superposition of the finite soil above the depth of the foundation pit of the existing building and the semi-infinite soil below the depth of the foundation pit of the existing building needs further consideration.

Wang et al. (2014) assumed that the sliding surface of the soil was a plane, considered the cohesion of the soil, and considered the normal and tangential interaction forces between the soil and the retaining wall and the foundation of the existing building. As shown in Figure 1, it is assumed that the earth pressure of finite soil is still distributed along the depth triangle. The calculation Formula 3 of finite soil pressure under this condition is obtained, and the results are compared with the finite element results, which confirms that this method is closer to the finite element solution. Wang Hongliang

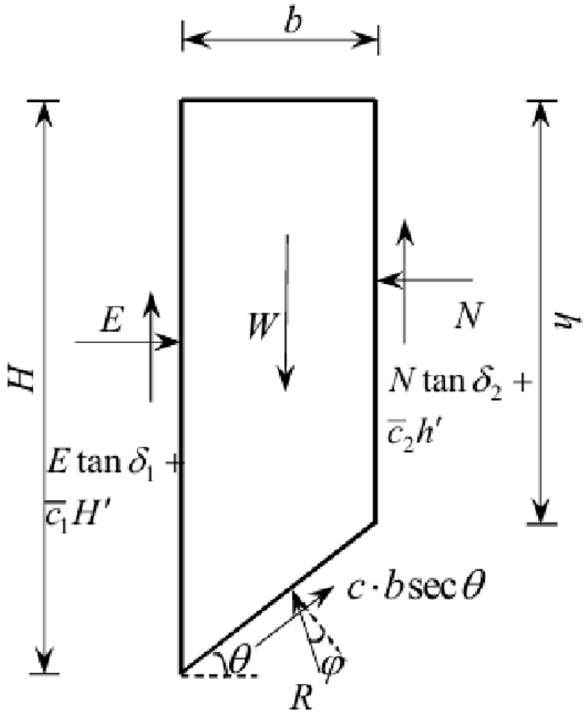

FIGURE 1
Finite soil force analysis diagram.

also pointed out the special situation when the cohesion between the retaining wall and the soil exceeds the gravity of the finite soil, and provided the applicable formula in this case. However, the angle of the sliding surface of the soil is simplified, and the fixed value of 45° + ϕ/2 is still used.

$$E = \frac{\gamma b\left(H - \frac{1}{2}b\tan\theta\right) - bc(\tan\theta + \cot(\theta - \varphi))}{\tan\delta_1 + m_b\tan\delta_2 + (1 - m_b)\cot(\theta - \varphi)} - \frac{\bar{c}_1(H - z_0) + \bar{c}_2(H - b\tan\theta - z_0)}{\tan\delta_1 + m_b\tan\delta_2 + (1 - m_b)\cot(\theta - \varphi)} \tag{3}$$

Among $m_b = N/E$.

Pang et al. (2009) based on the Coulomb earth pressure plane slip surface assumption, used the limit equilibrium method to derive the calculation formula of the passive earth pressure of the limited soil reserved in front of the wall when the central island method was used to excavate the foundation pit. The calculation results were compared with the finite element results, which showed that when the internal friction angle of the soil and the friction angle of the wall are small, the error was small, and the calculation formula met the engineering needs.

The study of theoretical calculation method of earth pressure is to establish an idealized model through appropriate simplified assumptions of engineering practice. According to the model, the calculation formula of earth pressure is obtained through theoretical derivation. When simplifying assumptions, it should be reasonable and as close as possible to the engineering practice. For example, the form of the assumed sliding surface of the soil should be verified by tests or retained by data provided by engineering measurements. As shown in Figure 2, the references from 1 to 4 are calculated and

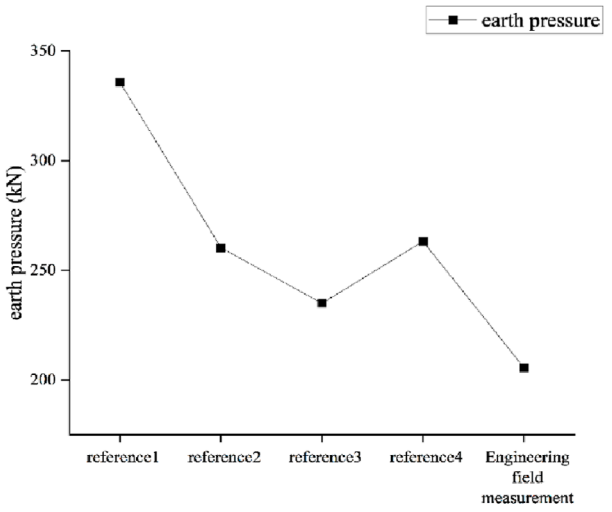

FIGURE 2
Comparison chart.

compared with the real-world data. It is shown that the reference 3 is approaching actual engineering values. That is to say the reference 3 is much more reasonable compared with another three references. Currently, the research assumes the retaining structure to be rigid, and the earth pressure law under the condition of the interaction between the retaining structure and the soil and the coordinated deformation can be further studied.

3 Study on earth pressure by numerical simulation method

With the development of computer technology, more and more attention has been paid to numerical simulation technology. Numerical simulation method can not only simulate the complex engineering environment, but also observe the failure mode intuitively, which is favored by researchers. However, this method has high requirements for the selection of parameters and the division of the grid. In some cases, the calculation results are deviated greatly because of the failure of convergence. At this time, other methods are needed to test the results.

Fan and Fang (2010) used the nonlinear finite element program PLAXIS to analyze the earth pressure of the rigid retaining wall near the stable rock surface from static to active conditions, and studied the acting position and distribution characteristics of the finite soil earth pressure between the rigid retaining wall and the stable rock surface. The effects of wall height and friction angle on the magnitude and location of earth pressure are also studied. The results show that the active earth pressure of finite soil is far less than the Coulomb earth pressure, and the active earth pressure position of finite soil is significantly higher than 1/3 of the wall height. The active earth pressure coefficient decreases and the active earth pressure position rises with the increase of the slope angle of the stable rock surface.

Wu et al. (2023) used FLAC3D software to establish a three-dimensional digital model of the retaining wall and the finite slope soil, simplify piles into beam elements and slopes into solid element sand verified the validity of the three-dimensional digital model through the change law of the inclination angle of the sliding plane of the finite slope soil and the change law of the passive earth pressure of the finite slope soil with the depth of the soil behind the wall. Then the model is used to simulate and analyze the influence of the parameters of retaining wall, such as soil parameters, slope angle and plaorm width on the earth pressure under the condition of translation. The simulation results show that with the increase of the plaorm width, the slope angle of the sliding surface of the finite slope decreases to zero at first and then increases gradually; the passive earth pressure presents a nonlinear distribution, and the active earth pressure presents a convex curve distribution.

Li and Zhou (2017) used the finite element analysis software ANSYS to study the earth pressure of the passive non-limit state of the translational extrusion of the retaining wall. The results show that the soil near the back of the wall forms a relative displacement area similar to an inverted trapezoid, and there are horizontal and vertical displacement differences between adjacent points in the area. The horizontal length of the relative displacement area (2 ~ 3) is the height of the wall, and the larger the wall displacement is, the larger the relative displacement area is. The distribution of non-limit state passive earth pressure of retaining wall in translation mode is similar to a straight line. When the earth pressure transits from the static state to the passive limit state, the growth rate of the total value of the horizontal passive earth pressure gradually slows down, and its value is always less than the Coulomb passive earth pressure. The larger the friction angle of backfill is, the larger the passive earth pressure of non-limit state is.

The visual failure mode of finite soil and the distribution curve of earth pressure can be obtained by numerical simulation, aiding in deriving formulas for earth pressure calculation, and can also be engineering design and practical applications to verify its correctness.

4 Study on earth pressure of soil by model test method

The model test method is to use similar materials, reduce the actual project to a certain proportion, simulate the actual construction process, and monitor the soil pressure and other parameters. Through the model test, we can intuitively get valuable experimental phenomena, and many scholars have carried out related research.

Frydman and Keissar (1987) conducted centrifuge model tests on a rigid retaining wall near a vertical rigid boundary to observe the change of earth pressure behind the wall from static to active conditions. The retaining wall is made of aluminum, allowing the wall to rotate around its base. The test results show that the distribution of active earth pressure is not triangular. The active earth pressure coefficient decreases significantly with depth. The location of active earth pressure is more than one third of the wall height.

Fang and Ishibashi (1986) and Khosravi et al. (2013) carried out the model test of rigid retaining wall under the mode of

translational movement. The results show that the distribution of earth pressure on the retaining wall is related to the mode of movement of the retaining wall, and the classical theory can not describe this phenomenon. The distribution of active earth pressure on retaining wall is parabolic in translation mode.

Cai (2020), Zhang et al. (2024) and Luo et al. (2022) studied the failure process and failure mode of active limit state of finite cohesionless soil with different widths in translational mode through the model test of movable retaining wall. The test results show that the compression of the soil width increases the inclination angle of the failure slip surface; when the soil width is small enough, the failure slip surface develops to the wall surface and then reflects to form the second slip surface, which develops to the soil surface. According to the different failure modes in the test results, the corresponding earth pressure calculation model is established, and the calculation method of the earth pressure of the finite width cohesionless fill under the translational displacement mode is derived according to the limit equilibrium method. The calculation results are compared with the existing test data to verify its applicability.

In addition, the slope gradient also has a significant impact on stability. Fang et al. (2022); Pipatpongsa et al. (2024); Fang et al. (2023) conduct a series of physical model experiments on arched slopes with different slope angles, a physical slope model under excavation is analysed through multi-field monitoring.

5 Conclusion and prospect

Due to the need of engineering, many experts and scholars have studied the earth pressure of slope retaining structure with different methods. The existing classical earth pressure theory can not meet the requirements of engineering safety and economy. How to calculate the earth pressure more accurately and reasonably has become an important and urgent subject. The paper provides a comprehensive review of existing research results based on three aspects: derivation of earth pressure calculation methods, investigation of earth pressure through model test methods, and study of earth pressure using numerical simulation methods, according to different research methodologies.

Through reading the literature, it is found that the existing research has the following shortcomings, In response to existing shortcomings, the following directions for follow-up research were identified.

(1) The delineation boundary between finite and semi-infinite soils is vague, and it is controversial how to correctly define finite soils; subsequent scholars can give the delineation conditions of finite and infinite soils and verify the correctness of the delineation conditions through experiments.
(2) The existing calculation methods based on Rankine semi-infinite soil pressure theory have the problems of insufficient calculation accuracy, too conservative and poor economy. In the future, when the theoretical study of earth pressure is conducted, efforts should be made to reduce the assumptions, improve the calculation accuracy, and increase the practical value of the calculation method. For the unavoidable simplified assumptions, the reasonableness and error of their assumptions should be supported by engineering real measurements or model tests.
(3) Existing studies using the limit equilibrium method assume that the soil sliding surface is planar, but there is a lack of engineering examples to verify, advanced multi-field monitoring system can be used to obtain the measured data, including the shape of the soil sliding surface, the angle of the sliding surface, and the effect of the change of the soil parameters on the soil sliding surface, in order to verify the reasonableness of the computational model.
(4) Most of the existing studies are aimed at homogeneous soil, without considering the impact of groundwater, and the earth pressure of heterogeneous soil and the existence of groundwater needs further study.
(5) The existing studies assume that the retaining structure is rigid, which is different from the actual situation. Subsequent scholars can consider the coordinated deformation between the retaining structure and the soil, which is closer to the actual situation.

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YZ: Writing–original draft. HW: Conceptualization, Investigation, Methodology, Writing–review and editing.

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Study on the chain-type failure mechanism of large-scale ancient landslides

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Large-scale ancient landslides are widely distributed in Southwest China, yet their reactivation mechanisms remain complex and poorly understood. On 25 July 2020, one such landslide in Liujing Village, Wulong District, Chongqing, China, experienced reactivation. This event exhibited variable movement characteristics across different areas and times, ultimately manifesting as a chain-type failure. Combining field investigations and drilling works, this study describes the fundamental characteristics of the Zhongbao landslide and the variation rules of the seepage field and the stability by numerical simulations. The failure mechanism is preliminarily revealed, and the failure influencing factors are discussed. The results show that, the landslide's progression was influenced by the stratigraphic lithology and the morphology of the sliding surface, resulting in two distinct turns during its movement. By analyzing the landslide's spatial morphology, direction of sliding, material composition, extent of the accumulation area, and dynamic behavior, we have categorized the Zhongbao landslide into five principal zones. The failure process can be segmented into four stages: initiation, shear-out, acceleration, and accumulation blockage. Heavy rainfall served as the primary trigger for the landslide, while the microtopography of the sliding surface significantly influenced the failure dynamics. The insights gained from this study offer valuable guidance for understanding the reactivation mechanisms of similar chained ancient landslides in the geologically analogous regions of Southwest China.

KEYWORDS

ancient landslide, failure mechanism, deformation characteristics, numerical analysis, GeoStudio

1 Introduction

Ancient landslides are landslides that have been inactive for a long time and the time of the last activity is not clear, usually consisting of mixed accumulations of complex genesis, dominated by lumpy soils, gravelly clasts, or pulverized clays interspersed with gravelly clasts, etc., with a disorganized and unstratified structure (Cruden and Varnes, 1996; Zhang et al., 2018). Ancient landslides are usually not easy to be recognized and are easily reactivated under the influence of rainfall infilt ration, artificial excavation, reservoir storage, etc., and are extremely destructive

due to their large amount of destabilized cubic meters (Georgi & Krastanov, 2015; Wartman et al., 2016). With the increase of human engineering activities and extreme climate in recent years, the resurgence of ancient landslides in southwest China has been increasing, further drawing attention to the study of ancient landslide deformation mechanisms (Guo et al., 2022). For example, the Leibo landslide in 2017 with a volume of 4.03 m^3 × 10^6 m^3, destroying under-construction roads and numerous buildings (He et al., 2019). The Jiangdingya landslide with a volume of 4.8–5.5 m^3 × 10^6 m^3, caused siltation of the river and buried toe villages and hydropower stations (Guo et al., 2019).

In-depth understanding of the reactivation mechanism of ancient landslides is crucial for implementing countermeasures and mitigating losses in engineering construction (Huang et al., 2021). A large number of studies have shown that the reactivation of ancient landslides is influenced by single or coupled factors such as geological formations, rainfall, reservoir level, and human activities, which lead to the deformation of landslides (Cheng et al., 2023; Dai et al., 2022; Qiu et al., 2024; Wei et al., 2024; Yang et al., 2023; Ye et al., 2024; Zhang et al., 2024).

Combined with centrifuge experiments, the deformation characteristics of the Cheyiping landslide were analyzed, which proved that even if the sliding surface is not deep, the sudden drop of the reservoir water level is the main controlling factor of the slope sliding. Zhang et al. (2020) conducted a preliminary analysis of the reactivation mechanism of Baiyangwan landslide through field investigation, drilling and on-site monitoring, and proved that the artificial slopes and valleys in mountainous areas may induce the elevation of groundwater level, and ultimately induce the reactivation of the landslide (Zhang et al., 2020). Tian et al. (2022) indicates that the formation of ancient landslides is closely related to the uplift of the Tibetan Plateau and the erosion of the Longwu River. Landslides characterized by zigzag sliding paths are relatively rare and present obvious directional changes, complicating risk assessment efforts (Tian et al., 2022). A case in point is the Niu'erwan landslide, which reactivated in 2020 and exhibited a sharp turn during its descent, resulting in two distinct mudslide zones. This event led to the destruction of eight houses, two critical roads, and extensive farmland damage (Zhou et al., 2022). The deformation and failure mechanisms of such ancient landslides remain inadequately understood, particularly the factors contributing to the development of these complex sliding patterns. Consequently, there is an urgent need for research to unravel these mechanisms and improve our predictive capabilities.

This study shows the fundamental features and deformation characteristics of the Zhongbao landslide, a prototypical large-scale ancient landslide characterized by zigzag patterns and a chain-type failure process. Combining field investigations, drilling, on-site shear tests, numerical analysis and laboratory shear tests, we conducted a preliminary analysis of its failure mechanism, specifically addressing the causes of its folded trajectory. Furthermore, we explored the significant influence of infiltration channels and rainfall on the landslide's reactivation. The findings of this research offer valuable insights into the reactivation mechanisms of ancient landslides under similar geological conditions in Southwest China, serving as a reference for future studies and risk management strategies.

2 Geologic setting

2.1 General description

Zhongbao landslide is located in Liujing Village, Wulong District, Chongqing, China. The region has complex topography, high mountains and deep valleys, and the overall terrain is high in the northeast and southwestern part of the country. The downward slope is mostly developed along the level of gray rock and shale, and the slope topography has a slope angle of 16°–55°, while the reverse slope is steep and localized as steep canyons. Landslide area near the deep cut along the Yanchang River, the formation of steep terrain, terrain height difference, coupled with long-term weathering, unloading effect, the formation of high steep slopes in the development of rock unloading Zone And fissure rock fragmentation zone, for the occurrence of landslides provide the conditions.

2.2 Climatic conditions

Landslide area belongs to the subtropical humid climate zone, warm and humid, abundant rainfall. The average temperature over the years is 18.1°. The average annual rainfall is 1191.8 mm, which indicating rainfall is abundant, However the time distribution is not uniform, the annual rainfall is mostly concentrated in April to September, with a rainfall of 846.9 mm, accounting for about 76% of the average annual rainfall. The study area is abundant with significant rainfall and karst water, whose combined effects significantly intensify the deformation and degradation of the slope's soft zones, fractured areas, and unloaded rock masses. Furthermore, the Canghe River's eroding action at the slope's base accentuates the steepness of the leading edge's topography. This geomorphological steepening furnishes propitious conditions conducive to the occurrence of landslide.

2.3 Geological formations

The landslide area is located in the southeastern edge of the Sichuan Basin, and the geotectonic structure is located in the Yangzi quasi-terraneous platform of Chongqing Taikai-o-Chongqing fold bundle of Wanzhou concave fold bundle range. The tectonic structure in the area is dominated by comb folds with a north-east-north-east orientation, and a series of pressure tectonic structures have been generated due to the extension of the Sichuan-Guizhou north-south radial tectonic belt, and a complex (S-shaped oblique connection) composite relationship is formed with the north-north-east-north-east tectonic structure, which makes the tectonic features more complicated. The regional tectonic system is characterized by the "blocking type" of geese rows arranged on the plane, and the fold axis is 15°–40°, and the axis is often in the shape of "S." Dorsal slope is narrow, narrow strip, two asymmetric wings, generally steep south east wing, north west wing slow; to the slope is wide and slow, two wings nearly symmetrical, stratigraphic dip angle 10°–30°. Based on the field investigation, the stratigraphic yield of the landslide is 135°–142°∠17°–26°.

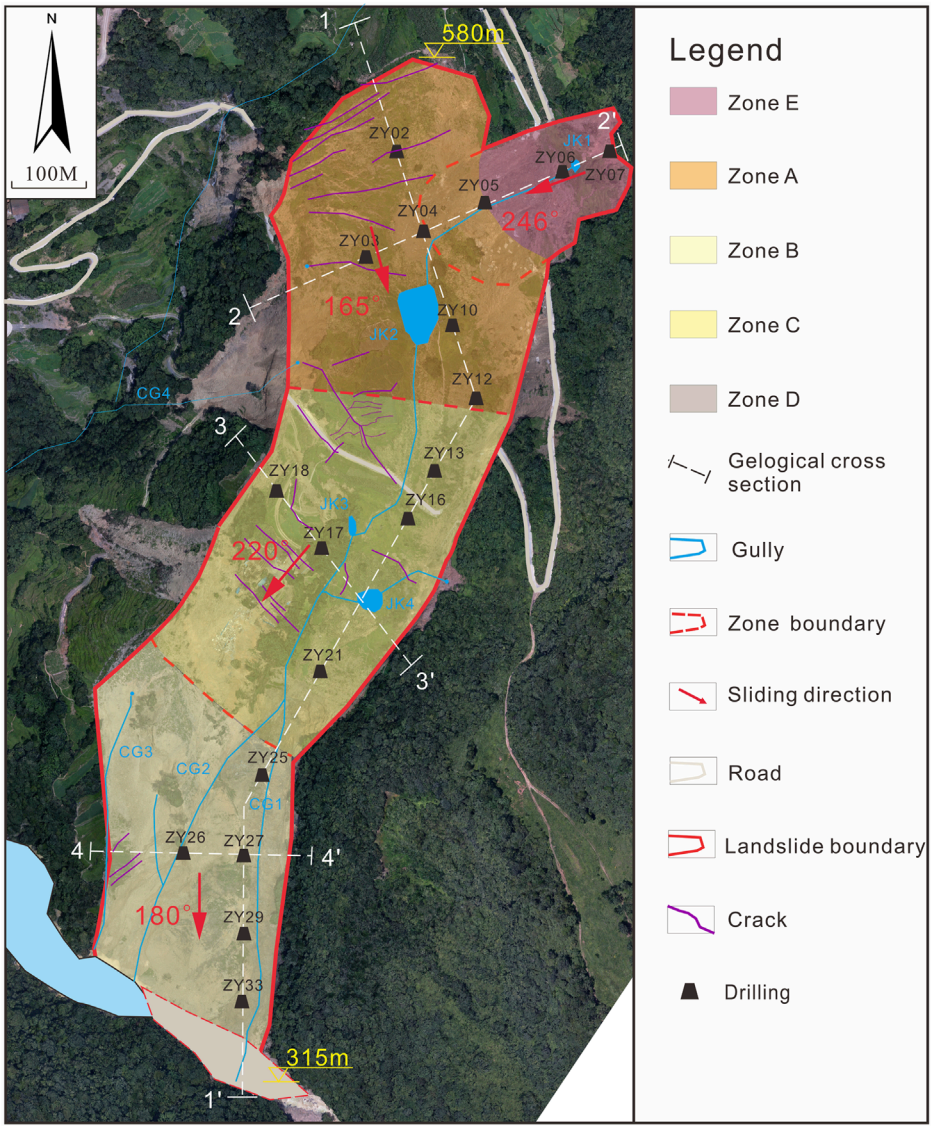

FIGURE 1
Plan view of the Zhongbao landslide. The landslide is divided into five subzones, which are the trailing edge nudging Zone A, extrusion and turning Zone B, leading edge tangential accumulation and stacking Zone C, weir counterpressure Zone D, and trailing edge soil slip Zone E.

3 Characteristics of landslides

3.1 Landslide characteristics

The overall plan form of Zhongbao landslide is in the shape of a "long tongue." There were two turns in sliding process, the main slip direction of 150°–220°, basically along the north-south direction of the spread (Figure 1). The longitudinal length is about 850 m, transverse width is about 200 m, thickness is about 3.5–66.2 m, volume is about 5.48 $m^3 \times 10^6$ m^3, which is a large rock-soil landslide. The slope angle of the rear edge of the landslide is 5°–12°, the slope angle of the middle edge is 8°–17°, and the slope angle of the front edge of the landslide is 25°–45°, with a general trend of steepness at the front edge and slowness at the rear edge (Figure 2). The volume of the landslide that collapsed into the river was about 54 $m^3 \times 10^3$ m^3, the width of the blocked river section was about 25–40 m, and the length of the blocked river was about 150 m.

3.2 Hydrogeolofical conditions

After the sliding of the Zhongbao landslide, four catchment pits JK1-JK4, four gullies CG1-CG4, and eight springs were formed in the landslide body (Figure 1). CG1 and CG2 have intermittent water flow in the gullies in the normal times, and are basically connected during the rainy season, while CG3 and CG4 do not have any water flow during normal times, and the water flow in the gullies intermittently exists in the rainy season, and is occasionally discharged downstream along with the mudslides. Directly converge into the downstream Yancang River, and CG4 converges with the seasonal washout on the outside of

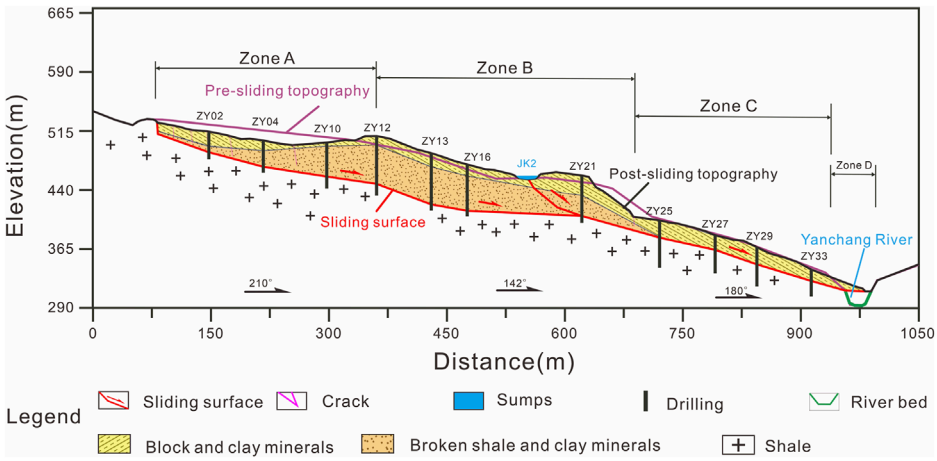

FIGURE 2
Geological section 1-1′ in Figure 3.

the landslide area to flow into the downstream Yancang River. Based on the simple hydrological observation in the field, the non-rainy season flow of CG1 and CG2 is about 0.05–0.3 m^3/s, and the rainy season flow is about 0.3–0.7 m^3/s; the rainy season flow of CG3 and CG4 is about 0.1–0.6 m^3/s.

Test pit seepage experiments were conducted in 20 boreholes in the study area and pumping experiments were carried out in boreholes ZY3, ZY18 and ZY27. The permeability coefficients of 4.33×10^{-5}~1.01×10^{-2} cm/s for the massive rock sandwiched powdery clay were obtained, which were dominated by weakly permeable-moderately permeable layers, and some strongly permeable layers existed at the back edge of the landslide; the permeability coefficients of 9.52×10^{-5}~6.30×10^{-3} cm/s for the fragmented rock body were obtained, which were dominated by weakly permeable-moderately permeable layers. Groundwater in the landslide area can be divided into loose rock pore water, bedrock fissure water and karst water according to the characteristics of water-bearing medium and storage state. Groundwater recharge in the study area mainly consists of atmospheric rainfall and karst water, and groundwater is generally rich.

3.3 Material composition

The material composition and structural characteristics of the Zhongbao landslide were revealed through detailed field investigations and drilling. In order to obtain the mechanical properties of the soil samples, *in situ* shear experiments and laboratory shear experiments were carried out to determine the shear strength and internal friction angle of the soil samples obtained from the sliding body and sliding surface (Table 1).

Sliding body: the sliding body is mainly composed of Quaternary Holocene avalanche deposits (Q_4^{col+dl}) and paleo-landslide accumulations (Q_4^{del}). There is a large difference between the trailing and leading edge of the landslide slide bodies. The trailing edge slide varies greatly in the vertical direction, with the upper part mainly consisting of massive rocky soil sandwiched with clay (Q_4^{col+dl}), which is about 3.5–18.4 m thick; the lower part mainly consists of fragments of rocky body sandwiched with clay (Q_4^{del}), which becomes thicker and thinner from north to south and west to east, with a general thickness of 20.0–66.2 m. The fore-edge slide is mainly consisting of massive rocky soil sandwiched with clay (Q_4^{col+dl}) with a similar character to that in the upper part of the trailing edge (Figure 2).

Sliding bed: the sliding bed mainly consists of greenish gray shale ($S_{2h\text{-}Sh}$) of Hanjiadian Formation in the middle part of the Liou system, with muddy structure, thin laminations, developed shale, the main mineral composition is clay minerals, and the fissures are more developed. Drilling holes ZY24, ZY25, ZY26, and ZY31 indicate that there are localized muddy and weak interlayers in the lower part of the rock body in Area C, but there is no sign of sliding.

Sliding zone:The sliding zone primarily consists of the ancient landslide accumulation layer (Q_4^{del}), characterized by gray-green and light yellow clayey soils interspersed with gravel. The zone is subject to intense pressure, resulting in predominantly light yellow and dark gray clayey soils with a high plasticity particle content ranging from 60% to 80%. These soils are notably sticky to the touch and exhibit a pronounced sludging effect, softening rapidly upon contact with water. Borehole investigations reveal that the sliding zone typically has a thickness ranging from 0.2 to 1.5 m, while exploratory wells expose a soil thickness of approximately 0.4 m within the sliding zone. The interface with the underlying hard rock stratum shows distinct signs of abrasion, and in places, a polished, mirror-like surface is observable (Figure 4C). Notably, the sliding zone's thickness at the rear edge of Area A is less than that at the central front, and the depth and thickness of the sliding zone on the eastern side exceed those on the western side.

4 Landslide reactivation deformation characteristics

According to the boreholes, the upper part of the landslide body in A and B areas is a loose structure of lumpy soil, and the lower part of the landslide body is a fragmented rock body and soil body with dense cementation and chaotic rock body

TABLE 1 Engineering geologic zoning.

Landslide subdivision	Length (m)	Width (m)	Average thickness (m)	Volume (10^6 m^3)	Slip angle (°)	Gradient (°)
Zone A	280	180	35	1.76	165	20
Zone B	300	170	25	2.55	220	9–11
Zone C1	220	60	50	0.05	180	18
Zone C2	290	80	4	0.35	180	21
Zone E	150	180	15	0.72	250	30–50
Volume of Zone D (10^6 m^3)	$54\ m^3 \times 10^3\ m^3$					
Volume of the landslide (10^6 m^3)	$5.48\ m^3 \times 10^6\ m^3$					

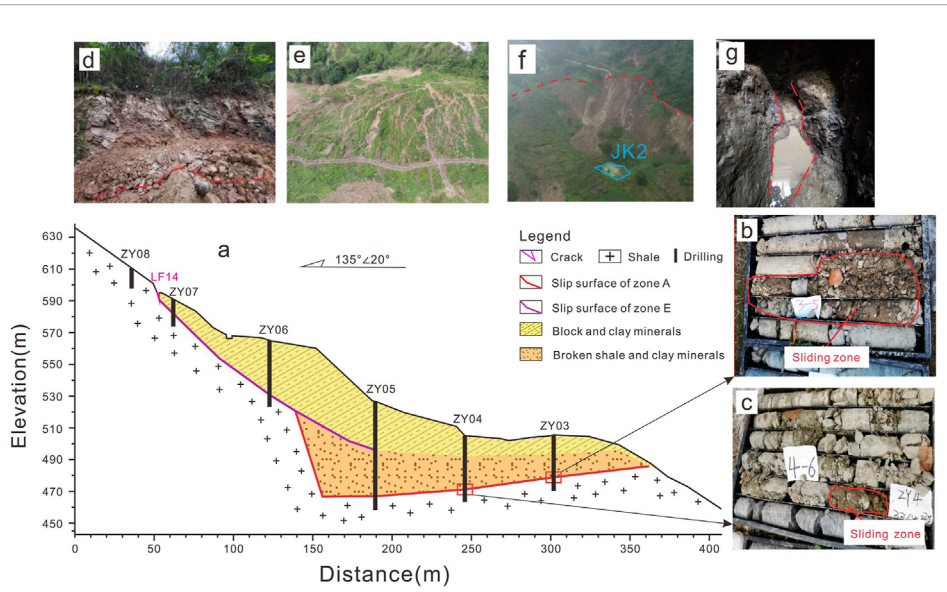

FIGURE 3
Cross-section of Area **(A)**. The sliding direction is towards the inside of the papera. **(A)** 2–2′ section **(B)** ZY3 slip zone, depth 24.4 m–27.0 m **(C)** ZY4 slip zone, depth 33.5 m–34.0 m **(D)** Folding of crushed rock after extrusion **(E)** West of the junction of Areas A and B, large number of plume fissures formed in the surface soil after extrusion **(F)** East of the junction of Areas A and B, catchment pit JK2 **(G)** TJ1 exposing tensile fracture faulting.

layer sequence. The Zhongbao landslide has obvious characteristics of ancient landslide accumulation body, so it is speculated that the Zhongbao landslide is an ancient landslide reactivation. The sliding direction of Zhongbao landslide has been turned twice at a large angle, and the overall direction of movement is in the form of a folding line. The deformation characteristics of different areas of Zhongbao landslide have obvious differences, the overall failure has obvious stages, and the reactivation deformation process has chain characteristics. According to the deformation history of the landslide, combined with the material composition and structural characteristics of the landslide, the landslide is divided into five subzones (Figure 1), which are the trailing edge nudging Zone A, extrusion and turning Zone B, leading edge tangential accumulation and stacking Zone C, weir counterpressure Zone D, and trailing edge soil slip Zone E. Their characteristics are shown in Table 1.

4.1 Zone A

Since 18 July 2020, a large number of surface cracks and tensile faults appeared in the surface layer of Area A. Detailed field investigations revealed its macrodeformation characteristics. A large number of feather-like cracks after extrusion can be seen in the upper surface layer on the west side of the junction location of Area A and Area B (Figure 3E), and the exposed rock body can be seen to be folded after extrusion of the fractured rock body (Figure 3D), and the results of the trenching indicate that the fractured rock

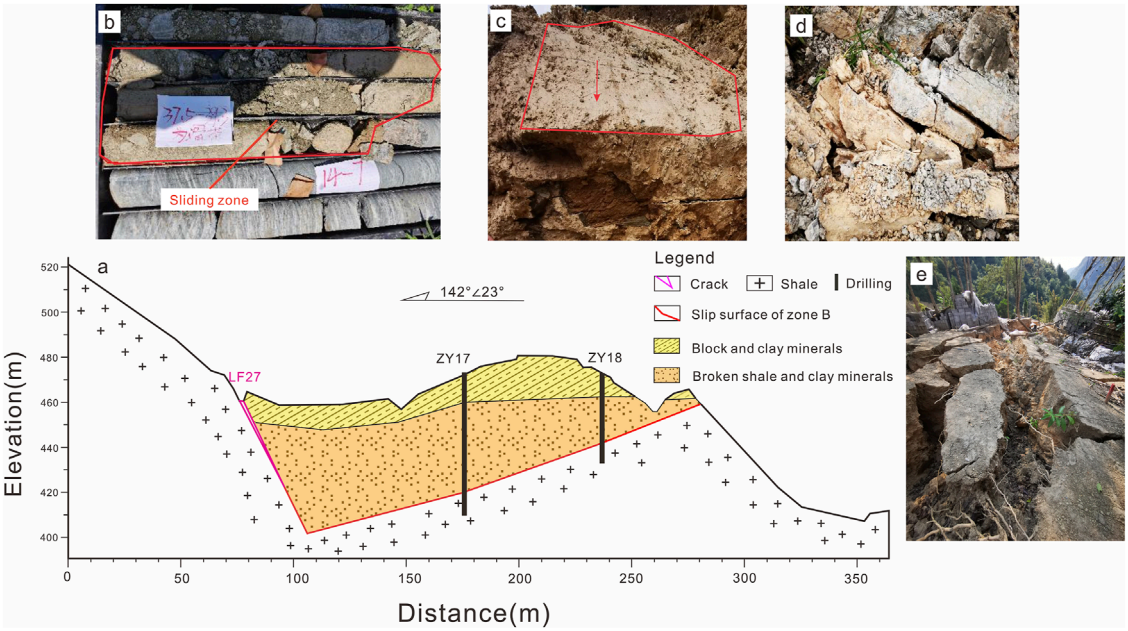

FIGURE 4
Section of Zone **(B)**. The sliding direction is towards the inside of the paper. **(A)** 3–3′ section **(B)** Core sample from sliding fracture zone **(C)** Smooth mirror friction marks **(D)** Front edge of Zone B pushing out cluttered rock mass **(E)** Fracture in central Zone B.

body in the lower part of Area A undergoes pulling and cracking wrongcanning, and the seams are developed (Figure 3G). According to the drilling, the eastern slide body is more fragmented than the central and western slide bodies, and the fractured rock body has messy stratigraphy.

4.2 Zone B

On 22 July 2020, Zone B began to slide slowly, with a sliding direction of 220°, forming pullout slots on both sides that continued to expand and also caused destruction of roads and cracking of building surfaces (Figure 4E). Drill hole 17 reveals that the slip zone in area B is mainly dominated by clay sandwiched with rubble blocks, and the rubble blocks are extruded and milled strongly, and part of them are rounded and arranged in a directional manner (Figure 4B). The back edge of area C can see that the sheared rock body of area B has been wrongly fractured, and part of the rock body can be seen to have a mirror-like abrasion (Figures 4C, D). The area B is sheared at the back edge of area C2, and the sheared rock body of the broken rock body has produced bending and bulging reversal, and the rock layer has been wrongly fractured.

4.3 Zone E

The sliding of the fractured rock body in Zone A of the trailing edge push resulted in the lower part of the soil body on the east side being adjacent to the air, and the upper part of the thick layer of soil body and sliding downward along the bedrock surface with a direction of 250° to form Zone E. The sliding of Zone E covered the upper part of Zone A, which increased the self-weight of Zone A. The *in situ* infiltration testing showed that a moderately permeable layer was formed in the middle and rear part of the slide body. The *in situ* infiltration testing showed that a moderately permeable layer was formed in the middle and rear part of the slip body, and a low permeability layer was formed locally. Surface water and groundwater from the trailing edge continued to pour in, forming catchment pit JK2 at the junction of zones A and B, with a water depth of about 2–5 m.

4.4 Zone C and Zone D

The Zone C can be subdivided into two subsections, C1 and C2, based on its deformation characteristics. On 24 July 2020, noticeable deformation commenced in the Zone C2,while multiple fissures emerged at the forefront of the Zone C1, accompanied by a series of clicking noises reminiscent of thunder that persisted over time. Although the shallow slide masses in the zones C1 and C2 partially entered the river, they did not create a barrier dam. With the leading edge becoming unstable and the trailing edge subjected to additional loading, the landslide as a whole experienced an accelerated downward movement, particularly in the AB area where a marked increase in velocity was observed. Concurrently, the landslide's sliding direction underwent another alteration, shifting from 220° to 180°.

On 25 July 2020, rainfall occurred in the landslide zone, at which time Zone C1 began to slide, Zone C2 slid twice, traces of secondary sliding were visible on the exposed landslide wall (Figure 5B), and the sliding body entered the river along the Cang River to form a weir. At the same time, due to rainfall, the surface rock and soil bodies in Zone C formed a debris flow and slid downward, accelerating the expansion of the weir, blocking the river length of about 150 m and depth of about 12 m.

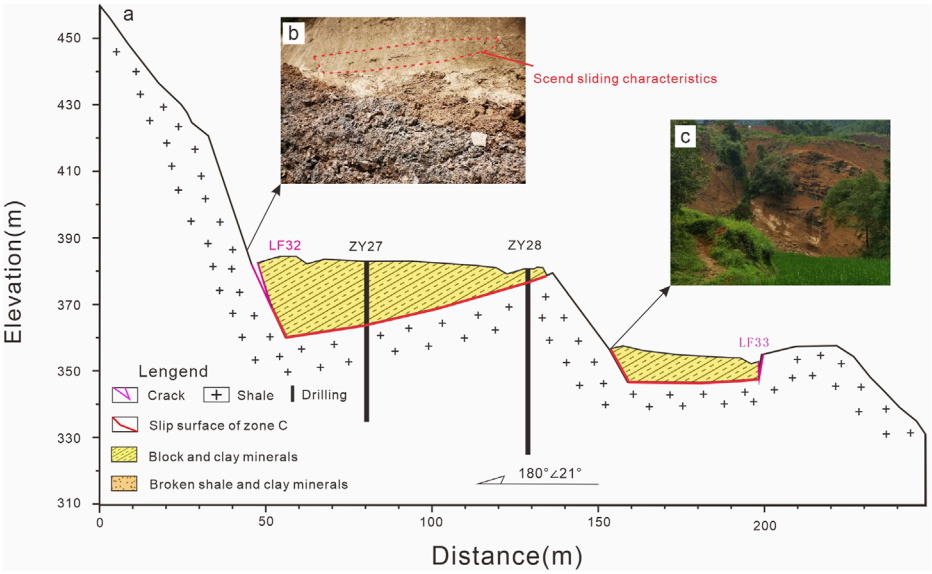

FIGURE 5
Cross section of zones C1 and C2. The sliding direction is towards the inside of the paper **(A)** 4–4′ profile **(B)** Secondary slide marks in Zone C2 **(C)** Eastern rubbing of Zone C1.

5 Numerical analysis of the landslide

5.1 Calculation model of the landslide

The numerical model (Figure 6) for seepage and FOS analysis was established using the GeoStudio software and the computational domain of the model was discretized into a mixture of triangular and quadrilateral elements, with a total of 17,472 nodes and 17,528 elements. Based on the numerical model of the Zhongbao Landslide (Figure 6), the SLOPE/W module was used to analyse the stability of the landslide under rainfall fluctuation by coupling the transient seepage field distribution data of the landslide obtained by the SEEP/W module at different time periods. The Morgenstern-Price limit equilibrium method in the SLOPE/W module was used to systematically analyse the variation of the stability of the zhongbao Landslide as rainfall changed for a duration of 20 days. The main physico-mechanical parameters used in the numerical analysis were selected based on the laboratory test results of the rock and soil mass of the landslide. Then, the values of the parameters used in the numerical model were finally determined by comparing the *in situ* measured groundwater and surface deformation data of the landslide with the results of the numerical inversion, as listed in Table 2.

5.2 Results

5.2.1 Seepage field simulation results

The relationship curve of pore water pressure with rainfall time at three typical monitoring points at the contact surface between the slip surface and bedrock is shown in Figure 7. There are obvious differences in the time to reach saturation across different areas (Figure 7). And the front reaches saturation first, followed by the middle and rear, which is presumed to be related to the thickness and the material. Under the action of groundwater and rainfall, the pore water pressure at point A is always higher than that at points B and C, which leads to the effective stress near point A is always in a lower state, which also cause the rear edge of the landslide to be the first to appear cracks and begin to slip.

5.2.2 Investigation of the variation of landslide stability with time

In the initial stage of rainfall, the FOS of the landslide is about 1.07, which is in a stable state; after that, with the continuous infiltration of rainfall the stability of the landslide decreases; after the extreme rainfall on July 15, the rate of decrease of the stability of the landslide increases until the stability of the landslide on July 22 falls to 0.99, which is in an unstable state. After that,the rate of decrease of the stability decreases continuously and stabilizes at 0.98 nearby (Figure 8). This result is consistent with the deformation of the landslide. In this process, continuous rainfall caused the pore water pressure of the sliding zone increased rapidly, the sliding mass transitioned from the saturated state to the supersaturated state and coupled with the influence of seepage formed by rainfall, the stability of the landslide greatly reduced.

6 Discussion

6.1 Predisposing factors and trigger

6.1.1 Geomorphology

The average slope angles of the three parts of the Zhongbao landslide slide surface from top to bottom, Zone A, Zone B, and Zone C, are about 20°, 10°, and 19°, respectively, while the slope

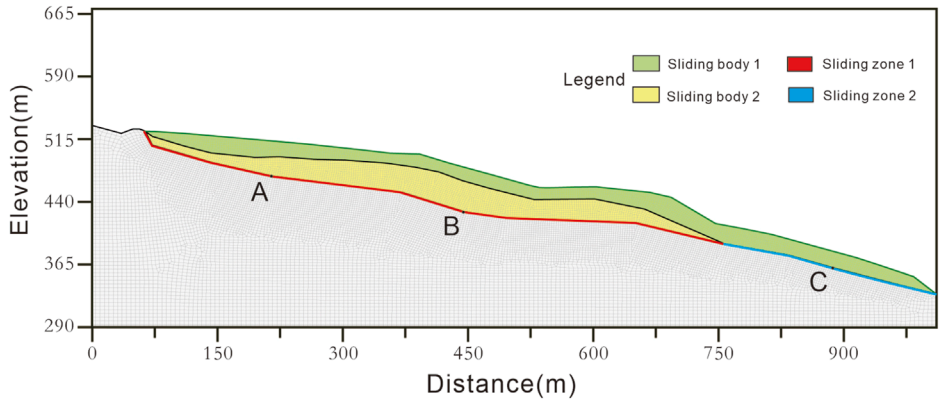

FIGURE 6
Finite element model of the Zhongbao landslide.

TABLE 2 The shear strength parameters of the materials.

	Moisture content (%)	Unit weight (kN/m^3)	Cohesive (kPa)	Internal friction angle (°)
Sliding body 1 (Q_4^{col+dl})	28.50	21.3	22.6	14.3
Sliding body 2 (Q_4^{del})	29.20	24.2	15.6	36.3
Sliding zone 1 Zone A&B	29.50	27.6	21.9	11.3
Sliding zone 2 Zone C	25.70	27.5	29.4	16.9

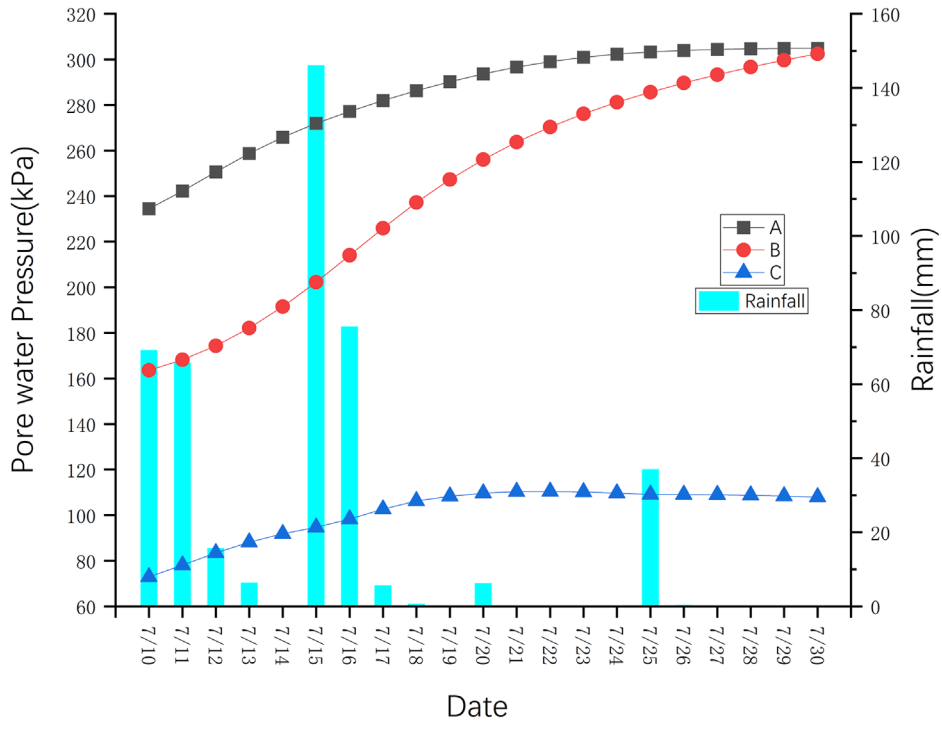

FIGURE 7
Relationship curves between pore pressure and rainfall time of typical monitoring points.

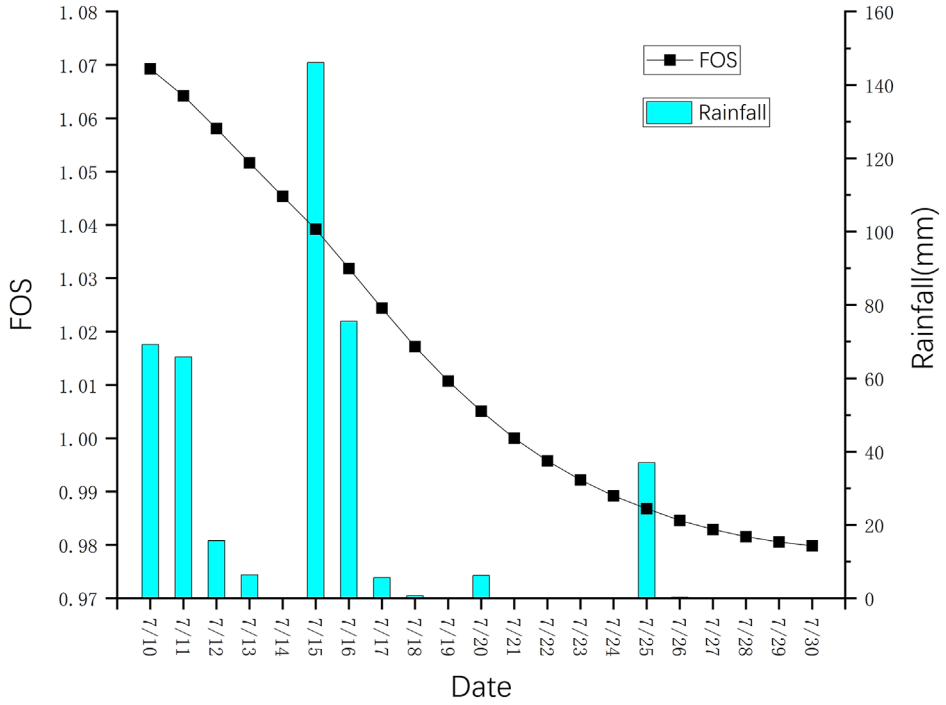

FIGURE 8
Relationship between safety factor and rainfall time.

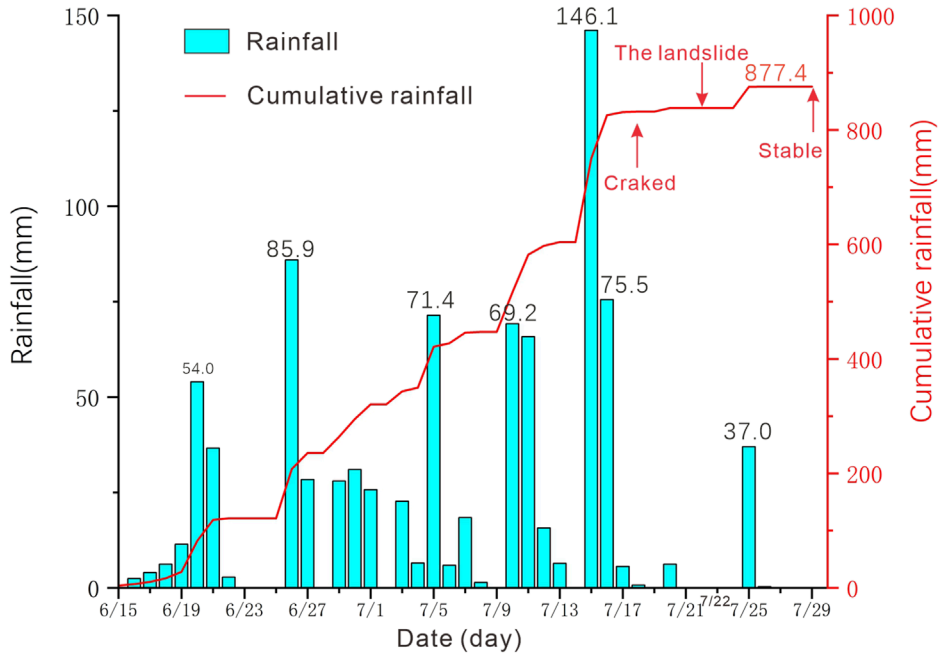

FIGURE 9
Rainfall monitoring data from Tongzi rainfall station which is 8.3 km far from Zhongbao landslide.

angle of Zone E is as high as 30~50°. The steep slope source zones in the upper part, Zone A and Zone E, provide activation conditions for landslide failure. The central part is gentle and provides a platform for landslide potential energy accumulation. The steep and narrow foot of the slope provides a channel for the landslide to enter the river (Zhou et al., 2022).

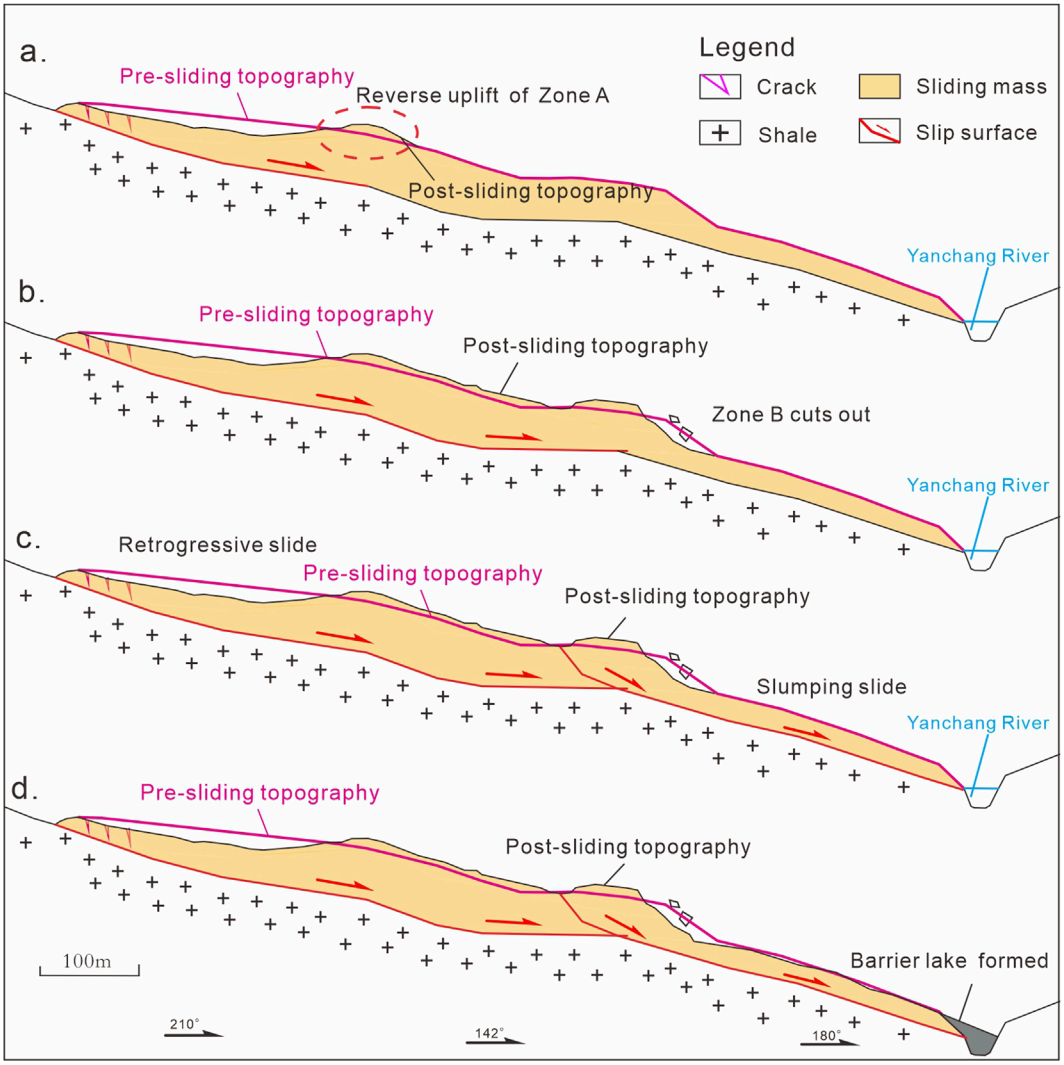

FIGURE 10
Characteristic diagram of instability. **(A)** Initiation phase. **(B)** Shearing out stage. **(C)** Acceleration phase. **(D)** Accumulation and blockage stage.

6.1.2 Persistent rainfall

Sustained rainfall as a trigger for landslides (Huang et al., 2022; Peruccacci et al., 2017; Senthilkumar et al., 2018; Wu and Yeh, 2020). There were several high-intensity rainfalls in the month prior to the failure of the Zhongbao landslide, with a cumulative rainfall of 227.2 mm in the first 3 days, and a cumulative rainfall during the slip period amounted to 43.6 mm (Figure 9). The continuous rainfall pooled through the surface into the middle and rear depressions of the landslide to allow the surface water to infiltrate downward, which would saturate the soft Zone Between bedrock surfaces with water, which would not only reduce the shear strength of the soft layer, but also soften the soils in the location of the interface of the soft layer, contributing to the reactivation of its landslide. Meanwhile, the presence of a moderately permeable layer at the trailing edge of the landslide keeps the shear strength of the soil body at a low level, creating favorable conditions for landslide slippage.

6.2 Possible failure mechanism

The occurrence of the Zhongbao landslide is the result of the combined effect of geological factors and rainfall factors. Based on the results of field site investigations, *in situ* experiments and laboratory experiments, combined with the deformation history of the Zhongbao landslide, its failure process is divided into four stages.

1. Initiation phase (Figure 10A). Under the action of rainfall and groundwater, multiple cracks appeared in Zone A, and then the landslide began to slide slowly. According to the surface deformation characteristics of Zone A combined with the characteristics of the borehole slip surface, it is hypothesized that the landslide body in the process of sliding, due to the east side of the ridge of the blocking constraints, resulting in the sliding of the fractured rock body biased to the west to produce steering, resulting in the lower part of the rock body

by the extrusion of some of the fractured rock body level of the inverted warping phenomenon. As a result, the slip direction of the landslide turned from 165° to 220°.

2. Shearing out stage (Figure 10B). Driven by Zone A, Zone B also started to slide slowly. Zone B sheared out at the upper edge of Zone C2, and part of the slide body flowed into Zone C2. The outcrop is broken and misaligned. Combined with the borehole results, it is hypothesized that Zone B was similarly blocked by the east side of the rock mass during the movement. Under the impetus of Zone B, sliding began to occur in Zone C2. At the junction of Zone B and Zone C, the sliding direction changed from 220° to 180°, and the angle of the sliding surface changed from 20° to 10°, which increased the anti-sliding force and the stability of the landslide.
3. Acceleration phase (Figure 10C). After the rainfall on the 25th, the deformation of the landslide was obviously accelerated. Sliding occurred in the upper part of Zone E, which was piled up on top of Zone A, increasing the deadweight of the slide; secondary deformation occurred in Zone C2, as evidenced by the traces of secondary sliding on the wall of the landslide (Figure 6B). The first two stages of sliding accumulated potential energy in the central platform, but due to the increase of the self-weight of the trailing edge and the sliding of the leading edge, the potential energy accumulated by the landslide began to be released, and the overall performance was accelerated sliding, which led to the sliding of the residential zone in Zone B by about 90 m.
4. Accumulation and blockage stage (Figure 10D). The landslide continued to move, and Zone C entered the river to form a weir, blocking the river and threatening the safety of residents along the downstream. Meanwhile, under the effect of rainfall and gravity, mudslides occurred in Zone C, gradually expanding the volume of the weir. It continued until 30 July 2020, when the sliding gradually stopped.

In summary, the Zhongbao landslide, as indicated by its deformation history and drilling results, is a large-scale rocky-soil landslide. Its reactivation is primarily driven by a combination of back-edge pushing and front-edge loosening. The inadequate drainage of the underlying bedrock prevented timely discharge of infiltrated rainwater, leading to a consequent reduction in shear strength of the sliding zone in zones A and B. During its movement, the landslide exhibited a sliding motion along the slip surface, characterized by the extrusion of soft clay against hard bedrock, which macroscopically manifested as a directional turn. The turning behavior of the Zhongbao landslide is influenced by both the stratigraphic lithology and the topography of the slip surface. A thorough understanding of the mechanisms behind such multi-directional steering landslides can enhance early warning systems for landslides in similar geological settings and contribute valuable insights into their deformation mechanisms.

7 Conclusion

This paper focuses on the Zhongbao landslide, conducting a comprehensive study through detailed field geological surveys, engineering geological investigations, and laboratory tests to elucidate its failure mechanism. The conclusions are as follows:

1. The Zhongbao landslide predominantly distributes elevations between 295–600 m. Its overall morphology resembles an elongated "tongue," having undergone multiple slides with two principal changes in direction. The main slip orientation ranges from 150 to 220°, extending approximately 850 m in length and 200 m in width, with a thickness varying from 3.5 to 66.20 m and an estimated volume of 5.48×10^6 cubic meters. This classifies it as a large-scale rocky-soil landslide.
2. According to the spatial morphology of the landslide, slip turn direction, material composition, accumulation Zone Combined with the movement process of the Middleburg landslide, the landslide was divided into five major zones respectively, namely, trailing edge push shift Zone A, extrusion turn Zone B, leading edge tangential accumulation and stacking Zone C, weir counterpressure Zone D, and trailing edge soil slip Zone E. The landslide was divided into five major zones, namely, trailing edge thrust Zone A, squeeze turn Zone B, leading edge tangential stacking and stacking Zone C, weir counterpressure Zone D, and trailing edge soil slide Zone E.
3. Prolonged rainfall facilitated the reactivation of the original ancient slide surface, leading to the formation of a continuous slip surface. Infiltration of surface water and groundwater into the bedrock's soft surface, which is structurally very loose, along with the persistent weakening effect of groundwater, has progressively reduced the shear strength of the weak surface, resulting in downward deformation of the landslide.
4. The Zhongbao landslide, characterized by a back-edge push, a loosened front edge, and a complete reactivation of the original ancient landslide accumulation, has impacted roads, houses, and navigation channels. The landslide's movement, influenced by the geotechnical properties and the slip surface morphology, underwent two directional shifts and formed a weir. This study provides insights for early warning and risk assessment of landslides in similar geological environments.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZL: Data curation, Methodology, Software, Writing–original draft, Writing–review and editing. ZD: Funding acquisition, Investigation, Methodology, Project administration, Writing–original draft, Writing–review and editing. SC: Writing–original draft, Writing–review and editing. ZY: Writing–original draft, Writing–review and editing. AZ: Data curation, Formal Analysis,

Software, Writing–original draft, Writing–review and editing. QX: Resources, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Influences of inflow rates on the breach characteristics of landslide dams

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Introduction: Dams formed by landslides may produce disastrous floods after dam outbursts. However, understanding of the influence of the inflow rate on the breaching characteristics of landslide dams is still at an early stage; in particular, the relationship between breaching width and depth are still unclear.

Methods: In this paper, we present the results of a series of laboratory tests that assessed seven inflow rates (1, 1.5, 2, 2.5, 3, 3.5, and 4 L/s).

Results and discussion: The results show that breaching characteristics for different inflow rates are similar and that there are three breach stages for different inflow rates. The peak discharge gradually increases as the inflow rate increases. With increasing inflow rate, the breach depth and width both increase. The ratio of breach width to breach depth increases from less than 1 to 1 progressively with increasing inflow rate. The breaching width and depth can be expressed by the function $W = \frac{\zeta}{1+e^{(-k(D-D_0))}}$. The shape parameter k has an exponential relationship with the inflow rate.

KEYWORDS

landslide dam, breach characteristics, inflow rate, breach width, breach depth

1 Introduction

Excessive rainfall, earthquakes, and reservoir water level fluctuations often cause landslides (Azadi et al., 2022; Qiu et al., 2024; Zhu et al., 2024; Ye et al., 2024), which can fall into river channels, choke rivers, and form landslide dams (Takahashi, 2007). More than 50% of landslide dams are broken by overtopping, and 85% fail within 1 year of formation (Costa and Schuster, 1988). Hazardous flooding may occur after the failure of these dams. For example, the Tangjiashan landslide dam (volume of 2×10^7 m^3) was the largest of 260 landslide dams triggered by the Wenchuan earthquake. Twenty-seven days after its formation, the dam breached, with a peak discharge of 6,500 m^3/s, resulting in a flash flood downstream (Liu et al., 2010). At least 2,423 people died in the 1933 flood caused by the failure of the large Diexi landslide dam on a river in Central China (Costa and Schuster, 1988). Understanding the breaching characteristics of landslide dams can help prevent flood outbursts.

Previous studies have focused on the process of breach development, the mechanism of failure, the development of dam breach (Hanisch, 2002; Zech et al., 2008; Pickert et al., 2011; Rozov, 2003; Cao et al., 2011a; Cao et al., 2011b; Dou et al., 2014), the calculation of the peak flow of a flood, and the simulation and prediction of flood routing

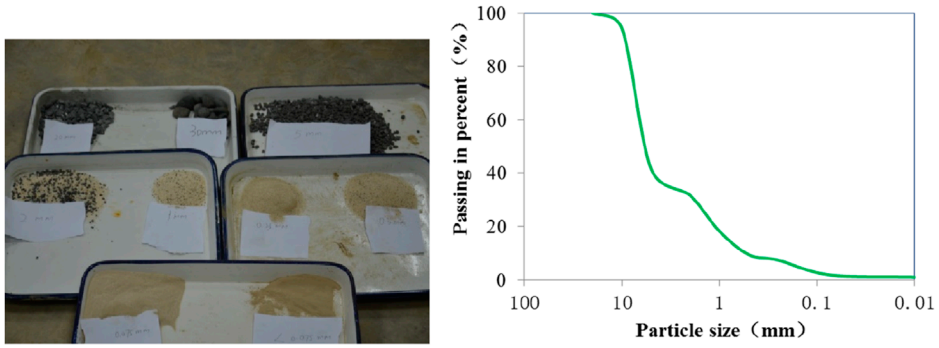

FIGURE 1
Experimental materials: **(A)** photograph of particles of different sizes and **(B)** particle size distributions of the soil.

(Singh and Quiroga, 1987; Fread, 1988; Walder and O'Connor, 1997; Macchione, 2008; Belikov et al., 2010; Ma and Fu, 2012; Fan et al., 2012). These studies have focused mostly on the dam failure process, including the evolution characteristics of breach discharge, the influence of the gradation of materials or initial moisture of materials on the landslide dam's breaching, and the changing characteristics of the breach. For example, the European Union launched the IMPACT project (Morris and Hassan, 2005) and the FLOOD site project (Morris et al., 2009), which combine large-scale (dam height of 4–6 m) field tests and small-scale flume tests for a detailed study of the impact of dam type, dam shape, and material composition (i.e., grain size gradation, density, moisture content, and cohesion) on the process of dam failure. Coleman et al. (2002) conducted a series of non-cohesive sand embankment overtopping tests to obtain a formula describing the geometry and dimensions of a breach. Javadi and Mahdi (2014) analyzed the failure mechanism of an impermeable rockfill dam and determined the critical water level at which the dam would overtop and the associations between the critical water level, dam height, upstream slope angle, downstream slope angle, and gravel size. Asghari Tabrizi et al. (2016) tested uniform sand with different degrees of compaction and established a dimensionless equation for the variation in breach size over time. Bento et al. (2017) conducted dam failure tests on a cohesive soil dam, observed the failure process with particle image velocimetry, and obtained a prediction formula for the hydrograph curve. Jiang and Wei (2019) studied the impact of the initial moisture content on the process of dam failure, focusing on the relationships between the initial moisture content and the failure discharge and erosion rate.

Although the characteristics of a breach and the magnitude of the resulting flood are well known to be controlled by many factors, these studies have focused on dam size and geometry, sediment characteristics, and initial water moisture. Inflow rate is an important factor in the failure process. Rifai et al. (2017) conducted experiments to investigate the impact of the inflow rate on the process of dam failure and reported that as the inflow rate increased, the time for a breach to develop significantly decreased. However, the quantitative relationships between the inflow rate and hydraulic parameters of a breach, such as the relationship between the inflow rate and breach discharge and the relationship between the inflow rate and breach size, are still unclear. This approach is unfavorable for fully understanding the mechanism of dam failure and predicting the hydraulic parameters of dam failure.

The characteristics of breach development can be characterized as the relationship between breaching width and depth, as shown by previous research, and can be characterized with a function. For example, Coleman et al. (2002) revealed that the relationship between breach width and depth can be described by a parabolic equation through experimental observations. Jiang et al. (2018), Jiang and Wei (2019), and Jiang et al. (2021) measured the breach width and depth during the failure process of a landslide dam model in the laboratory and reported that an exponential function existed between these two parameters. They also analyzed the influence of the mean diameter of materials on the coefficient of the breach width–depth function. Unfortunately, some questions remain unclear, such as whether there is a similar function type between breach depth and width for different inflow rates. What is the relationship between the coefficient of the breach width–depth function and the inflow rate?

In this work, we aim to improve the understanding of the influence of inflow rate conditions on the breach characteristics of landslide dams when triggered by overtopping. Thus, the relationships between breach parameters, such as peak discharge and breach sizes, and the inflow rate can be clearly described. With a series of flume tests, we analyzed the influences of the inflow rate on the breach discharge hydrographs, peak discharge, breach depth, and breach width. We discussed the relationship between breach width and breach depth. Finally, we investigated the relationship between the parameters of the breaching width-depth functions and the inflow rate.

2 Experimental setup and procedure

2.1 Experimental materials

This experiment uses sediment prepared in a manual configuration. We collected gravel, coarse sand, fine sand, and clay materials and divided them into nine groups based on particle size: 2–3 cm, 1–2 cm, 0.5–1 cm, 0.2–0.5 cm, 0.1–0.2 cm, 0.05–0.1 cm,

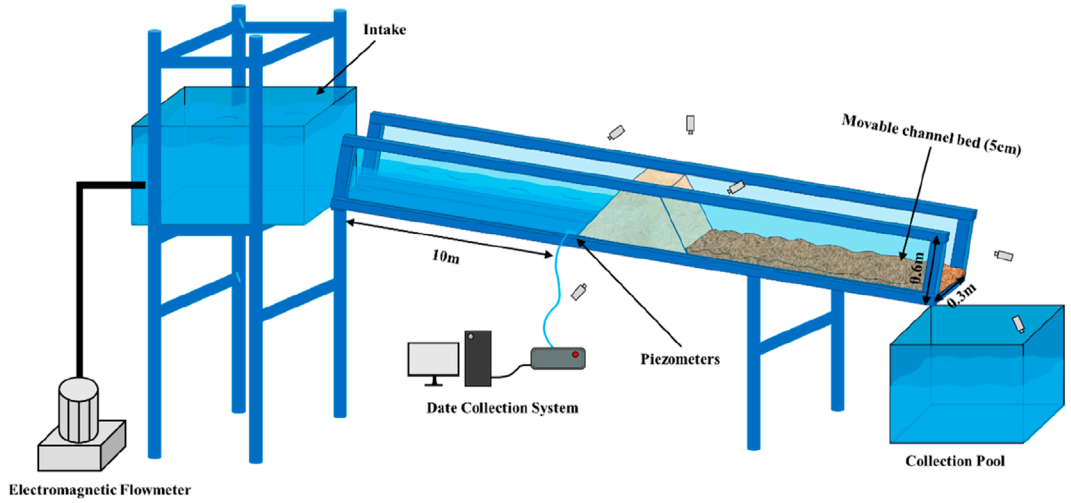

FIGURE 2
A sketch of the flume and its hydrological equipment.

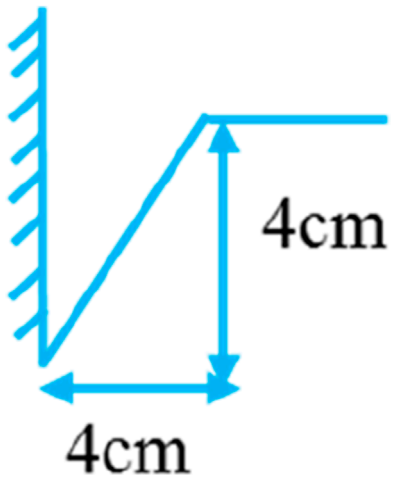

FIGURE 3
Size of the initial breach.

0.025–0.05 cm, 0.0075–0.025 cm, and <0.0075 cm. We mixed the particles of different groups and stirred them well. Particles of different sizes differed in color; for example, the gravel was black, coarse sand was white, and clay was dark yellow; thus, observing the movement of different soil particles during experiments was convenient (Figure 1A).

The largest particle diameter in the experimental materials was 2 cm, the median diameter D_{50} was 4.8 mm, and the non-uniform coefficient 12.0. To measure the proportion of those particles with diameters less than 5 mm, we adopted the pycnometer method; otherwise, the suspending weight method was adopted. The moisture content and dry density were 7.82% and 1.72 g/cm^3, respectively. The gradation curves are shown in Figure 1B.

2.2 Experimental setup

The experiments were carried out in a flume that was 15 m long, 0.3 m wide, and 0.6 m deep, with an adjustable slope angle of 0–30°, set to 1°. The flume was made of tempered glass with scales on both sides to facilitate the recording of the height of the breach bottom at different times during the experiment. The inflow rate was controlled by an electromagnetic flowmeter, and the measurement error was within ± 0.01 L/s. Different dam shapes led to differences in length along the channel. We set the upstream slope toe of the dam at 10 m from the tank. The inflow rates were set as 1 L/s (T-1), 1.5 L/s (T-2), 2 L/s (T-3), 2.5 L/s (T-4), 3 L/s (T-5), 3.5 L/s (T-6), and 4 L/s (T-7).

Cameras were deployed in front of the flume and on the dam crest to record changes in breaches during the dam failure process. A ruler was set at the dam crest. With the recorded video and the ruler, the breach width was obtained. We also set cameras at the top and both sides of the dam to record the bottom of the breach and measure the breach depth. A piezometer buried in front of the dam was used to collect water pressure data automatically. With the water pressure data, the water depth before the dam can be calculated based on hydrostatic pressure characteristics. Then, the outflow discharge was calculated using the water level difference between adjacent moments based on the water volume balance of the lake. The experimental setup were shown as Figure 2.

2.3 Experimental parameter settings

The slope angles upstream and downstream were set at 30° and 20°, respectively; the width of the dam crest was W=30 cm; and the initial dam height was H_b=30 cm. We preset an initial triangular breach at one side of the dam. Both depth and width were 4 cm (Figure 3).

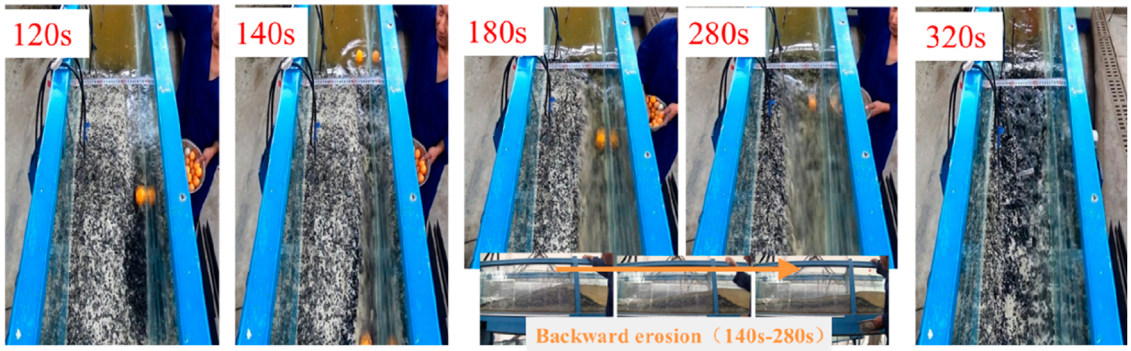

FIGURE 4
Images of dam and flow at different times for T-1, showing that overtopping erosion is the dominant factor for dam failure.

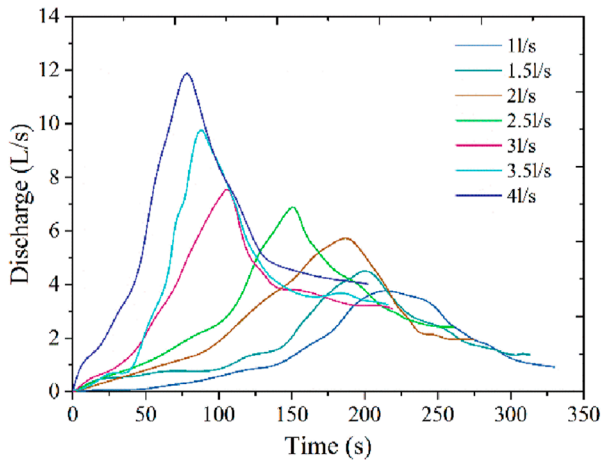

FIGURE 5
Breach discharge hydrographs for different inflow rates.

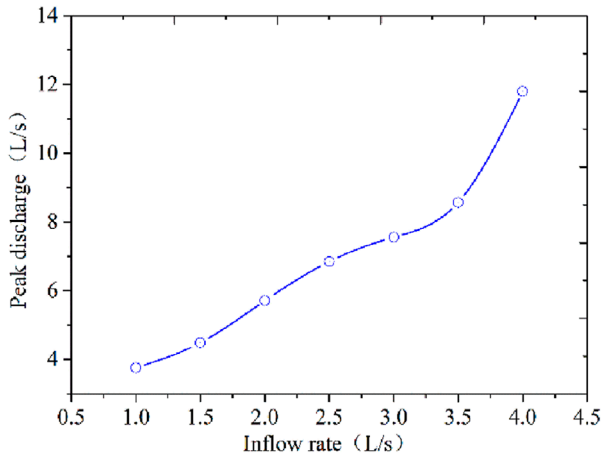

FIGURE 6
Relationship between peak discharge and inflow rate.

3 Experimental results

3.1 General features

The results show that the breaching characteristics of the dams in the tests were similar. The overtopping process in all the experiments had three identical phases. Taking T1 as an example for analyzing the breaching process of a landslide dam (Figure 4), the main characteristics of the three phases are explained as follows.

3.1.1 Phase I: slow development stage (0–140 s)

After the flow overtopped the initial breach, it began eroding the bottom and slope of the breach. We observed that the water moved down, carrying a small amount of sediment at the same time. Only small sediment particles were carried away because of the shallow water depth, slow velocity, and weak carrying capacity of the outflow water. Therefore, the sediment at the breach of the dam crest was dominated by the movement of the suspended load. When the flow was transported downstream, the flow velocity increased, and its erosion ability was enhanced, resulting in the formation of a narrow gully at the downstream slope. In addition, a small amount of sediment with a relatively large diameter was carried away and accumulates at the downstream slope, forming an obvious slope turning point. The breach slope collapsed intermittently on a small scale, and the breach shape at this stage was that of a rectangle, according to observations of Rozov (2003).

3.1.2 Phase II: rapid expansion stage (140–280 s)

As more sediment accumulated, the turning point developed upstream. When a certain amount of sediment had accumulated, it slid downward suddenly; then, the downstream slope became steep and the rate of outflow increased suddenly. Then, significant backward erosion occurred. With backward erosion at the upstream slope, the height of the upstream breach suddenly declined and the difference in height between the water surface and breach crest increased, leading to a sudden increase in outflow discharge. At this stage, more breach slopes lost their stability, and the scale of the unstable slope was larger than in Phase I. The average

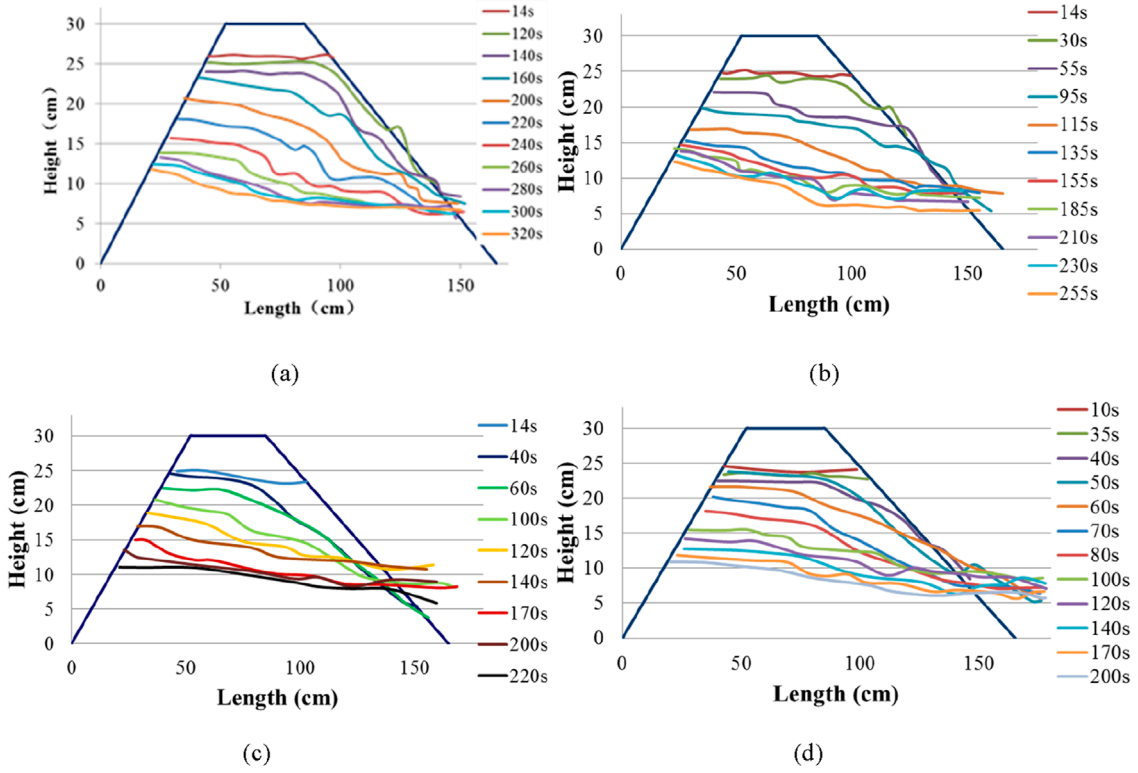

FIGURE 7
Temporal breach development for inflow rates at different times: **(A)** inflow rate of 1 L/s, **(B)** inflow rate of 2 L/s, **(C)** inflow rate of 3 L/s, and **(D)** inflow rate of 4 L/s.

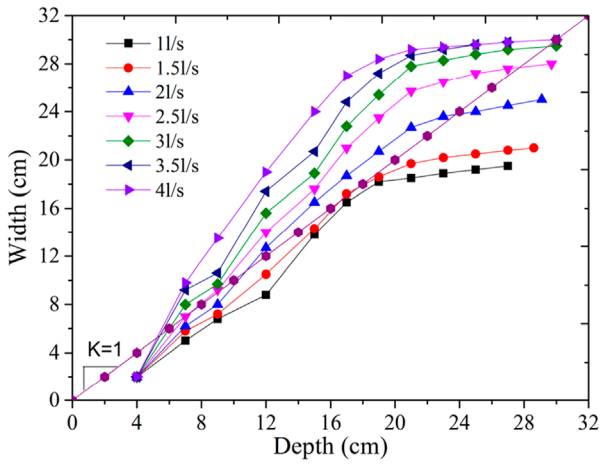

FIGURE 8
Relationship between breach width and depth for different inflow rates.

angle of the breach slope was less than 90°, and the shape of the breach was similar to that of a trapezoid. Among all the stages, the deepening and widening of the breach at this stage was the most rapid.

3.1.3 Phase III: rebalancing of the movement of water and sand (280–320 s)

After a rapid decrease in the water level in front of the dam, the outflow discharge gradually decreased and its carrying capacity gradually weakened. It then formed a coarse layer protecting the lower particles from being washed away. The motion of water and sand reached a new balance, indicating the end of the failure process. The frequency of breach slope slide occurrence was low, and the shape of the breach was that of a trapezoid.

3.2 Influence of inflow rate on discharge

The breach discharge hydrographs with different inflow rates are shown in Figure 5. This shows that when the flow was slow, the curve looks fat. As the flow increased, the rate of decline and growth rate increased, and the curve became thin. At the same time, the breaching time was shortened, and it reached the peak discharge earlier after the inflow rate increased. Under different inflow rate conditions, every 0.5 L/s, large differences in the breaching time and peak discharge arriving time were observed. The difference between 2.5 and 3 L/s reached a maximum, differing by 40 s in breach time and 45 s in peak discharge arrival time.

As shown in Figure 6, the peak discharge increased with increasing inflow discharge but does not follow a linear relationship.

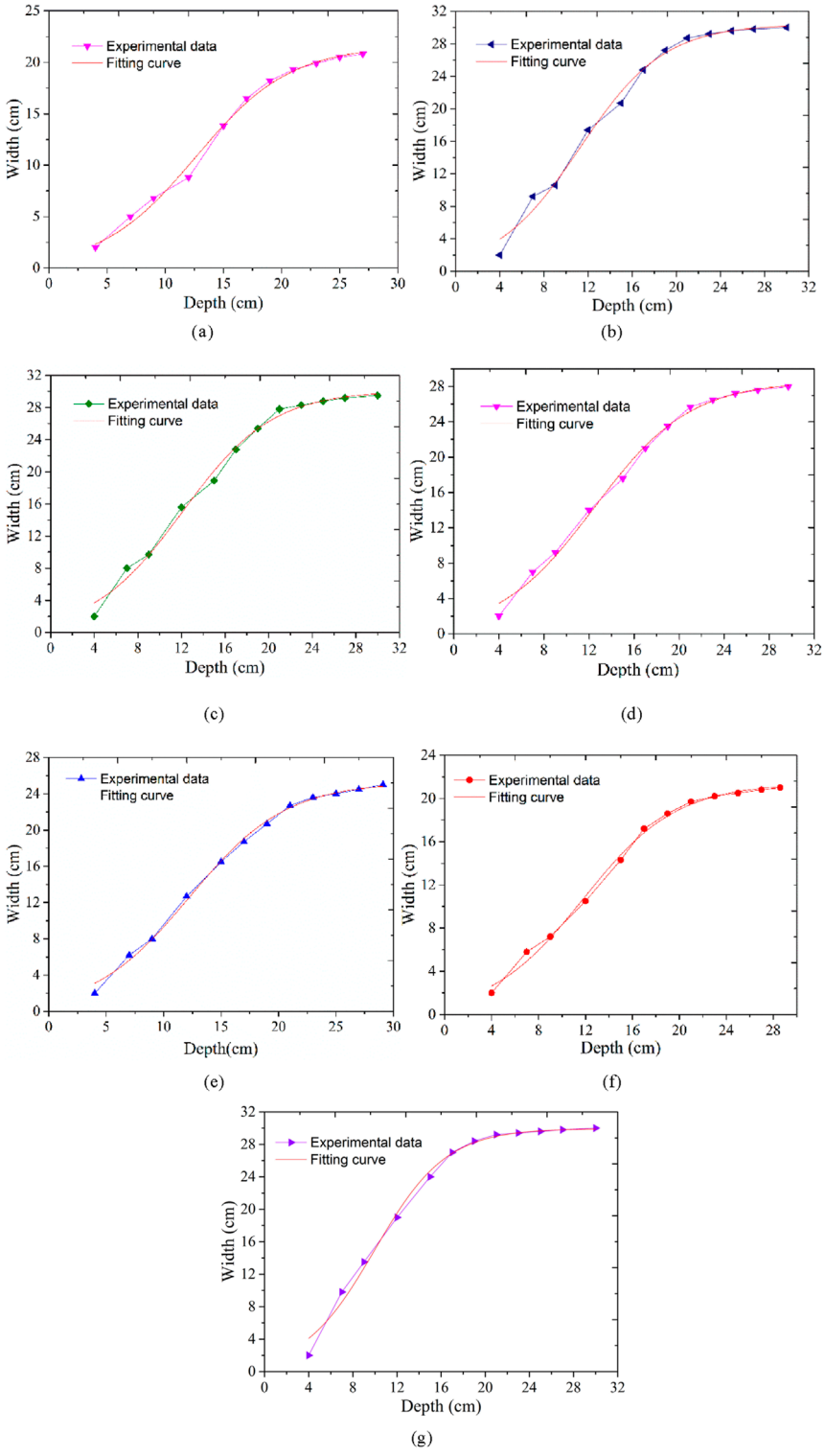

FIGURE 9
Comparison of the experimental data with fitting curves: **(A)** Test T-1, $\zeta = 20.086, k = 0.314, D_0 = 11.919$; **(B)** Test T-2, $\zeta = 21.393, k = 0.251, D_0 = 11.805$; **(C)** Test T-3, $\zeta = 25.281, k = 0.238, D_0 = 12.272$; **(D)** Test T-4, $\zeta = 28.606, k = 0.234, D_0 = 12.466$; **(E)** Test T-5, $\zeta = 30.107, k = 0.243, D_0 = 12.107$; **(F)** Test T-6, $\zeta = 30.396, k = 0.262, D_0 = 11.255$; **(G)** Test T-7, $\zeta = 29.944, k = 0.309, D_0 = 9.97$

For example, when the inflow discharge increased from 1 to 2 L/s, the peak discharge increased by approximately 2 L/s; however, when the inflow discharge increased from 3 to 4 L/s, the peak discharge increased by approximately 5 L/s. For the seven inflow rates, the corresponding maximum peak discharge was nearly three times the minimum discharge.

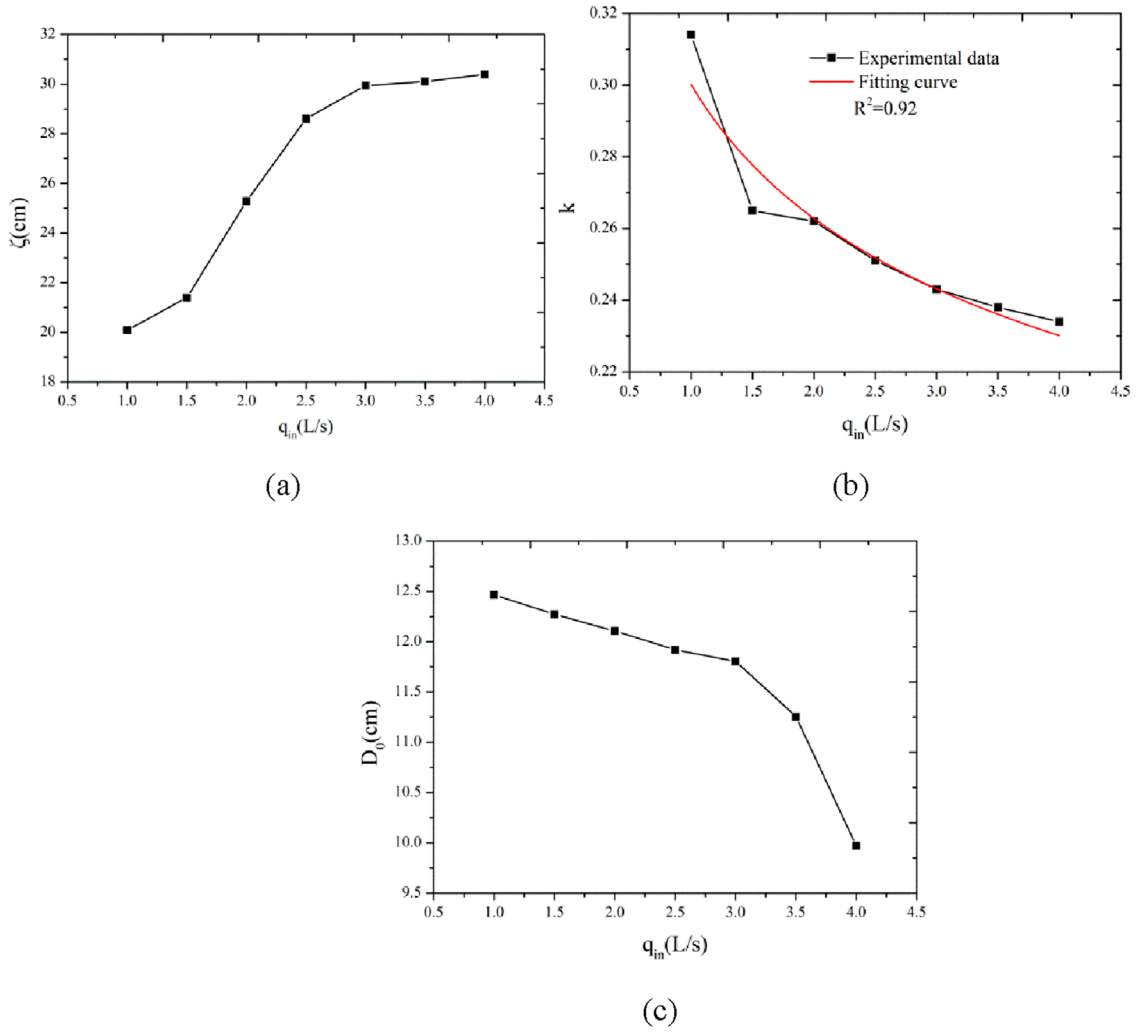

FIGURE 10
Variation in the parameters in Equation 1 with inflow rates **(A–C)**.

3.3 Influence of inflow rate on breach depth and width

Figure 7 shows the longitudinal profiles of the dam with inflow rates of 1, 2, 3, and 4 L/s. Under different inflow rates, the failure process remained characterized by slowly overtopped flow, backward erosion, and rebalancing of sediment and water. However, the difference is that the breach time for each phase was shortened in accordance with the increase in the inflow rate. This means that the incision rate increased with increasing inflow rate. The breach depths increased most rapidly during the backward erosion process under these four conditions. When the inflow rate was low (e.g., 1 and 2 L/s), the bottom of the breach was tortuous, exhibiting a distinct slope break point. However, many breakpoints may occur at the bottom of the breach at the same time. When the inflow rate increased to 3 or 4 L/s, the sinuosity at the bottom of the breach decreased and the slope break point remains, but its number decreased at the same point.

Figure 8 shows the relationships between breach width and depth under different inflow rate conditions. The whole curve can be divided into two parts. First, when the breach depth was less than a certain value (e.g., the breach depth is less than 22 cm for an inflow rate of 2 L/s), the curve was steeper, and the ratio of the width to depth increased with increasing inflow rate. Second, when the breach depth exceeded that value, the breach width tended to reach a certain value, although the depth increases. When the inflow rate was less (such as 1 and 2 L/s in this experiment), the curve was located below the straight line with a slope of K = 1, indicating that the breach widening rate is less than the breach incision rate throughout the whole failure process. Once the breach depth increased, it increased faster than the width. When the inflow rate increases (e.g., 2, 2.5, 3, 3.5, and 4 L/s), the curve was essentially above a straight line with a slope of K = 1. In this case, we deduced that the rate of breach widening was greater than that of breach incision widening. This suggests that breach widening increased with increasing inflow rate, as shown in Figures 7, 8. Simultaneously, with increasing inflow rate, the curve gradually

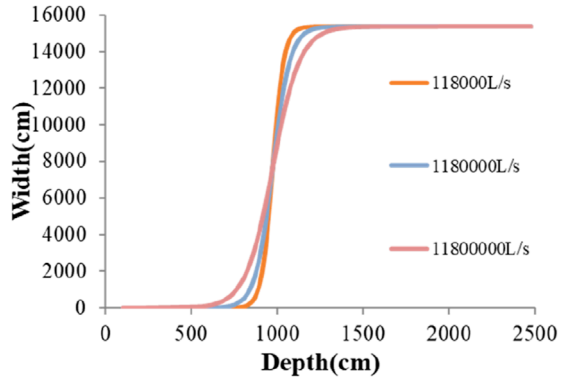

FIGURE 11
Breach width and depth curves for different inflow rates.

approached a straight line after dam failure. The breach width and depth gradually increased at the same level as the inflow rate.

3.4 The relationship between breach depth and width

Based on the breach width and depth curves (Figure 9), the breach width and depth all fit the following equation:

$$W = \frac{\zeta}{1 + e^{(-k(D-D_0))}}. \quad (1)$$

W is the breach width (cm), D is the breach depth (cm), and ζ (cm), k, and D_0 (cm) are parameters. ζ is the possible maximum breaching width. k is the shape parameter, which represents the steepness or deceleration of the curve, reflecting the width expansion rate of the breach. If the absolute value of k is larger, the breaching width expands faster; in contrast, the width expands more slowly. D_0 is the corresponding depth of the breach when it reaches half of the maximum breaching width.

The influence of the inflow rate on parameters ζ, k, and D_0 is shown in Figure 10. The value of ζ increases with q_{in}, and D_0 decreases with q_{in}. The parameter k in Equation 1 controls the shape of the equation, which decreases with q_{in}. The relationships between k and q_{in} can be described by Equation 2.

$$k = 0.3016 \times q_{in}^{(-0.195)}. \quad (2)$$

4 Discussion

The dam models all started with initial breaches at one side of the dam. When the water overtopped, the breach on the dam side was eroded, and the other side of the breach close to the glass of the flume was not erodible. Thus, the location of the initial breach in the tests corresponded to a one-sided breach in the field. From another perspective, the dam set up in the tests could be considered half of the complete dam, symmetrical to the initial breach.

The landslide dam models established in the laboratory are much smaller than landslide dams in the field. However, the failure characteristics of landslide dams with different inflow rates are still valuable for real-world applications. Equations 1, 2 need more data for validation because landslide dams in the field have more complex dam structures than models in the laboratory.

The parameter k in Equation 1 reflects the shape of the curve. Based on the measured data from the Tangjiashan landslide dam (Chen et al., 2014), we analyzed the influence of the inflow rate on parameter k. In the analysis process, we kept ζ and D_0 constant and used the regression Equation 2 to calculate k under different conditions. Figure 11 shows three orders of magnitude of inflow rates vs. breach width and depth. This indicates that the shapes of the curves are different; however, the difference in k is small for significantly different inflow rates. This means that the coefficient k could be taken as a constant value for different inflow rates as other conditions are the same when predicting the landslide dam breach size.

5 Conclusion

In this work, we studied in detail how the inflow rate affects the breaching characteristics of landslide dams. This research focused on the breaching process, breach hydrographs, and relationship between breach width and depth under different inflow rates.

The failure process for landslide dams is similar for different inflow rates. The process can be divided into three stages. Backward erosion plays a dominant role in the entire failure process.

Peak discharge increases with increasing inflow rate, while the breaching time decreases with increasing inflow rate. Breach width and depth both increase with increasing inflow rate. The breaching width-to-depth ratio also increases with increasing inflow rate. In addition, the ratio tends to be 1 after dam failure because of the increased inflow rate.

The breach width and depth follow the formula $W = \frac{\zeta}{1+e^{(-k(D-D_0))}}$. With increasing inflow rate, the coefficient ζ increases, and D_0 has the opposite trend. The coefficient k has an exponential relationship with the inflow rate.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XJ: conceptualization, investigation, methodology, software, visualization, writing–original draft, and writing–review and editing. ZZ: formal analysis, validation, visualization, and writing–original draft. HD: investigation and writing–original draft.

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Conflict of interest

Authors XJ and ZZ were employed by PowerChina Kunming Engineering Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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IC-IE-AKS-O: an automatic recognition method for coastal slope landslide areas

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Automatically and accurately identifying the deformation zone of coastal slope landslides is crucial for exploring the mechanism of landslides and predicting landslide disasters. To this end, this study proposes an integrated automatic recognition method combining Image Clipping (IC), Image Information Enhancement (IE), Adaptive K-means Clustering Segmentation (AKS), and Optimization (O): IC-IE-AKS-O, which achieves precise extraction of the deformation area in coastal slope landslide images. Firstly, due to the more complex natural environment of field slopes, to extend the monitoring duration, we introduce a hierarchical operation algorithm based on the HSV color model, which effectively mitigates the impact of sunlight, rain, and foggy weather on image recognition accuracy. Secondly, this study proposes a 2D landslide image segmentation technique that combines K-means clustering with global threshold segmentation for landslide images, enabling the segmentation of small image regions with precision. Finally, we combine image information enhancement technology with image segmentation technology. To verify its effectiveness, we identify a landslide image of a coastal slope in Pingtan. The method displays an average relative error of 5.20% and 5.14% in the *X* and *Y* directions, respectively. Its advantages are threefold: (1) The combination of image information enhancement and segmentation techniques can more accurately identify landslide areas that appear blurred in the image; (2) expanding the temporal dimension of coastal slope monitoring; (3) providing excellent boundary conditions and segmentation results. The practical application of this method ensures the stable and accurate operation of the coastal slope monitoring system, providing a safeguard for the sustainable development of marine safety.

KEYWORDS

landslide, image information enhancement, k-means, hsv, average relative error

1 Introduction

Coastal slope landslides usually cause huge casualties and property losses, and seriously restrict the sustainable development of marine ecology (Aksoy and Ercanoglu, 2012; Lan et al., 2022; Bednarczyk, 2018). Accurate identification of landslide deformation areas plays a decisive role in automated coastal slope monitoring (Wang H. et al., 2021; Ju et al., 2023; Ju et al., 2022; Wang et al., 2022a). In previous studies, scholars have mostly used image segmentation techniques to identify and determine landslide deformation areas, e.g., Ardizzone used elevation data collected by airborne LiDAR to identify and map landslides caused by rainfall (Ardizzone et al., 2007). Kurtz proposed a hybrid method based on segmentation/classification of regions that can detect and map landslides (Kurtz et al., 2014). Mondini used Very High Resolution (VHR) panchromatic and High Resolution (HR) multispectral satellite maps and proposed a method for semi-automatic identification and mapping of shallow landslides caused by recent rainfall (Mondini et al., 2011). Cheng et al. proposed an automatic landslide detection method based on remotely sensed imagery to achieve landslide mapping (Cheng et al., 2013). Rahardjo et al. used multilayered semantic networks to process satellite imagery and achieve semi-automatic landslide recognition (Rahardjo et al., 2014). Mwaniki utilized image enhancement to improve the accuracy of landslide recognition (Mwaniki et al., 2017). For mainstream automatic recognition with hyperpixel segmentation, Xie proposed a SAR image hyperpixel generation method based on significant difference and spatial distance, which adheres to the target contours and accurately responds to the boundaries of texture details in uneven regions (Xie et al., 2019). Zhu proposed a region merging method, which significantly improves the accuracy of hyperpixel segmentation by constructing a new energy function (Zhu et al., 2016). In order to recognize small-scale landslides, Hashiba extracted landslide regions with high accuracy by checking the appropriate area size using the superpixel SLICO method (Hashiba and Sonobe, 2020). Yang realized the recognition of deformed regions in small-scale landslide areas based on the change of image superpixel roughness during landslide deformation (Yang et al., 2019). Although the research objects of previous scholars are mostly biased towards inland slopes, the wide adaptability of image segmentation methods still provides a feasible basis for the identification of landslide areas on coastal slopes. Scholars have done less research on the identification of landslide areas on coastal slopes.

In addition, the coastal slope environment is relatively complex. Due to factors such as sunlight, rainy, and foggy weather conditions, the collected images are often blurry, which significantly affects the accuracy of image monitoring. If only high-clarity images are collected, the time available for monitoring using these images will also be limited. Therefore, for the identification of landslide areas on coastal slopes, it is necessary to enhance the information of the monitoring images on the basis of image segmentation techniques, so that the information of landslide areas and non-landslide areas in the images is clear, and the feasibility of subsequent monitoring is ensured (Fu et al., 2021; Liu et al., 2020; Liu et al., 2021). Researchers have also done a lot of research on image enhancement (Iqbal et al., 2020; Fu and Cao, 2020). For example, Tang et al. proposed an AIEBHE method based on adaptive dual HE, which uses the separation point of the histogram as the median intensity and adaptively modifies the limit of each sub-platform histogram (Tang and Mat Isa, 2014). Paul et al. improved the image by using the average of the histogram peaks as a separation threshold and equalizing the blur-based sub-histograms separately (Paul et al., 2021). Ooi et al. proposed the RSIHE method, which is a dynamic quadrant histogram equalization approach under platform constraints, where the cropping limits of the four sub-histograms are determined based on the average image intensity of each self-histogram (Ooi and Mat Isa, 2010). Moreover, the HSV color space is robust to color distortion, so image contrast enhancement can be achieved by converting the image from RGB color space to HSV color space (Liu et al., 2023). In addition, Retinex-based low-light image enhancement is also being widely applied (Meylan and Susstrunk, 2006; Fu et al., 2018; Wang et al., 2022b). However, most of the above studies use existing test sets or landscape maps for testing, while the ones on slope image information enhancement are relatively lacking, making it difficult to solve practical problems.

In sum, although numerous researchers have made considerable contributions to the identification of landslide areas on slopes, there is still a paucity of research on the automatic identification of such areas in coastal slopes under complex weather conditions. Therefore, in this paper, a new algorithm is proposed to address the shortcomings of the image information enhancement techniques for actual coastal slopes. The algorithm utilizes the HSV color model and operates hierarchically to achieve the denoising of rain, fog and sunlight in the image. By comparing with other algorithms, it is found that the improved image information enhancement algorithm has a better effect of de-fogging and suppressing excessive waterfall light. Secondly, this paper proposes a two-dimensional segmentation technique for landslide images based on combined K-means clustering with global threshold segmentation, which can segment tiny image regions and provide good boundary conditions and segmentation results to recognize the deformed areas of coastal slopes with high accuracy. The final fusion of image enhancement algorithm and coastal slope landslide area identification method extends the time dimension of monitoring and eliminates the influence of sunlight refraction and rainy and foggy weather on slope monitoring.

2 Automatic identification method

The method of this study is shown in Figure 1. Firstly, the overall characteristics of the collected images are judged. Secondly, the clarity of the images is judged, and the images with lower clarity are segmented using two-dimensional image segmentation algorithm after adopting im-proved information enhancement techniques; for images with higher clarity, they are segmented directly using K-mean clustering algorithm. After segmentation, the image should be denoised to get the final recognition result.

2.1 Image clipping

The saved image data always contains some irrelevant background areas, which causes information confusion and reduces

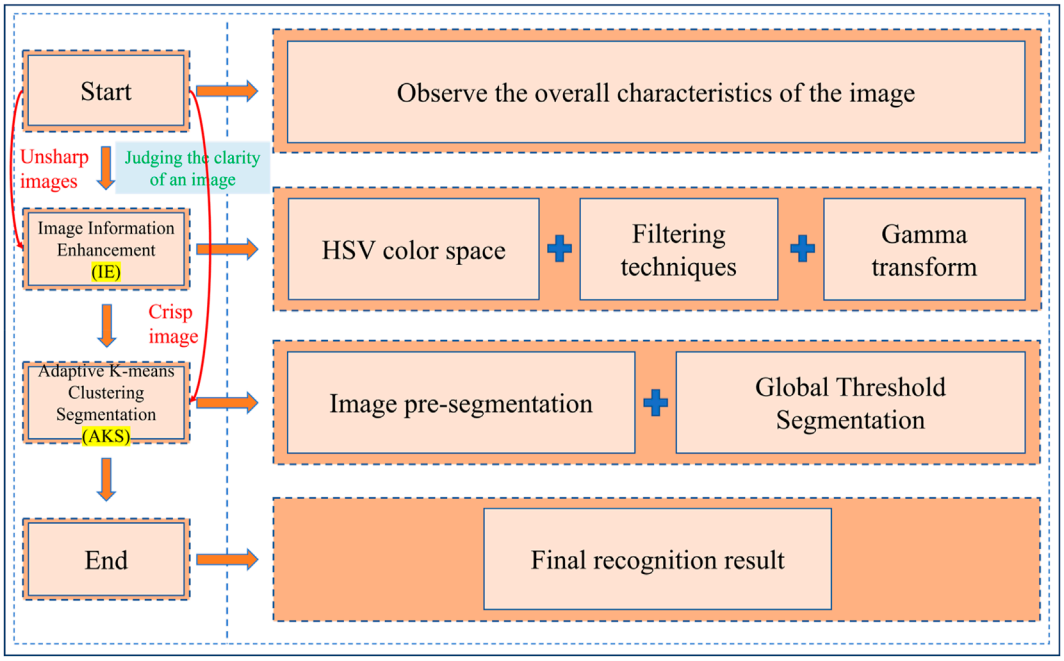

FIGURE 1
The method of the study.

the efficiency and accuracy of image processing. We need to crop the original image and retain the area to be processed.

2.2 Image information enhancement

The image samples of field slopes present more complex information, such as rain, fog, and direct sunlight, which can make the RGB information of the image unclear and unable to accurately identify the landslide area. Therefore, it is necessary to use image information enhancement techniques to ensure that the identified image has clear and complete color information. Methods such as the HSV color model, filtering processing, and Gamma transformation are mostly simple and effective and can be used to enhance key image feature information and improve image analysis efficiency. We have selected some common methods and made combinations and improvements to them to find a suitable method for image information enhancement.

2.3 Image segmentation technology

Image segmentation is a key technology in computer vision, involving dividing an image into multiple regions or objects. Segmentation methods based on thresholding, edges, regions, and clustering are mostly simple and effective and can be used to obtain key image feature information and improve image analysis efficiency. We have chosen the above four image segmentation methods to identify a small number of different coastal slope landslide images to find a suitable segmentation method for the landslide area. After the selection of the image segmentation method is completed, it is usually necessary to improve different methods, such as the fusion of threshold and clustering segmentation methods, to achieve automatic identification of images.

2.4 Optimization

The initial recognition image usually contains a considerable amount of noise and features that are not connected to other areas, so we should remove the noise. In addition, if there is a considerable amount of noise near the target boundary and at the connected target boundary in the initial recognition result image, we need to perform morphological operations on the image to eliminate the impact of noise.

3 Method application

3.1 Research data

The area studied in this paper is located within the Pingtan Comprehensive Pilot Zone (Deng et al., 2023; Gao et al., 2023; Su et al., 2021; Deng et al., 2022), Fujian Province (Figure 2).

Pingtan Island is located between 25°15′and 25°45′north latitude and 119°32′and 120°10′east longitude. The area is mainly composed of marine plains. There are 126 islands and 702 rocky reefs in Pingtan Comprehensive Pilot Zone, with a winding coastline. The annual precipitation is 1,196.2 mm and the average annual temperature is 19.5°C. Pingtan Island is located on the northwest



FIGURE 2
Map of the study area.

side of the Taiwan Strait, bordering the Pacific Ocean, and is one of the most frequent areas in China for typhoon coastal slopes. With steep mountain ranges and the development of sea-eroded terraces in the area, the coastal side slopes are subjected to seawater intrusion all year round. This has led to various types of natural disasters, resulting in serious impacts on the production and life of the people in the region. An image monitoring system has been set up in the study area, and the monitoring is a long-term unattended automated dynamic monitoring, capturing photographs at regular intervals.

As shown in Figure 3, we first set up an automatic monitoring system at the experimental site, using a pre-programmed RGB high-definition camera to capture images every 10 mins from 9:00 a.m. to 7:00 p.m. under various weather conditions, including sunny, cloudy, and rainy days. The camera was installed at a fixed height of approximately 15 m and positioned at a 45-degree angle. The proposed method was then applied to process the actual images of the Pingtan coastal slope.

3.2 Image data preprocessing

In the image monitoring platform, we found that when the time is between 9:00 and 19:00, sunlight is more abundant, which can meet the requirements of two-dimensional monitoring. Even if the area under study is affected by rainy and foggy weather, it is still possible to meet the monitoring requirements through the existing light conditions and the improved image information enhancement technique proposed above.

As shown in Figure 4, the information in the original monitoring image includes ocean, grass, sky and slope information, while the area we want to recognize only includes the slope information in the image. The irrelevant background increases the difficulty of recognition and makes the recognition information more complicated. Therefore, the interference of irrelevant information needs to be removed. After comparative analysis (time, accuracy, ease of operation and characteristic information of the slope monitoring image), we found that the physical coordinates of the area where the cracks are generated in the slope do not change

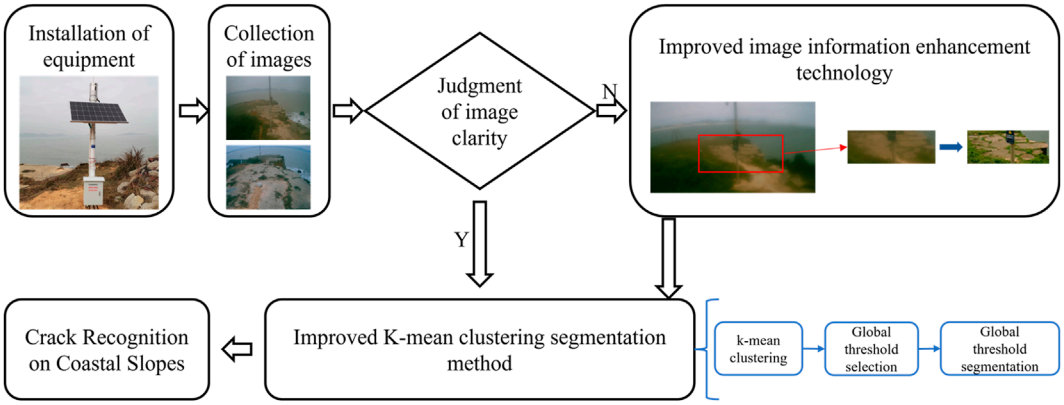

FIGURE 3
Flowchart of actual processing.

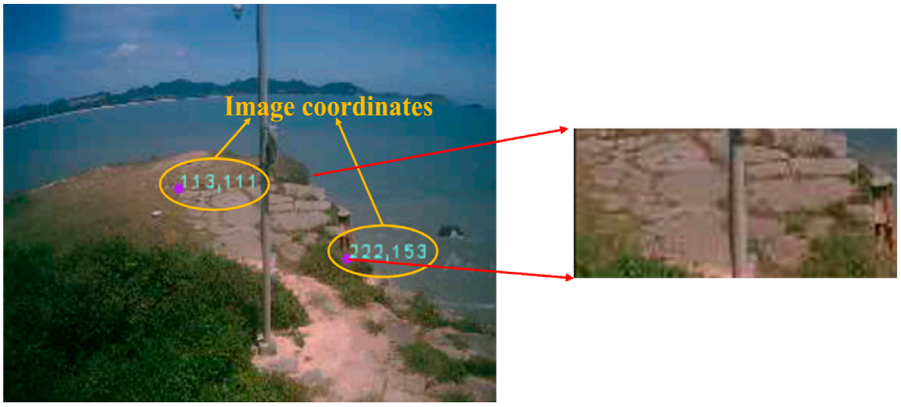

FIGURE 4
Irrelevant background information removal.

much, so we can use the way of setting up the mask to remove the interference of irrelevant background, so as to make the recognition information more specific.

3.3 Multi-indicator image clarity discrimination methods

3.3.1 Brenner gradient function

The Brenner gradient function is a simple gradient evaluation function that evaluates image sharpness by calculating the square of the difference between the gray levels of two adjacent pixels. This method is simple and easy to use, but it has some limitations.

$$D(f) = \Sigma_y \Sigma_x |f(x+2,y)\text{-}f(x,y)|^2, \quad (1)$$

where, $D(f)$ - image sharpness, $f(x,y)$ - the gray value corresponding to the image pixel point (x,y).

The Brenner gradient function computes the squared differences in intensity between a pixel and its neighbors in both horizontal and vertical directions. By squaring the differences and summing them up, the function amplifies large intensity changes and suppresses small ones. This amplification of intensity changes enhances the detection of edges.

3.3.2 Tenengrad gradient function

The Tenengrad gradient function is a method used to evaluate image sharpness, which uses the Sobel operator to extract the gradient values in the horizontal and vertical directions respectively. This method is able to assess image sharpness more accurately, but the amount of computation is also relatively large.

$$T(f) = \Sigma_y \Sigma_x |G(x,y)| \quad (G(x,y) > T), \quad (2)$$

where $G(x,y)$ takes the following form:

$$G(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)}, \quad (3)$$

Here, T is the set edge detection threshold, and G_x and G_y are the Sobel horizontal and vertical edge detection operator convolutions at pixel point (x,y), respectively. We generally use the following Sobel

operator template for edge detection:

$$G_x = \frac{1}{4}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \quad (4)$$

$$G_y = \frac{1}{4}\begin{bmatrix} -1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}, \quad (5)$$

The Tenengrad gradient function relies on the gradient information of the image. For sharp images, the gradient values in edge regions are typically large, resulting in a higher Tenengrad gradient value. Conversely, blurry images have smaller gradient values in edge regions, leading to a lower Tenengrad gradient value. Thus, computing the Tenengrad gradient function allows for the assessment of image sharpness, with larger values indicating sharper images.

We use two evaluation metrics to assess the clarity of the read images. Based on the existing images with high clarity, we judge the thresholds $D(f)$ and $T(f)$ in this study, which calculated from the Equation 1 and Equations 2–5 respectively. If $D(f)$ and $T(f)$ are less than the set threshold, the image needs to undergo quality enhancement before image segmentation.

3.4 Image information enhancement based on HSV color space

In this section, we have used HSV color model and bilateral filtering with gamma transform to process the images in different haze cases. This is because:

(1) The colors in the RGB color space are mixed by the three base colors of red, green and blue. Although it can express rich color information, it is not intuitive enough for the expression of image brightness information. The HSV (Hue, Saturation, Value) color model is a way of representing colors based on how humans perceive them. It decomposes colors into three components:

1) Hue: Represents the type of color, indicating its position on the color wheel. Hue is typically represented as an angle ranging from 0° to 360°, starting from red, passing through yellow, green, cyan, blue, magenta, and looping back to red. Hue determines the basic category of the color.
2) Saturation: Describes the purity or intensity of a color. Saturation measures the amount of gray in a color. Higher saturation values result in more vivid colors, closer to pure colors, while lower saturation values produce desaturated or pastel colors. A saturation of 0 results in a grayscale color, containing only brightness information.
3) Value: Represents the brightness or lightness of a color. Value measures the brightness of the color. Higher values result in brighter colors, while lower values lead to darker colors. A value of 0 corresponds to black, and maximum value corresponds to white.

The HSV color model provides a more intuitive way to describe colors, making color adjustments easier and more consistent with human perception. By manipulating these three components—hue, saturation, and value—one can generate a wide range of colors and achieve easier color selection, editing, and matching.

(2) Filtering techniques are constantly evolving with the aim of separating information at different scales in an image more accurately. Bilateral filtering is a nonlinear spatial filtering method that takes into account the Euclidean distance and the difference between the values of the output pixel and other pixels in the neighborhood when determining the filter coefficients (Nabahat et al., 2022; Wu et al., 2022; Niu and Wang, 2022; Rajyalakshmi et al., 2022; Lv et al., 2022). This means that it considers the difference between the spatial domain and the value domain at the same time. On the other hand, methods that only consider the spatial domain (e.g., Wiener filtering and Gaussian filtering) are not very effective in protecting the edge information; methods that only consider the value domain blur the whole image and do not effectively protect the detail information. The bilateral filter integrates the spatial domain and the value domain to influence the filtering, and can keep the edge clear in noise reduction and smoothing, which is an excellent edge preserving filter.

(3) Gamma transform (Qi et al., 2022; Tang et al., 2022; Wang W. et al., 2021) is mainly used to correct images with too much or too little gray and enhance their contrast. It achieves the correction effect by enhancing the details in low or high gray areas. For images that are overexposed resulting in high overall brightness and low contrast, image information enhancement is particularly effective using Gamma transform.

The flow of the image information enhancement technique developed in this paper is shown in Figure 5, and the specific steps are detailed in Table 1.

After the image quality enhancement, the clarity of the image is further improved, and the influence of rainy and foggy weather on image monitoring is eliminated.

3.5 Adaptive K-means clustering segmentation

In this subsection, we propose an automatic identification method of two-dimensional slope instability region combining K-means clustering and global threshold segmentation algorithm. The core idea of the K-means clustering image segmentation method is to group the pixels of the image using the K-means clustering algorithm, so that pixels with similar features are grouped together, while pixels with different features are grouped into different groups. During initialization, the algorithm randomly selects K pixels as cluster centers. Then, the algorithm traverses each pixel in the image, calculates their distances to each cluster center, and assigns each pixel to the group where the closest cluster center is located. After grouping the pixels, the algorithm recalculates the center of each cluster, which is the average of the features of all pixels in that cluster. Then, the algorithm repeats the steps of pixel assignment and cluster center update until the cluster centers no longer change or the preset number of iterations is reached. Through this method, the image is segmented into K regions, with pixels in each region having similar features. This segmentation helps extract target objects from the image or simplify the image content, facilitating subsequent image processing and analysis.

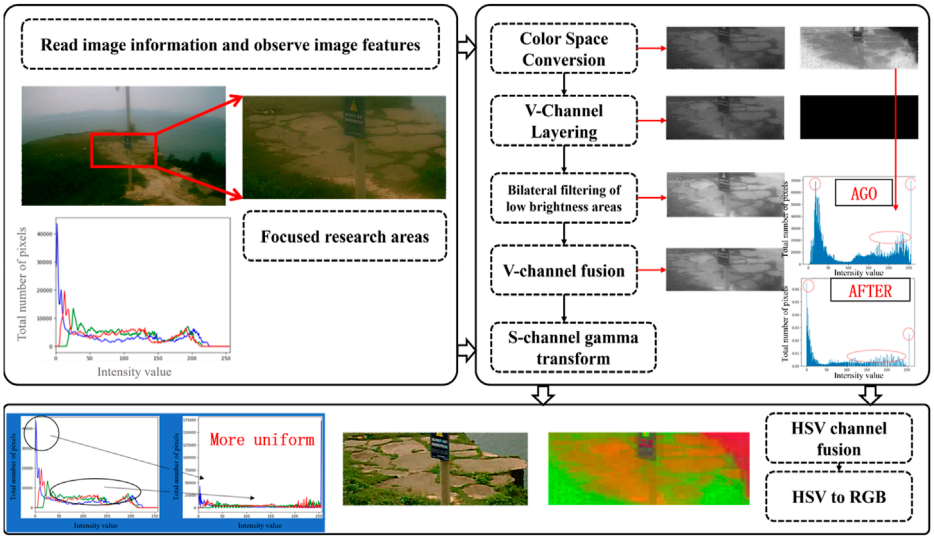

FIGURE 5
Flow chart of information enhancement technology.

TABLE 1 Step-by-step table of image enhancement techniques.

Step	Element
1	Read the image RGB information, convert the image space to HSV and then separate it into H, S and V channels individually
2	Perform layering processing on the v-channel, i.e., select the threshold I and divide the v-channel into overexposed regions and non-over-exposed regions. In this study, we set the threshold I for the v-channel exposure region to 30
3	Perform luminance-based adjustment and bilateral filtering on the non-over-exposed region to further enhance its luminance and contrast while retaining good boundary information; the overexposed region is left unoperated
4	Superimpose the non-over-exposed region of the V-channel with the overexposed region after information enhancement to obtain a new V-channel
5	Perform gamma transformation on the S-channel to further enhance and smooth the saturation of the image
6	Perform fusion of the processed HSV channel to further convert the HSV image to RGB image to obtain the final image information enhancement results

After determining the recognition location, we use K-mean clustering to pre-segment the image, and test it by setting different K values to select the optimal solution. When K=2, due to the mask setting, the slope area and the mask area are distinguished into two classes, and the landslide information cannot be reflected in the slope area; when K=8, K=16, K=64, due to the high number of set clusters, the slope area is over-divided, which results in the variability of the threshold setting in later data processing, and the continuity of the process cannot be guaranteed; when K=4, the mask area, the landslide area, non-landslide area and other information are accurately distinguished into four categories, which makes later data processing easier. Therefore, in this paper, K=4 is the optimal setting value.

Global threshold segmentation (Liu et al., 2022) is the use of a threshold value to segment the entire image into two regions: the target object and the background object. The threshold is usually a constant value that can be determined from global information. In this subsection, we observe the grayscale histograms of the pre-segmented image at different moments. Since the K value is chosen as 4, the grayscale values in the grayscale histogram of the pre-segmented image contain only four pieces of information, in which the grayscale value of the landslide region is higher than the other three types of information. So, in this subsection, the global threshold value is chosen as 100, which can separate the landslide region from the other regions (Figure 6).

4 Results and discussion

4.1 Image information enhancement results and discussion

4.1.1 Image information enhancement results

We apply the improved image enhancement technique to the fuzzy monitoring images in different time periods and get the results as in Figure 7.

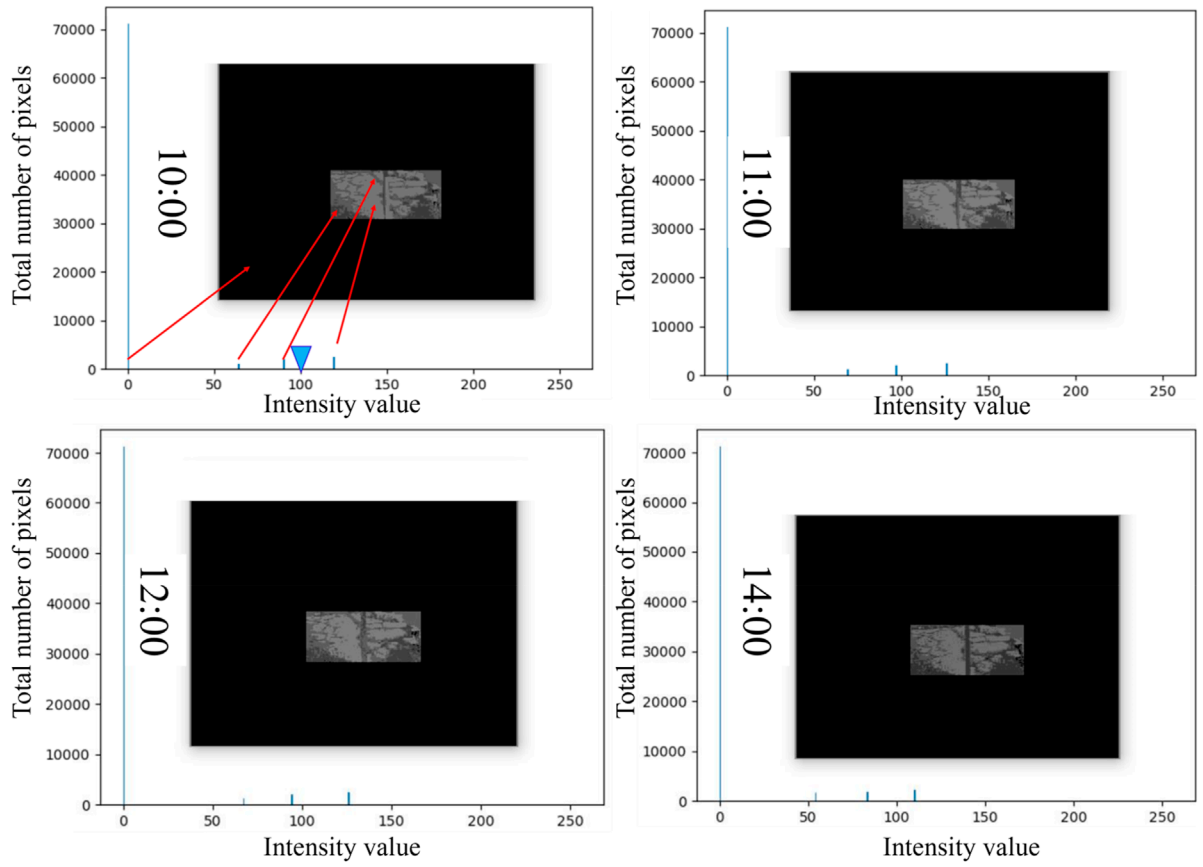

FIGURE 6
Global threshold selection graph.

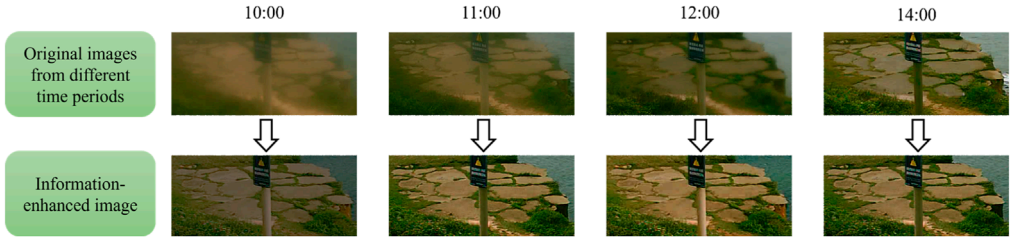

FIGURE 7
Information enhancement results.

4.1.2 Objective evaluation

Subjective evaluation is easily affected by external factors. In order to objectively verify the merits of the algorithm, two image quality evaluation metrics are introduced in this section for judgment (Zhao et al., 2017).

Peak Signal-to-Noise Ratio (PSNR) is a commonly used metric to measure the degree of image variations; the larger the PSNR value, the lesser the image variations, the lesser the distortion, and the better the image quality. Structural similarity (SSIM) is used to evaluate the quality by comparing the differences between images before and after processing. It calculates the product of image contrast, structural information and brightness as a comprehensive evaluation criterion; the higher the SSIM value, the better the processing effect.

As can be seen from Figure 8, the peak signal-to-noise ratio of this paper's algorithm is 16.28, and the structural similarity is 0.90, which is significantly better than other algorithms. The objective evaluation index proves the superiority of this paper's image information enhancement technology and its adaptability to the actual situation of coastal slopes.

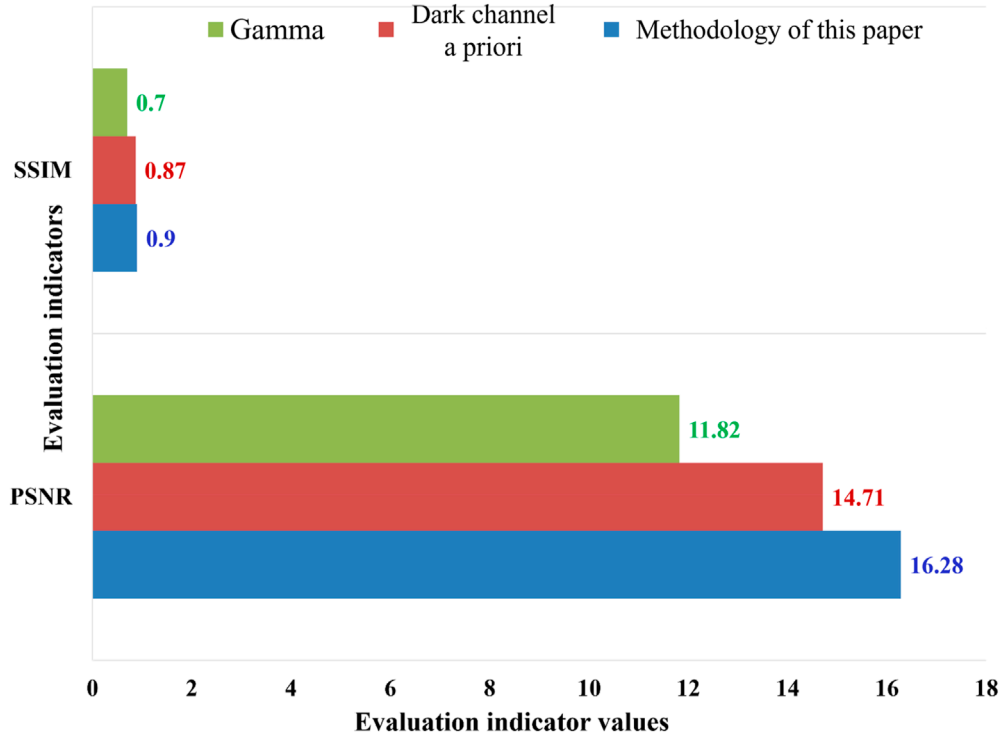

FIGURE 8
Image enhancement quality evaluation.

4.2 Image segmentation results and discussion

In this subsection, as shown in Figure 9, we manually draw three actual damage maps of landslide areas at different time periods and compare them with the contours recognized by this paper's method (IC-IE-AKS-O) to get the damage contour area comparison effect map. We import the contour comparison map into CAD, and use CAD to draw the point coordinates of different contours. The damaged area contour follows the principle of "x coordinate is the same y is different" or "x coordinate is different y is the same" to randomly select the coordinate points on the contour map, extract the corresponding coordinate points on the contour and carry out the relative error calculation. The error calculation formula is contained in Equations (6) and (7) (Yuan et al., 2023). The results of the error calculation are shown in Table 2.

$$R^i_{error} = \left|R^i_{seg} - R^i_{real}\right| / R^i_{real} \times 100\%, \tag{6}$$

$$\overline{R}_{error} = \sum_0^n R^i_{real} / N, \tag{7}$$

Here, R^i_{error}、 R^i_{seg}、 R^i_{real}、 $\overline{R}_{error}$ represent the segmentation error of the ith sampling point, the segmentation value of the ith sampling point, the true value of the ith sampling point, and the average segmentation error of all sampling points, respectively.

As shown in Table 2, the relative error in the X and Y directions using the IC-IE-AKS-O method is 5.20% and 5.14%, respectively. These values fall within the acceptable range for automatic landslide detection and represent a significant improvement over conventional image segmentation techniques commonly employed in coastal slope monitoring. Traditional methods, such as K-means clustering and basic thresholding, often struggle to cope with the complex environmental challenges of coastal regions, especially in adverse weather conditions. By integrating advanced image enhancement techniques and employing a multi-stage segmentation process, our method consistently delivers higher accuracy, even when the original images are affected by fog or sunlight refraction. Additionally, our method excels in segmenting small regions with high precision, distinguishing it from other approaches that tend to over-segment or under-segment images based on the chosen number of clusters.

Future research will aim to further refine the algorithm to reduce segmentation errors, particularly in cases where the slope surface is composed of heterogeneous materials or when rapid changes in weather conditions occur during monitoring. Furthermore, we plan to explore additional optimizations to enhance computational efficiency, enabling real-time application in dynamic monitoring systems.

4.3 The role of image information enhancement

In the actual slope image segmentation, due to the influence of variable weather conditions at the site, under the fixed time selection, i.e., 9:00–19:00, the performance of the slope monitoring image information is not obvious in some time periods, and the landslide

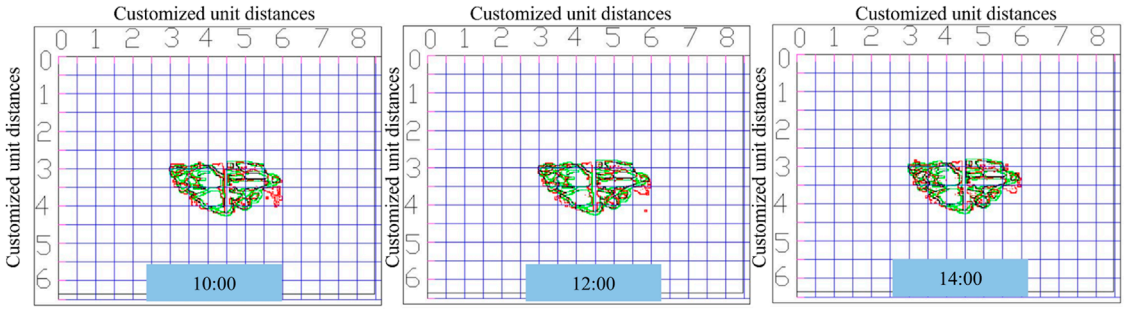

FIGURE 9
Comparison plot of error analysis contours.

TABLE 2 Table of error analysis results.

Image Source	Times	Relative error analysis	
		X- /%	Y- /%
Pingtan Coastal Slope	10:01	3.35	2.15
	12:01	7.16	10.14
	14:01	5.10	3.13
Average relative error		5.20	5.14

deformation areas cannot be accurately recognized even with the K-mean clustering algorithm. Using image information enhancement technology, the slope monitoring image information within these time periods can be significantly enhanced, and by combining it with the improved K-mean clustering segmentation party, the time range of landslide monitoring is expanded, the basic data of landslide monitoring is enriched, and the recognition accuracy of landslide areas is improved, which makes the program run steadily under the time series.

4.4 Analysis of the factors influencing errors

From the error analysis results of the method in this paper, it can be seen that there are still minor errors in the identification method. One of the factors contributing to the errors in this approach is the variability in environmental conditions, including changes in sunlight, fog, and rain, which may affect the image clarity and segmentation accuracy. Additionally, the removal of irrelevant background information might not always be perfect, leading to small inconsistencies in the segmented regions. In terms of image resolution, slight differences between monitoring intervals can also introduce segmentation errors, particularly in areas with fine details.

To mitigate these errors, several steps have been taken. First, the multi-indicator image clarity discrimination methods (e.g., Brenner gradient function, Tenengrad gradient function) ensure that only images meeting a specific clarity threshold are processed. Additionally, the use of the HSV color space for image enhancement, combined with bilateral filtering and gamma correction, helps to reduce the impact of varying lighting conditions on the segmentation results. Furthermore, the combination of K-means clustering with global threshold segmentation provides robust boundaries, reducing segmentation errors in landslide regions with complex contours. These measures have helped keep the relative error within a relatively low range (~5%).

5 Conclusion

In this paper, we proposed a complete set of landslide deformation area identification methods (IC-IE-AKS-O) for a coastal slope. First, a new algorithm was proposed according to the deficiencies of the current image enhancement technology. Through experimental comparison, it was found that the improved algorithm has better visual de-fogging effect and has practical application value. Secondly, a landslide image segmentation technique based on combined K-means clustering with global thresh-old segmentation was proposed. It is hereby summarized that: the fusion of image information enhancement technology and image segmentation technology expands the time range of field slope monitoring, which makes the recognition under the influence of rain, fog and sunshine have higher accuracy and robustness compared with the simple image segmentation method; the preprocessing of the image can

effectively provide convenience for the pre-segmentation of the image in the later stage, while the original image cannot be well recognized due to the redundancy of information; the image segmentation method based on the K-mean clustering can be more effective for the smallest landslides. The image segmentation method based on K-mean clustering can segment tiny image regions and can provide good boundary conditions and segmentation results. The relative error calculation results show that the method proposed in this paper has low relative errors in the *X* and *Y* directions, which are 5.20% and 5.14%, respectively, and can recognize the deformation regions of micro-fractured coastal slopes with high accuracy.

In the future, we plan to extend the application of the IC-IE-AKS-O method to a broader range of geographic areas, encompassing both coastal and inland slopes with diverse geological conditions. To improve the method's adaptability, we will fine-tune it for regions with varying soil compositions, vegetation coverage, and climatic conditions. For instance, inland slopes may experience distinct weather patterns, such as frost or drought, which could impact the effectiveness of the image enhancement and segmentation algorithms. We anticipate that, with adjustments to the HSV color space parameters and clustering techniques, the proposed model will achieve similar performance in other environments.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

PL: Conceptualization, Investigation, Validation, Writing–original draft. WL: Methodology, Writing–original draft. DL: Funding acquisition, Investigation, Project administration, Supervision, Writing–review and editing. CC: Formal Analysis, Project administration, Resources, Supervision, Writing–review and editing. TF: Visualization, Writing–review and editing. RG: Visualization, Writing–review and editing. AD: Writing–review and editing. MH: Writing–review and editing. ZL: Formal Analysis, Writing–review and editing.

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Conflict of interest

Authors PL and WL were employed by Zhuhai Da Hengqin Co., Ltd. Author PL was employed by Zhuhai Da Hengqin City Investment Construction Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Enhancing slope stability prediction through integrated PCA-SSA-SVM modeling: a case study of LongLian expressway

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China is one of the regions most frequently affected by landslides, which have significant socio-economic impacts. Traditional slope stability analysis methods, such as the limit equilibrium method, limit analysis method, and finite element method, often face limitations due to computational complexity and the need for extensive soil property data. This study proposes a novel approach that combines Principal Component Analysis (PCA), Sparrow Search Algorithm (SSA), and Support Vector Machine (SVM) to improve the accuracy of slope stability prediction. PCA effectively reduces data dimensionality while retaining critical information. SSA optimizes SVM parameters, addressing the limitations of traditional optimization methods. The integrated PCA-SSA-SVM model was applied to a dataset of 257 slope stability samples and validated using five-fold cross-validation to ensure the model's generalization capability. The results show that the model exhibits superior performance in prediction accuracy, precision, recall, and F1-score, with the test set achieving an accuracy of 84.6%, a recall of 84.7%, a precision of 83.1%, and an F1-score of 84.6%. The model's robustness was further validated using slope data from the LongLian Expressway, demonstrating high consistency with the actual stability status. These findings indicate that the PCA-SSA-SVM-based slope stability prediction model has significant potential for practical engineering applications, providing a reliable and efficient tool for slope stability forecasting. Classify the training samples through cross-validation, using the accuracy of cross-validation as the fitness of the sparrow individual. Retain the optimal fitness value and position information.

KEYWORDS

machine learning, side slope stability, PCA, SSA-SVM, prediction

1 Introduction

China is notably one of the regions in Asia, if not the world, that frequently witnesses landslide disasters. According to credible sources (Li et al., 2022; Moayedi et al., 2019; Wei et al., 2021; Xie et al., 2021), between 2011 and 2020, the country experienced over 100,000 geological disasters, of which a staggering 70,000 were landslides, leading to more than 5,000 casualties. The economic impact was profound, resulting in direct losses amounting to 45 billion yuan (Hu et al., 2021). Considering the annual number of geological disasters, it's alarming to

note that landslides consistently constitute over half of these incidents. These landslides, predominantly resulting from slope instability, unleash a multitude of repercussions. They not only cause severe property damage but also result in casualties, traffic disruptions, destruction of homes, hindrances in daily life, and considerable production losses.

To illustrate the scale and implications of such events, let's consider a significant landslide incident from 2019 in Shuicheng County, Liupanshui City, Guizhou Province. This colossal landslide was triggered primarily due to rainfall infiltration causing slope instability. The aftermath was devastating: the surrounding houses crumbled, resulting in numerous casualties. The direct economic ramifications of this single event reached CNY 190 million, with the volume of displaced land estimated to be around 1.8 million m^3.

Therefore, accurate analysis and evaluation of slope stability hold significant practical importance. Through effective analysis, treatment, and protection of slopes, casualties and economic losses can be prevented or reduced. Currently, the primary methods used both domestically and internationally include the limit equilibrium method, the limit analysis method, and the finite element method. The limit equilibrium method is one of the first applied to slope stability analysis due to its clear concept and straightforward calculations. Duncan (1996) further analyzed and discussed the influence of different simplified methods and assumptions on the limit equilibrium analysis results of slopes. However, due to its various assumptions, this method has evolved into several different classification methods, typically divided into strict and non-strict segmentation methods. The basic idea of the limit analysis method to solve the slope stability coefficient is to first divide the assumed slip surface into oblique strips, then establish a coordinated velocity field based on the deformation coordination basis, and finally calculate according to the principle that internal energy dissipation equals the external force. Sloan (1989) improved and optimized the lower bound principle finite element method combined with a mathematical programming method to find the lower bound solution of the slope stability safety factor. Although the limit analysis method is widely used in geotechnical engineering, it is challenging to analyze complex shapes and heterogeneous geotechnical engineering cases. Moreover, due to the subjective assumptions made by the limit analysis method, its further application has been significantly limited. As one of the most widely used numerical analysis methods, the finite element method has developed into two main research directions: the finite element strength reduction method and the finite element limit equilibrium method. Zienkiewicz et al. (1975) proposed an alternative analytical approach that eliminates the necessity of presupposing the configuration of the sliding surface. Central to this methodology is the systematic reduction of strength parameters, namely cohesion (c) and internal friction angle (φ). The decrement value of these parameters at the critical juncture is designated as the stability coefficient for the geomaterial mass.

Stability coefficient is one of the important indexes to evaluate whether the slope is unstable. The stability coefficient values obtained by using different slope stability analysis methods under different working conditions need to be systematically verified (Wang et al., 2022; Zhang W. et al., 2022). For different types and different conditions of slopes, it is necessary to judge the practicability of these methods. However, it is often computationally intensive, requires specialized software and highperformance computer hardware, and requires detailed soil property data (Zhang et al., 2023). Recently, machine learning has found efficacious applications across various civil engineering challenges, notably in slope stability evaluation. The stability of mine slopes is influenced by a myriad of factors that exhibit substantial intercorrelation, necessitating heightened precision in predictive modeling (Xu et al., 2013; Suman et al., 2016; Luan et al., 2023; Lu and Rosenbaum, 2003).Combined with the artificial intelligence algorithm that has emerged in recent years, experts and scholars at home and abroad have proposed many practical models for slope stability prediction research, and have achieved good results. By training a large amount of data, machine learning models can capture the complex relationship between soil and slope characteristics without the need for a clear physical or empirical model. For example, Gu et al. (2009) employed the PCA-GEP algorithm for slope stability prediction and analysis, obtaining favorable outcomes. Chen et al. (2014) utilized PCA in tandem with the BP neural network to anticipate varying types of slope stability, resulting in satisfactory model outcomes. Meanwhile, Bu et al. (2009) introduced a realcoded DE-BP neural network predictive model leveraging the differential evolution algorithm (DE), achieving noteworthy predictive precision. BP neural network models, despite their widespread application in pattern recognition and predictive modeling, exhibit some clear limitations. The primary issue is their propensity to get trapped in local minima, potentially leading to suboptimal model performance. Additionally, BP networks often struggle with overfitting, particularly when dealing with small datasets or a large number of features. They also require significant training time and resources, especially when the network architecture is deep. In the face of these limitations, Support Vector Machine (SVM) models demonstrate their strengths. SVMs enhance classification efficiency by maximizing the margin of the decision boundary, making them more effective in dealing with nonlinear problems and demonstrating superior generalization capabilities when predicting unknown data. The kernel trick in SVMs enables them to efficiently handle highdimensional data, and they are generally less prone to overfitting, which is particularly valuable for complex pattern recognition challenges. Zhang et al. (Bu et al., 2009), aiming for rapid evaluation of the stability of redbed highway slopes, established a model centered around the SVM algorithm for quick assessment of such slopes, applying it to 16 slopes along the Renmu-Xin Expressway. However, the performance of the SVM model can significantly diminish without proper data preprocessing. Jin et al. (Zhang S. et al., 2022), on the other hand, employed the Sparrow Search Algorithm (SSA) to optimize the Support Vector Machine (SVM), creating an SSA-SVM model for intelligent prediction of slope instability, demonstrating notable advantages in forecasting such events. Ding et al. (Jin et al., 2022) proposed a slope stability prediction model based on Principal Component Analysis (PCA) and Support Vector Machine (SVM), where PCA was used to extract principal components as inputs for SVM training. The results indicated that this method could reduce the dimensionality of input variables and enhance the precision of slope stability prediction in engineering. However,

previous studies, while effective, often faced challenges with high-dimensional datasets and computational demands. Conventional models struggled with multicollinearity among input variables, leading to less accurate predictions and increased computational complexity. Our study introduces an innovative approach that leverages the strengths of three robust techniques: Principal Component Analysis (PCA), the Sparrow Search Algorithm (SSA), and Support Vector Machines (SVM). PCA effectively reduces the number of features in a dataset while retaining crucial information, simplifying subsequent model training and computational demands. SSA, an emerging optimization technique known for its strong global search capabilities and fast convergence, optimizes the parameters of the SVM, addressing limitations of traditional optimization methods used in previous studies. SVM excels in classification and regression tasks, providing superior generalization capabilities compared to other machine learning models. By combining these three approaches, the PCA-SSA-SVM model can effectively process high-dimensional data, improve prediction accuracy through optimal parameter selection, and achieve high-precision predictions. This integrated method is particularly suited for complex data processing tasks that require feature dimensionality reduction, model parameter optimization, and high-precision predictions. Our study introduces a novel hybrid model for slope stability prediction, addressing limitations of previous models. By reducing dimensionality and optimizing model parameters simultaneously, our approach enhances predictive performance and computational efficiency. The application of this model to real-world engineering data, such as the LongLian Expressway slopes, demonstrates its practical utility and effectiveness, achieving a high degree of accuracy and reliability in predictions. In this research, parameters such as rock weight (γ), cohesion (C), internal friction angle (φ), slope height (H), slope angle (β), and pore water pressure (γu) are designated as input variables, with the slope safety factor serving as the output variable. PCA is used to reduce the dimensionality of these input variables, selecting fewer and linearly independent factors for data prediction. The SSA-SVM model then trains these new input variables. This methodology presents an innovative avenue for slope stability forecasting, addressing limitations of previous studies and providing a robust, accurate predictive model.

2 Method

2.1 Principal component analysis

Principal Component Analysis (PCA) is a statistical method used to simplify the dimension of the data set while retaining as much variability as possible in the original data. It is widely used in data compression, feature extraction and data visualization.

Step.1 Centralize the data (reduce the mean value of each dimension to 0), as shown in Equation 1.

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_{x_j}} \tag{1}$$

where $\bar{x}_j$ is the arithmetic mean of x_{ij} , σ_{x_j} is the standard deviation of x_{ij}, $i = 1, 2, \ldots, m, \cdot j = 1, 2, \ldots, n$.

Step.2 Calculate the covariance matrix of the data as shown in Equation 2.

$$\operatorname{cov}(z_i, z_j) = \frac{\sum_{k=1}^{n} (z_{ik} - zj)(z_{jk} - zj)}{n-1} \tag{2}$$

Step.3 Calculate the eigenvalues and eigenvectors of the covariance matrix, as shown in Equation 3.

$$\| \lambda E - R \| = 0 \tag{3}$$

Step.4 Eigenvalues are arranged in descending order, and the eigenvectors associated with the first k largest eigenvalues are chosen to form a projection matrix. When the cumulative contribution of the current q principal components exceeds 85%, it indicates that they capture a predominant portion of the overall information.

Step.5 This projection matrix is used to transform the original data into a new kdimensional space. After principal component analysis, the initial variables x_1, x_2, .., x_n are transformed into the relationship of n comprehensive index factors y_1, y_2, .., y_n, as shown in Equation 4.

$$\begin{cases} y_1 = c_{11}x_1 + c_{12}x_2 + \cdots c_{1n}x_n \\ y_2 = c_{21}x_1 + c_{22}x_2 + \cdots c_{2n}x_n \\ \vdots \\ y_n = c_{c1}x_1 + c_{c2}x_2 + \cdots c_{cn}x_n \end{cases} \tag{4}$$

in the formula, c_{ij} and y_i are not related to each other, and c_{ij} satisfies $c_{i1}^2 + c_{i2}^2 + \cdots + c_{in}^2 = 1$. Therefore, the number of initial variables is reduced to achieve the purpose of dimensionality reduction.

2.2 Sparrow search algorithm model

Sparrow Search Algorithm (SSA) is a novel swarm intelligence optimization algorithm proposed in 2020, inspired by the foraging and antipredator behavior of sparrows (Ding et al., 2011; Zhang S. et al., 2022; Jin et al., 2022). SSA is not constrained by the differentiability, derivability, and continuity of the objective function. It boasts strong global search capability, excellent stability, and fast convergence. As a novel and well-organized metaheuristic algorithm, SSA can be employed to solve optimization problems across various fields.

Assuming there are N sparrows in a D-dimensional search space, and the position of the *i*th sparrow in the D-dimensional search space is denoted as $X_i = [x_{i1}, x_{i2}, x_{id}, .., x_{iD}]$. The position of the population X is composed of N sparrows, detailed, as shown in Equation 5.

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{ND} \end{bmatrix} \tag{5}$$

in the equation, x_{id} represents the position of the *i*th sparrow in dimension D. Here, the accuracy of slope stability is employed as the fitness function, continuously updating the optimum value to achieve the best recognition rate. The fitness values FX for all sparrows can be represented as shown in Equation 6.

$$F_X = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_i \end{bmatrix} \tag{6}$$

In SSA, the fitness value FX represents energy reserves, and f denotes the fitness function. During the search process, producers with higher energy reserves obtain food first. Generally, 10%–20% of the population are producers responsible for finding food, and their foraging search range is larger than that of the predators. At the same time, producers should update through Equation 3.

$$X_{id,t+1} = \begin{cases} X_{id,t} \times \exp\left(\frac{-i}{\alpha T}\right), R_2 < S_T \\ X_{id,t} + Q \times L \; R_2 \geqslant S_T \end{cases} \tag{7}$$

In the formula, t is the current iteration number; $X_{id,t+1}$ is the position of the ith sparrow in dimension d during thet +1) iteration; T is the maximum number of iterations; α is a uniformly distributed random number,α∈(0,1]; Q is a random number following the normal distribution; L is a 1 × d matrix where all elements are 1; R_2 is the alert value, R_2∈[0,1]; ST is the safety value, ST∈[0.5,1].

WhenR_2<ST, there are no predators around the foraging area, and producers can perform extensive search operations. When R_2 ≥ ST, the scout sparrows in the swarm have identified a predator and immediately alert the other sparrows. The sparrows in the swarm then begin antipredatory behaviors, adjusting their search strategy and quickly moving to a safe area. During the foraging process, apart from the producers, all sparrows act as seekers looking for the best foraging area. The seekers update their position according to Equation 7.

When $i > n/2$, the *i*th seeker gets no food and is in a state of starvation, with low adaptability. Such a sparrow is likely to fly to another place to forage and gain higher energy. When $i \leq n/2$, the *i*th seeker finds a random position near the current best position x_b to forage, as shown in Equation 8.

$$X_{id't'+1} = \begin{cases} Q \times \exp\left(\frac{x_{wd,t} - x_{id,t}}{\alpha T}\right), i > \frac{n}{2} \\ x_{bd,t+1} + \left|x_{id,t} - x_{bd,t+1}\right| A^+ L, i \leqslant \frac{n}{2} \end{cases} \tag{8}$$

In the equation, $x_{wd,t}$ is the worst position of the sparrow in the dth dimension during the *t*th iteration; x(bd, t + 1) is the best position in the dth dimension during the (t + 1) iteration; A is a 1 × d matrix, each of its elements is randomly assigned to 1 or −1, ensuring $A^+ = AT$.

When danger is detected, the sparrows at the edge of the population will quickly move to a safe area to obtain a better position, while the sparrows in the middle of the population will move randomly to approach other sparrows. The mathematical expression for the movement is, as shown in Equation 9.

$$X_{ddt+1} = \begin{cases} x_{bdt} + \beta(x_{id,t} - x_{bdt}), f_t \neq f_b \\ x_{id,t} + K\left(\frac{x_{ddt} - x_{wdt}}{|f_i - f_w| + \varepsilon}\right), f_t = f_b \end{cases} \tag{9}$$

in the formula, x_{bdt} is the best global position of the alert sparrows during the tth iteration; β is a step length control parameter, a random number from the normal distribution with a mean of 0 and a variance of 1; K is a random number indicating the direction of sparrow's movement, also a step length control parameter, and

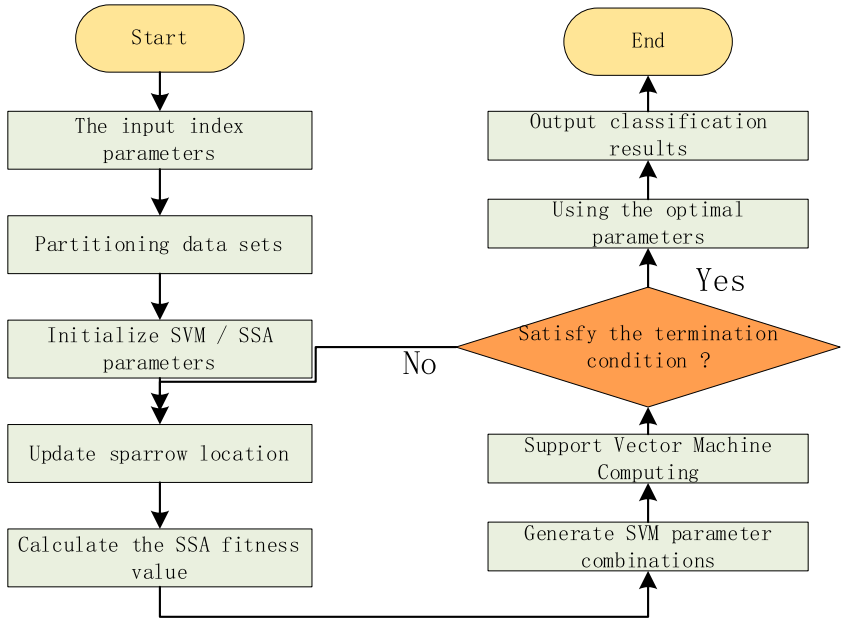

FIGURE 1
SSA-SVM process.

K∈[−1,1]; ϵ is a small constant to avoid division by zero; f_i is the fitness value of the *i*th sparrow; fb is the best fitness value of the current sparrow swarm; f_w is the worst fitness value of the current sparrow swarm.

When $fi = f$b, the sparrow is at the edge of the population, easily targeted by predators; when $fi \neq f$b, the sparrow is in the middle of the population. Once the sparrow is aware of the threat from a predator, it will move closer to other sparrows and adjust its search strategy to avoid being attacked.

2.3 SSA-SVM model

The protagonist of the algorithm is the sparrow, each individual sparrow having only one attribute, which is its position, representing the location of the food it has found. Each sparrow may undergo three states of change: 1) acting as a discoverer, leading the population to forage; 2) being a follower, chasing the discoverer to find food; 3) having a vigilance mechanism, abandoning foraging upon detecting danger. The optimization parameters in the sparrow algorithm are the penalty parameter c and kernel function parameter g in SVM (Support Vector Machine). The fitness function is the SVM's prediction accuracy on the test set.

The selection of SVM penalty factor *C* and kernel function parameter g greatly influences the classification results. At the same time, the SSA algorithm has strong global search capability and is suitable for optimizing SVM's penalty factor *C* and kernel function parameter g to obtain a better parameter combination. By using a certain number of sparrows for global optimization, the optimal parameter combination can be obtained. Then, the optimal *C* and g obtained by the SSA optimization algorithm are used to establish the SVM identification model and obtain the diagnostic results. The process of optimizing SVM using the SSA algorithm is shown in Figure 1, with specific steps as follows:

First, determine the input and output of the fault diagnosis model. Extract fault features as the input of the diagnostic model and determine the target output values. Establish training and testing sample sets. Specifically, the data was divided into training and testing sets with a ratio of 9:1.

Initialize the related parameters of the sparrow search algorithm, including population size, maximum number of iterations, C, and g. Update the position according to Equations 7–9

Calculate the fitness value of the sparrow individual's new position, compare the updated fitness value with the original optimal value, and update the global optimal information.

Determine whether the number of iterations meets the termination condition. If not, repeat step (3); otherwise, stop, output the optimal parameters, input the test set samples into the optimal SVM model, and output the diagnostic results.

3 Slope stability prediction model based on PCA-SSA-SVM

3.1 Method principle

For the assessment of slope stability, identifying the most prominent influencing factors is imperative. In this research, slopes with a Factor of Safety (FOS) exceeding 1.3 were classified as stable.

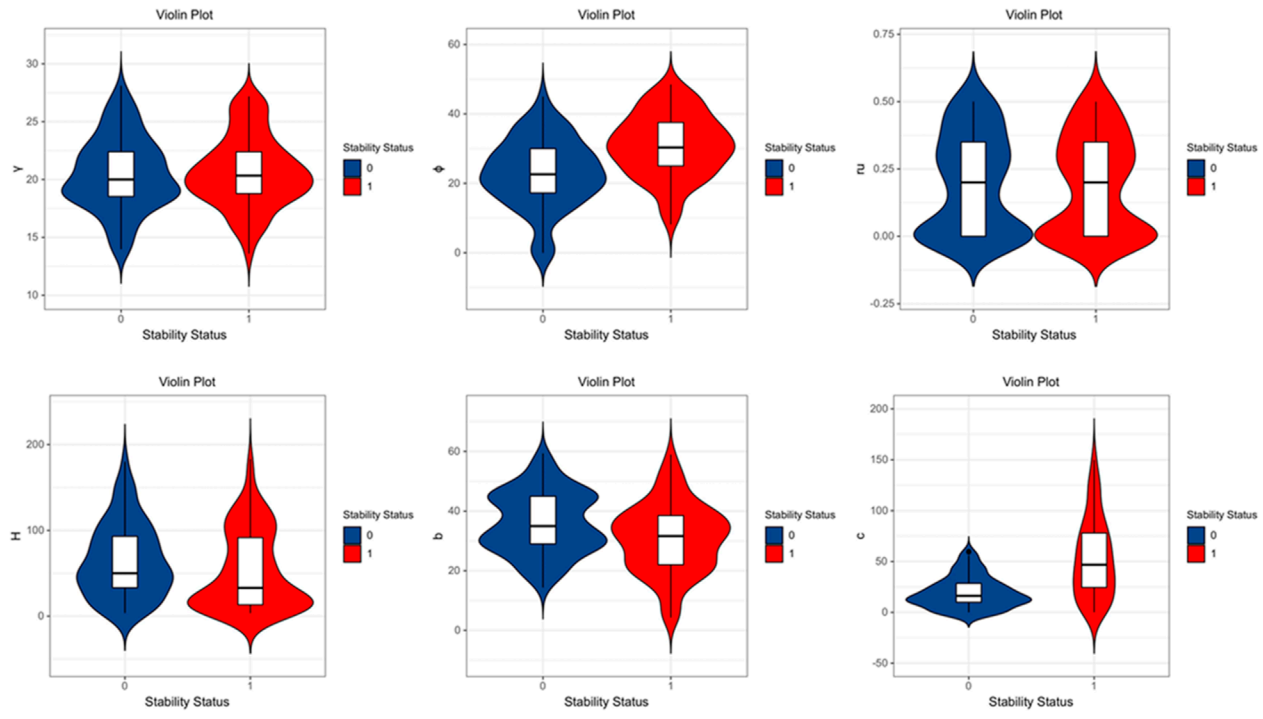

FIGURE 2
Slope characteristic parameters distribution violin figure.

The stability of slopes is categorized into two groups: stable (coded as 1) and unstable (coded as 0). Historically, slope stability prediction efforts have utilized project data for both training and prediction datasets. However, this often results in a limited amount of training data, leading to suboptimal accuracy in the developed models.

To address this limitation, the present study aggregates numerous referenced engineering cases (Emina et al., 2008; Kardani et al., 2021; Zhang R. et al., 2023; Zhang Y. et al., 2023), amassing a total of 257 experimental datasets to evaluate the model's efficacy. The comprehensive dataset is presented in Supplementary Table 1. The slope characteristic parameters vary across different slopes. Visual analysis can illustrate the characteristic parameter information of the slope in different states and qualitatively analyze the slope's condition to some extent.

In evaluating each characteristic parameter, the violin plot shows the distribution of characteristic parameters under different slope conditions, as shown in Figure 2. Among the different characteristic parameters, the violin shapes of the stable and unstable state data are similar, with few or no outliers, indicating that the dataset is reasonably constructed. The data scatter distribution is delineated in Figure 3.

To further analyze the data, this paper provides descriptive statistics for six indicators, as shown in Table 1. Given that the total

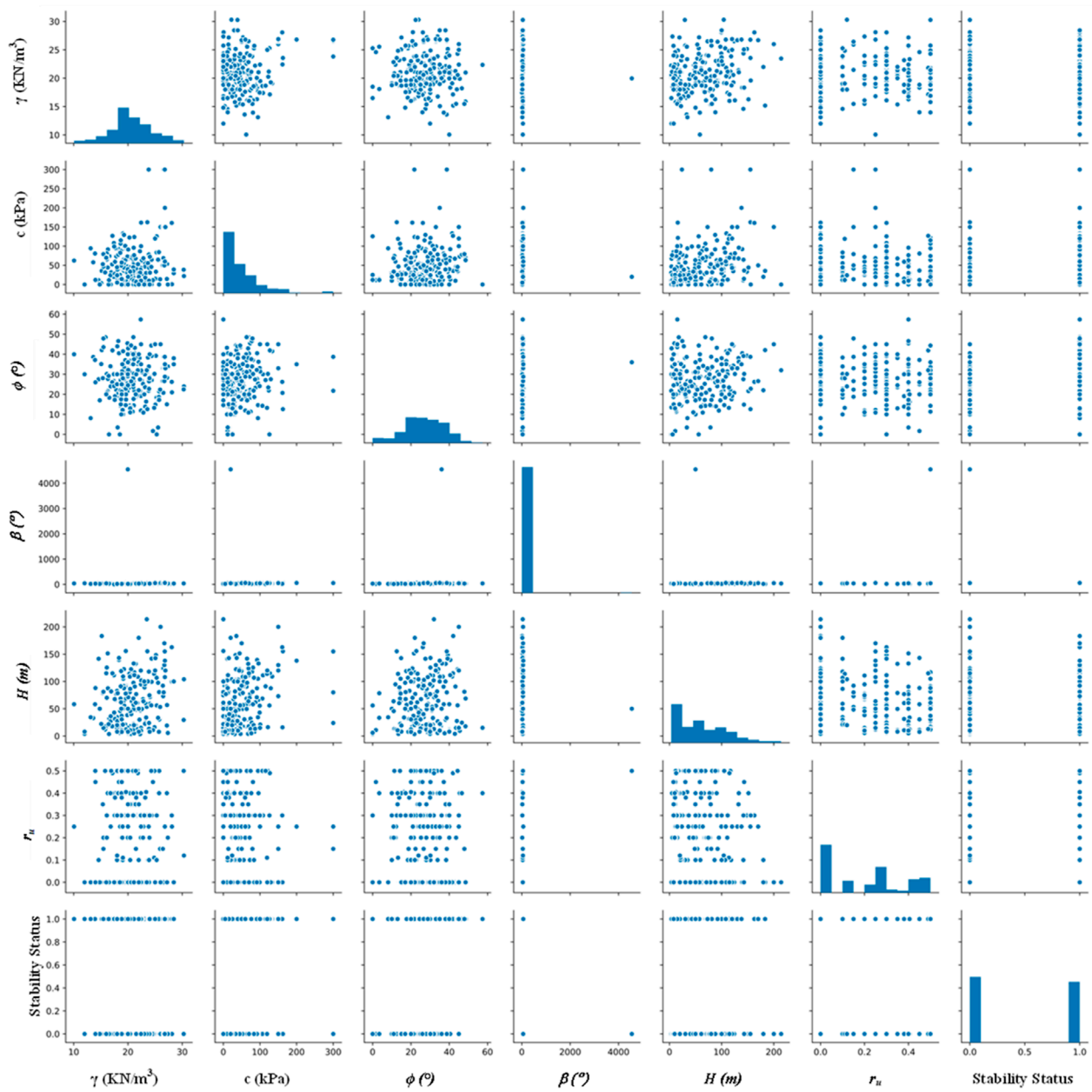

FIGURE 3
Scatter plot of each index.

sample size is less than 500, the Shapiro-Wilk (S-W) test is employed to assess the normality of multiple analysis items. The data for the analysis items γ and φ follow a normal distribution. Their median and mean values are close, skewness and kurtosis are near zero, and the significance *P*-values are 0.051 and 0.052, respectively, which are higher than the commonly used 0.05 significance level, so the null hypothesis of normality cannot be rejected (Sah et al., 1994).

However, the data for *c*, *β*, *H*, and γ_u do not follow a normal distribution. Even though the kurtosis and skewness of *H* are within the common normal distribution range, the significance *P*-value

TABLE 1 Statistical description of samples.

Name	Sample size	Median	Average value	Standard deviation	Skewness	Kurtosis	S-W test
γ	257	20.31	20.588	3.593	0.117	0.164	0.989 (0.051 ∗)
c	257	30.81	46.172	48.228	2.289	7.967	0.791 (0.000 ∗∗∗)
ϕ	257	26.81	26.732	10.565	−0.218	0.085	0.989 (0.052 ∗)
β	257	33.33	51.059	281.957	15.993	256.174	0.052 (0.000 ∗∗∗)
H	257	50	60.803	46.798	0.793	0.015	0.922 (0.000 ∗∗∗)
γ_u	257	0.2	0.194	0.181	0.261	−1.395	0.852 (0.000 ∗∗∗)

Note: ∗∗∗ represents a significance level of 1%. ∗∗ represents a significance level of 5%. ∗ represents a significance level of 10%.

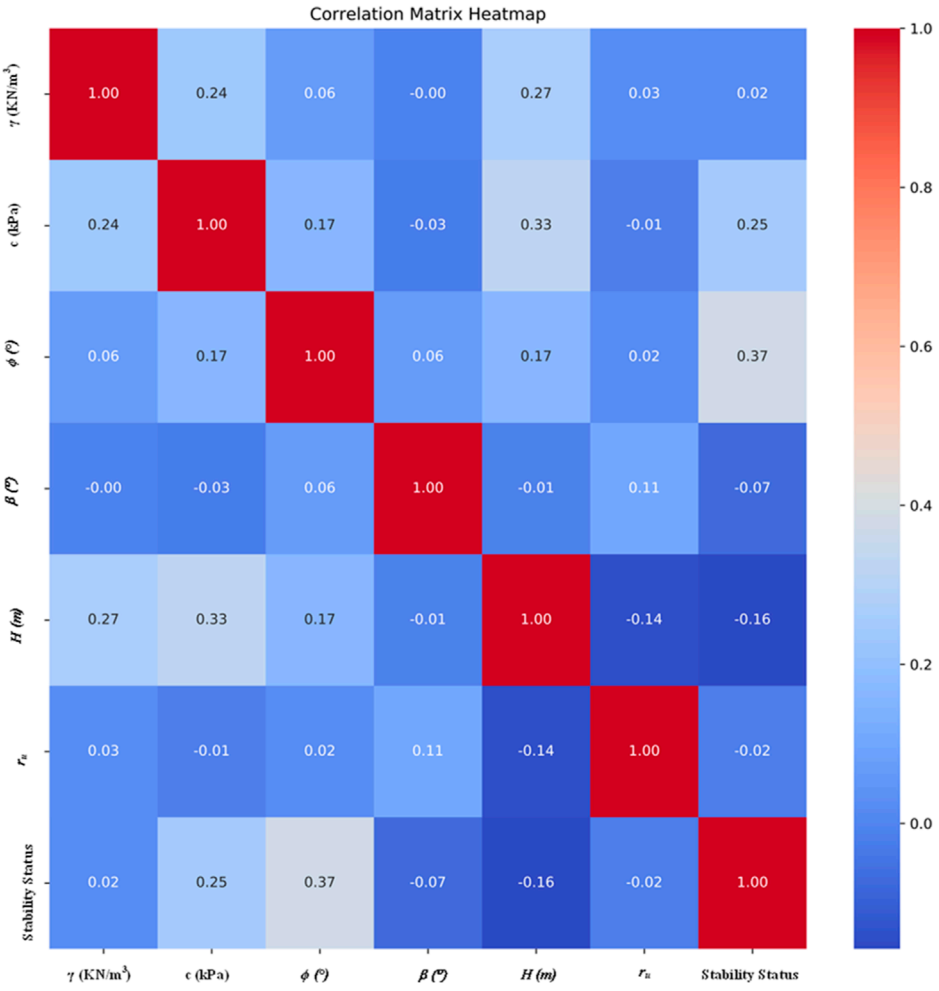

FIGURE 4
Correlation matrix heat map.

remains at 0.000, clearly indicating a departure from normality. Among the six analysis items, two meet the criteria for a normal distribution, while four do not.

Variable correlation analysis is an important part of statistics, which is mainly used to explore whether there is a relationship between two or more variables. In order to prevent data redundancy in the model, which affects the prediction accuracy of the model, the correlation coefficient between the two variables in the data set is calculated to determine whether there are redundant characteristic variables and determine the correlation between variables, see Figure 4. According to the correlation analysis table, it can be observed that there is a positive correlation between γ and c and H, among which the correlation with H is the most significant. c mainly has a strong positive correlation with H, and also has a certain degree of positive correlation with φ. φ shows positive correlation with c and E. The relationship with all other variables is relatively weak, but the positive correlation with ϕ is slightly more obvious. H not only has a significant positive correlation with γ and c, but also has a certain negative correlation with γu. In general, the correlation between H and several other variables is the most prominent, especially the positive correlation with γ, c and the negative correlation with γu; the correlation with all variables is relatively weak.

3.2 PCA analysis

In constructing the slope stability prediction model, six key factors related to slope stability status are incorporated. Given the multidimensionality of data derived from these factors, model training becomes challenging. To address this, Principal Component Analysis (PCA) is applied to transform this high-dimensional dataset into a reduced-dimensional space while preserving the original data's information content as much as possible. This approach helps isolate the most significant principal components, thereby reducing model complexity and enhancing training efficacy. The procedural steps for PCA analysis, as detailed in Section 2.2, are outlined below:

Step 1. Suitability Assessment: Initially, both the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests are performed to determine the data's suitability for PCA, as shown in Table 2. A KMO value exceeding 0.8 is optimal, while values between 0.7 and 0.8 are considered moderate. KMO values below 0.6 may be deemed unsuitable. The KMO test results revealed a KMO value of 0.604.

TABLE 2 PCA feasibility test.

KMO test and bartlett test		
KMO value		0.604
Bartlett sphericity test	Approximate chi-square	75.447
	df	15
	P	0.000 ***

Note: *** represents a significance level of 1%. ** represents a significance level of 5%. * represents a significance level of 10%.

Additionally, Bartlett's sphericity test results showed a significant P-value of 0.000 ***, which is significant at the respective level. This rejects the null hypothesis, indicating correlations among the variables and affirming the appropriateness of proceeding with PCA.

Step 2. Determining the Number of Principal Components: To ascertain the required number of principal components, examine the variance elucidation table and the scree plot. Table 3 lists the variance contribution rate of each principal component to the original variables, which helps in selecting the number of principal components by considering the descending trajectory of eigenvalues. During PCA, the cumulative variance elucidation rate typically approaches 90%. Based on the information in the variance elucidation table, five principal components are identified as input parameters for the SSA-SVM model.

Step 3. Analysis of principal component load coefficient: Table 4 load coefficient combined to reveal the importance of hidden variables behind each principal component.

Step 4. Spatial Representation of Principal Components: The dimensions of numerous principal components are condensed to two or three principal components, and their spatial orientation is depicted using quadrant diagrams. Extracting two or three principal components allows for a clearer visualization of their spatial interrelations. However, since this study extracts five principal components, their spatial distribution cannot be effectively illustrated using the primary mapping technique.

Step 5. Constructing the Principal Component Equation 10: Based on the component matrix, the component formula for each principal component is formulated and its weight is determined, as shown in Table 5.

$$\begin{cases} y_1 = 0.367 \times \gamma + 0.435 \times c + 0.259 \times \phi - 0.015 \times \beta + 0.456 \times H - 0.091 \times r_u \\ y_2 = 0.079 \times \gamma + 0.029 \times c + 0.305 \times \phi + 0.604 \times \beta - 0.119 \times H + 0.629 \times r_u \\ y_3 = 0.522 \times \gamma + 0.108 \times c - 0.575 \times \phi - 0.363 \times \beta - 0.101 \times H + 0.537 \times r_u \\ y_4 = 0.254 \times \gamma - 0.109 \times c - 0.614 \times \phi + 0.705 \times \beta + 0.199 \times H + 0.368 \times r_u \\ y_5 = -0.73 \times \gamma + 0.770 \times c - 0.413 \times \phi + 0.088 \times \beta + 0.129 \times H + 0.196 \times r_u \\ y = 0.306 \times y_1 + 0.212 \times y_2 + 0.178 \times y_3 + 0.165 \times y_4 + 0.37 \times y_5 \end{cases} \tag{10}$$

Step 6. Comprehensive score output: Finally, calculate and output the comprehensive score based on PCA and the principal component data are shown in Supplementary Table 2.

3.3 PCA-SSA-SVM model construction and training

Utilizing the SSA-SVM approach, an slope stability prediction model is developed. Python software is chosen for scripting the SSA algorithm to enhance the SVM model. After applying principal component analysis (PCA), the initial six evaluation indicators for slope stability are substituted by five principal components. The output variable denotes the safety condition of the slope.

3.4 Model evaluation indicators

The accuracy (ACC), recall rate (TPR), precision rate (PPV) and F1-score were used to evaluate the prediction effect of

TABLE 3 Variance interpretation form.

Component	Characteristic root	Explanatory rate of variance (%)	Cumulative variance interpretation rate (%)
1	1.645	27.418	27.418
2	1.142	19.03	46.449
3	0.957	15.949	62.398
4	0.889	14.818	77.216
5	0.736	12.264	89.48
6	0.631	10.52	100

TABLE 4 Factor load coefficient table.

Name	Principal component_1	Principal component_2	Principal component_3	Principal component_4	Principal component_5	Common degree
γ	0.337	0.232	0.35	−0.338	0.246	0.961
c	−0.253	0.144	−0.078	0.65	0.381	0.855
ϕ	0.045	−0.153	0.053	−0.251	0.411	0.996
β	0.305	0.287	0.108	0.528	0.483	0.994
H	0.751	0.002	0.022	−0.047	−0.03	0.631
γ_u	−0.1	0.302	−0.542	−0.356	0.312	0.931

TABLE 5 Composition matrix table.

Name	Principal component_1	Principal component_2	Principal component_3	Principal component_4	Principal component_5
γ	0.367	0.079	0.522	0.254	−0.73
c	0.435	0.029	0.108	−0.109	0.77
ϕ	0.259	0.305	−0.575	−0.614	−0.413
β	−0.015	0.604	−0.363	0.705	0.088
H	0.456	−0.119	−0.101	0.199	0.129
γ_u	−0.091	0.629	0.537	−0.368	0.196

Consequently, an aggregate score for each principal component can be derived. The novel variable formulations for the five principal components are delineated as.

PCA-SSA-SVM. The calculation formula is, as shown in Equations 11–13 (Khajehzadeh et al., 2022):

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$TPR = \frac{TP}{(TP + FN)} \tag{12}$$

$$PPV = \frac{TP}{(TP + FP)} \tag{13}$$

TP: True positives, where actual positive samples are correctly predicted as positive; TN: True negatives, where actual negative samples are correctly predicted as negative; FN: False negatives, where actual positive samples are incorrectly predicted as negative; FP: False positives, where actual negative samples are incorrectly predicted as positive.

The F1-score, also referred to as the F-measure, serves as a comprehensive metric that evaluates the model's precision (PPV) and recall (TPR) as shown in Equation 14. It is computed as the harmonic mean of precision and recall, with values spanning

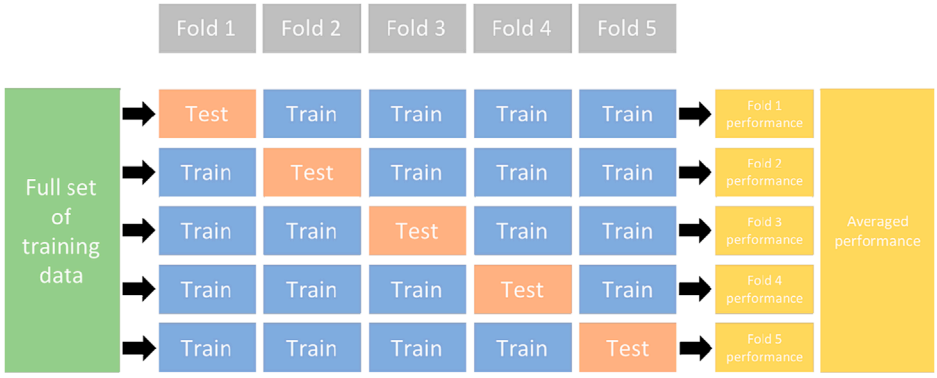

FIGURE 5
5-Fold cross-validation.

TABLE 6 Model prediction evaluation.

Name	Accuracy rate	Recall rate	Precision rate	F1
Training set	0.952	0.922	0.981	0.951
Test set	0.846	0.847	0.831	0.846

TABLE 7 Comparison of model predictions using 5-fold cross-validation.

Name	Accuracy rate	Recall rate	Precision rate	F1
SVM	0.654	0.571	0.727	0.64
SSA-SVM	0.731	0.801	0.75	0.772
PSO-SVM	0.825	0.753	0.781	0.832
GA-SVM	0.826	0.71	0.802	0.786
PCA-SSA-SVM	0.846	0.847	0.831	0.846

between 0 and 1. A score of 1 indicates impeccable accuracy, while a score of 0 denotes the poorest accuracy.

$$F_{1-score} = 2\frac{PPV \cdot TPR}{PPV + TPR} \quad (14)$$

3.5 Cross-validation

To further enhance the model's generalization ability and prevent overfitting during the training process, this study employs 5-fold cross-validation, as illustrated in Figure 5. Initially, the original training dataset D is randomly divided into k equally sized subsets: D1, D2, D3, D4, and D5. Let Dj and D-j = D/D_j denote the j-th test set and the corresponding training set, respectively, for each iteration.

3.6 Prediction results and analysis

During the data preprocessing phase, the initial dataset was randomly permuted to create a modified dataset. To enhance the model's generalizability, 231 data entries were designated as the training set, while the remaining entries were reserved for testing. Utilizing the PCA-SSA-SVM approach, a comprehensive prediction was executed on the 257 slope stability data entries. Combining 5-fold cross-validation with model parameter optimization, the results show that the SSA-SVM model's performance under different parameters indicates that the optimal value for the penalty coefficient (C) in the SVM model is 9.426, and the optimal value for the kernel parameter (gamma) is 0.03.

The exhaustive outcomes are presented in Table 6. The prediction outcomes from the test set are compared with the actual results, with a subsequent analysis conducted in conjunction with the predictions for each state, as depicted in Figure 6.

Based on the data presented in Table 7, the PCA-SSA-SVM model exhibits the highest accuracy, recall, precision, and F1 score compared to the other models. Its accuracy rate is notably high at 84.6%, its recall rate is excellent at 84.7%, and its precision rate is impressive at 83.1%. The SSA-SVM model, with an accuracy rate of 73.1%, a recall rate of 80.1%, and a precision rate of 75%, performs better than the simple SVM model across all metrics, suggesting that incorporating the SSA algorithm improves performance. The PSO-SVM model shows a strong performance with an accuracy rate of 82.5%, a recall rate of 75.3%, and a precision rate of 78.1%, while the GA-SVM model has an accuracy rate of 82.6%, a recall rate of 71%, and a precision rate of 80.2%. Both the PSO-SVM and GA-SVM models exhibit better performance than the SVM model but are slightly lower than the PCA-SSA-SVM model in accuracy and F1 score.

Based on the provided metrics, combining PCA with the SSA algorithm yields the best results among all the models. This

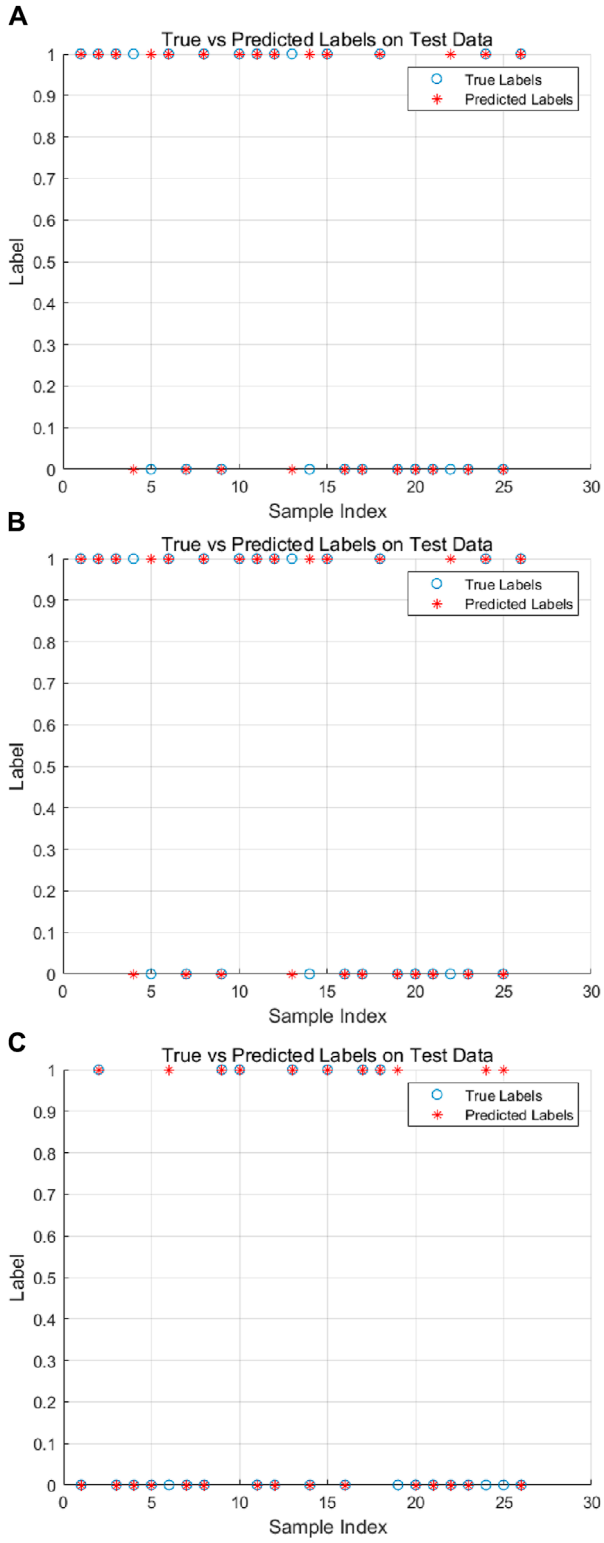

FIGURE 6
Comparison of model prediction results. **(A)** SVM **(B)** SSA-SVM **(C)** PCA-SSA-SVM.

integrated approach significantly enhances prediction accuracy and effectiveness, showcasing its superiority in handling high-dimensional data and optimizing model performance. The PCA-SSA-SVM model's robustness and high precision make it an ideal choice for slope stability prediction in engineering applications.

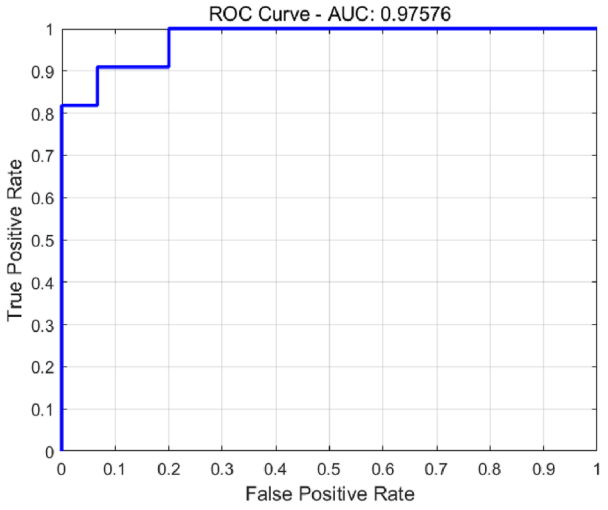

FIGURE 7
Receiver-operating characteristiccurve.

In order to comprehensively evaluate the performance of the model, this study drew the ROC (receiver operating characteristic) curve and calculated the AUC (area under the curve) value, see Figure 7. The ROC curve is an effective tool for visually demonstrating the relationship between the true positive rate and the false positive rate of the model under various thresholds. The AUC value is the area under the ROC curve, which provides us with a single quantitative indicator of model performance. The AUC value is usually between 0.5 (no discrimination) and 1.0 (perfect discrimination). The model of this study obtained an AUC value of 0.9758, which strongly indicates that the PCA-SSA-SVM model performs well in the slope stability prediction task.

4 Engineering verification

4.1 Engineering background

The Guangdong Province's Longchuan to Huaiji Expressway in China is a part of the original national highway network "7,918"plan, specifically marked as the 17th cross route. A significant portion of this route is the Longchuan to Lianping section of the Guangdong Province Longchuan to Huaiji Expressway, commonly referred to as the "LongLian Expressway". This project is located in the mountainous terrain of northern Guangdong, crossing through Heyuan and Shaoguan cities, encompassing four counties and thirteen towns.

The starting point of the LongLian Expressway is at K206 + 222 in the Old Long Town of Longchuan County, where it connects with the already operational Meihe Expressway. The endpoint is at K334 + 200 in the Tangxia Village, Longxian Town, Wengyuan County, Shaoguan City. The total length of the route is 127.978 km,

TABLE 8 Slope data of LongLian Expressway.

No.	γ (KN/m3)	c (kPa)	ϕ (°)	(°)	H (m)	γ_u	Stability status
1	17.93	78.20	18.49	33.42	120.79	0.0	1
2	18.02	40.92	21.18	21.86	34.56	0.1	0
3	25.76	64.11	21.40	15.76	30.38	0.5	0
4	21.03	21.23	17.72	5.79	57.31	0.0	1
5	25.74	31.42	17.23	30.03	80.53	0.4	1
6	18.80	14.40	25.02	19.98	30.06	0.0	0
7	18.77	30.01	9.99	25.02	50.00	0.1	1
8	19.97	19.96	36.00	45.50	50.00	0.5	1
9	26.70	50.00	26.60	50.00	34.04	0.2	1
10	26.80	90.00	28.80	59.00	42.37	0.3	1

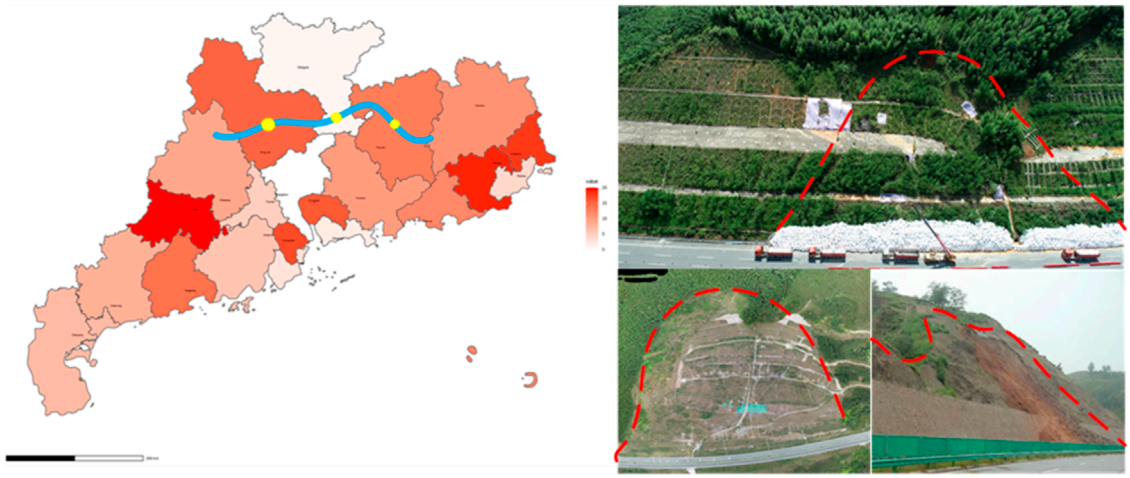

FIGURE 8
Project location map and slope site.

with a designed speed of 100 km/h, adhering to the technical standards of a two-way four-lane expressway, as shown in Figure 8.

4.2 Slope profile

4.2.1 Stratigraphic lithology

The surface layer consists of silty clay and sandy clay soil, with plastic to hard plastic consistency. The underlying strata comprise entirely to strongly weathered andesite porphyry and moderately weathered diorite. The fully weathered andesite porphyry is yellow-brown in color, showing complete weathering with substantial disruption of the original rock structure. The core of the rock manifests as hard soil columns, with a soft rock quality that tends to soften and disintegrate when in contact with water, locally interspersed with isolated stones. The strongly weathered andesite porphyry appears yellow, yellow-gray, or yellow-brown, with a major portion of the original rock structure destroyed, exhibiting a medium-grain structure and blocky construction. The mineral composition includes quartz, feldspar, and mica, with the rock core primarily displaying fragmentary and blocky forms, block diameters ranging from 2 to 6 cm, and a minor amount appearing as debris. Joints and fissures are well-developed with some fissure surfaces being impregnated with iron-manganese material, displaying uneven weathering, soft rock quality, and fragmented rock mass. The moderately weathered diorite is gray with a medium to coarse-grain structure and blocky construction. Its mineral composition also includes quartz, feldspar, and mica, with well-developed joints and fissures. The rock core manifests as columnar or short columnar structures, with joint lengths ranging from 10 to



FIGURE 9
Engineering verification prediction results.

70 cm, producing a brittle sound when struck, indicating hard rock quality and a relatively intact rock mass.

4.2.2 Hydrogeological overview

Surf ace Water: The surface does not exhibit perennial water flow; transient surface runoff only occurs post-rainfall during the rainy season.

Groundwater: The groundwater is composed of upper soil layer pore water and deep bedrock fissure water, with a relatively small water content. The primary source of replenishment relies on the infiltration of atmospheric precipitation, with the discharge base level being the streams at the bottom of the slopes. During the period of this survey, no groundwater levels were detected within the drilled depths.

4.3 Slope data

There are 10 large and small slopes in LongLian Expressway, including 7 unstable slope samples and 3 stable slope samples, as shown in the Table 8.

4.4 Verification based on PCA-SSA-SVM model

Utilizing the well-trained PCA-SSA-SVM model for slope stability prediction, the results are illustrated in Figure 9. From the provided data, it can be observed that the PCA- SSA-SVM model predictions align with the actual stability status data of the LongLian Expressway slopes at most points. Specifically, among the ten data points, the PCA- SSA-SVM model predictions match the actual stability status at nine points. Only at one data point does the model prediction deviate from the actual stability status.

5 Discussion

While the PCA-SSA-SVM model demonstrated high accuracy and robustness, several limitations must be addressed to enhance its applicability and performance in real-world scenarios.

1. Model Limitations: Although the PCA-SSA-SVM model showed excellent performance on the test set, the study does not deeply explore potential limitations in practical applications. The presence of nonlinear relationships between features or potential outliers in the slope dataset may affect the model's predictive performance. Furthermore, the model's adaptability to slope data under varying geological conditions or climatic environments requires further investigation.
2. Feature Selection and Optimization: While PCA effectively reduces the dimensionality of the data, the specific rationale for selecting the six features used in this study was not elaborated. Future research should explore feature engineering and optimization techniques to further enhance model predictive performance. Introducing additional features related to slope stability could enrich the model inputs and improve accuracy.
3. Model Comparison and Validation: Although comparisons with SVM and SSA-SVM models were presented, a comparative analysis with other advanced machine learning methods was not included. Future research could investigate the performance of models such as Random Forest, Gradient Boosting Trees, or Deep Learning techniques on the same dataset. Such comparisons would help establish the superiority of the PCA-SSA-SVM model and provide a more comprehensive evaluation of its performance.

6 Conclusion

Within this study, the PCA methodology is employed to examine and process the six evaluative indices affecting slope stability across 257 data samples. From these, five principal components are derived, serving as input variables for the SSA-SVM. Subsequently, a PCA-SSA-SVM predictive model for slope stability is formulated. The accuracy of the model is further evaluated by engineering verification. A detailed analysis of the model's predictive outcomes and associated errors yielded the subsequent findings.

1. The PCA methodology adeptly addresses the multicollinearity challenge inherent among factors influencing slope stability, streamlining the model's input variables and enhancing simulation efficiency.
2. The model's precision, robustness, and adaptability were gauged via metrics such as precision, recall, and the F1-score. The test set outcomes were 84.6%, 84.7%, and 84.6%, respectively. With an AUC value of 0.9758, the model's accuracy and adaptability are deemed commendable.
3. The accuracy of the PCA-SSA-SVM model was validated using the slope data from the LongLian Expressway. Among the 10 provided samples, only the prediction for sample 1 was

incorrect. The results indicate that the PCA-SSA-SVM based slope stability prediction model can be effectively applied in engineering practice to achieve slope stability forecasting.

4. The model's classification performance has not taken into account factors such as the slope's geometric shape, soil quality of the slope body, and external influencing elements. Further research is required in the future, especially when using machine learning algorithms to estimate slope stability, to continue refining and enhancing feature parameters.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JH: Investigation, Methodology, Software, Writing–original draft. DL: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Resources, Writing–original draft, Writing–review and editing. WL: Writing–original draft. QY: Writing–review and editing.

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Conflict of interest

Authors JH, WL, and QY were employed by Guangxi Geology and Mineral Construction Group Co., Ltd. Author DL was employed by Guangxi Shengfeng Construction Group Co. Ltd.

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Supplementary material

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Study on the mining response law and coal burst risk assessment of an isolated working face

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With the increasing demand for coal resources and the unreasonable arrangement of subsequent working faces, mining activities in isolated working faces are more likely to induce coal burst accidents. In this study, the minimum distance principle is utilized as the risk assessment indicator and the quantitative theory is introduced to evaluate coal burst risk in isolated working faces. Through a case study in 1,304 isolated working face of Yangcheng Coal Mine, the key factors affecting the risk of coal burst were identified, and a three-dimensional coal burst risk assessment model was constructed to evaluate the risk of the isolated working face. The results show that as the working face advances, the abutment pressure and elastic strain energy density in front of the working face increase to the peak value in a positive exponential relationship at first and then decrease to *in situ* stress, which presents an upward convex trend. Under different excavation steps, the concentration coefficient of the peak stress gradually increases. The influence range of the abutment pressure of the working face gradually increases. Compared with one-dimensional and two-dimensional evaluation functions, the three-dimensional function significantly improves the accuracy of risk assessment and successfully identifies strong coal and gas outburst risks. Additionally, the model not only enhances the precision of risk assessment but also quantifies the assessment parameters.

KEYWORDS

coal burst, risk evaluation, isolated working face, quantitative theory, elastic strain energy density

1 Introduction

Coal burst is a typical dynamic disaster often accompanied by the sudden ejection of coal during underground mining activities (Zhao et al., 2018a; Wen et al., 2019; Tai et al., 2022; Wang P. et al., 2024). In recent years, there has been a significant expansion of coal mining operations, with corresponding increases in mining depths. As the mining depths increase, the engineering conditions encountered in mining activities become

more complex, particularly the issue of high *in situ* stress due to mining depth, faults, and tectonic areas with isolated working faces (Guo et al., 2017; Zhao et al., 2018b; Li et al., 2022; Wang et al., 2024a; Wang et al., 2024b). Under the action of high stress accumulation and complex tectonic stress, the instability of island working faces is more likely to occur. The reason for this is the substantial accumulation of elastic energy, which can potentially lead to significant geotechnical hazards such as mine earthquakes or severe coal burst accidents (Xie et al., 2015; Pan et al., 2018; Li et al., 2021; Li et al., 2024). The instability of isolated working faces poses a severe threat to the safety of coal mining operations and has been responsible for numerous casualties. Therefore, it is imperative to develop effective methods for risk assessment and dynamic failure prediction.

Coal burst risk evaluation methods can be categorized into the following: qualitative evaluation method and quantitative evaluation method. The qualitative method assesses the risk of coal burst by summarizing the characteristics of the coal burst phenomenon. Based on the characteristics of mine micro-seismic data, Cao et al. (2022) proposed a neural network for coal burst prediction that is driven by the fusion of data and knowledge. Zhou J. et al. (2022) investigated the coal burst mechanism of isolated working surfaces and established a numerical model to describe the evolution of static and dynamic stress. The mechanism of coal burst disasters is highly complex, involving numerous influencing factors throughout the disaster's preparation and development process. For instance, island mining on a coal face can lead to high stress accumulation before catastrophic failure, which may then trigger a coal burst. These prediction models struggle to quantify the relationships between control factors and the timing and location of coal burst accidents, which hampers the ability to accurately and scientifically evaluate the risk of coal bursting (Guo et al., 2019; Xu et al., 2019; Cao et al., 2023). However, the aforementioned evaluation methods primarily offer a qualitative assessment of prevention measures prior to coal mining, rather than providing a quantitative analysis.

To improve the accuracy of coal burst evaluations, quantitative evaluation methods are introduced to study the coal burst grade evaluation model for isolated working faces. The quantitative evaluation methods mainly include the comprehensive index method (Ahmad et al., 2021), possibility index diagnosis method (Zhou K. Y. et al., 2022), and fuzzy mathematics method (Tang et al., 2010). The comprehensive index method describes the relationship between coal burst risk and various mining conditions. Wu et al. (2019) optimized the least square support vector machine (LSSVM) method through the particle swarm optimization algorithm and proposed a new probability model for tunnel coal burst prediction using Copula's theory. Dou et al. (2018) analyzed the multi-dimensional information of micro-seismic data during the mining process, conducted early warning of coal burst events through comprehensive analysis, and established a multi-parameter index normalization system for the early warning of micro-seismic coal burst. Di et al. (2023) proposed a comprehensive early-warning mode based on a deep learning algorithm through the comprehensive analysis of micro-seismic, acoustic emission and electromagnetic radiation signals. Wang et al. (2015) established a multi-index model for predicting coal mine rock burst by combining fuzzy matter theory, information entropy theory, and proximity theory. He et al. (2017) performed a comprehensive analysis of stress distribution and dynamic stress perturbations based on stress monitoring. Using Bayesian networks, Wang et al. (2022) quantified the probabilistic relationship between rock burst and its different types, and predicted the occurrence probability of rock burst by integrating multiple indicators. Moreover, Du et al. (2021) adopted the Bayesian method and combined the traditional comprehensive index method with the likelihood index diagnosis method to build a comprehensive risk assessment. Liu et al. (2023) established a multi-layer fuzzy comprehensive evaluation model based on the analytic hierarchy process–fuzzy comprehensive evaluation (AHP-FCE) method. Several influencing factors of rock burst risk were determined, and the evaluation model was calculated using a second-order fuzzy mathematical calculation method. It was found that the evaluation results are consistent with those of the comprehensive index method and the possibility index method. Dong et al. (2013) conducted a study on the AHP applied to the coal mine safety evaluation. Sun et al. (2009) combined fuzzy mathematics and neural networks to propose a fuzzy neural network prediction model for rock burst risk. These quantitative evaluation methods contribute to a more precise and data-driven approach to assessing coal burst risk, which is essential for the effective management and prevention of coal burst incidents in mining operations. The quantitative evaluation method is a significant branch of multivariate analysis methods and serves as an effective tool for processing quantitative data (He et al., 2023; Hao and Niu, 2014; Hu et al., 2014; Wang et al., 2012). This approach allows for the development of more effective strategies to mitigate the risks and enhance the safety of coal mining operations. Furthermore, quantitative theory evaluation and forecasting methods can overcome the limitations of scoring or indexing methods, providing a more robust framework for assessing and managing the risks associated with coal burst disasters. The traditional quantitative model has made some progress in evaluating the risk of rock burst, but there are still areas for improvement. For example, the comprehensive index method captures the relationship among risk factors from a holistic perspective, but its weight allocation relies on expert judgment and is susceptible to subjective influence. The fuzzy mathematical method has an advantage in predicting uncertainty, but it is limited by the complexity of establishing fuzzy sets and defining membership functions. The possibility index diagnostic method is effective in rapidly identifying high-risk areas, but it still lacks in providing complex multivariate analysis. Quantitative theoretical evaluation and prediction techniques are used in this study not only because of their competence in data analysis but also because of their ability to overcome the shortcomings of scoring or indexing methods.

Drawing on the aforementioned research, this study performs a comprehensive examination of coal outburst risk assessment for isolated mining faces, grounded in quantitative theory and the principle of minimum distance. Through the detailed analysis of geological and engineering parameters that influence coal outburst risk, a three-dimensional evaluation model is developed. The utility of various assessment methodologies is further evaluated by integrating numerical simulations with case studies for comparative analysis. This paper is organized as follows: Sections 2, 3 present a numerical simulation analysis on the abutment pressure and elastic strain energy during the mining process; Section 4 establishes a coal burst grade evaluation model for isolated working faces based on

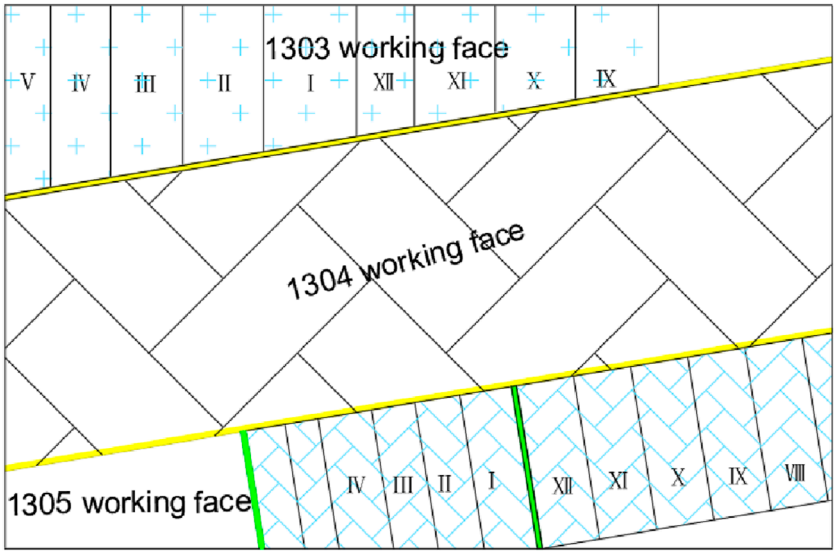

FIGURE 1
Schematic diagram of 1,304 working face.

quantitative theory and the principle of minimum distance; and finally, conclusions are presented in Section 5.

2 Methodology

2.1 Geological and mining conditions

The mining level of working face 1,304 at Yangcheng Coal Mine is −650 m, and the coal seam is 3# coal, which is highly prone to bursts. The ground elevation ranges from 38.3 to 39.5 m. The coal seam floor elevation of the working face is between −535 and −660 m. The length of the working face is 184 m, and the mining advance length is 870 m. The dip angle of the coal seam in the working face varies from 17° to 21°, with an average of 19°. The thickness of the coal ranges from 7.0 to 8.2 m, with an average of 7.5 m. The minable index of 3# coal is 1, the coefficient of variation is 18.6%, and the coefficient of hardness is between 2 and 3, which belongs to medium-hard coal seam. The overburden of the working face is a thick and hard basic roof, which can accumulate extensive elastic properties, and poses potential mine burst hazards. According to the identification of the General Coal Research Institute, the lower part of 3# coal has a weak burst-prone characteristic, and the upper part of 3# coal has a strong burst-prone characteristic. The layout plan of the mining area for working face 1,304 is shown in Figure 1.

In addition, the pore structure of coal samples was characterized using the non-destructive nuclear magnetic resonance system. The magnetic field intensity of the test system is 0.3 ± 0.05 t, the operating temperature is 32°C, and the frequency range is 2–30 MHz. The porosity of three typical coal samples is 8.89%, 8.31%, and 8.94%, with an average porosity of 8.71%. The T_2 spectra of typical coal samples are shown in Figure 2.

2.2 Numerical modeling

FLAC^{3D} is used to study the energy evolution and abutment pressure of island working faces under the condition of three-sided mining (Wu and Wong, 2012). Based on the energy principle, the distribution of elastic strain energy for coal-rock mass compiled using Fish language in ASD reveals the evolution of the elastic strain energy in front of the coal wall under different advancing steps. The numerical calculation model is established according to the geological conditions of the 1,304 island working face in the Yangcheng Coal Mine. The detailed geometry of the constructed model is shown in Figure 3.

The size of the model is 540 m × 300 m × 232 m (length × wide × height), which consists of 432,000 zones and 451,369 grid points in total. The coal-rock mass is assumed as the elastoplastic material, and the Mohr–Coulomb criterion is adopted. The boundary conditions are horizontal constraints in the x- and y-directions; vertical constraints at the bottom, free boundaries at the top, and equivalent loads ($q = \gamma h$) in the vertical direction are applied at the top boundary of the model to simulate the self-weight of the overlying strata. γ is the average unit weight of the overlying strata of the model, taken as 24 kN/m^3. h is the average distance from the upper part of the model to the surface, taken as 650 m. Thus, the equivalent load can be obtained as 15.3 MPa. The null zone is used to simulate the excavation of two working faces 1,303 and 1,305, which are equivalent to the goaf of working face 1,304. Furthermore, to account for the influence of the boundary effect, 50-m-wide coal pillars are reserved at the boundary along the x-direction, 30-m-wide coal pillars at the boundary along the y-direction, and 5-m-wide roadway protection coal pillars at the sides of the transport drift.

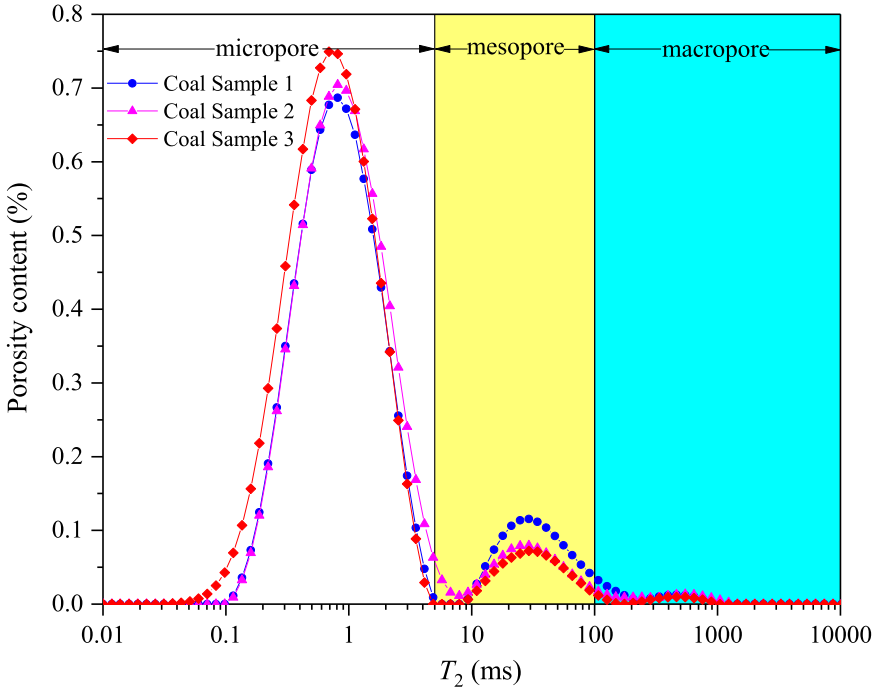

FIGURE 2
T_2 distribution of typical coal samples.

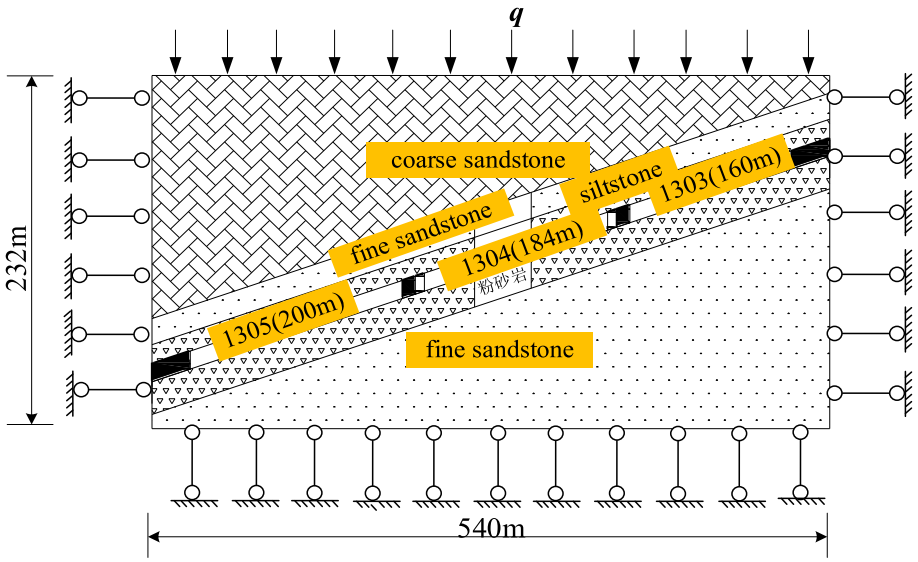

FIGURE 3
Model geometry.

2.3 Physical and mechanical parameters

The mechanical parameters of the coal-rock mass layer in the model are determined according to the actual rock mechanical properties of the Yangcheng Mine, as listed in Table 1. It should be noted that E_b represents the bulk modulus, ρ represents the density, T represents the thickness, E_s represents the shear modulus, c represents the cohesion, σ_t represents the tensile strength, and φ represents the internal friction angle.

According to the mechanical characteristics of the coal-rock mass, the coal-rock mass will be damaged in different forms when the load borne by the coal-rock mass is greater than its ultimate strength and will maintain a certain residual strength after plastic deformation and failure. Therefore, the Mohr–Coulomb criterion is

TABLE 1 Physical and mechanical parameters of coal-rock mass.

Rock stratum	Lithology	T (m)	ρ (kg/m^3)	E_b (GPa)	E_s (GPa)	c (MPa)	σ_t (MPa)	φ (º)
Roof	Coarse sandstone	10	2,500	24	14	10.3	8.9	37
	Medium-fine sandstone	14	2,600	20	11	8.3	4.9	37
	Siltstone	10	2,630	15.6	10.8	7.2	5.0	44
Coal seam	3# Coal	7.5	1,370	2.9	1.65	3.5	1.9	30
Floor	Siltstone	4	2,500	15.6	10.8	7.2	5.0	44
	Fine sandstone	14	2,570	23	12	7.5	2.2	32

utilized in this study. The modified Mohr–Coulomb model strength criterion is as follows:

$$\begin{cases} f_s = \sigma_1 - \sigma_3 \dfrac{1+\sin\varphi}{1-\sin\varphi} + 2c\sqrt{\dfrac{1+\sin\varphi}{1-\sin\varphi}} \\ f_t = \sigma_t - \sigma_3 \end{cases}, \quad (1)$$

where σ_1 is the maximum principal stress, σ_3 is the minimum principal stress, c is the cohesion, and φ is the internal friction angle. From Equation 1, when $f_s > 0$, the coal-rock mass is damaged due to shear failure, and when $f_s < 0$, the coal-rock mass is damaged due to the tensile failure.

3 Numerical results

To study the distribution of the abutment pressure of the working face under different advancing steps, the monitoring points are arranged at three positions along the advancing direction of the working face, namely, the side of the transportation drift, the side of the return air drift, and the middle of the working face.

Based on the energy principle, the elastic strain energy density of coal-rock mass compiled by Fish language presented in FLAC^{3D} is used to study the space–time distribution of elastic strain energy density in coal-rock mass in the stope under different advancing steps. The characteristics of strain energy are adopted to reveal the dynamic response in the mining process of the working face. By setting up coal pillars with different widths, the distribution of the inner abutment pressure and the residual elastic strain energy in the coal pillars under different coal pillar widths is obtained. The instability failure of the coal pillars in the isolated working face can be revealed. After the simulated calculation is completed, the values of the monitoring points are exported. The data processing software applications are used to obtain the distribution of the abutment pressure and elastic strain energy in front of the coal wall. The results are analyzed to obtain the cloud nephogram of the abutment pressure and the elastic strain energy in front of the coal wall. Finally, the stress distribution and the evolution of energy accumulation are quantitatively obtained.

3.1 Abutment pressure of the isolated working face

3.1.1 Influence of the excavation step on abutment pressure

This section discusses the impact of different excavation steps on the hazard risk of an isolated working face by obtaining the distribution of abutment pressure in front of the isolated working face under seven excavation steps, namely, 30, 60, 90, 120, 150, 180, and 210 m. According to the built-in data output and post-processing functions, the stress of each unit of coal-rock strata is derived. Figure 4 shows the bearing abutment distribution in front of the coal wall of the isolated working face. It should be noted that the stress concentration coefficient is the ratio of the maximum stress to the average stress.

Figure 4 shows that the abutment pressure in front of the coal wall of the working face increases to the peak stress in a positive exponential relationship at first and then gradually decreases to the original rock stress in a negative exponential relationship, showing an upward convex trend. With the increase in the advancing step, the peak abutment pressure in front of the working face gradually increases, and the peak stress appears at 8~10 m in front of the working face. With the increase in the advancing step, the concentration coefficient of peak stress gradually increases, and the influence range of the abutment pressure of the working face gradually increases. When the working face advances 30 m, the peak abutment pressure in front of the coal wall of the working face is 36.7 MPa, and the stress concentration coefficient is 2.45. When the working face is advanced by 90 m, the peak abutment pressure in front of the working face is 49.5 MPa, and the stress concentration coefficient is 3.3. The hazard risk is relatively high when the working face is advanced by 30 m. When the advancing distance of the working face is advanced by 150 m, the peak abutment pressure in front of the working face is 58.5 MPa, and the stress concentration coefficient is 3.9. When the working face is advanced by 180 m, the peak abutment pressure in front of the working face is 63.3 MPa, and the stress concentration coefficient is 4.22. The stress concentration is relatively high when the working face is advanced by 90 m, and the hazard risk is correspondingly increased. When the advancing distance of the working face is advanced by 210 m, the peak abutment pressure in front of the coal wall is 69.8 MPa, and the stress concentration coefficient is 4.65. It can be further inferred

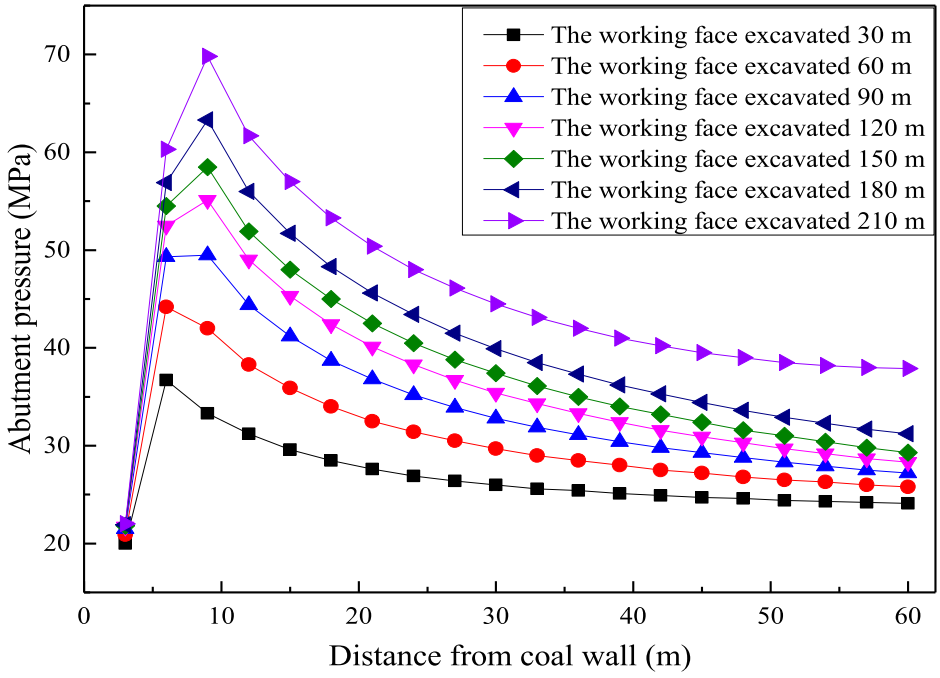

FIGURE 4
Abutment pressure distribution of the working face in different advancing steps.

that with the continuous advancement of the working face, the stress gradient in front of the working face gradually increases. The stress concentration coefficient exceeds the critical value of the hazard risk, indicating that the hazard risk in the working face gradually increases.

3.1.2 Influence of buried depths on abutment pressure

In this section, we discusses the influence of different coal seam depths on the impact risk of isolated working faces by studying the distribution of the abutment pressure in front of the isolated working faces under three buried depths, namely, 400, 600, and 1,000 m.

The distribution of the abutment pressure in front of the island working face under different buried depths is shown in Figure 5. Figure 5 shows that the peak abutment pressure is 42 MPa when the buried depth of the coal seam is 400 m. The concentration coefficient is 4.2. The position of peak stress is 6 m away from the working face. When the buried depth of the coal seam is 600 m, the peak abutment pressure in front of the working face is 52.5 MPa. The concentration coefficient of peak stress is 3.5. The peak stress position is 8 m away from the coal wall of the working face. When the buried depth is 1,000 m, the peak abutment pressure in front of the working face is 84.6 MPa. The concentration coefficient of peak stress is 3.38. The position is 10 m away from the working face. Compared with the different buried depths of the coal seam, the peak abutment pressure in front of the coal wall gradually shifts to the deep part of the coal seam. With the increase in the buried depth, the abutment pressure in front of the coal wall increases first and then decreases. The underlying physical mechanisms of this phenomenon are multifaceted and involve the interaction of various factors. With the increase in the buried depth, the self-weight stress transmitted by overlying strata is intensified, which causes the abutment pressure of working face to increase primarily. This phenomenon manifests itself in a more pronounced stress concentration as the coal-rock is subjected to enhanced compression. In addition, the mechanical properties of coal-rock change with the increase in buried depth. At deeper depths, the evolution of peak stress may migrate deeper into the coal seam, thus reducing the peak stress near the coal wall. In addition, as the depth of burial increases, the overlying rock tends to be rigid, thus storing more elastic energy, which leads to an increase in stress intensity. However, after a certain critical depth, the plasticity of coal-rock mass increases, the ability of rock strata to transfer stress weakens, and eventually, the peak stress decreases.

3.2 Elastic strain energy of the isolated working face

3.2.1 Elastic strain energy density

According to the principle of strain energy density of the elastomer under a three-dimensional stress state derived in elasticity,

$$U = \frac{1}{2}\left(\sigma_x\varepsilon_x + \sigma_y\varepsilon_y + \sigma_z\varepsilon_z + \tau_{yz}\gamma_{yz} + \tau_{zx}\gamma_{zx} + \tau_{xy}\gamma_{xy}\right), \quad (2)$$

where U is the strain energy density of the elastomer, kJ/m^3; σ_y, σ_z, τ_{yz}, τ_{zx}, and τ_{xy} present six stress components at any point in the elastomer; and ε_x, ε_y, ε_z, γ_{yz}, γ_{zx}, and γ_{xy} present six strain components at any point in the elastomer.

The elastic body is regarded as an isotropic body. According to the generalized Hooke's law, the relationship between stress and

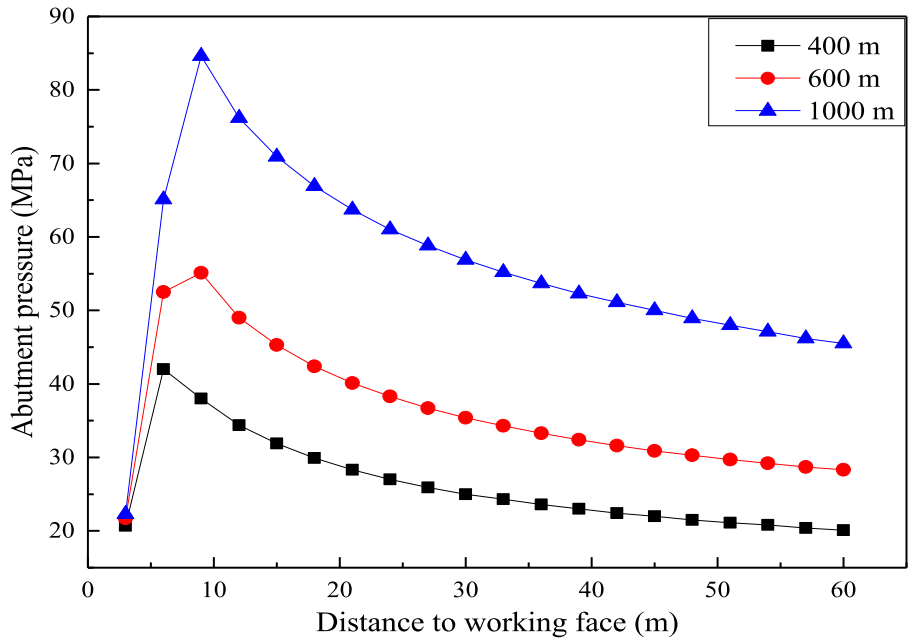

FIGURE 5
Abutment pressure distribution of the front wall with various buried depths.

strain at any point in the elastic body is

$$\begin{cases} \varepsilon_x = \frac{1}{E}\left[\sigma_x - \mu\left(\sigma_y + \sigma_z\right)\right], \gamma_{yz} = \frac{1}{G}\tau_{yz} \\ \varepsilon_y = \frac{1}{E}\left[\sigma_y - \mu\left(\sigma_z + \sigma_x\right)\right], \gamma_{zx} = \frac{1}{G}\tau_{zx} \\ \varepsilon_z = \frac{1}{E}\left[\sigma_z - \mu\left(\sigma_x + \sigma_y\right)\right], \gamma_{xy} = \frac{1}{G}\tau_{xy} \end{cases}, \quad (3)$$

where E is the modulus of elasticity, μ is the lateral pressure coefficient, and G is the shear modulus.

There is a relationship among E, μ, and G:

$$G = \frac{E}{2(1+\mu)}. \quad (4)$$

Substituting Equations 3, 4 into Equation 2, the strain energy density expressed by the stress component is

$$U = \frac{\left(\sigma_x + \sigma_y + \sigma_z\right)^2 - 2(1+\mu)\left(\sigma_y\sigma_z + \sigma_z\sigma_x + \sigma_x\sigma_y - \tau_{yz}^2 - \tau_{zx}^2 - \tau_{xy}^2\right)}{2E}. \quad (5)$$

From Equation 5, it can be found that the strain energy of the roof rock under the three-dimensional stress state is in a quadratic relationship with its internal stress, that is, the higher the stress on the coal-rock in front of the coal wall, the greater the accumulated elastic strain energy.

3.2.2 Influence of the excavation step on elastic strain energy

Based on the built-in data output and post-processing functions of FLAC^{3D}, six stress components of each unit of coal and rock strata in the middle of the working face are derived, and the elastic strain energy distribution of coal-rock strata along the advancing direction is calculated by substituting Equation 7, as shown in Figure 6.

Figure 6 shows that the peak strain energy gradually increases. The peak elastic strain energy is located 8 m in front of the coal wall of the working face with increasing excavation steps. With the increase in the advancing distance of the working face, the elastic strain energy in front of the working face increases. The hazard risk in front of the working face increases accordingly. When the excavation step is 30 m, the peak strain energy is 136.43 kJ/m^3. The roof rock layer of the working face is subject to large bending deformation, which causes elastic energy accumulation in the coal layer. Compared with the advancing distance of 30 m, the elastic strain energy in front of the coal wall of the working face increases slightly under the condition of the working face of 60 m. The peak strain energy density is 198.9 kJ/m^3, and the peak strain energy also appears 8 m in front of the coal wall. When the working face is advanced by 90 m, the elastic strain energy in front of the working face continues to increase. The peak strain energy density is 248.27 kJ/m^3. When the working face is advanced by 120 m, the peak elastic strain energy in front of the working face is 302.19 kJ/m^3, which is significantly higher than that of 90 m. When the advancing distance of the working face is 150 m, the peak strain energy in front of the working face is 341.79 kJ/m^3. When the excavation step is 180 m, the elastic strain energy density reaches 400.5 kJ/m^3. When the working face is advanced by 210 m, the peak elastic strain energy reaches 485.65 kJ/m^3.

In the process of underground coal mining, the forward movement of the working face will cause a change in the stress distribution in the front and adjacent areas of the coal seam, which has a significant impact on the coal pillar. These pillars absorb most of the stress transmitted by the overlying rock, resulting in a large expansion of the stress concentration area. This expansion is accompanied by a sharp increase in the elastic energy density within these regions. In addition, the advance of the working face disrupts

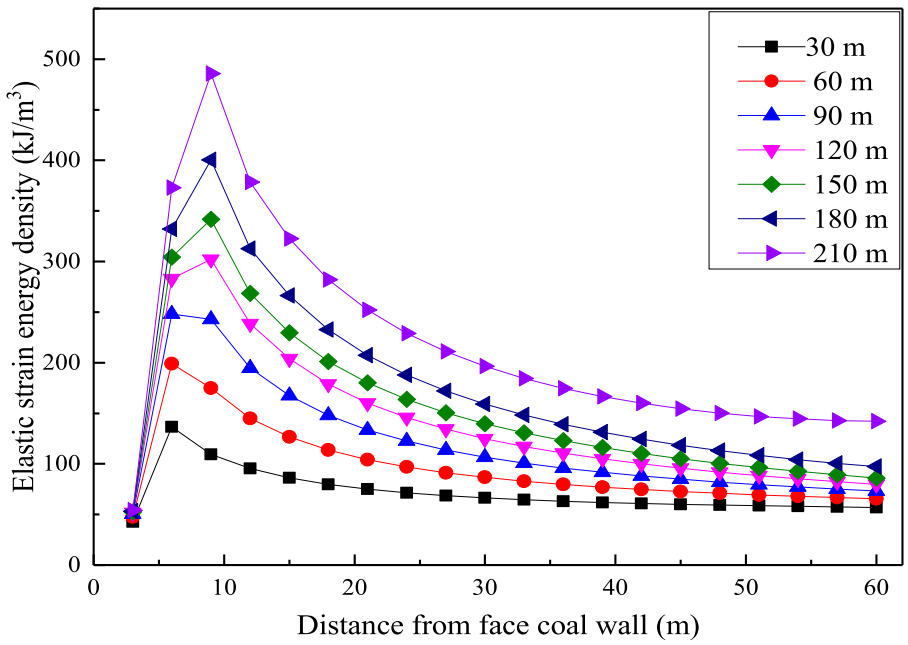

FIGURE 6
Elastic strain energy distribution curve of the working face in the direction of face advance.

the initial stress balance, resulting in the elastic deformation of rock strata and coal seams. This deformation is physically manifested as an accumulation of energy or a significant increase in elastic energy density. With the increase in the mining step, the deformation of the coal seam and surrounding rock is more obvious, the stress adjustment speed is faster, and more elastic energy is accumulated. Therefore, with the advance of the working face and the increase in the mining step, the elastic energy density in the unexcavated coal seam in front also increases due to the continuous stress transfer process.

The relationship between the peak of strain energy density in front of the coal wall and the excavation step is fitted, as shown in Figure 7, and the fitting formula is obtained:

$$y = 0.44953 + 1.91453^{*} exp(0.00396^{*}x). \quad (6)$$

From Equation 6, it can be found that the correlation coefficient R^2 is 0.9704. With the increase in the excavation step, the peak elastic strain energy in front of the working face gradually increases, and the impact hazard of the working face also gradually increases.

3.2.3 Influence of burial depths on elastic strain energy

To reveal the influence of the burial depth on the strain energy of coal wall, this section takes a mining height of the coal seam of 7.5 m as the fixed value and the buried depth of the coal seam as the variable to investigate the evolution of elastic strain energy in front of the isolated working face under the three buried depths of 400, 600, and 1,000 m.

Based on the built-in data output and post-processing function of FLAC^{3D}, the distribution curve of elastic strain energy density in front of the working face at different buried depths is calculated by deriving six stress components of each unit of the coal rock strata under three cases of 400, 600, and 1,000 m, and substituting them into Equation 5, as shown in Figure 8. It can be found that the peak elastic strain energy in front of the working face is 181.07 kJ/m^3 when the mining depth is 400 m. The peak elastic strain energy density is 6 m away from the coal wall of the working face. When the buried depth is 600 m, the peak elastic strain energy in front of the working face is 302.19 kJ/m^3. The distance between the peak strain energy is 9 m away from the coal wall of the working face. When the buried depth increases to 1,000 m, the peak elastic strain energy in front of the working face is 712.22 kJ/m^3. The peak elastic strain energy is 10 m away from the coal wall of the working face. Compared with the burial depths of 400 and 600 m, the peak elastic strain energy gradually shifts to the inner of the coal seam when the burial depth increases to a deeper depth.

4 Coal burst risk assessment

4.1 Impact risk assessment of the 1,304 working face

The 1,304 working face is an island working face, and the mine has potential impact risk. To obtain the hazard score coordinates of the region, we can substitute the reaction values of the working face on different items and categories, which are (0, 1, 0), (0, 1, 0), (0, 0, 1), (1, 0, 0), (0, 1, 0), (0, 0, 1, 0), and (0, 0, 1) into the discriminant score function. Subsequently, the distance from this point to the center coordinates of the four grades are 0.3159, 0.3165, and 0.3155 m. Finally, according to the shortest distance theory, the score coordinate of the evaluation area is close to the center coordinate listed in Table 2 (level 4). Therefore, the impact hazard

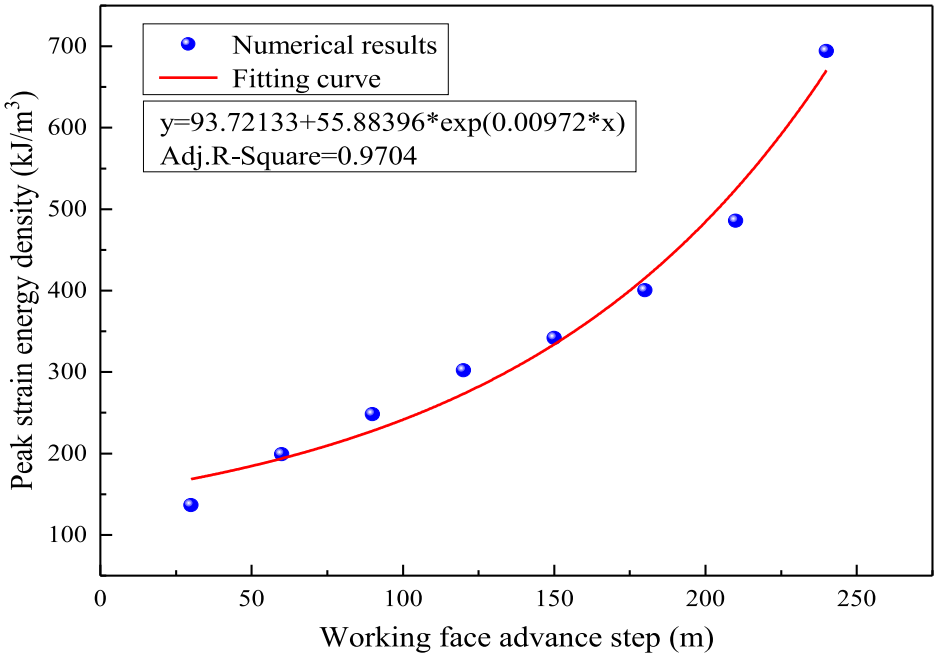

FIGURE 7
Fitting results of peak elastic strain energy density under different face advances.

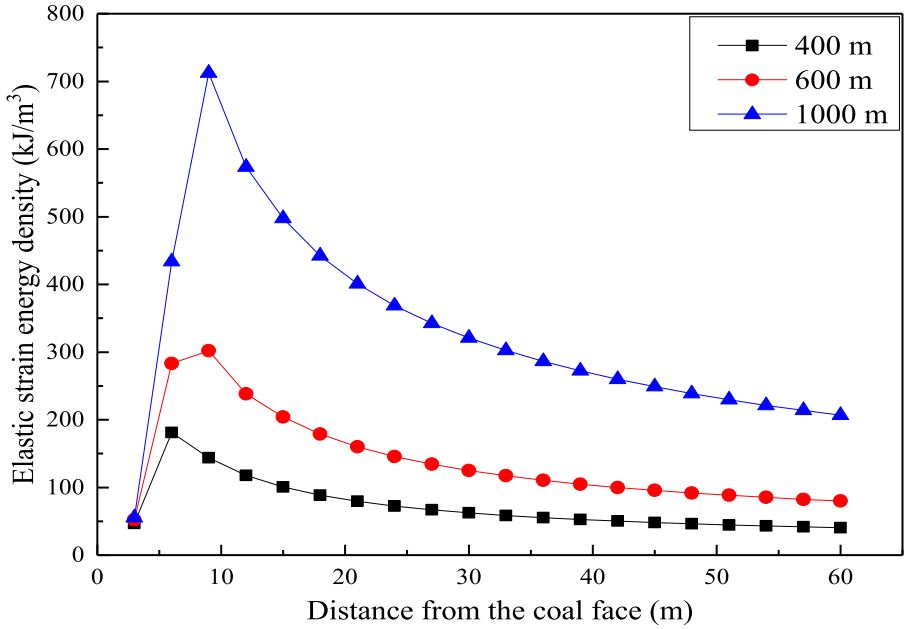

FIGURE 8
Elastic strain energy of the front wall under various mining depths.

level of the 1,304 island working face is 4; that is, it is a strong impact risk.

The coal burst of the working face is affected by numerous factors such as the physical and mechanical properties of coal-rock mass, geological overview, and mining technical conditions. In quantitative theory, qualitative variables are regarded as items. The various possible situations of items are regarded as categories. Based on the analysis of the factors affecting the induced coal burst, the risk evaluation model of mine coal burst is established by using the relevant theory. The risk of mine regional coal burst is evaluated by using the evaluation model. Based on the specific mining conditions and geological situation of the working face, this study divides the

TABLE 2 Items and categories of the evaluation model.

Project	Category	Project	Category
X_1: Coal seam impact tendency	C_{11}: Weak impact C_{12}: Medium impact C_{13}: Strong impact	X_5: Roof impact tendency	C_{51}: Weak impact C_{52}: Medium impact C_{53}: Strong impact
X_2: Dip angle of coal seam	C_{21}: Near horizontal coal seam C_{22}: Gently inclined coal seam C_{23}: Inclined coal seam	X_6: Horizontal tectonic stress	C_{61}: High-level renovation C_{62}: Medium-level renovation C_{63}: Low-level reconstruction
X_3: Coal seam thickness	C_{31}: Medium thickness C_{32}: Thick coal seam	X_7: Degree of stress accumulation	C_{71}: Low-level accumulation C_{72}: Moderate-level accumulation C_{73}: High-level accumulation
X_4: Buried depth of the coal seam	C_{41}: Less than 500 m C_{42}: 500–700 m C_{43}: Greater than 700 m		

coal burst risk degree of the island working face into four grades: 1, no coal burst risk; 2, weak shock hazard; 3, moderate shock hazard; and 4, strong shock hazard.

4.2 Quantitative theory modeling

In order to obtain modeling data, 60 modeling samples are determined from previous literature and engineering cases, that is, 16 level-1 samples ($n_1 = 16$), 16 level-2 samples ($n_2 = 16$), 16 level-3 samples ($n_3 = 16$), and 12 level-4 samples ($n_4 = 12$). It is specified that when a sample reacts on C_{jk} ($j = 1, 2, 7$; $k = 1, 2, 3$), the value is 1; otherwise, it is 0. According to the major influencing factors inducing the impact hazard of the isolated working face, seven evaluation items are given. In the process of establishing the impact risk assessment model of the isolated working face, the key geomechanical and geotechnical conditions related to the impact risk of the isolated working face are studied by carefully analyzing the selected parameters. The bursting tendency of the coal seam is determined by examining the coal quality type, hardness, and explosive ability of the coal seam, which directly affect the response of the coal seam to sudden pressure change. There is a significant correlation between the hardness of coal and its bursting. The direction of the coal seam affects the stress distribution and may lead to increased stress concentration in some areas, thus increasing the risk of the isolated face. The thickness of the coal seam is the decisive factor of stress release in the process of extraction. The thicker the coal seam, the greater the elastic energy, the greater the energy released in the process of mining, and the greater the possibility of impact risk in the isolated working face. The buried depth affects the ground pressure of the coal seam, and the deeper coal seam bears more ground pressure, which increases the possibility and severity of stress concentration, and is easy to be harmed by the impact of the isolated working face. In addition, geological discontinuities, such as roof conditions, play a crucial role in explaining stress transfer within coal seams. The coal seam with a complex structure or through multiple fracture zones has greater risk of stress concentration and coal seam explosion. In addition, the site stress conditions and cumulative stress levels are considered, which reflect the overall state of stress changes and stress accumulation caused by mining activities. Each project is divided into several categories, of which there are k categories in the j project. A total of 20 categories are listed in Table 2.

4.2.1 Modeling proposed

Using $\delta_{ti}(j,k)$ represents the reaction value of the ith sample in the tth hazard level on the jth item and the kth category. After $\delta_{ti}(j,k)$ is arranged in the original order, the reaction matrix is

$$X = \left(\delta_i^t(j,k)\right)_{60\times 20}. \tag{7}$$

According to the quantitative theory, the risk score model is

$$y_i^t = \sum_{j=1}^{7}\sum_{k=1}^{r_j} \delta_i^t(j,k) b_{jk}, \tag{8}$$

where y_i^t is the risk score of the ith sample of the tth risk level and b_{jk} is the undetermined constant, which is called the category score and recorded as

$$y = \left(y_1^1, y_2^1, \cdots, y_{16}^1, \cdots y_1^4, \cdots y_{12}^4\right)^T, \tag{9}$$

$$b = \left(b_{1,1}, b_{1,2}, \cdots b_{7,1}, b_{7,2}, b_{7,3}\right)^T. \tag{10}$$

Then, Substituting Equations 9, 10 into Equation 8, can be expressed as

$$y = Xb. \tag{11}$$

According to the Fisher principle, the problem of category score b in Equation 11 can be transformed into fnding the maximum characteristic root of its characteristic equation λ:

$$Cb = \lambda Db. \tag{12}$$

The corresponding equation satisfies the eigenvector:

$$b^T Db = 1. \tag{13}$$

Among Equations 12, 13,

$$C = \left(\overline{X} - \overline{\overline{X}}\right)^T \left(\overline{X} - \overline{\overline{X}}\right), \tag{14}$$

$$D = \left(X - \overline{\overline{X}}\right)^T \left(X - \overline{\overline{X}}\right). \tag{15}$$

Equations 14, 15 are the inter-group dispersion matrix and total dispersion matrix, respectively. Among Equations 16–19, Both $\overline{X} = \left(\left(\overline{\delta}^{t}(j,k)\right)\right)_{60\times20}$ and $\overline{\overline{X}} = \left(\left(\overline{\overline{\delta}}(j,k)\right)\right)_{60\times20}$ have the same dimension as X.

$$\overline{\overline{X}} = \begin{pmatrix} \overline{\overline{\delta}}(1,1)\cdots\overline{\overline{\delta}}(1,3)\overline{\overline{\delta}}(2,1)\cdots\overline{\overline{\delta}}(7,1)\cdots\overline{\overline{\delta}}(7,3) \\ \overline{\overline{\delta}}(1,1)\cdots\overline{\overline{\delta}}(1,3)\overline{\overline{\delta}}(2,1)\cdots\overline{\overline{\delta}}(7,1)\cdots\overline{\overline{\delta}}(7,3) \\ \cdots \\ \overline{\overline{\delta}}(1,1)\cdots\overline{\overline{\delta}}(1,3)\overline{\overline{\delta}}(2,1)\cdots\overline{\overline{\delta}}(7,1)\cdots\overline{\overline{\delta}}(7,3) \\ \overline{\overline{\delta}}(1,1)\cdots\overline{\overline{\delta}}(1,3)\overline{\overline{\delta}}(2,1)\cdots\overline{\overline{\delta}}(7,1)\cdots\overline{\overline{\delta}}(7,3) \end{pmatrix}_{60\times20}, \tag{16}$$

$$\overline{\delta}(j,k) = \frac{1}{n}\sum_{t=1}^{n_t}\delta_i^t(j,k), \tag{17}$$

$$\overline{\overline{\delta}}(j,k) = \frac{1}{60}\sum_{t=1}^{4}\sum_{i=1}^{n_1}\delta_i^t(j,k) = \frac{1}{60}\sum_{t=1}^{4} n_t\delta_i^t(j,k), \tag{18}$$

$$\overline{X} = \begin{pmatrix} \overline{\delta}^{(1)}(1,1)\cdots\overline{\delta}^{(1)}(1,3)\overline{\delta}^{(1)}(2,1)\cdots\overline{\delta}^{(1)}(7,1)\cdots\overline{\delta}^{(1)}(7,3) \\ \cdots \\ \overline{\delta}^{(1)}(1,1)\cdots\overline{\delta}^{(1)}(1,3)\overline{\delta}^{(1)}(2,1)\cdots\overline{\delta}^{(1)}(7,1)\cdots\overline{\delta}^{(1)}(7,3) \\ \overline{\delta}^{(2)}(1,1)\cdots\overline{\delta}^{(2)}(1,3)\overline{\delta}^{(2)}(2,1)\cdots\overline{\delta}^{(2)}(7,1)\cdots\overline{\delta}^{(2)}(7,3) \\ \cdots \\ \overline{\delta}^{(3)}(1,1)\cdots\overline{\delta}^{(3)}(1,3)\overline{\delta}^{(3)}(2,1)\cdots\overline{\delta}^{(3)}(7,1)\cdots\overline{\delta}^{(3)}(7,3) \\ \cdots \\ \overline{\delta}^{(4)}(1,1)\cdots\overline{\delta}^{(4)}(1,3)\overline{\delta}^{(4)}(2,1)\cdots\overline{\delta}^{(4)}(7,1)\cdots\overline{\delta}^{(4)}(7,3) \\ \cdots \\ \overline{\delta}^{(4)}(1,1)\cdots\overline{\delta}^{(4)}(1,3)\overline{\delta}^{(4)}(2,1)\cdots\overline{\delta}^{(4)}(7,1)\cdots\overline{\delta}^{(4)}(7,3) \end{pmatrix}_{60\times20}. \tag{19}$$

As matrices C and D are singular matrices, we refer to the solution given by Dong (1979). The score vectors of three categories are calculated using MATLAB, and the corresponding characteristic roots are 1.10, 0.32, and 0.51, respectively.

$$\begin{aligned} y_1 = {} & -0.03C_{12} - 0.05C_{13} + 0.04C_{22} + 0.03C_{23} \\ & + 0.01C_{32} - 0.02C_{42} - 0.06C_{43} - 0.05C_{52} \\ & + 0.07C_{53} - 0.01C_{62} + 0.22C_{63} + 0.11C_{72} + 0.26C_{73}, \end{aligned} \tag{20}$$

$$\begin{aligned} y_1 = {} & 0.13C_{12} - 0.05C_{13} - 0.13C_{22} - 0.08C_{23} \\ & - 0.22C_{32} + 0.03C_{42} - 0.21C_{43} - 0.19C_{52} \\ & - 0.01C_{53} + 0.05C_{62} + 0.06C_{63} - 0.23C_{72} - 0.07C_{73}, \end{aligned} \tag{21}$$

$$\begin{aligned} y_1 = {} & -0.05C_{12} - 0.06C_{13} + 0.17C_{22} - 0.03C_{23} \\ & + 0.01C_{32} - 0.12C_{42} - 0.20C_{43} - 0.13C_{52} \\ & + 0.06C_{53} - 0.01C_{62} + 0.06C_{63} - 0.05C_{72} - 0.17C_{73}. \end{aligned} \tag{22}$$

The mean vector of the sample response of the tth risk level is recorded as

$$\left(\overline{\delta}^{(t)}(1,1),\cdots\overline{\delta}^{(t)}(1,3),\overline{\delta}^{(t)}(2,1),\cdots\overline{\delta}^{(t)}(7,1),\cdots\overline{\delta}^{(t)}(7,3)\right)^T. \tag{23}$$

The discriminant function is obtained by substituting it into Equations 20–23, and three scores are obtained, denoted as $y_1^{(t)}, y_2^{(t)}, y_3^{(t)}$ and recorded as

$$V^{(t)} = \left(y_1^{(t)}, y_2^{(t)}, y_3^{(t)}\right)^T. \tag{24}$$

V(t) is the central coordinate of the sample score of the tth hazard level, and the central coordinates of the four levels are obtained from Equation 24, as listed in Table 3.

The evaluation standard is based on the principle of minimum distance. Taking 3D analysis as an example, a certain place in the mine is considered, its response value δ (j,k) on various items is investigated and brought into the discriminant function, and three scores, namely, y_1, y_2, and y_3, are obtained, recorded as $V = (y_1, y_2, y_3)^T$. In l dimensional Euclidean space, the distance from inspection point v to each central coordinate X. If $\left\|V - V^{(t_0)}\right\| = \min_t \left\|V - V^{(t)}\right\|$, then the impact grade here is $\| V - V^{(t_0)} \| = \min \| V - V^{(t)} \|$.

TABLE 3 Center coordinates of different levels.

Level	Central coordinates
1	(−0.04, −0.27, −0.18)
2	(0.00, −0.40, −0.03)
3	(0.11, −0.41, −0.27)
4	(0.24, −0.27, −0.13)

TABLE 4 Hazard risk evaluation of the 1,304 island working face.

Level		Error magnitude		
		One-dimensional	Two-dimensional	Three-dimensional
1	16	2	1	2
2	16	1	2	1
3	16	2	2	1
4	12	2	1	1
Accuracy		88%	90%	91.7%

4.2.2 Modeling verification

The model has three scoring functions, so one-dimensional, two-dimensional, and three-dimensional evaluation methods can be used to train the model. The test results of the one-dimensional evaluation analysis are only the first score function and the first component of (V_1–V_4); the two-dimensional evaluation analysis using the first two score functions and the first two components of (V_1–V_4) and the three-dimensional evaluation analysis are listed in Table 4.

Table 4 shows that compared with the 1D and 2D evaluation results, the accuracy obtained using the 3D analysis method is higher, and the corresponding evaluation effect is relatively ideal. Therefore, the 1D and 2D analysis results are ignored. Finally, the 3D evaluation results are taken as the analysis method of hazard risk evaluation of 1,304 island working face in this study.

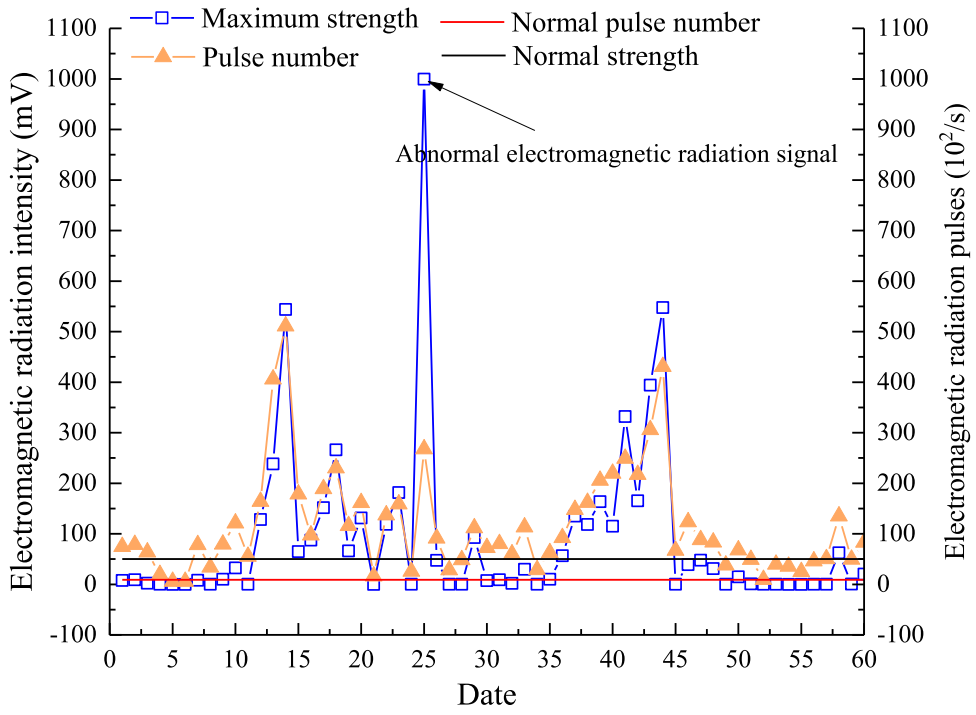

FIGURE 9
Evolution of the electromagnetic radiation signal at an advance of 30 m of the working face (Wang et al., 2014).

4.3 Analysis of electromagnetic radiation of 1,304 working face

It is well known that electromagnetic radiation from coal-rock is a phenomenon where electromagnetic energy is emitted outward during the deformation and fracture of coal-rock under load. The occurrence of a rock burst is the process of mass energy release when the strength limit of the coal-rock mass is reached after the process of energy accumulation. Figure 9 shows the evolution of electromagnetic radiation information in the advanced roadway in front of the coal wall of the working face. It is important to note that the horizontal axis dates in Figure 9 range from 1 August 2012 to 30 September 2012. As observed in Figure 9, the electromagnetic radiation intensity and pulse number of the coal body fluctuated around the normal value during August 1–August 8 and August 27–September 4, indicating that the internal stress level of the coal body was normal during these two periods. From August 9 to August 14 and from September 5 to September 12, the electromagnetic radiation intensity and pulse number of coal continued to increase significantly, with the amplitude of increase reaching or even exceeding about 10 times the normal value, suggesting a sharp increase in stress during these periods. The higher stress levels led to intensified internal fracturing and friction within coal, resulting in stronger electromagnetic radiation signals. On August 25, an abnormal electromagnetic radiation signal with a pulse number of up to 1×10^5 was recorded, which was analyzed as an electromagnetic field interference signal. Before the "8.14 event" and "9.12 event," the electromagnetic radiation intensity and pulse number of the coal body had been continuously increasing. It can be concluded that there is usually a period of continuous increase in the internal stress of the coal body before a rock burst occurs, and it is the continuous and sharp increase in the internal stress of the coal body that triggers the rock burst event.

Based on the above analysis, it was found that the silent period of micro-seismic events, the continuously increasing period of electromagnetic radiation intensity of the coal body, and the continuously increasing period of the electromagnetic radiation pulse number of the coal body are the precursor information of rock burst. These precursor information are converted into early-warning parameters of rock burst, and a multi-parameter early-warning method of rock burst precursor information needs to be proposed. Therefore, when the working face is judged to be at risk of rock burst, the drilling cutting method is used to identify the localized areas at risk of rock burst. Subsequently, pressure relief measures such as blasting, coal seam water injection, and drilling pressure-relieving holes are used to decompress and mitigate the risk in the coal seam until the danger of rock burst is eliminated.

5 Conclusion

(1) With the increase in the advancing step, the abutment pressure and elastic strain energy density in front of the working face increase to the maximum in a positive exponential relationship at first and then decrease due to *in situ* stress, which presents

an upward convex trend. The influence range of the abutment pressure of the working face gradually increases.

(2) With the increase in coal thickness and burial depth, the peak abutment pressure and elastic strain energy density in front of the coal wall gradually increase. The position of occurrence gradually moves away from the coal wall. The concentration coefficient of peak strength gradually increases, indicating that the deeper the coal seam is, the greater the possibility of coal burst.

(3) Based on the quantitative theory and the minimum distance principle, the impact risk assessment model of isolated working faces is established. Compared with the evaluation results of one-dimensional and two-dimensional analyses, the accuracy of the three-dimensional analysis method is relatively higher, indicating that the accuracy of the evaluation effect is higher.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

GL: methodology and writing–original draft. RL: funding acquisition and writing–review and editing. LH: software, visualization, and writing–original draft. ML: data curation, formal analysis, and writing–original draft. JZ: data curation, formal analysis, and writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Failure mechanism and dynamic process of landslide triggered debris flows—an example from Chongqing, China

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Shallow landslides and debris flows triggered by heavy rainfall are widespread catastrophic geological disasters in mountainous areas. Landslides with complex terrain are often the material source of debris flows as a disaster chain. However, the failure mechanism and dynamic process of landslide triggered debris flow are still not clear. In July 2023, an obvious rockslide occurred during heavy rainfall in Changtan Town, Chongqing City, Southwest China, resulting in one death and seven houses collapsed. In this paper, back analysis in the dynamic process of the Yanghuachi (YHC) landslide triggered debris flow is carried out by the coupled particle flow model and elastic viscoplastic model. The reults indicate that the sliding body moves downward along the sliding surface, pushing the loose deposits at the lower part of the landslide to slip and then extending along the gully to the right bank of the Modao River. The overall movement duration of the landslide in the study area is approximately 180 s, with a maximum sliding velocity of about 22.08 m/s and a final deposition thickness of approximately 10.91 m. This study provides a methodology for analyzing the dynamic process of landslide triggered debris flows.

KEYWORDS

landslide triggered debris flow, particle flow, elasto-viscoplastic, failure mechanism, dynamic process

1 Introduction

In recent years, geological disasters such as collapse and landslide have occurred on the bedding or near bedding rock mass in areas like high mountain areas, geologically active zones, river valleys, and canyons, particularly under the influence of heavy rainfall (Cheng et al., 2023; Chen et al., 2023; Yang et al., 2023; Wei et al., 2024; Ye et al., 2024; Liu et al., 2024). When a landslide destabilizes the rock and soil mass, it drives a large amount of debris, soil and rock, forming a highly concentrated and fluid debris flow (Ortiz-Giraldo et al., 2023). This fluid moves rapidly down the hillside with high speed and strong erosive force, eroding and destroying obstacles in its path, including buildings, roads and vegetation, and potentially causing numerous casualties, thereby significantly increasing the disaster's impact. (Hungr et al., 2001; Chen et al., 2006). Recent typical landslide and debris flow disaster events in Table 1. These events all involve

TABLE 1 Typical landslide and debris flow events in the world.

Name	Time	Place	Disaster situation
Guishan landslide - debris flow Wang et al. (2003)	1999.6	Japan	Four people were killed and many houses were destroyed
Guinsaugon Landslide Catane et al. (2007)	2006.2.17	Philippines	Many villages were destroyed and 1,191 people were killed by flooding the paddy fields and schools in the alluvial fan
Mount Meager Landslide Guthrie et al. (2012)	2010.8.6	Canada	There were no casualties in the incident, but the direct cost was approximately $ 10 million
Kedarnath Landslide Champati Ray et al. (2016)	2013.6.16	India	Thousands of people were killed and buildings were destroyed, causing serious damage to the pilgrimage area
(Wulipo landslide) Gao et al. (2017)	2013.7.10	Sichuan, China	It caused 166 deaths and 11 buildings were buried or damaged
Dagou landslide Peng et al. (2015)	2013.7.22	Gansu, China	A total of 137 houses of 9 villagers were destroyed and buried, causing serious disasters
Shuicheng landslide Gao et al. (2020)	2019.7.23	Guizhou, China	21 houses were destroyed, 77 people were buried, 51 people were killed, and the volume of the sliding body was 70×10^4 m^3
Wangcang landslide Guo et al. (2021)	2020.8.14	Sichuan, China	The entire landslide volume is more than 10,000 cubic meters. The collapsed gravel buried the entire road, and the vehicle personnel were unable to pass. More than 20,000 people in the two townships along the line were blocked, resulting in three deaths and two houses destroyed

the transformation process from landslide triggered debris flow, which have resulted in significant loss of life and property.

This kind of debris flow is mostly caused by the instability of shallow landslide caused by heavy rainfall. These debris flow accumulate in the main channel to form channel debris flows (Igwe et al., 2015; Liu et al., 2021a; b, Qiu et al., 2024). It is an extremely fast flow-type landslide that often propagates long distances from its source in steep rivers (Arghya et al., 2022; Trujillo-Vela et al., 2022). The transformation of landslide triggered debris flow usually occurs suddenly, and the location is mostly located on the high slope. It is difficult to observe the whole movement process completely when the disaster occurs. Domestic and foreign scholars focus on the movement of landslide triggered debris flow, and the research methods are mainly physical model and numerical simulation (An et al., 2019; Ouyang et al., 2013).

Although the numerical simulation of simple debris flow is increasingly in-depth, the simulation research on the evolution of landslide triggered debris flow is still in the preliminary stage. The numerical simulation of debris flow mostly adopts a single numerical model. For example, Hungr and Evans (2004) and Scott and Hungr. (2004), McDougall, (2006) developed DAN3D software based on the equivalent fluid analysis theory of scraping rate, and successfully inverted the process of landslides such as Frank, Nomash River and Zymoetz River in Canada, which has become an efficient method for landslide dynamics analysis. Yin et al. (2016) used the SPH principle to reproduce the motion transformation process of landslide-debris flow disaster chain induced by artificial landfill. Chen et al. (2020) used Open LISEM software to simulate the initiation and flushing process of debris flow in Longxi River Basin of Dujiangyan City. It is concluded that long-term rainfall leads to the softening of loose accumulation of landslide, which eventually leads to the transformation of landslide damage to debris flow disaster. However, although these methods can simulate the long-distance propagation process of debris flow, it is difficult to effectively simulate the deformation of landslide and transform it into the dynamic conversion process of debris flow.

However, for high-level landslides, the instability movement will wrap the soil along the line to form a debris flow. It is difficult to effectively simulate the process of landslide instability, scraping the soil along the shovel, forming debris flow and long-distance propagation by using a single numerical simulation. At present, two numerical models are used to simulate the process of landslide movement and long-distance propagation of debris flow. For example, Hsu and Liu (2019) used a combination of TRIGRS and DEBRIS-2D models to simulate shallow landslides and subsequent debris flows caused by rainfall infiltration. Panpan et al. (2022) used the elastic-viscoplastic model and the particle flow model to invert the landslide barrier event in Guang 'an Village, Chongqing in 2017, and used the calibrated numerical model and parameters to predict the failure of the deformation zone III. Lee et al. (2023) used TiVaSS and Deb2D models to analyze the phenomenon of slope collapse and the signs of sliding during collapse, and effectively identified the deterioration effect of landslide-debris flow events on dam function. In the data, it is still found that the provenance in the study area is rich. If the landslide slides again, it will form a more serious secondary debris flow disaster, which will eventually affect the safety of residents on both sides of the gully.

In this paper, the Yanghuachi landslide is taken as the case study Based on the field investigation, the numerical simulation is used to back-analyze the movement process of the landslide into debris

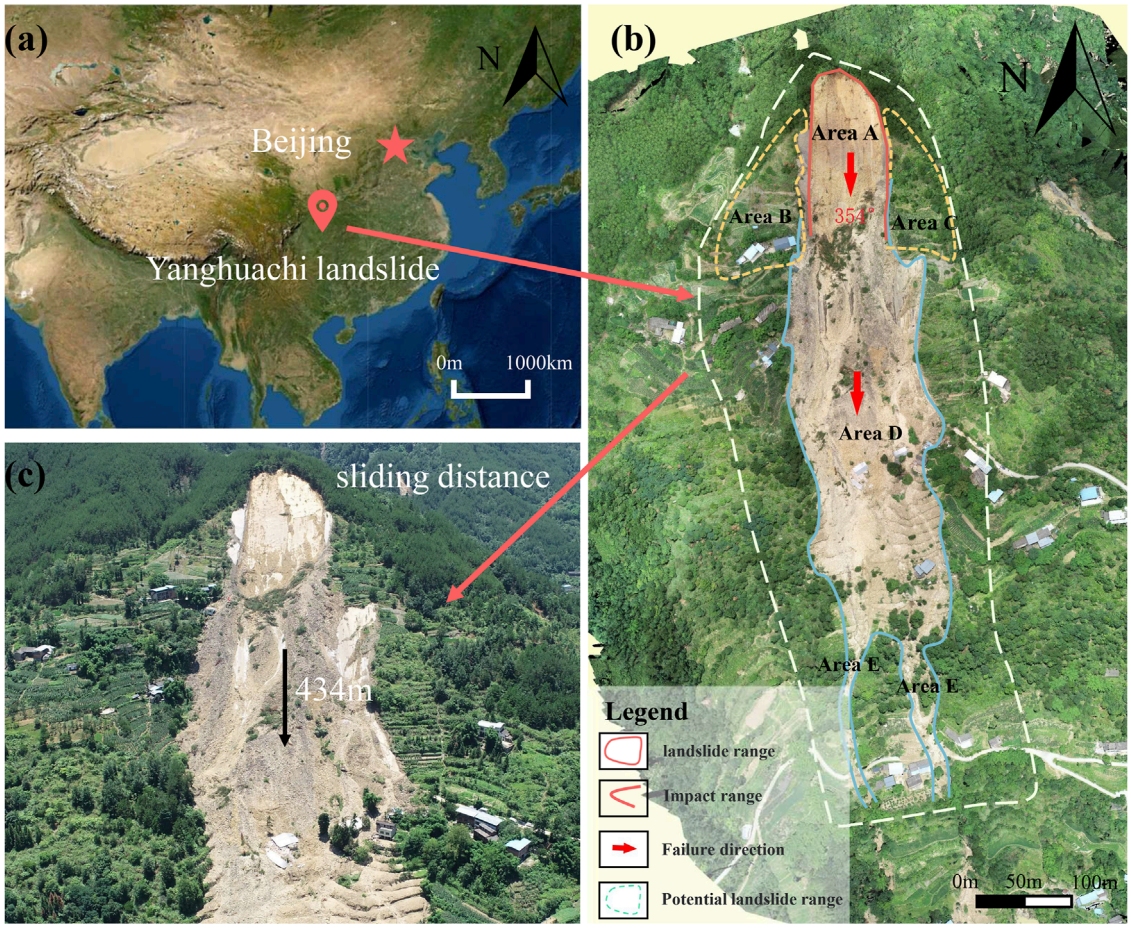

FIGURE 1
(A) landslide location map of the Yanghuachi landslide; **(B)** drone photo of the Yanghuachi landslide from top view; **(C)** The larger view of area A.

flow event. The dynamic characteristics are analyzed to obtain the movement speed and final accumulation state of the landslide at different times, and the movement process of the landslide triggered debris flow is revealed.

2 Geological and geomorphological setting

In July 2023, a series of geological disasters were triggered by a sudden torrential rain in Wanzhou District of Chongqing City. The most severe event among them was the Yanghuachi landslide, which resulted in the damage of seven houses, the loss of one life, and the burial of 200 m of village roads (Figure 1A). Affected by the heavy rainfall on July 4, the upper landslide body of Yanghuachi landslide slipped and then continuously loaded and hit the debris accumulation area on the slope. Following the disintegration of the deposit, it became obstructed at the forefront of the D area and then dispersed downward through the adjacent gullies on both sides. As it moved, the material interacted with rainwater, triggering secondary debris flow disasters.

The terrain of Yanghuachi landslide is steep, and the lithology is mainly shale. The surface layer is Quaternary Holocene artificial accumulation layer, colluvial layer and landslide accumulation layer, with a distribution thickness of 1–2 m. The sliding area is rectangular in shape, with dimensionos of 90 m in width and 180 m in length, totaling an area of about 1.62×10^4 m^2. The thickness ranges from 2 to 8 m, averaging around 5 m, with a volume of about 8.1×10^4 m^3. The sliding direction is 354°. Currently, the A area has slipped downward to produce scraping and accumulation extrusion, only some residual bodies exist in the local slope, and the volume of the residual body is about 0.8×10^4 m^3. The upper shale fragment is composed of silty clay (Q_4^{del}), while the lower part consists of sandy shale ($J_{1Zl\text{-}Sh}$). A muddy weak interlayer separates the shale layers (Figure 1B).

It is estimated that the total volume of the landslide is about 30.3×10^4 m^3. The upper section consists of rock mass, the middle section involves soil mass compressed by debris deposition, and the lower part involves debris flow. The landslide exhibits a generally 'tongue' shape (Figure 1C), extending in a north-south direction. The leading edge of the landslide ranges in elevation from 482–484 m, while the trailing edge stands at 720–728 m (Figure 2). The middle section is characterized by

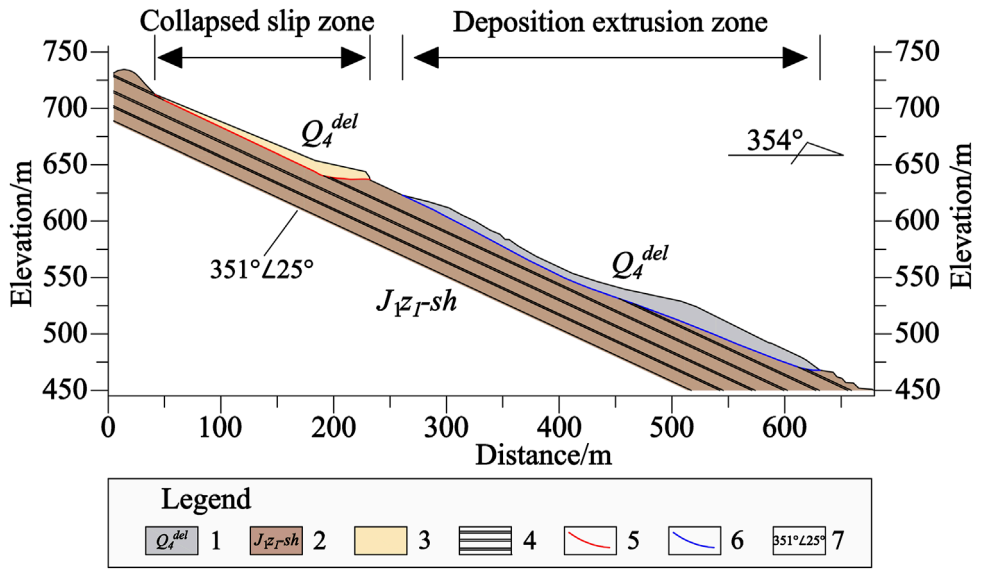

FIGURE 2
Engineering geological profile of Yanghuachi landslide.

steps and slopes, covered with a significant amount of soil. The western upper part is bounded by the scar, while the lower section is enclosed by landslide accumulation and gullies. The landslide is segmented into five areas: collapsed area A, potential slump areas B and C, debris deposition area D, and debris transport area E.

3 The landslide propagation

3.1 Characteristics of landslide movement

Based on the topography of the study area and the observed landslide deposits, the landslide into debris flow can be divided into three areas: source area, impact scraping area and tranportion and deposition area.

3.1.1 Source area

Landslide failure occurred at 5:00 a.m. on July 4. The Yanghuachi landslide is a medium-sized rock-soil mixed landslide, which is mainly caused by the infiltration of surface water into the steeply inclined cracks at the trailing edge, which reduces the physical and mechanical properties of the argillized weak interlayer between the layers, resulting in the slip of the upper shale body along the layer. The sliding direction of the sliding body is 354°, the distribution thickness is about 2–8 m, the rear edge rock mass is thin about 2–4 m, the front edge is thick about 6–8 m, the overall thickness is 2–8 m, and the average thickness is about 5 m. At present, the landslide has slipped downward to produce scraping and accumulation extrusion. Only part of the residual body exists in the slope, and the volume of the residual body is about 0.8×10^4 m^3. After the left trailing edge of the landslide collapses, it moves to the leading edge, and the occurrence of the rock stratum is curved and nearly horizontal (Figure 3).

3.1.2 Impact scraping area

The rock and soil mass on the lower steep slope of the slump area is scraped by the accumulation of the upper slump body. At the same time, it is affected by rainfall and diffuses downward to the upper part of the D area (Figure 1B). The surface material of the D area produces scraping, loading and pushing, so that the surface soil slope of the D area slips and forms a scraping area (Figure 4). The elevation of the rear part of the area is about 630 m, and the elevation of the front part is about 460 m. There are some residual materials in the rear edge. The debris accumulation in the D area is squeezed and destroyed in the front house, and the local accumulation is higher. The upper part of the landslide area is superimposed on the accumulation body on the original slope. The thickness of the lower debris accumulation area is about 1–7 m, the average thickness is about 5 m, and the volume is about 25.2×10^4 m^3.

3.1.3 Tranportion and deposition area

Due to the steep terrain, it slips along the slope to the original gully. Under the condition of a large number of water migration and topography, the kinetic energy is converted into potential energy, and the flow rate is faster. The loose deposits at the bottom of the original gully also enter the debris flow, and the gully is impacted to the existing accumulation area. The flow valley area is the area of Erguanyan, Yanghuachi and Changtanba. The elevation of the trailing edge is about 230 m, the elevation of the leading edge is about 460 m, the thickness of the accumulation is about 4–6 m, the average thickness is about 5 m, and the slope angle is 25°–48°. The gully is circular, the cutting depth is generally 2–3.5 m, and the width of the gully bottom is 1.2–3 m (Figure 5). In the range of the circulation area, the upper part of the valley is mainly exposed to the bedrock, and the lower part is the accumulation layer. There are a large number of accumulation blocks on both sides of the valley, and obvious debris flow

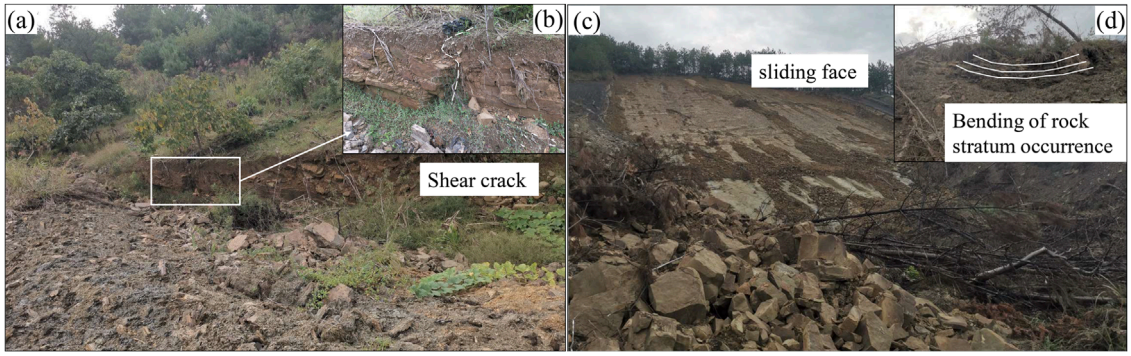

FIGURE 3
Photos of landslide source area [**(A)** shear joint between the right side wall of potential slip zone **(B)** and zone **(A)**; **(B)**. shear joint; **(C)**. landslide wall in the collapsed slip zone; **(D)**. the occurrence of rock strata in the left trailing edge is curved and nearly horizontal].

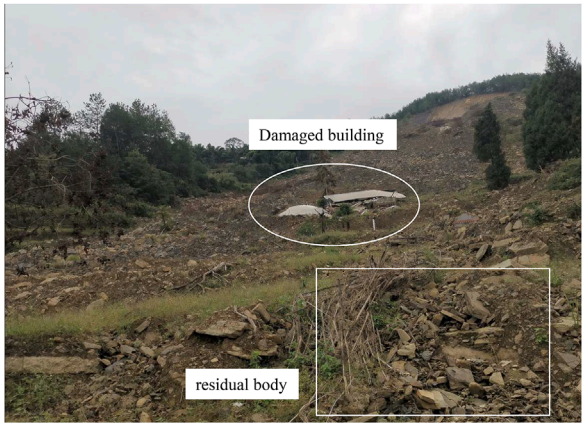

FIGURE 4
The whole picture of landslide impact scraping area.

impact traces such as scratches can be seen at the bottom of the valley.

These three regions jointly reveal the whole development process of landslide-type debris flow. From the initial source area of the landslide, after impact and scraping, the debris flow is finally formed and deposits are formed downstream.

3.2 Deformation and failure mechanism of landslide

The Yanghuachi landslide is stepped, the front edge is a steep slope, the middle has a wide platform, and the rear edge is steep. The gullies on both sides of the landslide are the boundary of the landslide, and the free front of the landslide provides sufficient topographic and geomorphic conditions for the formation of the landslide.

The Yanghuachi landslide is a bedding rock landslide. The slope is mainly composed of shale, and there is a argillized weak interlayer between the shale layers. Under the long-term extrusion of the trailing edge slope, the leading edge slope deforms and the rock mass is free, which provides conditions for the instability and failure of the landslide. During the heavy rainfall on July 22, because the middle and rear slope of the landslide is a multi-stage platform and residential area that has been artificially transformed, the middle and rear roads, housing construction and slope retaining walls of the landslide are placed in the soil layer, which is equivalent to loading on the landslide body, aggravating the deformation and failure of the landslide and unfavorable for rainwater discharge.

Rainwater infiltrates along the cracks at the trailing edge of the slope, but the underlying bedrock of the slope is shale, which is an impermeable layer, which increases the weight of the landslide, softens the weak interlayer between the layers, and reduces the shear strength of the muddy interlayer. Under the combined influence of factors and external factors, the sliding force of the slope is increased, the anti-sliding force is reduced, and the slope is destabilized.

Based on the field investigation, the landslide area was preliminarily divided according to the accumulation characteristics and the event was restored: under long-term rainfall, the strength of the structural plane in the sliding source area decreased and the sliding was unstable, and the landslide body impacted the debris accumulation body at the lower part of the scraper. The sliding source area is mainly composed of shale, the bedding is very developed, and the accumulation body is basically disintegrated under the action of impact scraping. After that, the two are mixed and moved in the direction of 354°, which destroyed several houses. Because the original terrain is a flat platform, some sliding bodies have accumulated. From the on-site accumulation, it is shown that the disintegration of the sliding body in the source area is very sufficient. The terrain drops sharply in front of the platform, and part of the sliding bodies continue to move and scrape the soil on both sides of sides. In this process, the clay minerals in the debris flow continue to increase and move along the main gully, the rainfall in the whole basin continues to converge, and the water content of the mixture continues to increase, which leads to the transformation of the landslide triggered debris flow.

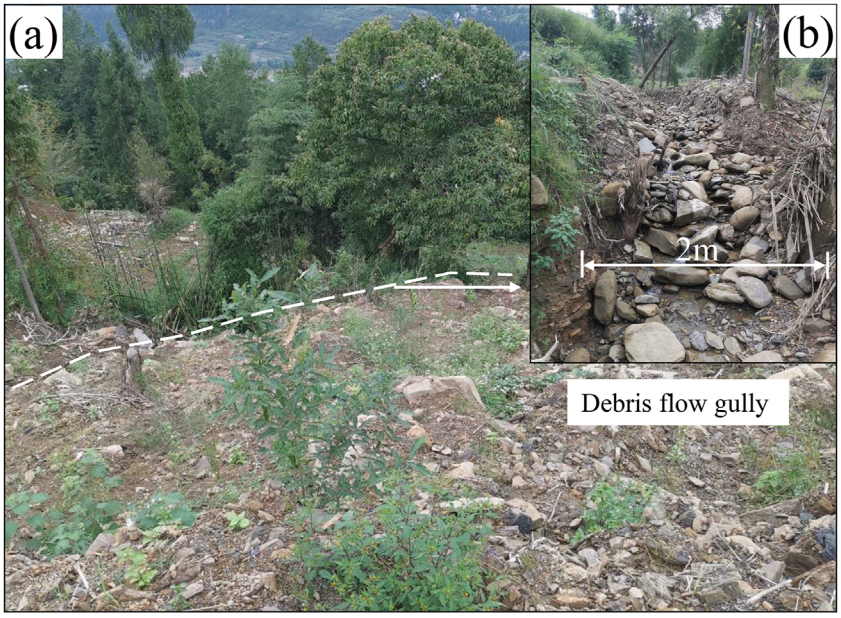

FIGURE 5
Debris flow gully in landslide circulation area [**(A)** debris flow gully on the right side of E area; **(B)**. stone at the bottom of gully].

4 Back-analysis of the process of landslide propagation

4.1 Numerical model

4.1.1 The elasto-viscoplastic and particle flow models

In order to accurately understand the dynamic evolution of Yanghuachi landslide event, this paper uses FLOW3D to establish a three-dimensional numerical model, and comprehensively uses the elastic-viscoplastic model and particle flow model to simulate the whole process of deformation and failure of the Yanghuachi landslide into debris flow.

In the whole process of movement, the upper sliding will collide with the lower debris accumulation, which leads to the movement of the whole landslide. The elastic viscoplastic model is used to simulate the deformation of the sliding process of the upper bedding rock sliding body. The particle flow model is used to describe the movement characteristics of the loose deposits to the gully on both sides of the middle debris accumulation and the lower debris flow. The particle flow model simulates the movement process of debris flow fluid, which can effectively couple the movement of fluid and particles, so as to simulate the movement process of real landslide triggered debris flow (Luo et al., 2022).

The elasto-viscoplastic model can effectively model the significant deformation of geotechnical materials in motion, and simulate the landslide as a continuous and equivalent fluid. In this model, the overall stress state is regarded as the superposition of viscous stress and elastic stress. Among them, the model predicts the linear relationship between the increase of elastic stress and strain. In addition, after applying strain in a short period of time, if the strain continues to increase and the elastic stress exceeds the yield threshold, the influence of viscous stress becomes particularly significant. At this time, the material will yield and exhibit fluid-like flow characteristics.

The stress tensor can be divided into deviatoric stress part and isotropic stress part Panpan et al. (2022):

$$\frac{\partial \tau'_E}{\partial t} + \nabla \cdot \left(u\tau'_E\right) = 2GD'(x,t) + \tau'_E \cdot W + W^T \cdot \tau'_E \tag{1}$$

$$\frac{\partial p}{\partial t} + \nabla \cdot (up) = -Ke + 3\alpha K\left[\frac{\partial T}{\partial t} + \nabla \cdot (uT)\right] \tag{2}$$

In Equations 1, 2, τ'_E is the deviatoric stress part of elastic stress; G is the shear elastic modulus; E is the strain tensor; W is the vorticity tensor; D' is the partial tensor part of the strain rate tensor; u is the velocity of sliding matter; p is pressure; α is a linear thermal expansion coefficient, which is not considered in this study; K is the bulk modulus; e is the volume strain, T is the total temperature.

In order to predict yield effects, the Mises yield criterion is applied as follows (Equation 3):

$$II_{\tau'_E} = \frac{Y^2}{3} \tag{3}$$

If the stress on the material exceeds the yield criterion, the elastic stress relaxation obeys Equation 4:

$$\tau'_E = \sqrt{\frac{2Y^2}{3II_{\tau'_E}}}\tau'_E \tag{4}$$

where Y is the yield stress limit, and $II_{\tau'_E}$ is the second invariant of the deviation part of the elastic stress tensor. The tensor is applied to the Navier-Stokes equations of the flow momentum balance.

After the upper mountain impacts the loose deposits, the movement of the loose deposits has a flow-like movement

characteristic, which can be described by the particle flow model of Mih (1999). Mih's particle flow shear stress equation (Equation 5) is:

$$\tau_g = \tau_i + \tau_v = 7.8\mu_f \frac{\lambda^2}{1+\lambda}\frac{du}{dy} + \rho_s \frac{0.015}{1+0.5\frac{\rho}{\rho_s}} \frac{1+e}{(1-e)^{0.5}} \left(\lambda D \frac{du}{dy}\right)^2 \quad (5)$$

In the formula: μ_f and ρ are the viscosity and density of the fluid between particles; ρ_s is the density of particles; e is the correlation coefficient with solid impact; D is the diameter of the particle; λ is the maximum volume ratio function, $\lambda = D/S$, S_{c0} is the average distance of the particle center point; du/dy is the average velocity of particle flow.

The equation includes the fluid viscosity and the solid impact correlation coefficient. The viscosity is a constant, and the solid impact correlation coefficient is related to the characteristics of solid particles and fluids. This equation is in good agreement with the results of a large number of particle flow physical experiments carried out by different people (Mih, 1999). This study uses this formula to control the movement of loose deposits after the failure of Yanghuachi landslide.

At the same time, the two-phase flow energy exchange model (Flow Science, 2016) is used to consider the energy exchange generated during the collision between the sliding mountain and the lower deposit. The coupling model of granular flow and elasto-viscoplasticity adopts the incompressible fluid model with different densities. Assuming that the density of the elasto-viscoplastic fluid is ρ_1, the density of the granular flow is ρ_2, f represents the volume fraction of the elasto-viscoplastic fluid in the composition mixture, and the volume fraction of the granular flow in the mixture is expressed by1-f.

Equations 6–10 are derived from the Flow Science (2016) Flow-3D V11.0 user's manual. The continuous momentum balance formula (Equation 6) of elasto-viscoplastic fluid is:

$$\frac{\partial u_1}{\partial t} + u_1 \cdot \nabla u_1 = -\frac{1}{\rho_1}\nabla P + F + \frac{K}{f\rho_1} u_r \quad (6)$$

The momentum balance formula (Equation 7) of granular flow is:

$$\frac{\partial u_2}{\partial t} + u_2 \cdot \nabla u_2 = -\frac{1}{\rho_2}\nabla P + F - \frac{K}{(1-f)\rho_2} u_r \quad (7)$$

where u_1、u_2 are the velocity of elastic-viscoplastic fluid and particle flow; F is the pressure of the object; P is pressure; K is the drag coefficient related to the interaction between the two stages; in Equation 9, u_r is the relative velocity difference between different phases Equation 8 in Mih (1999).

$$u_r = u_2 - u_1 \quad (8)$$

The volume-weighted average velocity formula (Equation 9) of the mixture is:

$$\bar{u} = fu_1 + (1-f)u_2 \quad (9)$$

The drag force formula for each unit volume is:

$$K = \frac{1}{2} A_2 \rho_1 \left(C_D U + 12\frac{\mu_1}{\rho_1 R_2}\right) \quad (10)$$

In the formula, A_2 is the cross section area of each unit volume in the particle flow; ρ_1 and μ_1 are the density and dynamic viscosity of viscoelastic-plastic fluid, respectively; U is the relative velocity of solid fluid; C_D is a user-specified drag coefficient, which is a dimensionless number. R_2 is the average particle size.

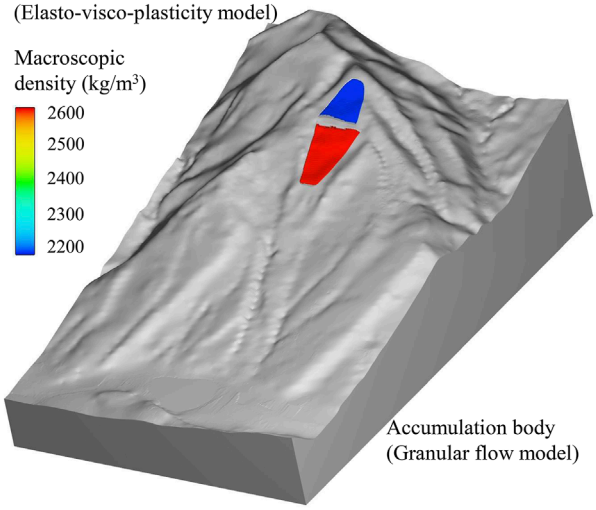

FIGURE 6
Three-dimensional numerical model of Yanghuachi landslide.

4.1.2 Model establishment

The digital elevation model of Yanghuachi landslide is drawn according to the engineering geological survey profile and plan, and the volume is about 30.3 × 10^4 m^3. According to the 1:10,000 topographic map, a three-dimensional numerical simulation model of Yanghuachi landslide was established (Figure 6). The model area includes the slope to the right bank of Modao Creek, and the terrain contour line is imported into the materilise magics three-dimensional modeling software to generate the terrain entity. The generated terrain entity is imported into FLOW3D software to check whether the model is complete.

In order to improve the calculation efficiency and avoid affecting the size of the study area, the minimum elevation and maximum elevation of the three-dimensional calculation model of Yanghuachi landslide are set to 220 m and 750 m respectively, and the height difference (Z direction) is 530 m. The length (X direction) and width (Y direction) of the model are 1,390 m and 2,150 m, respectively.

The initial state of the calculation model is static. The Z min surface is the zero-flow wall boundary, and the Z max surface (water surface) is the zero-pressure boundary, that is, the free surface. The X min surface (valley), X max surface, Y min surface and Y max surface are all outflow boundaries, that is, the open boundary, and the fluid can flow freely. According to the results of the model test, the grid of the required calculation area is divided. According to the terrain size and the computer operation ability, the unit grid is divided into 3 m × 3 m × 3 m, a total of 29,574,722 units.

4.1.3 Parameters

The particle collision grain restitution coefficient, grain density, global vent coefficient, and average grain diameter in the particle flow model are all field measured values (Table 2). After calibration, the two parameters of fluid density and fluid viscosity are comprehensively valued.

TABLE 2 Physical parameter using for the particle flow model.

Parameter	value	Parameter	value
Fluid density/(kg/m^3)	1,000	Grain restitution coefficient	0.7
Fluid viscosity/(kg/ms)	0.001	Average grain diameter/m	0.2
Grain density/(kg/m^3)	2,600	Global vent coefficient	0.02

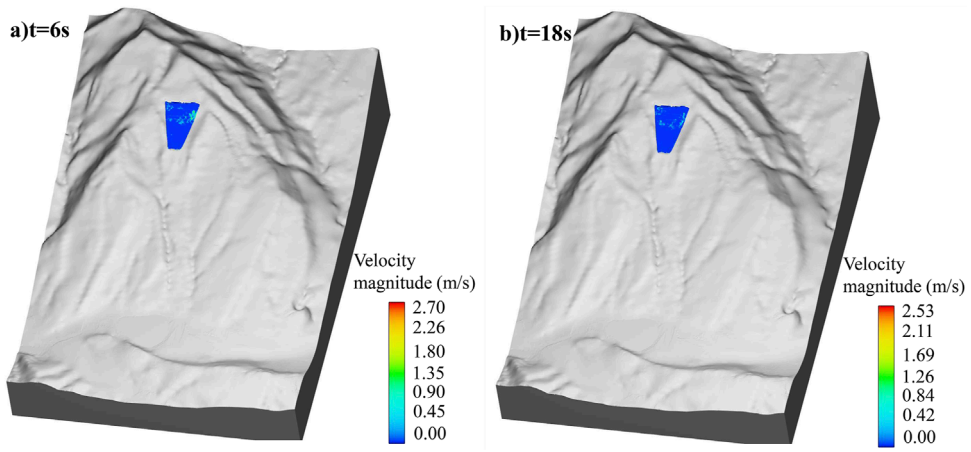

FIGURE 7
Instantaneous velocity field diagram of middle and lower accumulation body of slope under natural state. **(A)** t = 6s, **(B)** t = 18s.

4.2 Numerical model check

4.2.1 Comparative analysis of motion process

When constructing the calculation model, the sliding area is divided into the upper rock and soil mass and the lower accumulation body. It is assumed that the lower accumulation body should remain stable without the action of the unstable sliding of the upper rock and soil mass. Based on this assumption, the stability of the lower deposit is calculated before the simulation. The calculation results (Figure 7). When t = 6 s, only a small displacement occurs in some areas of the lower deposit and the velocity is small (less than 1 m/s). When t = 18 s, most of the lower accumulation body has stopped moving, and only a few areas still creep forward at an extremely slow speed. From the whole movement process of a single accumulation body, there is no obvious change in the shape of the accumulation body. With the increase of time, the movement speed of the accumulation body continues to slow down, and finally stops moving. Although the effect of erosion is not considered, the existing model can also reproduce the whole process of motion by adjusting the parameters. In summary, the particle flow model for the accumulation body is in line with the stability requirements of the slope.

4.3 Analysis of landslide dynamic process

When the particle flow model slides, the collision on the elastic viscoplastic model will produce a series of motion processes. From the beginning of landslide sliding, a total of 92 s is calculated. From the motion pattern diagram of each period in the study area (Figure 8), it can be seen that when t = 4 s, the upper sliding body is unstable and slides, and the main sliding direction is 354°. The potential energy is converted into kinetic energy, and the front edge of the scraping area below the impact shear outlet begins to impact at a speed of about 19.59 m/s. When t = 8 s, part of the rock and soil mass enters the scraper area at a speed of about 22.08 m/s, continuously impacts the accumulation body in the scraper area, takes away the surface weathered rock and soil mass, and continuously disintegrates into debris flow. Compared with Figure 7B, under the push of the sliding body, the accumulation body began to uplift upward and slide downward, and the speed gradually accelerated.

When t = 50 s, the sliding body continues to move after the leading edge of the scraping shovel area converges, and the average speed in front is about 13.33–8.89 m/s. The accumulation body driven by the rear began to move at a speed of 8.89 m/s-4.44 m/s, passing through the housing area and destroying and burying the house. When t = 68 s, the rock and soil mass has slipped through the scraping shovel area, and the rock and soil mass enters the two gullies to move downward due to the influence of the terrain, and the flow rate is about 19.21 m/s. When t = 84 s, there are still some accumulation bodies left in the scraper area at the trailing edge, and most of the rock and soil mass continue to move downward along the gullies on both sides. The average velocity of the lower accumulation body is about 8.70–11.50 m/s, and the average velocity of the upper

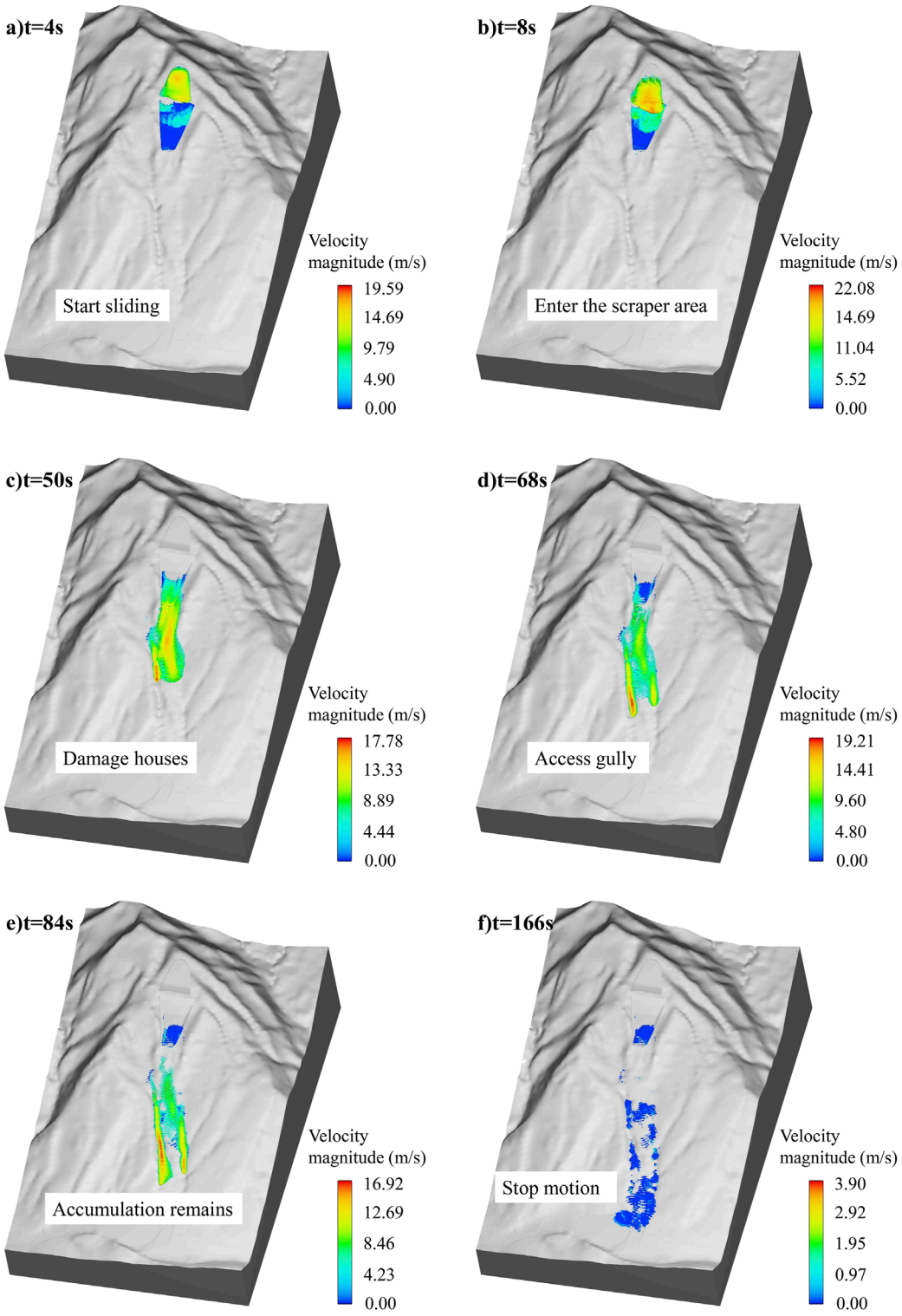

FIGURE 8
Slope movement process diagram. **(A)** t = 6s, **(B)** t = 8s, **(C)** t = 50s, **(D)** t = 68s, **(E)** t = 84s, **(F)** t = 166s.

sliding body is about 8.46–5.56 m/s. When t = 166 s, the front edge of the front sliding body has stopped moving around the river, and the speed of the rear sliding body is greatly reduced due to the blocking and resistance of the front accumulation body.

Figure 8 shows the velocity change process of the whole process of landslide transforming debris flow. On the whole, after the instability of the upper slope of the Yanghuachi landslide started, the speed increased greatly in a short period of time, and then maintained a

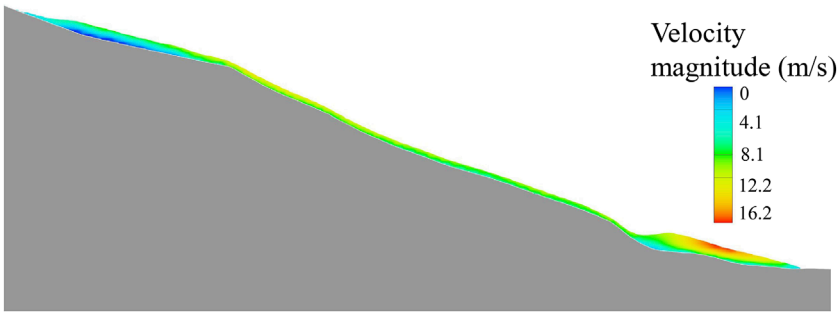

FIGURE 9
Landslide velocity cross section along the main movement direction.

speed of about 17 m/s for a certain distance, and then the overall speed began to decrease. At 166 s, most of the movement of the debris flow stopped, and the speed converged to zero. By extracting the model data, the overall average speed of the landslide was 16 m/s. As shown in Figure 8C, 50%–60% of the Y-axis positive direction is intercepted along the sliding direction of the landslide, and the velocity section of the landslide is obtained in the Y-axis positive direction (Figure 9). In the vicinity of 50 s, the maximum velocity of the landslide surface unit is 16.2 m/s. From the cross section of Figure 9, the velocity of the landslide shows an increasing distribution pattern in the transition from the base to the surface, which reflects that the bottom of the landslide may have experienced significant shear strain. The solid materials in the landslide body are mainly distributed in the middle and lower parts of the landslide under the action of gravity. At the same time, in the process of eroding the riverbed, the movement speed of these materials is relatively slow due to the obstruction of the riverbed. In contrast, the upper part of the landslide is less hindered by the bottom, so its movement speed is relatively fast.

4.3.1 Analysis of landslide accumulation state

At 180 s, the movement process of landslide turning into debris flow is basically over, and the accumulation form has been basically formed. From the accumulation pattern of the landslide (Figure 10), at 180 s, most of the residual body of the slope is concentrated in the debris flow circulation area, and the local residue is in the impact scraping area, which is close to the actual situation of the landslide (Figure 5B). The upper part of the gully in the circulation area is mainly exposed to bedrock, and the lower part is the accumulation layer. There are a large number of accumulation bodies on both sides of the gully. The accumulation thickness is about 4.44–10.91 m, the average thickness is about 7 m, and the maximum thickness of the final accumulation is about 10.91 m. The thickness of the bottom of the accumulation form changes from thick to thin, which conforms to the accumulation form after the landslide movement process stops.

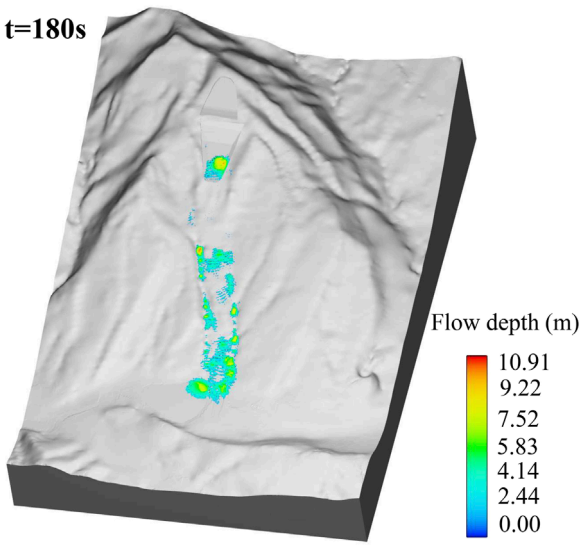

FIGURE 10
Yanghuachi landslide accumulation form diagram.

5 Discussion and conclusion

On 4 July2023, a heavy rainfall in Changtan Town, Wanzhou District, Chongqing City, Southwest China triggered a landslide-type debris flow. Through field investigation and numerical simulation, the characteristics of the landslide disaster, especially the dynamic mechanism of particle flow during the movement, were studied. The following conclusions were obtained.

(1) The total volume of Yanghuachi landslide is about 30.3 × 10^4 m^3. The upper part is a consequent rock landslide, the middle part is a soil landslide squeezed by debris accumulation, and the lower part is a compound geological disaster chain of debris flow. After the landslide slides, there are five deformation zones on the slope, and the amount of landslide in the collapsed area is about 1.62 × 10^4 m^3.

(2) The formation of the Yanghuachi landslide is the result of the interaction of its unique step-like topography, geological structure and heavy rainfall events. The topography of the landslide is step-like, and the shale layer is sandwiched with argillized weak interlayer. The long-term extrusion leads to the deformation of the front edge. The heavy rainfall on July 22, coupled with the loading of artificial facilities such as roads and houses, resulted in rainwater infiltration and increased

self-weight of the slope, which eventually triggered landslide instability.

(3) The elastic-viscous-plastic model coupled with the particle flow model is used to simulate the process of instability movement, scraper soil and long-distance movement of Yanghuachi landslide. The maximum velocity of the landslide is about 22.08 m/s, the overall movement time is about 180 s, and the maximum accumulation depth is about 10.91 m. The numerical calculation results are in good agreement with the actual situation of field investigation, and the coupling calculation model can be used to simulate the dynamic process of landslide motion-scraping, pushing-damming etc.

In this paper, the numerical simulation software is used to simulate the landslide-debris flow. However, due to the complexity and uncertainty of the actual geological environment, the landslide-debris flow in different regions is quite different, and its motion characteristics must be different from this paper. Therefore, the simulation of other cases needs to continuously compare and correct the simulation results with the field measured data. Real-time data such as landslide deformation and rainfall intensity are obtained by monitoring equipment, and various parameters in the model are constantly adjusted to ensure the accuracy and reliability of the simulation results. At the same time, in order to better predict and mitigate landslide and debris flow disasters, monitoring and early warning of such landslides should be deployed in advance, and emergency measures should be taken quickly in the near-sliding stage, such as strengthening the slope, dredging the water flow, and reducing the source of materials to prevent the occurrence of landslides.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

FW: Conceptualization, Formal Analysis, Investigation, Methodology, Software, Supervision, Writing–original draft, Writing–review and editing. ZD: Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Writing–original draft, Writing–review and editing. AZ: Conceptualization, Formal Analysis, Methodology, Writing–review and editing. SC: Conceptualization, Formal Analysis, Methodology, Writing–review and editing. QX: Funding acquisition, Investigation, Resources, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A framework for flood inundation extraction based on microwave and optical remote sensing images

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Introduction: Effective monitoring and evaluation of floodwaters are essential for disaster prevention and mitigation. The flood inundation range can be obtained by using traditional simulation methods, but these methods still have shortcomings. This work proposes an optimization method for traditional methods.

Methods: This study aims to introduce an effective solution for the rapid and accurate extraction of flood inundation areas, emphasizing the enhancement of extraction speed and dynamic monitoring throughout the flood event. The solution uses a normalized difference water index (NDWI), a refined threshold method, and a filtering process for microwave (radar) images. Sentinel-1 SAR (Synthetic Aperture Radar) and Sentinel-2 MSI (Multi-spectral Image) images served as the primary data sources. The Sentinel-2 images were preprocessed to extract pre-flood water bodies, while the Sentinel-1 SAR images were processed using the proposed filtering method to identify post-flood inundation areas.

Results: The application and validation of this framework are demonstrated through the case of the 2020 flood event in Tongling, Anhui Province. The framework's performance was validated through comparison with ground truth data, yielding high kappa accuracies of 98% for optical images and 89% for Synthetic Aperture Radar. The findings highlight the framework's ability to capture high-accuracy changes in flood inundation areas and to characterize the dynamic process of flood inundation area changes.

Discussion: This study contributes to the field by enhancing the extraction speed and scope of water bodies from SAR images and improving the quality of microwave remote sensing data processing. It offers valuable insights for emergency rapid response and situational awareness in the context of extreme weather events and associated flood disasters.

KEYWORDS

flood, inundation extraction, remote sensing images, tongling, sentinel-1 SAR images, sentinel-2 MSI images

Highlights

1. Constructing an accurate and effective algorithm for flood inundation.
2. Mapping flood extents by combining Sentinel-1 SAR and Sentinel-2 MSI images.
3. Identifying the distribution of flood risks at different levels.
4. Analysis the flood extent area changes and its driving factors.

1 Introduction

With the advent of global warming and human interference, extremely heavy rainfall has become a frequent occurrence, often resulting in destructive and extensive flood disasters (Tellman et al., 2021; Nkwunonwo et al., 2020; Czajkowski et al., 2018). According to statistics from the Chinese Ministry of Water Resources and the National Disaster Reduction Center, between 1991 and 2022, an average of approximately 2020 people perished or were reported missing annually due to flood disasters, incurring an average annual economic loss of 160.4 billion yuan. This has had a significant impact on the country's economic and social development (Liang et al., 2023; Wu et al., 2021; Xia et al., 2017). Therefore, scientifically addressing flood disasters, dynamically monitoring floods in near real-time and at a high-frequency and finely analyzing the spatiotemporal evolution patterns before and after floods are crucial for flood prevention and disaster reduction.

Remote sensing technology, leveraging the distinct spectral characteristics of geographic features, excels in obtaining spatial information about large water bodies and enables fully automatic flood monitoring. Typically, the location and area of water bodies are determined by constructing models in the near-infrared band. Commonly utilized methods include the water body index method, single-band threshold method, supervised classification method, support vector machine method (Li et al., 2020; Nguyen et al., 2023) and various algorithm-based approaches (Wang et al., 2022; Lv et al., 2022). Characterized by its timeliness and cost-effectiveness, routine detection often involves using satellite remote sensing to extract water information for applications such as water resource surveys, land use, river and lake monitoring, reservoir monitoring, flood inundation analysis and emergency monitoring. The evolution of remote sensing water body extraction has transitioned from initial manual visual interpretation to the integration of spectral and spatial information (Song and Xu, 2019). The focus has shifted from objectively interpreting water bodies to enhancing the efficiency of extracting flood disaster information, with automated high-precision extraction primarily based on automatic classification according to the spectral characteristics of land features, thereby improving the accuracy of water body extraction (Zhu et al., 2024a). It focuses on addressing challenges like slow extraction speed and poor quality of optical images caused by thick cloud (Nanehkaran et al., 2022; Nanehkaran et al., 2023a; Nanehkaran et al., 2023b).

Optical and radar remote sensing are the primary data sources for flash flood research. Optical remote sensing provides detailed information and facilitates data acquisition through various high-precision extraction techniques (Li et al., 2020). However, it is susceptible to interference from adverse weather conditions, particularly rain. Notably, combining the hybrid water body index model (CIWI) and the single-channel thresholding method is also an approach that can extract water bodies with high accuracy and low interference of noise shadows in the extraction results (Zheng et al., 2020). This method can generate high-resolution images, discerning between different land features, including the scattering information from building shadows and water bodies, which is crucial for delineating flood inundation areas. In addition, the automatic extraction method of water bodies combined with GIS data integrated with visible remote sensing and the method based on the change of upper limit have results (Sui et al., 2016; Chen et al., 2019). Despite improvements in the accuracy of flood inundation mapping from optical remote sensing, weather conditions, particularly rain, continue to pose significant challenges.

The advantage of radar remote sensing lies in its robust penetration through clouds and fog, unaffected by weather conditions, with the capability to operate continuously under all weather conditions, directly extracting water body ranges under adverse weather conditions (Zhu et al., 2024b; Nanehkaran Y A et al., 2022). Its drawback is the lower extraction accuracy and the relatively cumbersome processing involved. The band threshold method is a prevalent technique for processing radar remote sensing images to delineate flood inundation areas. Cao and Liu, (2006) applied this method to extract water body extents from ASAR data. Furthermore, various approaches, including the Otsu algorithm, object-oriented methods, U-Net, and the H-FCM algorithm, have shown high accuracy in flood inundation mapping. For instance, Rahman and Thakur, (2018) employed time-series Synthetic Aperture Radar (SAR) images combined with density slicing to precisely delineate flood inundation areas. Tiwari et al. (2020) successfully extracted the flood-affected region in Kerala using the Otsu algorithm on Sentinel-1 SAR data. Wang et al. (2021) assessed the comparative accuracy of the object-oriented, U-Net, and Otsu methods for water body extraction using Sentinel-1 SAR images. Pan et al. (2022) introduced a method leveraging the KECA algorithm for feature extraction, thereby enhancing robustness. Wang et al. (2023) suggested the use of a multi-branch dual-contrast learning model to enhance image classification accuracy. These techniques have further improved the robustness and accuracy of feature extraction and image classification in flood mapping.

The SAR processing and analysis involve data input, multi-view processing, filtering, geocoding or radiometric calibration, water body extraction, and post-processing of results (Qiu et al., 2022; Wei et al., 2024). The extraction of flood inundation from SAR images is mainly based on the difference in the strength of the backscattered microwave signals from the ground surface, identifying the flood inundation range. However, the method of extracting water bodies using SAR images has garnered increased attention. For example, Wang et al. (2020) proposed the H-FCM algorithm, integrating river positions extracted from optical remote sensing images into post-flood SAR images, thereby improving detection accuracy. Radar remote sensing, which actively emits microwaves, is not hindered by weather conditions and possesses strong penetration through obstacles, thus enhancing the accuracy of water body extraction (Qingsheng

et al., 2022). Consequently, the integration of radar remote sensing and optical remote sensing images, along with the combination of SAR data and intelligent water body extraction algorithms to delineate flood inundation ranges, has progressively become a focal point of research. In addition, the method of integrating machine learning models with INSAR technology, along with DEM data at the best resolution, is also of significant importance for reducing risks such as landslides in various locations (Ahangari Nanehkaran et al., 2022; Cemiloglu et al., 2023; Mao et al., 2024)

In summary, scholars both domestically and internationally have achieved substantial success in extracting flood inundation ranges using remote sensing technology. However, there is a paucity of analysis regarding the extraction speed and dynamic changes throughout the entire flood process. Additionally, the extraction of water bodies from microwave (radar) remote sensing images necessitates a vast amount of data. Utilizing the filtering processing provided by the ENVI 5.3 platform is time-consuming and demands high computer hardware specifications. The absence of filtering processing can impair the accuracy of water body extraction. Therefore, the objective of this study is to employ optical remote sensing to extract the pre-flood water body range as a reference. This study will concentrate on the dynamic changes in the flood inundation area, propose a filtering processing method based on microwave (radar) remote sensing images and construct and validate a framework for extracting flood inundation ranges based on a comprehensive water index method and threshold method. In this study, the validity of the model was verified using Tongling as the study area and using what data for the 2020 flood. The research outcomes are expected to enhance the speed and scope of water body extraction from SAR images, improve the quality of filtering processing for microwave (radar) remote sensing data and offer a reference for disaster early warning and situational awareness prompted by extreme weather events.

2 Study area and data

2.1 Study area

Tongling located in the south-central part of Anhui Province and downstream of the Yangtze River, covering the latitude between 30°38′N and 31°09′N and the longitude of 117°04′E and 118°09′E (Figure 1). It is characterized by a monsoon climate with hot and rainy summers, high rainfall and increased runoff (Ye et al., 2024). For the Yangtze River in Tongling, its flood season typically occurred in July and August. The leading to significant variations in annual river runoff and frequent flooding disasters. Furthermore, Tongling's flat terrain, small elevation differences and slow water flow contribute to its susceptibility to flood retention and flooding disasters (Qi, 2015). In July 2020, due to the inflow from the upper reaches of the Yangtze and continuous heavy rainfall, the water level in Tongling rose rapidly. The entire flood process started in July and lasted for about 2 months until early September. By July 7, the water level in the Tongling section of the Yangtze River had exceeded the warning level, resulting in a continuous expansion of the flooded area. On July 17, the second flood of 2020 formed in the upper reaches of the Yangtze River. By the end of July and early August, the water levels in the rivers, lakes and reservoirs in Tongling gradually receded and the flood control level was reduced from level one to level two, leading to a gradual decrease in the flooded area. By the end of August, due to several consecutive sunny days, the flood in Tongling gradually receded. Figure 1B illustrates some of the details of the development-peak-recession scenarios for the Copperopolis 2020 flood, in relation to changes in the corresponding emergency response measures.

2.2 Data sources

The study concentrated on a significant flood event that took place in Tongling, Anhui Province in July 2020. To capture flood extents, the Sentinel-2 MSI images before flood disaster and Sentinel-1 SAR images after flood disaster were collected. The SAR images recorded water inundation extents at eight time points. The detailed information of each dataset was outlined in Table 1. The Sentinel-1 data originated from the European Space Agency (ESA) and consisted of Ground Range Detected (GRD) Level-1 data, featuring VH polarization and operating in Interferometric Wide Swath (IW) mode. These radar data had been subjected to multi-view and geocoding corrections, which rendered geographic registration unnecessary. The Sentinel-2 data, also provided by ESA, existed in the form of unprocessed Level-1C data products that had undergone systematic geometric correction. Meanwhile, high resolution images from Google Earth platform were utilized. These were obtained from the Resource and Environment Science Data Platform of the Chinese Academy of Sciences (https://www.resdc.cn/). Heavy rainfall process data from Anhui Meteorological Bureau, Water Conservancy Yearbook.

The preprocessing of optical images primarily relies on the Sen2Cor plugin within the Sentinel Application Platform (SNAP), developed by the European Space Agency. This process includes radiometric correction, geometric terrain correction, noise removal, and transformation of backscattering coefficient images. The Sen2Cor module within SNAP is specifically invoked for atmospheric correction, and the corrected data is then resampled to a 10 m resolution using ArcMap. For SAR data, the SARscape plugin of the ENVI5.3 platform is utilized for microwave image preprocessing, which involves multi-view processing, single-image filtering, data enhancement, and geo-correction. These steps are essential for the extraction and analysis of flood inundation areas. The analysis was further enhanced by the incorporation of ground truth data, which included a diverse range of terrains and urban settings. This inclusion was essential for ensuring the representativeness and accuracy of the study. High-resolution imagery and field survey data were also integrated to substantiate the findings and provide a comprehensive basis for validation. These additions are crucial for the robustness of the study's conclusions and for meeting the rigorous standards of academic research. The determination of thresholds was carefully calibrated to clearly distinguish water bodies from non-water bodies in the images, utilizing a variety of data sources to ensure the precision and reliability of the results.

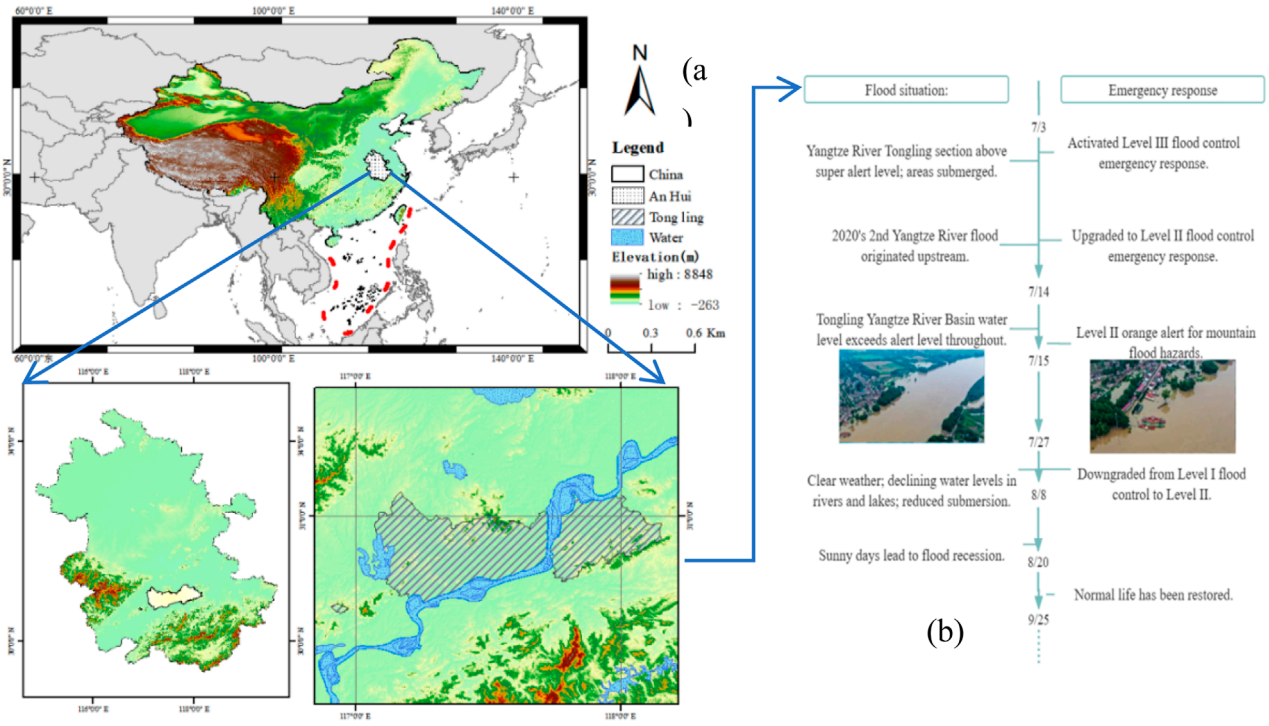

FIGURE 1
(A): Geographic location of Tongling; **(B)** the flooding process (Image from China Emergency Information Network ("https://cneb.gov.cn/" and https://www.emerinfo.cn/).

TABLE 1 Information on satellite remote sensing images.

Satellite/Sensor	Observation time	Product level	Spatial resolution	Data source
Sentinel-1/SAR-C	2020-07-03, 2020-07-15, 2020-07-27, 2020-08-08, 2020-08-20, 2020-09-01, 2020-09-13, 2020-09-25	Level-1 GRD	10 m	https://scihub copernicus.eu/dhus
Sentinel-2/MSI	2020-04-26	Level-1C L1T	10 m	https://scihub copernicus.eu/dhus

3 Methodology

3.1 Building a framework for flood extraction

This study processed radar images from multiple revisit cycles post-disaster, including correcting the radar remote sensing water body range and removing permanent water bodies, and then the actual flooded areas were obtained. Utilizing GIS for visualization operations, the flooded areas from multiple periods and the initially obtained optical remote sensing reference are composited to obtain dynamic information on the changes in flooded areas. This paper initiates the process by normalizing rivers, lakes, reservoirs and other water bodies, amassing a dataset of 1,058 water body sample points and 579 non-water body sample points for verification purposes. Integrating these with pre-existing ground truth samples, the classification accuracy was ascertained using the confusion matrix method. Taking the major flood event in Tongling, Anhui in 2020 as an example, water bodies are first extracted from Sentinel-2 satellite optical remote sensing images. After calibration and correction using the Sen2Cor plugin, the permanent water body range is obtained using SNAP resampling and the NDWI index. Water bodies are then extracted based on Sentinel-1 SAR images. For the Sentinel-1 SAR images, filtering and correction work was conducted using the SARscape plugin. The filtering operation in IDL environment is performed. The arithmetic mean smoothing filter was used to derive a threshold from the differences between water and land bands. In this way, a distributed water body extraction model is developed to dynamically obtain the flooded area by excluding permanent water bodies. This framework will extract water bodies before and after flood disaster in Tongling, using Sentinel-2 images and Sentinel-1 SAR images, respectively. Finally, accuracy validation of kappa coefficient was calculated. The specific methodology is described in Figure 2.

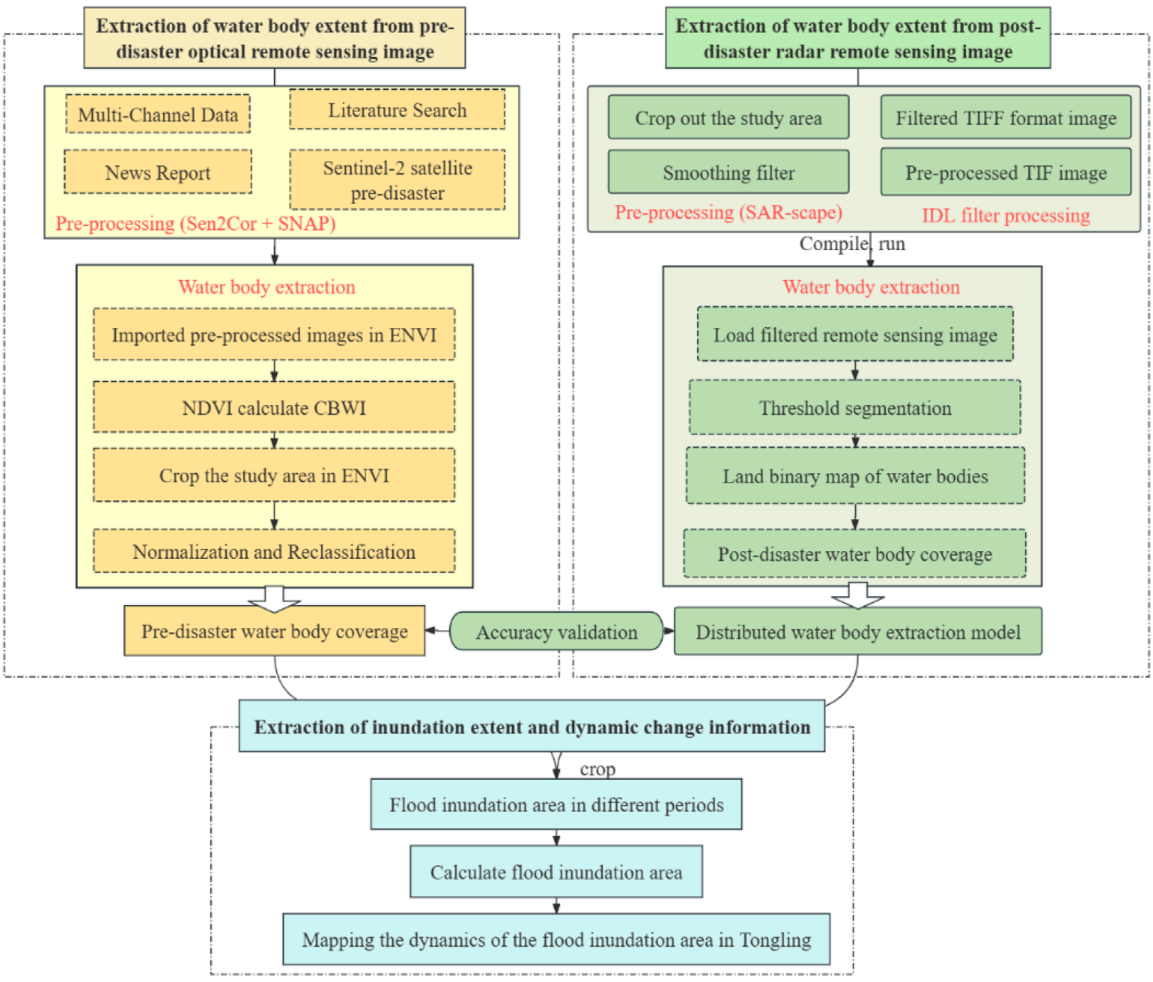

FIGURE 2
Flood inundation extraction framework based on comprehensive water body index method and threshold method.

3.2 Key methods

The Normalized Difference Water Index (NDWI) was employed to identify water bodies. The NDWI was calculated using the Formula 1:

$$\mathrm{NDWI} = \frac{\mathrm{Green} - \mathrm{NIR}}{\mathrm{Green} + \mathrm{NIR}} \tag{1}$$

where Green represents the green band of Sentinen-2 images; NIR represents the near-infrared band of Sentinen-2 images. This process allowed for the minimization of vegetation's influence and the enhancement of water features in the images.

IDL was employed for its user-friendly nature and its established role in geographic remote sensing data processing. This study primarily utilizes IDL (Interactive Data Language) for processing SAR from radar remote sensing. Utilizing IDL's built-in smooth function to apply smoothing filtering algorithms to the radar images. Recognizing that the brightness of objects in the images corresponded to the echo intensity, which was determined by the radar's backscatter coefficient. Employing a threshold segmentation method to differentiate water bodies, which typically exhibit lower backscatter coefficients and thus appear darker, from non-water bodies. Applying a specific formula to calculate the backscatter coefficient using a threshold (M) that distinguishes water bodies from non-water bodies in the image. Identifying the threshold M by experimenting with different values and using the formula to determine the backscatter coefficient for water bodies. Segmenting colors based on established thresholds to clearly differentiate water bodies from non-water bodies in the images. The specific Formula 2 is as follows:

$$\mathrm{Water\,body} = \begin{cases} 1, \delta < \mathcal{M} \\ 0, \delta > \mathcal{M} \end{cases} \tag{2}$$

where δ represents the backscatter coefficient and $\mathcal{M}$ is the threshold used to distinguish water bodies from non-water bodies in the image. To swiftly differentiate between water bodies and non-water bodies in the images, a threshold segmentation method is proposed.

3.3 Water body and flood inundation extraction in the framework

In the study, integration of Sentinel-2 satellite imagery was utilized, focusing on bands B3 and B8 to process and extract water bodies.

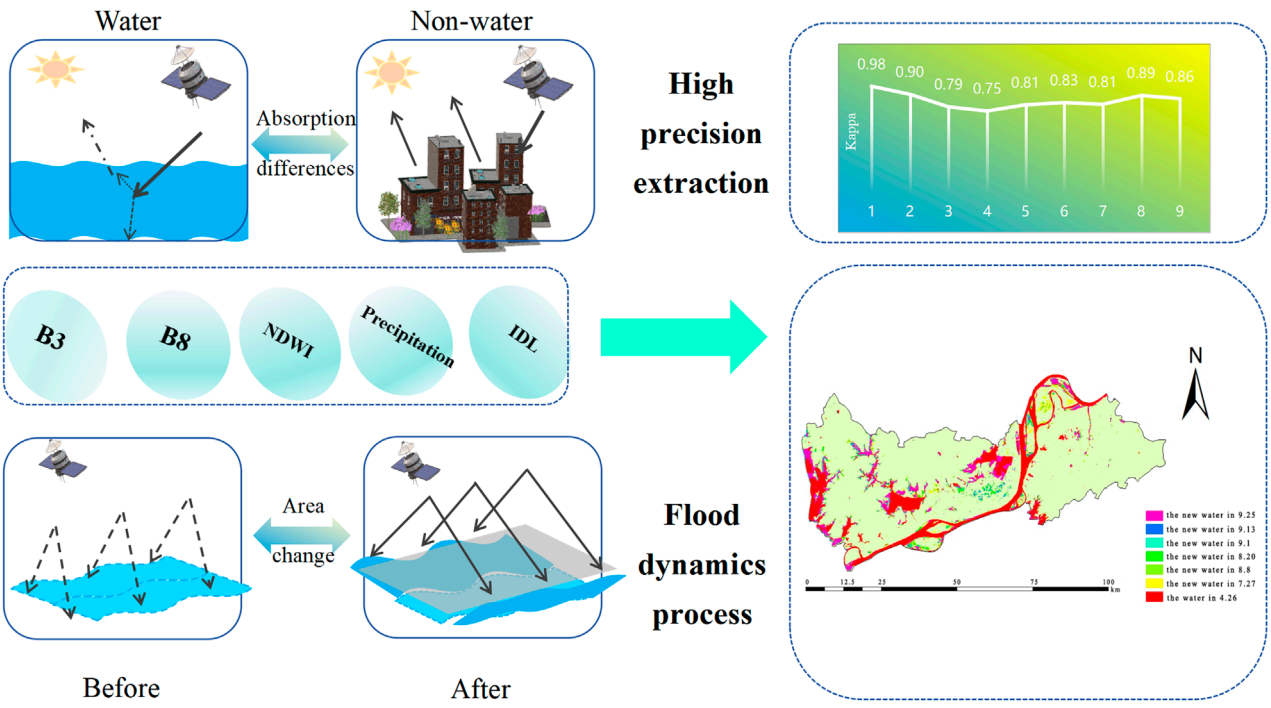

FIGURE 3
Flood inundation extraction technological process.

The methodology incorporated filtering techniques to mitigate noise, followed by normalization and reclassification in ArcGIS10.6. Pixels with values below the threshold of 0.15 were classified as water bodies, while those exceeding this value were categorized as non-water areas. This approach facilitated the clear delineation of the extent of permanent water bodies. Subsequently, processing of radar remote sensing data was executed using the IDL programming language, which included a smoothing function to refine the microwave image data. As shown in Figure 3. A smoothing filter algorithm was applied to reduce the impact of objects with strong edges, enhancing the precision of water body extraction. The distribution data of water bodies within the target area were obtained through band thresholding and IDL filtering. Further refinement of flood inundation area extraction was carried out in ArcGIS, following georeferencing and projection correction. The presence of permanent water bodies, such as the Yangtze River and Tianjing Lake, was accounted for by utilizing Sentinel-2 satellite data as a base layer. This step was essential for the accurate exclusion of these features from the Sentinel-1 satellite SAR data. The area of inundation for each period was determined by calculating pixel counts from the attribute table of the flood inundation range, providing a comprehensive analysis of flood dynamics within the study area.

4 Results

4.1 Water body extraction results

4.1.1 The water body extraction distribution

In this study, a methodology was developed to delineate water bodies and gather their distribution data within the target area. Band thresholding and IDL filtering methods were employed to process the satellite imagery, enabling the extraction of water body extents and the identification of flood inundation areas. The spatial distribution of water bodies was mapped using Sentinel-2 satellite optical data, which provided high-resolution green and near-infrared bands essential for the Normalized Difference Water Index (NDWI) calculation.

Figure 4D displays the outcome of processing with the IDL language program. When compared to Figure 4C, which shows the image before the application of the smoothing function, it is evident that the post-filtering image exhibits a smoother and more continuous visual effect. The disturbances and noise at the edges are significantly reduced, resulting in a clearer image that is more conducive to interpretation and analysis. The smoothing filter algorithm implemented in IDL has proven effective in optimizing microwave image data, thus laying a solid foundation for further analysis and applications. Figure 5 presents the flood inundation areas after geographic registration and projection correction. The manuscript describes the variations in water body extents in Tongling City across different dates, as shown in Figures 5A–H. These figures provide a detailed account of the changes in water body distribution over time, highlighting the dynamic nature of flood inundation and the factors influencing it.

Furthermore, the study examines the influence of permanent water bodies, such as the Yangtze River and Tianjing Lake, on the extent of flood inundation. To account for these factors, water extraction data from Sentinel-2 satellite images were utilized as a reference map. This map was instrumental in excluding permanent water bodies from the Sentinel-1 satellite SAR data, which allowed for the accurate mapping of flood inundation areas for each respective period. Figure 5 illustrates the results of this process,

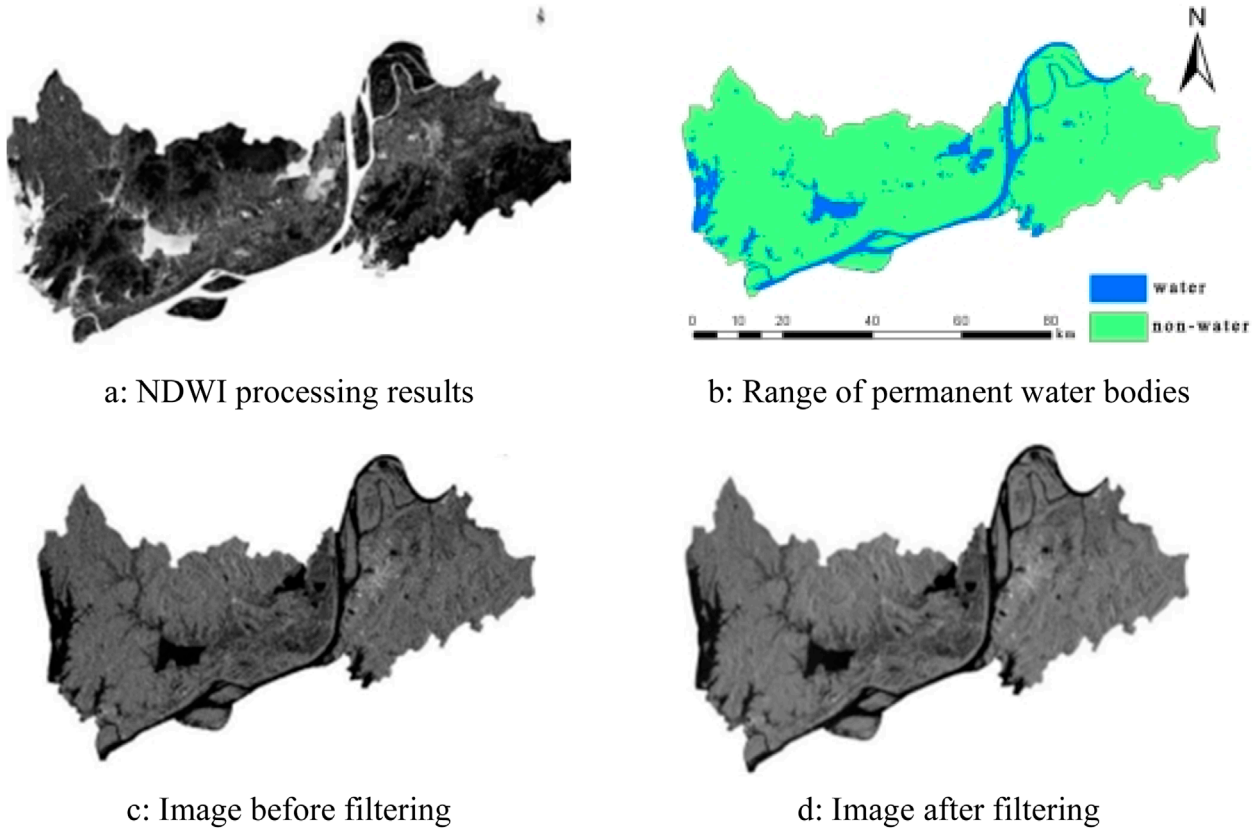

FIGURE 4
IDL algorithm based remote sensing image smoothing filtering processing results **(A)**: NDWI processing results; **(B)** Range of permanent water bodies; **(C)** Image before filtering **(D)** Image after filtering).

showcasing the refined delineation of flood inundation areas, free from the influence of permanent water bodies. This approach ensures that the flood risk assessment is based on accurate and up-to-date spatial data, providing valuable insights for flood risk management and mitigation strategies.

It also examines the influence of permanent water bodies, including the Yangtze River and Tianjing Lake, on the extent of flood inundation. To this end, water extraction data from Sentinel-2 satellite images is utilized as a reference map. This map facilitates the exclusion of permanent water bodies from the Sentinel-1 satellite SAR data, thereby enabling the accurate mapping of flood inundation areas for each respective period, as demonstrated in Figure 5.

4.2 Extraction accuracy for flood

This paper embarked on a meticulous process, beginning with the normalization of rivers, lakes, reservoirs, and other water bodies. A comprehensive dataset was compiled, comprising 1,058 water body sample points and 579 non-water body sample points, all meticulously gathered for verification. These samples were harmoniously integrated with existing ground truth data, and the classification accuracy was meticulously determined using the confusion matrix method. The outcomes of this analysis are meticulously detailed in Table 2.

The results of this rigorous evaluation are compelling: the method proposed in this study has achieved a water body extraction accuracy that exceeds 80%, with a baseline extraction accuracy that impressively surpasses 87%. Remarkably, the overall accuracy not only meets but exceeds expectations, reaching 89%, and the Kappa coefficient, a critical measure of precision and reliability, impressively exceeds 0.75.

Upon a meticulous analysis of the classification accuracy data presented, it becomes evident that the precision rates for both water and non-water classifications are exceptionally high, signifying a robust extraction process. The water body extraction precision varies, with a low of 87.54% recorded on July 27 and a peak of 98.69% on April 26. Similarly, the baseline precision for water bodies follows a comparable trend, with the highest value noted on the same date (April 26) at 99.54%. For non-water body extraction, precision rates consistently remain above 90%, with the exception of the July 15 measurement, which temporarily dips to 81.00%. The overall precision percentages, reflecting the combined accuracy of both classifications, are equally remarkable, ranging from a low of 89.12% on July 27 to a high of 98.92% on April 26. These figures demonstrate the method's high accuracy and consistency over time. The slight decrease in precision for both water and non-water classifications on

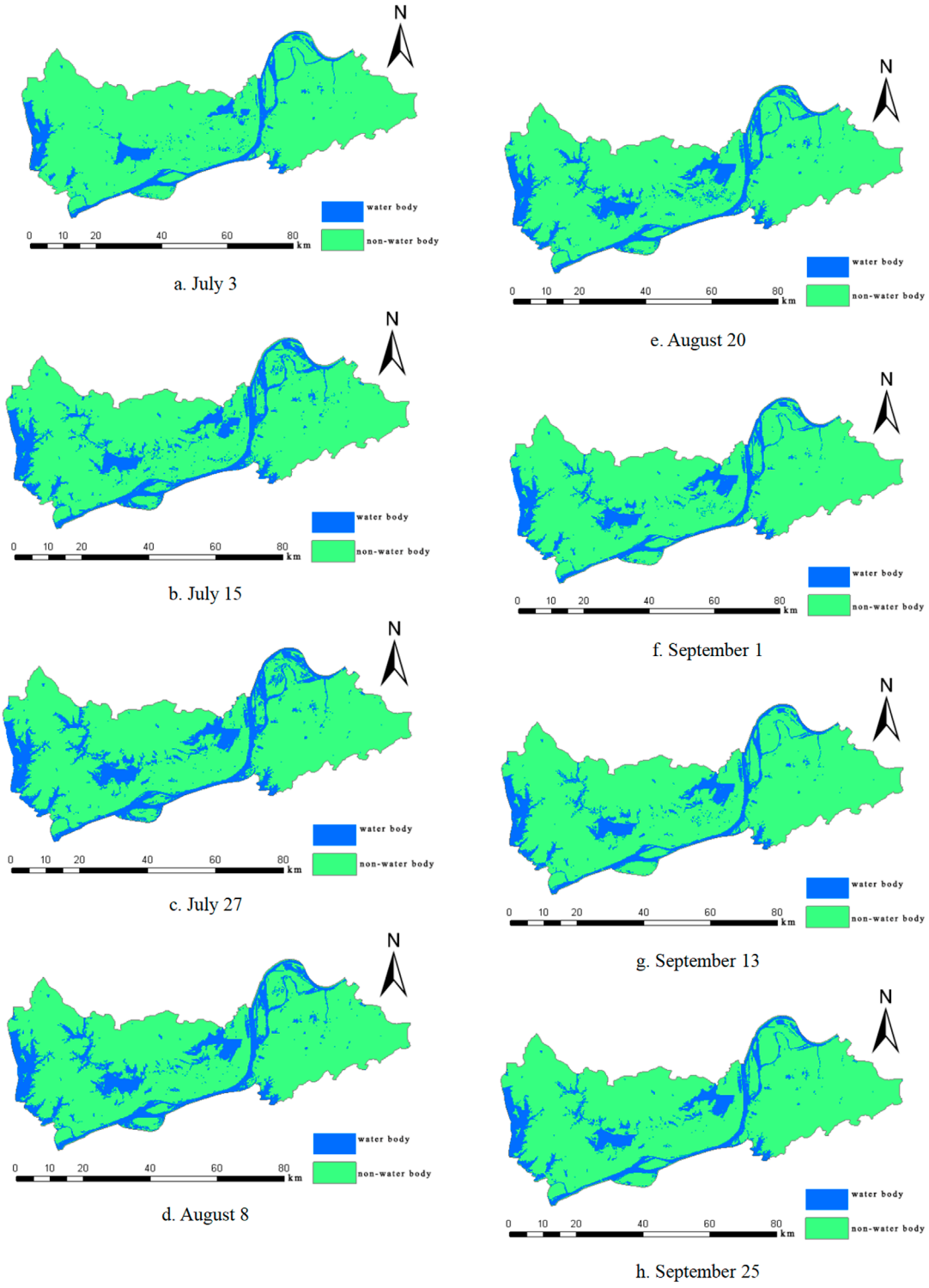

FIGURE 5
The water body extraction distribution in Tongling from July to September 2020. **(A)** July 3, **(B)** July 15, **(C)** July 27, **(D)** August 8, **(E)** August 20 **(F)** September 1, **(G)** September 13, **(H)** September 25.

July 15 and July 27 is an anomaly that may warrant further investigation.

The Kappa coefficients, which measure the agreement between observed and expected classifications, are substantial across all dates. The lowest value, 0.7511, was recorded on July 27, while the highest, an impressive 0.9774, was noted on April 26. A Kappa coefficient above 0.8 typically indicates strong agreement, suggesting that the classification method employed is not only reliable but also consistently effective for all the dates under consideration.

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TABLE 2 Classification accuracy.

Data	Classification	Extraction precision %	Baseline precision %	Overall precision %	Kappa coefficient
April 26	Water	98.69	99.54	98.9216	0.9774
	Non-water	99.29	97.96		
July 3	Water	97.84	93.80	95.2438	0.9034
	Non-water	92.04	97.20		
July 15	Water	90.21	95.84	90.5925	0.7888
	Non-water	91.42	81.00		
July 27	Water	87.54	96.98	89.1265	0.7511
	Non-water	93.12	74.78		
August 8	Water	90.69	96.69	91.4478	0.8078
	Non-water	93.31	81.87		
August 20	Water	91.61	96.98	92.3030	0.8275
	Non-water	93.81	83.77		
September 1	Water	91.59	95.75	91.5699	0.8121
	Non-water	91.53	83.94		
September 13	Water	95.70	96.79	95.1130	0.8926
	Non-water	94.00	92.06		
September 25	Water	93.39	97.45	93.8913	0.8639
	Non-water	94.93	87.39		

4.3 Spatiotemporal variation characteristics of flood inundation areas

The spatial distribution of flood inundation is extracted using multi-temporal data from Sentinel-1 and Sentinel-2, capturing dynamic information on flood changes over time. Extent of inundation is the extent of change in the area of a water body before and after a flood event. As illustrated in Figure 6. A detailed analysis of the flooded areas in Tongling throughout 2020 revealed a distinct pattern in the flood event's progression.

During the flood, the period of rising water was comparatively shorter than the period of receding water. The smallest observed flooded area was approximately 15 km^2on July 3, while the largest extent of flooding, around 230 km^2, was recorded around July 27. The area affected by flooding expanded prior to July 27 and subsequently contracted. From late August through September, the flooded area oscillated around 98 km^2, indicating a stabilization phase. The temporal characteristics of the affected area can be summarized as follows:

On July 27, there was a significant increase in the flooded area due to heavy rainfall and swift inflow from the upstream Yangtze River, which overwhelmed the flood discharge capacity. The inundation began in the Yangtze River section and progressively spread to the northern and northeastern parts of the region, peaking on July 27. Post-July 27, the flooded area started to diminish as the rainfall subsided and water levels in rivers and lakes dropped. Soil moisture saturation also resulted in reduced infiltration and a slower recession of water bodies. Although the flooded area in the Yangtze River section of Tongling began to recede, the overall reduction was minimal. From September 1, there was a marked decrease in the flooded area, which by September 25 had reduced to less than half of its maximum extent. This reduction aligns with the implementation of flood response measures and flood prevention efforts by Tongling authorities.

4.4 Dynamic changes in flooded areas

The high-risk areas affected by the flood mainly include the banks of the Yangtze River, Baitu Lake, Baidang Lake, Fengsha Lake and Chenyao Lake in the northern and central parts of Tongling, with the eastern region less affected and the rest of the areas basically unaffected by the flood. Although the flood mainly concentrated

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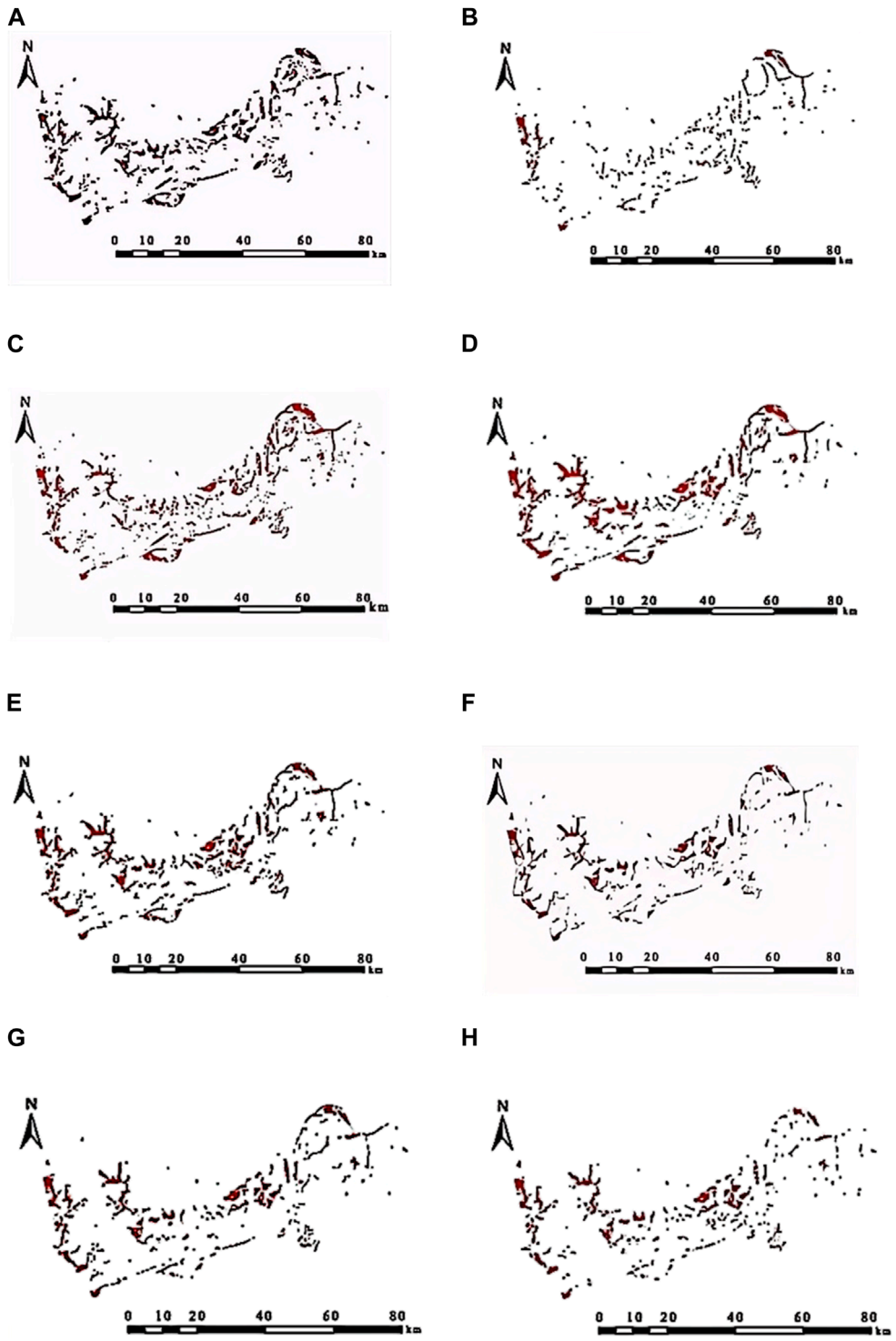

FIGURE 6
Flood inundation range variation chart. **(A)** July 3, **(B)** July 15, **(C)** July 27, **(D)** August 8,**(E)** August 20, **(F)** September 1, **(G)** September 13, **(H)** September 25.

along the banks of the major rivers and lakes, combined with the statistical chart of the flooded areas at different time phases, this heavy rainfall still caused a large area to be submerged. The flood mainly occurred from early July to the end of August, lasting for nearly 2 months, belonging to the critical period of flood prevention known as the upstream in July, downstream in August. In September, the numerical value of the flooded area began to fluctuate and some seasonal water bodies may have become permanent water bodies. At this time, the entire flood process has ended. Therefore, based on July 27, near the peak of the flooded area, dynamic maps of the flooded areas during the rising and receding periods of the flood were drawn, as shown in Figures 7A, B.

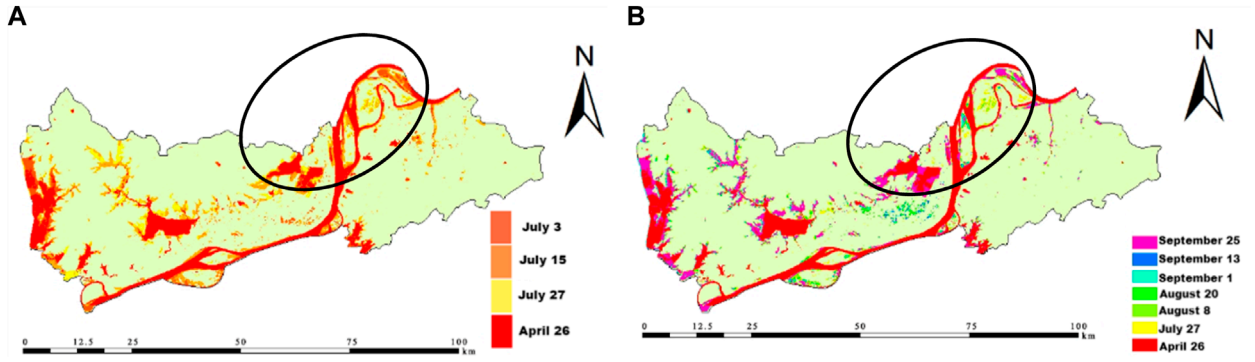

FIGURE 7
Dynamic process of flood inundation extent in Tongling **(A)**: Flood rise period **(B)**: Flood receding period.

Further analysis of the trend of the flood is provided below. Considering the weather conditions: from early July to the July 27, rainfall continued, leading to the growth period of the flooded area. During this time, the water levels of rivers and lakes rose rapidly and the flooded area mainly concentrated on the northern and western foothills. From the end of July to early August was the stable period of the flooded area. Due to occasional light to moderate rain, the flooded area remained large until August 8. The main reason for the inundation in the northern and western regions was the diversion of ridges to gentle terrain. From the end of August to September 1, the weather was clear, marking the unstable period of the flooded area, with water levels gradually decreasing around the northern and western foothills. After September is the period of flood recession and post-disaster reconstruction. During this time, except for the northern and western foothills, where water accumulation may become permanent due to topography, the other areas generally returned to pre-disaster levels. The rate of decline in water level in the Tongling section of the Yangtze River main stream was greater than that in the northern and western regions. It can be seen that the water level rose rapidly in the early stage and after measures such as downstream flood discharge, it also decreased rapidly. The duration of flooding was longer, mainly concentrated in the foothills of the western and northern regions. Based on the above research, it is suggested that the management strategy of Tongling in the future should focus on strengthening embankments of rivers, lakes and other water bodies before the summer flood season on July 27, after July 27, attention should be paid to dredging work around the lakes at the foothills of the northern and western sides and improving the drainage system in the central urban area to ensure rapid flood discharge and restoration of production and life.

5 Discussion

In this study, a method for identifying flood ranges using SAR, enhanced through filter improvements via the IDL programming language, is developed. This paper constructs a framework to extracting flood inundation areas from Sentinel-2 images in green and NIR bands and Sentinel-1 SAR images, employing a comprehensive water index method and threshold method. Focusing on Tongling in Anhui Province, which endured severe flooding in 2020, this paper utilizes Sentinel-2 optical images pre-flood and Sentinel-1 radar images post-flood to extract water volumes for the area.

The specific results captured detailed spatiotemporal dynamics of the flood inundation areas in Tongling, demonstrating the method's reliability to record changes over time with good accuracy. Compared with actual data, the framework achieves an accuracy rate of 98% for optical images and 89% for SAR, which well meets the goal of accurately delineating flood inundation areas. This highlights the method's potential for timely and precise flood monitoring across different regions and scenarios. However, some limitations of this method are observed, such as a slight decrease in the classification accuracy of water and non-water areas on July 15 and July 27. This issue may be attributed to environmental uncertainties, such as variations in image quality, seasonal changes, or difficulties in distinguishing water from similar features under certain conditions.

In future studies, flood inundated areas mapping could incorporate additional remote sensing data sources or integrate machine learning algorithms to improve classification accuracy. Testing the framework under diverse geographical and climatic conditions will provide valuable insights into its universality and robustness. The capture of dynamic change information in this paper also represents an exploratory step towards flood management in small watersheds under urbanization development. Future research may concentrate on real-time data processing to expedite the response of disaster management and warning systems.

6 Conclusion

This paper takes Tongling, severely affected by the major flood disaster in Anhui Province in 2020, as the research area. This study constructs a framework for extracting flood inundation areas from optical image data in bands Green and NIR using a comprehensive water index method and threshold method. This study utilizes Sentinel-2 optical images obtained prior to the flood in Tongling, Anhui Province and Sentinel-1 radar images post-flood occurrence for water extraction. Finally, the flood inundation range

and dynamic change information of Tongling, Anhui Province, are obtained. The conclusions are as follows:

(1) The framework has achieved accuracy in water body extraction, with rates exceeding 98% for optical images and over 89% for SAR. The high precision rates and Kappa coefficients are a testament to the classification method's reliability in differentiating between water and non-water bodies.
(2) An accurate depiction of the affected area distribution in Tongling was achieved. From July 3 to September 13, the average affected area in Tongling was approximately 126 km^2. The central region was the most impacted, followed by the northern region, whereas the eastern region incurred the least damage.
(3) The spatial distribution analysis revealed that the western part of Tongling was more severely affected by the floods than the eastern part, with the Yangtze River section serving as a dividing line. The higher-risk areas were predominantly concentrated in the central and northeastern parts of Tongling.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

QT: Conceptualization, Formal Analysis, Resources, Writing–review and editing. LL: Formal Analysis, Writing–original draft, Writing–review and editing. SL: Project administration, Writing–review and editing. LX: Writing–original draft, Writing–review and editing. KS: Validation, Writing–review and editing. SW: Software, Writing–review and editing. DW: Funding acquisition, Methodology, Writing–review and editing.

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Conflict of interest

Author KS was employed by IEM Holding., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Experimental investigation into effects of material and energy regulation of debris flow by using check dams with different porosities

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The design of check dam openings for debris flow control has been identified as a longstanding challenge, with no definitive solution yet identified. In this study, a quantitative analysis of the control efficacy of check dams with varying opening rates is presented. Field investigation data of 67 check dams located in Wenxian County, Gansu Province, were utilized to gain a preliminary understanding of their running state and damage situation. Building upon this, five check dams with opening rates ranging from 2.1% to 10.4% were designed and subjected to testing. Parameters including volumetric water content, pore water pressure, deposit morphology, and particle size distribution were analyzed to investigate the effect of varying opening rates on debris flow control. The results showed that: 1) As the opening rate of the check dams increased, the peaks of volumetric water content and pore water pressure behind the dam first decreased and then stabilized. When the opening rate was increased to 6.3% or higher, these parameters reached stable values. 2) Check dams with different opening rates all demonstrated good effects in retaining the coarse and sluicing the fine, resulting in the average particle size behind dams was coarsened by 2.65 times. This coarsening was primarily attributed to an increase in the proportion of retained particles within the 2–5 mm size range. 3) An optimal opening range of 4.2%–6.3% was identified for effective debris flow control. Compared with other dams, Dam II with opening rate 4.2% exhibited superior performance in mitigating flow energy and intercepting coarse particles, but it imposed stringent strength-related requirements.

KEYWORDS

debris flow, check dam, opening rate, soil and water parameters, control effect

1 Introduction

Debris flows are among the most common geological phenomena in China's mountainous regions and are characterized by sudden outbreaks, brief duration, and a strong destructive power (Cui, 1999; Deng et al., 2021; Wei et al., 2024). According to the United States Geological Survey (Hübl et al., 2009; Di et al., 2008), debris flows can be classified into soil-driven and water-driven flows based on the dynamics of their genesis,

where the latter have a low frequency of outbreak and are difficult to identify. This is a weak link in research on debris flow-induced disasters (Takahashi, 2007; Hübl et al., 2003; Choi et al., 2018; Iverson et al., 2010). Debris flow control works can be used to regulate the scale of the damage caused by them. Gravity dams are the major structure used to this end and can be divided into closed-type and open-type according to their structure (Armanini et al., 2005; Fei and Shu, 2006). Closed-type dams exhibit poor permeability and are prone to silting, which affects their regulatory function, and can even amplify the scale of debris flow due to their failure. Open-type dams are a complementary optimization of closed-type dams in which discharge culverts are drilled into the dam to intercept coarse particles and discharge fine ones, and to separate water from rock to significantly extend their service life (Zhou et al., 2020; Sun et al., 2021; Ruan et al., 2021). Open-type dams are thus a popular subject of research on debris flow prevention (Shima et al., 2016; Wendeler and Volkwein, 2015; Lin et al., 2017). Choi et al. (2018), conducted a series of flume tests to prove that slit dams can mitigate the energy of debris flow. Dong et al. (2022) found that adding discharge culvert (open-type dams) does not significantly reduce the strength of the dam but can mitigate the destructive effect of debris flows on it.

Studies have mainly focused on the interaction between the diameter of the opening and the size of particles in debris flows (Jeong and Lee, 2019; Rossi and Armanini, 2019). However, only a small number of studies have considered how the opening ratio can mitigate silting of dams and debris flow transfer Zhou et al. (2020) and Rossi and Armanini (2019) have shown that excessively low opening ratios result in poor dam permeability making the dam susceptible to clogging and failure. They emphasize that a balance between the regulatory effects of the dam and its safety should be sought in engineering design, highlighting that a reasonable opening ratio is critical for the preventative efficacy of check dams. Conversely, excessively high opening ratios cannot yield the desired check effects, and affect the safety of the dam. In an exploration of the regulatory effects of the opening ratio on the dynamics of water and soil in debris flow Jia et al. (2011), found that the flow variation through a dam with an opening ratio of 2.2% was about twice that of a dam with an opening ratio of 6.6%. Jeong and Lee (2019), Wang and Huang (2013), and Hu et al. (2020) qualitatively investigated the response relationship between the slit size Iverson et al., 2010 of the dam and the impact force of debris flow, concluding that the slit size significantly influences the velocity of debris flow and silting.

In summary, the design of the opening of the check dam primarily relies on the empirical settings. Relatively little quantitative research has been devoted to the laws of the response of the parameters of water and soil behind dams to their opening ratios. To scientifically guide the design of the opening of dams in projects to block debris flows, it is essential to quantitatively investigate the relationship of material and energy regulation between the opening ratio of the check dam and debris flows.

The goal of this research is to determine when the opening ratio of the check dam is optimal for debris flow prevention. Field investigation and indoor flume tests were conducted. By controlling the debris flows through check dams with varying opening ratios, parameters such as particle size distribution, pore water pressure, volumetric water content, and volume of sediment behind the check dams were investigated to comprehensively evaluate their regulatory performance. The regulatory effect of check dams on the particle composition of debris flows was studied using the law of variation in particle gradation behind dams with varying opening ratios. By analyzing the variance in parameters of water and soil behind dams with different opening ratios, the regulatory effect of check dams on the conversion of debris flow energy was explored.

2 Field investigation

2.1 Overview of the research area

Gansu Province is in northwest China at the junction of the Loess Plateau, the Qinghai–Tibet Plateau, and the Inner Mongolia Plateau, and has complex and diverse geological conditions. Wen County in Longnan City is in southeast Gansu Province (Figure 1). It is a zone of intersection between the westward extension of the western Qinling Mountains and the eastward extension of the Minshan Mountain range. The terrain is steep, the geological structure is well developed, seismic activity is frequent, the ravines are vertical and horizontal, and high mountain valleys are interspersed and distributed. Landslides and collapses are prevalent in the gullies, and loose materials are abundant. The region is located south of 33° North latitude and belongs to the marginal zone of the subtropics. The average annual precipitation in the area in the last decade was 513.2 mm/year, with abundant rainfall that provided favorable conditions for the formation of debris flows. There are a total of 256 large and small gullies for debris flows in the county, with a developmental density of 0.051 gullies/km^2. Debris flows mostly occur from June to September each year and are all induced by rainfall (Zhou et al., 2022; Zhu et al., 2024; Yu et al., 2016; Xie et al., 2019). They occur suddenly and with great momentum, pose a direct threat to important facilities, such as the towns, villages, and trunk lines for traffic in the area, and severely affect the normal life and order of production of the locals (Cui et al., 2015; Wang et al., 2024). To reduce the damage caused by them, interception dams and drainage ditches have been built in many basins, and have helped prevent major disasters.

2.2 Survey results

We surveyed and collected data on 67 check dams installed in 24 representative debris flow gullies in Wenxian County, Gansu Province (Figure 2). The results are shown in Table 1. The forms of damage to the check dams included overall rush destruction, and damage to the auxiliary dams, their overflow holes, and their shoulders and foundation. A comparison of closed and permeable check dams showed that the rate of rush destruction of closed dams was 24% and their rate of silting (the check dams had been silted up) was 83%, while the rate of rush destruction of permeable dams was only 6% and their rate of silting was 57%. This shows that installing drainage culverts can help regulate the composition of debris flows, extend the silting time of the storage capacity of check dams, and improve their service life. We also found during our investigation that check dams with higher opening rates still had empty reservoirs after more than 10 years of operation, which means that prevention and treatment had not had a significant

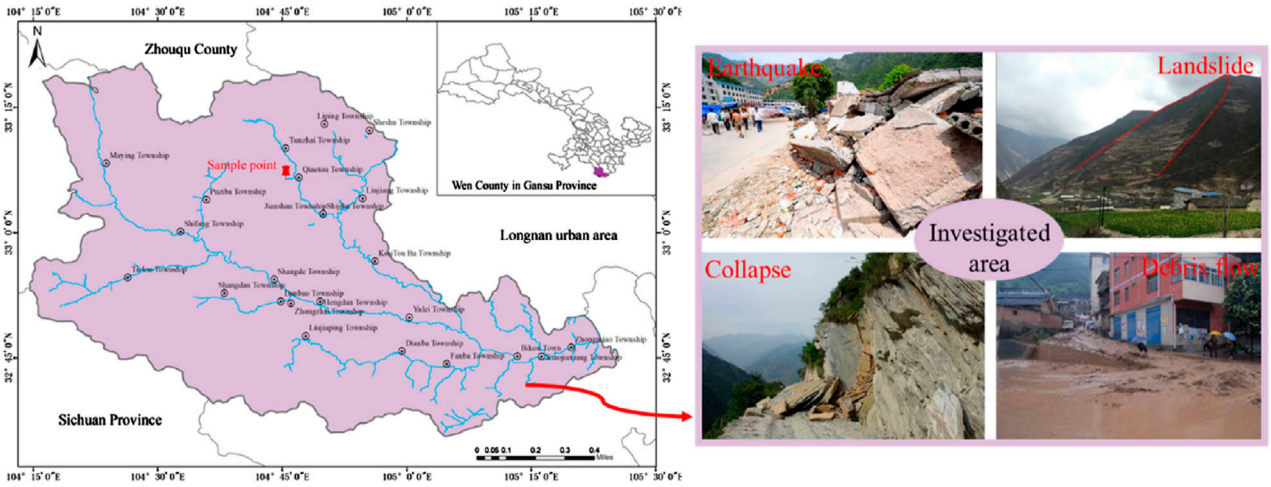

FIGURE 1
Geographical location of the study area.



FIGURE 2
Retaining dams with different opening rates, including those with no culvert, one culvert, two culvert, three culverts.

effect. Therefore, a higher opening rate was not necessarily better for preventing silting behind the dam. A comparison of the status of operation of silted and non-silted check dams showed that the rate of damage to the former was 48%, while that to the lat ter was less than 5%. This shows that once the storage capacity of the check dams had been silted up, the probability of damage to them increased. This is because, on the one hand, the water level in front of the dam had increased to lift debris flows and increase the area of contact between them, and the overflow holes and dam shoulders to enhance erosion and destruction. On the other hand, the increased energy of debris flows increased impact-induced damage to the foundation or the revetment downstream once the debris flows had overflowed from the dam.

3 Experimental schemes

Our field survey revealed that check dams with different opening rates had different effects in terms of controlling debris flow. To investigate the internal control mechanism and identify the optimal opening rate, we designed five check dams with different opening rates for flume tests of the debris flows, The experimental plan is

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TABLE 1 Investigation information of barrier dams.

Serial number	name	Number of drainage culverts	Storage condition	Damage condition	Serial number	name	Number of drainage culverts	Storage condition	Damage condition
1	Baiyi ba gully (3#)	0	F	●	35	Fanchang gully (1#)	1	F	●
2	Beidashan gully (0#)	0	F	●	36	Fanchang gully (2#)	1	F	●
3	Beidashan gully (1#)	0	F	●	37	Shang gully (2#)	1	M	●
4	Beidashan gully (2#)	0	F	●	38	Shang gully (1#)	1	M	●
5	Beidashan gully (1*)	0	F	●	39	Shanshui gully (3#)	1	E	●
6	Guo Jiapo mining area	0	F	●	40	Shanshui gully (2#)	1	F	●
7	GaoCang gully (2#)	0	M	●	41	Shanshui gully (1#)	1	F	●
8	Guan jia gully (2#)	0	F	●	42	Gao Cang gully (1#)	1	M	●
9	Jia chang gully (1#)	0	F	●	43	Guanjia gully (1#)	1	M	●
10	Jia chang gully (2#)	0	F	●	44	Caiyin gully (2#)	1	E	●
11	Jia chang gully (3#)	0	F	●	45	Caiyin gully (1#)	1	F	●
12	Longtoushan dam (1#)	0	F	●	46	Lijiaba gully (0#)	1	F	●
13	Majiaba (3#)	0	F	●	47	Lijiaba gully (1#)	1	F	●
14	Majiaba (2#)	0	F	●	48	Lijiaba gully (2#)	1	F	●
15	Majiaba (1#)	0	F	●	49	Lijiaba gully (3#)	1	M	●
16	Maijia gully (1#)	0	M	●	50	Longtoushan (2#)	1	F	●
17	Qujia gully (2#)	0	F	●	51	Maijia gully (2#)	1	M	●
18	Qujia gully (3#)	0	F	●	52	Maijia gully (4#)	1	E	●
19	Shangde town Wangjia gully (1#)	0	F	●	53	Qujia gully (1#)	1	F	●
20	Shangde town Wangjia gully (3#)	0	F	●	54	Shangde town Wangjia gully (2#)	1	F	●

(Continued on the following page)

TABLE 1 (*Continued*) Investigation information of barrier dams.

Serial number	name	Number of drainage culverts	Storage condition	Damage condition	Serial number	name	Number of drainage culverts	Storage condition	Damage condition
21	Bikou town Wangjia gully (4#)	0	F	●	55	Shangde town Wangjia gully (1*)	1	F	●
22	Bikou town Wangjia gully (3#)	0	M	●	56	Bikou town Wangjia gully (2#)	1	M	●
23	Bikou town Wangjia gully (1#)	0	M	●	57	Yangdu gully (1#)	1	E	●
24	Wei gully (1#)	0	M	●	58	Yangdu gully (2#)	1	E	●
25	Wei gully (2#)	0	F	●	59	Yangdu gully (3#)	1	F	●
26	Yangdu gully (4#)	0	F	●	60	Yeshupo (3#)	1	F	●
27	Yangdu gully (5#)	0	F	●	61	Yeshupo (2#)	1	F	●
28	Zhangliba gully (1#)	0	F	●	62	Zhangjia gully (2#)	1	F	●
29	Zhangjia gully (1#)	0	F	●	63	Zhangjiagou (3#)	1	E	●
30	Baiyiba gully (4#)	1	F	●	64	Zhangjia gully (4#)	1	F	●
31	Baiyiba gully (5#)	1	F	●	65	Maijia gully (3#)	2	M	●
32	Baiyiba gully (3#)	1	E	●	66	Bifeng gully (1#)	3	M	●
33	Bifeng gully (2#)	1	M	●	67	Bifeng gully (3#)	3	E	●
34	Damo gully (1#)	1	F	●					

Note: F–full stock; M–half Empty storage; E–Empty storage; ●Washout; ●Damaged; ●Intact.

shown in Table 2. Soil samples for the tests were taken from 100 m behind check dam No. 3 in the Beishan Gully of Wencheng County in Longnan City, Gansu Province, with geographical coordinates of 32°50′49.5″N–104°45′32.9″E (Figure 1).

3.1 Experimental apparatus

The tests were carried out in the landslide and debris flow laboratory of the Institute of Geological Natural Disaster Prevention of the Gansu Academy of Sciences. The experimental setup is shown in Figure 3 and mainly included brackets, water tanks, flumes, areas of deposition, sedimentation pools, and data acquisition systems. The flume was 6,500 mm long, 500 mm wide, and 800 mm high. The bottom was made of stainless steel and the sides were made of transparent organic glass. The contact surface was smooth, because of which the influence of boundary effects on the results could be ignored.

The range of flume gradients was 0°–40°. The gradient of the gully in which the sampling point was located was approximately 9° and was used as the flume gradient in the tests. After removing

TABLE 2 Model test conditions.

Test number	Groove width (cm)	Slope	Barrier dam scheme	Channel start-up plan				
				Accumulated body length (cm)		Stacked body type	Height	Experimental water
				Upper base	Bottom		(cm)	(m^3)
1–1	50	9°	porosity 2.12%	100	200	trapezoid	50	0.9
1–2			porosity 4.24%					
1–3			porosity 6.35%					
1–4			porosity 8.47%					
1–5			porosity 10.59%					

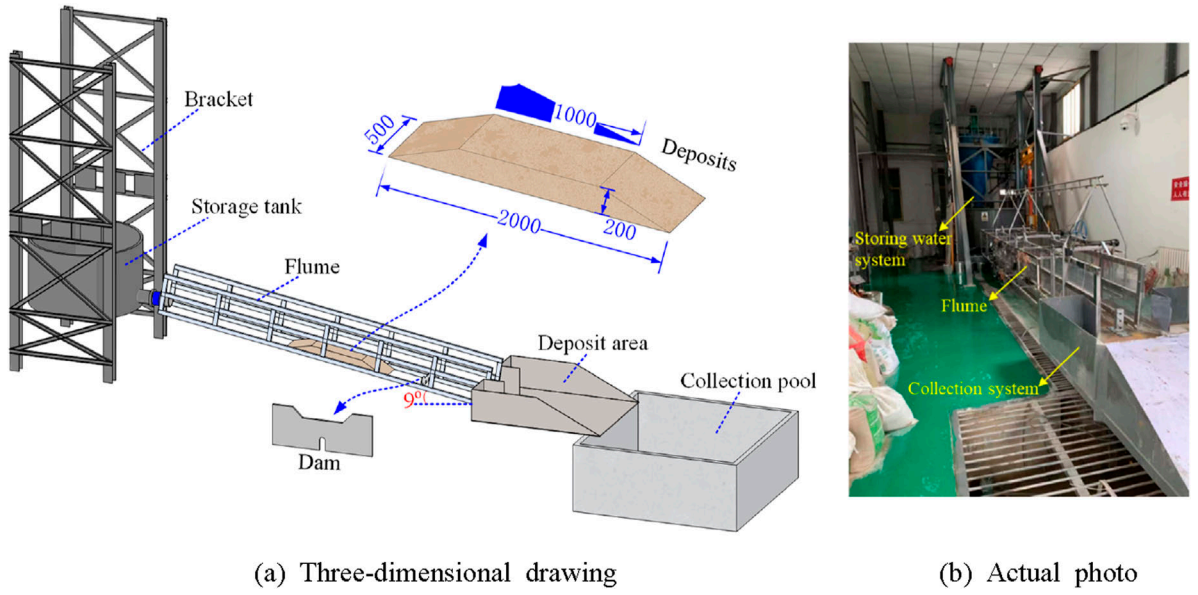


FIGURE 3
Test setup. **(A)** Three-dimensional drawing. **(B)** Actual photo.

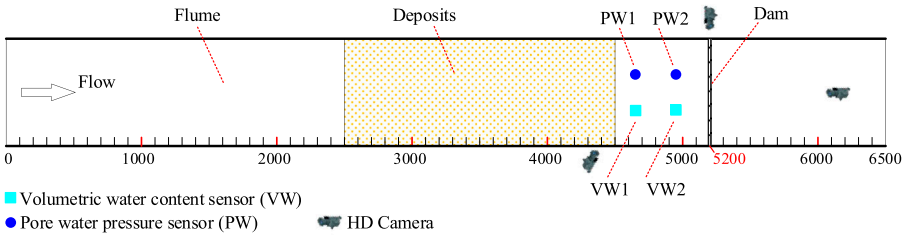
particles larger than 10 cm, the gully deposit was simplified into a trapezoid with the dimensions shown in Figure 3A. The total mass of the deposit was 250 kg, and its density was 1.68 g/cm^3. According to a preliminary test, 0.9 m^3 of water discharge at a time could ensure that the deposit in the ditch was completely activated to form debris flows.

3.2 Instrument arrangement

Figure 4 shows that the body of the dam was placed 2,500 mm from the outlet. The area between the water tank and the dam was the zone of flow of clean water to ensure that it could smoothly flush through the body of the dam. The check dam was set at 5,200 mm from the outlet to ensure that the soil and water were fully mixed to form the debris flow before encountering the check dam. Sensors to detect the pore water pressure and volumetric water content were installed behind the dam to monitor changes in them during the check of debris flow. Two sensors were arranged in each group at distances of 4,650 mm (Location 1) and 4,950 mm (Location 2) from the outlet. In addition, an HD camera was arranged on each of the upper parts of the check dam, the side face of the water tank, and the opposite side of the test platform to fully observe the phenomena.

3.3 Design of check dam

Adjacent check dams are usually far apart in practice, and thus rarely protect one another. Most check dams in a gully operate independently. Therefore, we used a single dam form and changed only the number of drainage holes in the check dam (to change the



(a) Schematic diagram of sensor layout



(b) Actual photo of sensor layout

FIGURE 4
Sensor layout. **(A)** Schematic diagram of sensor layout. **(B)** Actual photo of sensor layout.

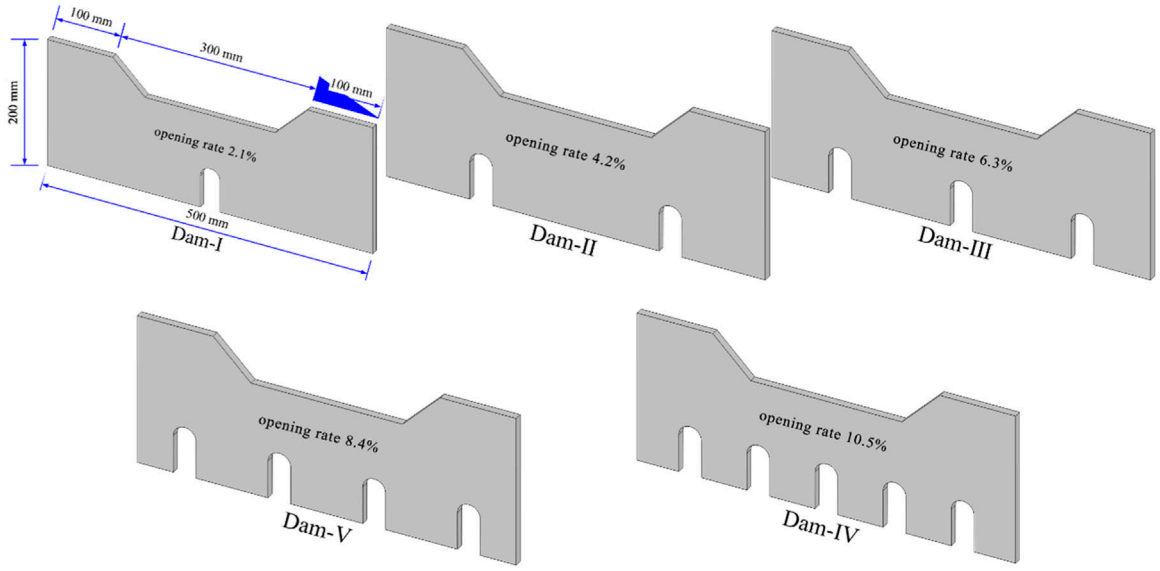


FIGURE 5
Check dam types.

rate of its opening) to simulate its protective effect to determine the optimal range of its opening rate. Figure 5 shows that we designed five types of dams. The height of each drainage hole was 65 mm, its width was 30 mm, and the radius of the arc was 15 mm. The rates of the opening of Dams I to V were 2.1%, 4.2%, 6.3%, 8.4%, and 10.5%, respectively.

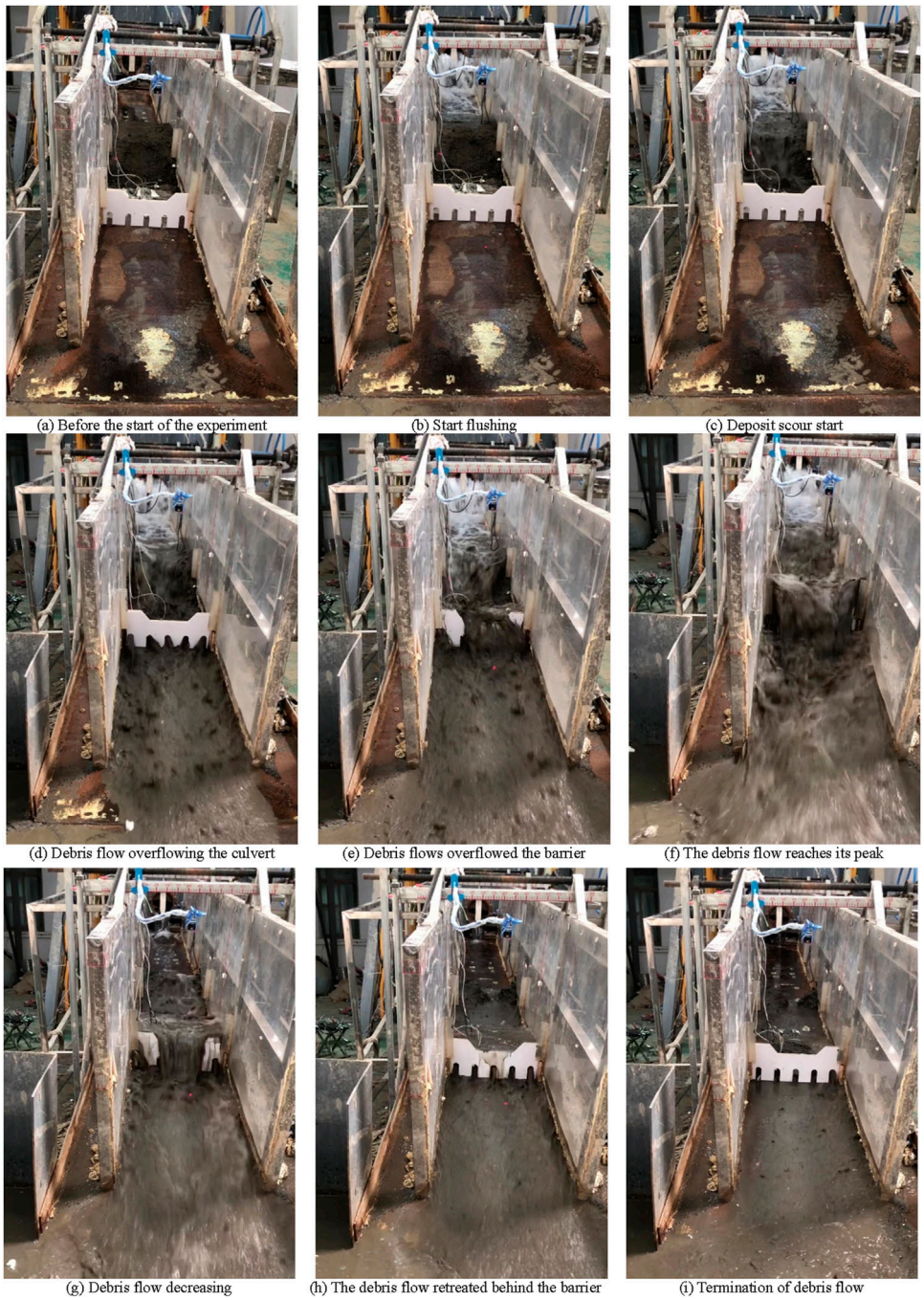


FIGURE 6
The whole process of the Dam-V test. **(A)** Before the start of the experiment. **(B)** Start flushing. **(C)** Deposit scour start. **(D)** Debris flow overflowing the culvert. **(E)** Debris flows overflowed the barrier. **(F)** The debris flow reaches its peak. **(G)** Debris flow decreasing. **(H)** The debris flow retreated behind the barrier. **(I)** Termination of debris flow.

4 Test phenomena

Figure 6 shows that the interaction between the debris flow formed by loose deposits scoured in the gully channel and the downstream check dam was intense. The debris flow underwent roughly the same three evolutionary stages under different opening ratios: the stages of debris flow through the dam, the growth of debris flow, and the decline in it. We consider dam V as an example, as shown in Figures 6A–E. The first stage involved debris flow through the dam and lasted for 4 s. The debris flow formed by the upstream collapse arrived rapidly at the check dam and flowed through the drainage holes, that is, the flow-through capacity of the drainage holes was adequate to accommodate the debris flow. The second stage involved the growth of the debris flow and lasted for 10–13 s.

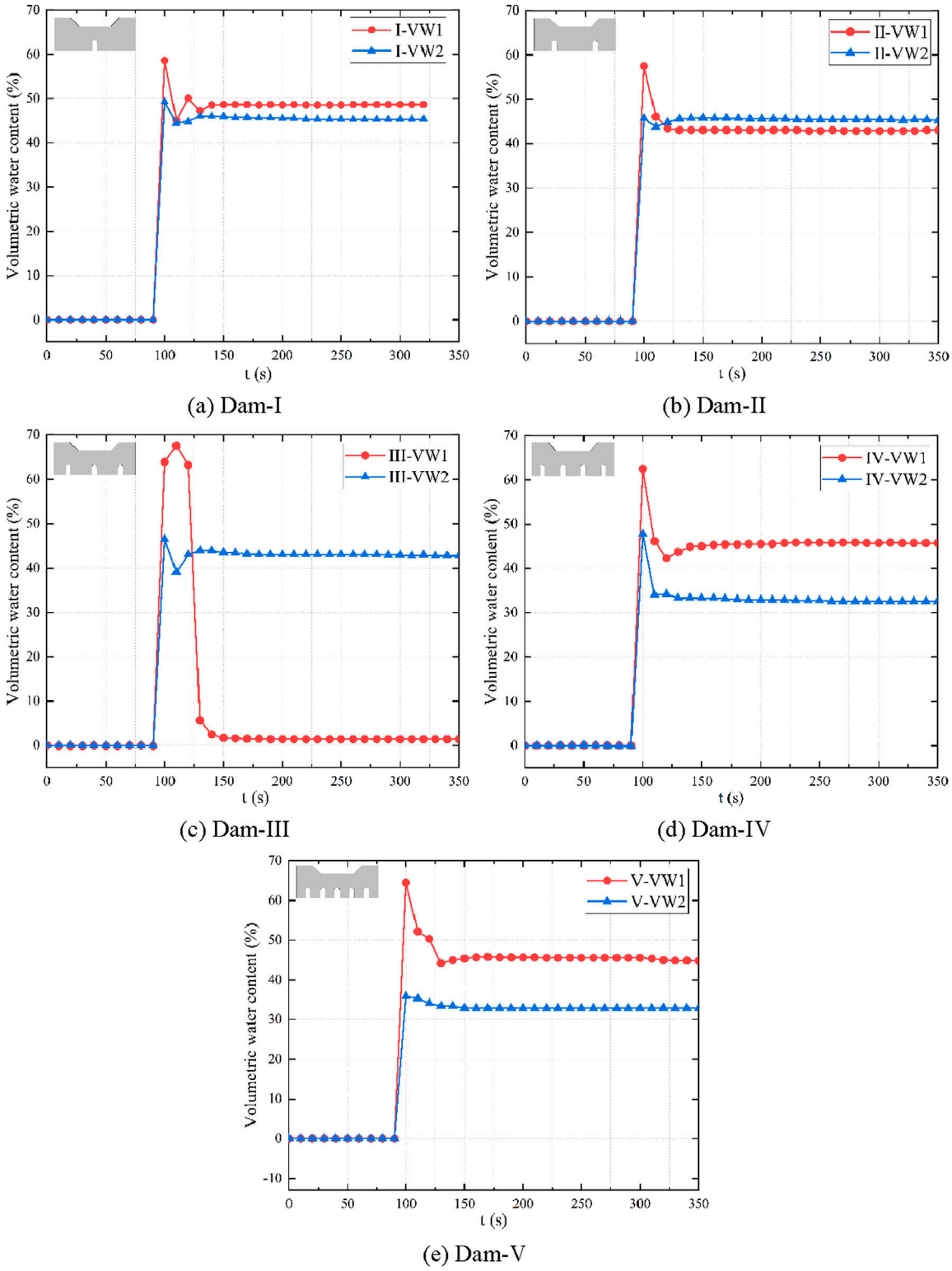


FIGURE 7
Changes in pore water pressure. (**A**) Dam-I. (**B**) Dam-II. (**C**) Dam-III. (**D**) Dam-IV. (**E**) Dam-V.

In this stage, loose materials from upstream continued to join the debris flow. The latter continued to increase in volume, was blocked by the dam, and eventually had a larger volume than the flow-through capacity of the drainage holes of the dam. The water level behind the dam rose continuously, and the peak rate of debris flow was obtained (Figure 6F). Fine particles moved downstream over

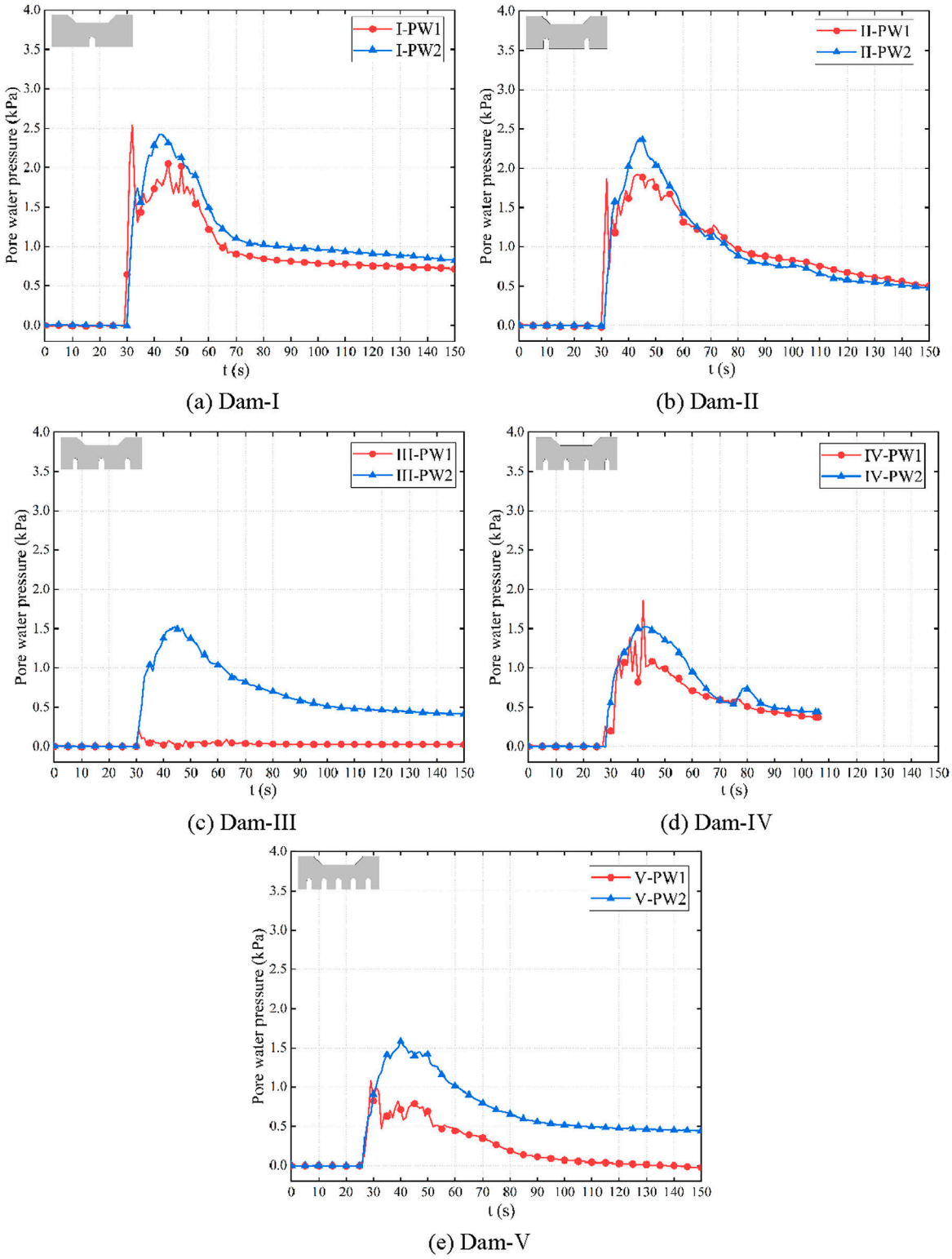


FIGURE 8
Changes in volume moisture content. (**A**) Dam-I. (**B**) Dam-II. (**C**) Dam-III. (**D**) Dam-IV. (**E**) Dam-V.

the spillway with the debris flow while coarse particles accumulated rapidly behind the dam. The third stage featured the decline in debris flow, as shown in Figures 6G–I, and lasted for 46–60 s. As the opening ratio increased, the duration of this stage first increased and then decreased. This stage was the longest for dam III (opening ratio, 6.3%), at 60 s. As the upstream inflow weakened, the content

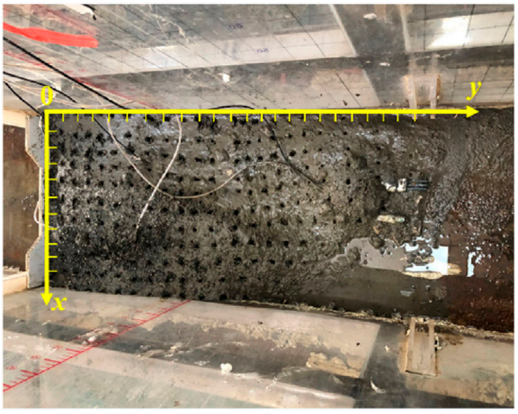


FIGURE 9
The schematic diagram for measuring the depth of sediment level.

deposited behind the dam tended to stabilize and slowly drained through the drainage holes.

After the test, we observed solid substances in front of and behind the check dam. Most coarse particles had been intercepted by the check dam to form a body of deposit behind it, while fine particles and sandy slurry had flowed through the dam downstream. This indicates that the check dam was able to separate water from stones in the debris flow and change its material composition. In addition, the morphology of the bodies of deposit behind dams with different opening ratios varied, indicating that the opening ratio of the check dam was an important factor influencing its regulation of debris flow.

5 Experimental results and analysis

To further analyze the interaction between the debris flows and different types of dams, we analyzed changes in the volumetric water content and pore water pressure at different locations behind the dam to indirectly determine the process whereby the check dam regulated the energy of the debris flows. We examined the laws of changes in the quality and particle composition of sedimentary materials behind dams with different opening rates to determine their ability to regulate debris flows.

5.1 Volumetric water content

Figure 7 shows the curve of variations in the volumetric water content at different locations behind the dam under the action of debris flow. It exhibited an overall "single-peak" pattern of variation, that is, it increased rapidly to its maximum value after the formation of debris flow and then decreased rapidly to a relatively stable value. The final volumetric water contents after the stabilization of debris flow for dams I–V were 45.5%, 45.6%, 43%, 32.9%, and 32.9%, respectively, showing an overall trend of a gradual decrease with an increase in the opening rate. When the opening rate was 6.3%, the final volumetric water content did not change.

5.2 Pore water pressure

Figure 8 shows the curves of variations in the pore water pressure over time. They can be divided into three stages: stages of stability, rapid increase, and recession. The curves exhibited an overall "single-peak" pattern. That is, after reaching the peak, the pore water pressure began to decrease slowly and then tended to stabilize. Because location 1 first encountered the debris flow, PW1 generally occurred earlier than PW2. Under the impact of the head of the debris flow, the value of PW1 fluctuated to a greater extent than that of PW2. Because the conditions of the formation of debris flow and the slope of the flume remained constant during the test, the initial energy of the debris flow was fixed. The pore water pressure attained its peak after 43 s for dams I–IV. For dam V, which had a higher permeability than the other dams, the pore water pressure reached its peak after 40 s. The peak values of PW2 for dams I and II were 2.42 kPa and 2.39 kPa, respectively, and the drop in these values was not significant. The peak value of PW2 of dam III dropped sharply to 1.52 kPa, a decrease of 36.4%. The peak values of PW2 of dams IV and V were 1.52 kPa and 1.58 kPa, respectively, nearly identical to that of dam III. This indicates that as the opening rate of the dams increased, the efficiency of debris flow passing through the check dams improved, the effective area of contact between the debris flow and the check dam decreased, and the pore water pressure therefore decreased accordingly. However, the pore water pressure behind the dam did not exhibit a simple trend of decrease. When the opening rate was 6.3%, the pore water pressure did not change significantly, which is similar to the law of change in the volumetric water content.

5.3 Deposit morphology

Once the experiment had been completed and the debris flow in the flume had completely stopped running, we considered the check dam as the x-axis and the gully bed along the longitudinal direction as the y-axis to measure the morphology of the deposits behind the check dam. We used vertical and horizontal spacings of 50 mm to insert a steel ruler into the deposits behind the dam to measure the depth of mud (Figure 9) and used this information to generate a 3D graph of the deposits (Figure 10). It clearly and intuitively showed the morphology of the deposit when debris flows passed through the different types of check dams.

Figure 10 shows that owing to the low porosity of dams I and II, the deposit behind these dams was significantly higher than those behind the other types of dams. The deposit was particularly high within 60 cm behind the dam, with maximum heights of 16.3 cm and 15.7 cm for dams I and II, respectively (Figures 10A, B). The height of the deposit then decreased rapidly. For dams III–V, which had relatively large pores, the morphology of the deposit behind the dam was relatively gentle, with maximum heights of 12.9, 10.3, and 13 cm, respectively. This indicates that when the opening rate of the check dam was 6.3%, the morphology of the deposit behind it tended to be gentle. Continually increasing the opening rate had little effect on the maximum height of the deposit behind the dam.

The volume of the sedimentation body behind the dam is obtained by 2D volume integration of the sedimentation shape surface behind the dam, as shown in Figure 11. The sedimentation

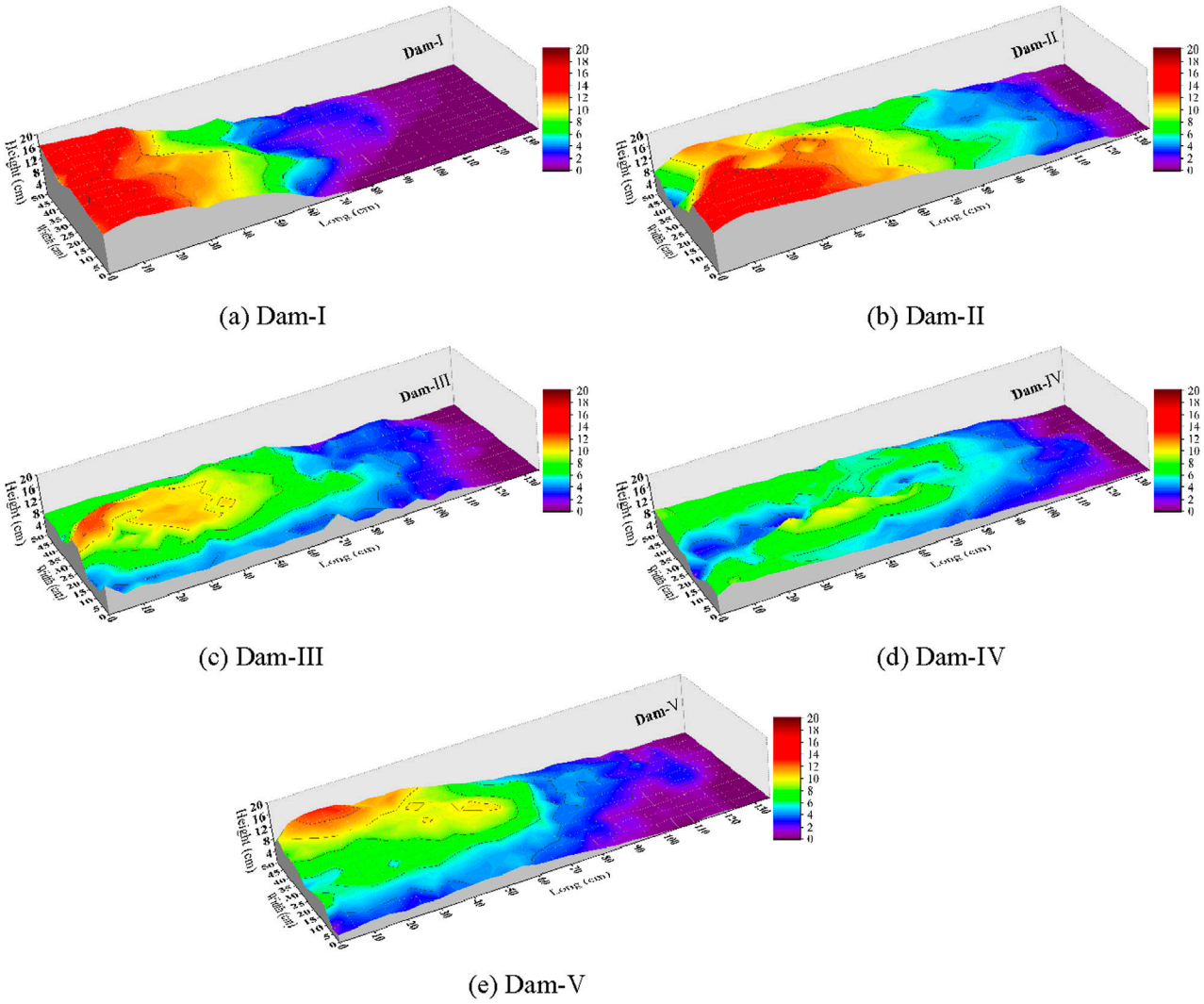


FIGURE 10
Deposit morphology behind the dam. (**A**) Dam-I. (**B**) Dam-II. (**C**) Dam-III. (**D**) Dam-IV. (**E**) Dam-V.

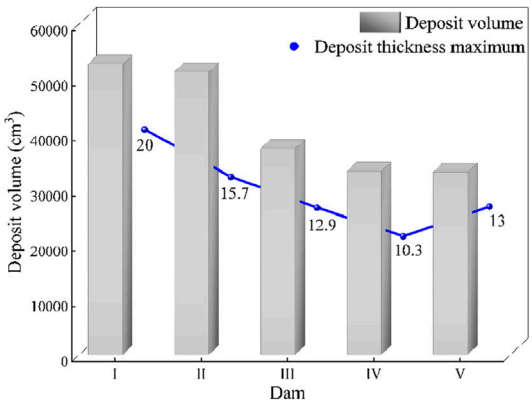


FIGURE 11
Dry mass of deposits and Changing amplitude.

volume of Dam-I and Dam-II is close to each other, while the sedimentation volume of Dam-III decreases rapidly and then slowly. When the opening rate is greater than 8%, the sedimentation volume behind the dam remains unchanged, indicating that a good effect of water-sediment separation has been achieved. Further increasing the opening rate has little effect on improving water-sediment separation. But it may affect the structural strength of the dam.

5.4 Particle size distribution of deposits behind the dam

Retaining the coarse and sluicing the fine is an important function of the check dam. Intercepting large particulate material can reduce the kinetic energy of debris flows and mitigate their destructive power while draining fine particulate material to

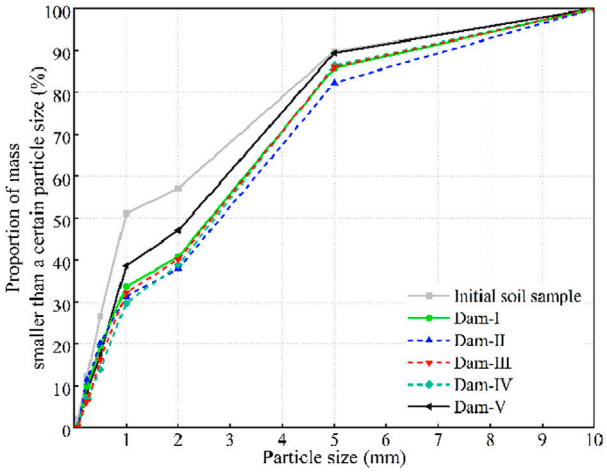


FIGURE 12
Accumulated grading curve of deposits.

downstream reduces the burden on the storage capacity of the check dam and improves its efficiency. By comparing and analyzing the particle size distribution of the original soil samples and deposits behind the dam, we quantitatively assessed the effects of the interception of coarse particles and draining of fine particles by the check dam. We dried the original soil samples and deposits behind the dam and then used 500 g of each for a sieve analysis test to obtain the accumulated grading curves of the deposits behind different types of dams, as shown in Figure 12. Compared with those of the original soil samples, the grading curves of samples from different types of dams shifted to the right. That is, the overall particle size became coarser, and this verifies the interception of coarse particles and the draining of fine particles by the check dam.

The Lagrange interpolation method was used to determine the median particle diameter d_{50} of deposits to characterize their degree of coarsening (Cui et al., 2015; Wang et al., 2024), as shown in Table 3. There was no significant linear relationship between the degree of coarsening of the deposits behind the dam and its opening rate. The maximum value of d_{50} of dam II was 2.82 mm, about 2.9 times that of the initial soil sample, while dam V exhibited a more significant extent of reduction, with its value of d_{50} decreasing to 2.21 mm. This shows that simply increasing the opening rate of the dam did not maximize its interception of coarse particles. The results showed that there was an optimal interval in this regard. The average value of d_{50} in the test was 2.60 mm in the range of opening rates of 2.1%–10.5%. These deposits behind the dam were coarser than the initial soil sample by about 2.65 times.

In addition, the particle size distribution of the deposits behind the check dams with different opening rates was not the same. To analyze this trend for different types of dams, we plotted curves of the particle size distribution of deposits behind the dams as shown in Figure 13. All the soil samples exhibited a law of bimodal distribution. Under varying opening rate conditions, the particle size distribution of the deposits behind the dam changes from 0.5–1 mm to 2–5 mm, with more than 40% falling in this range. Dam IV had the highest concentration of 48%, followed by Dam III with 46%. Figure 12 shows that the value of d_{50} of the deposits behind the dam increased when the ratio of particles with sizes in the range of 2–5 mm increased.

6 Discussion

The opening ratio is a key measure influencing the regulatory effect of check dams on debris flows (Bai et al., 2014; Liu et al., 2020). It can efficiently change the dynamic water–soil relationship and the composition of solid materials of debris flows, thereby reducing their destructive power on downstream structures and ensuring disaster prevention. We discuss the impacts of check dams with different opening ratios on the energy and material composition of debris flows, and then comprehensively evaluate their regulatory effect.

6.1 Relationship between check dams with different opening ratios and energy of debris flow

The conditions used to trigger debris flow were the same in all our experiments. The slope of all channel beds was 9° and the locations of the check dams were fixed. The results show that it took 2 s for the debris flow to reach the front of the dam, indicating that its initial velocity was the same in each case, i.e., all the debris flows had equal initial energy. As shown in Equation 1, the initial energy was converted into dissipation energy generated during the interaction between the debris flow and the check dam, according to the principle of energy dissipation (Gao et al., 2022), and constituted the final energy that continued to move downstream:

$$E_0 = E' + E_1 \tag{1}$$

where E_0 is the initial energy of the debris flow (J), E' is the dissipation energy generated during its interaction with the check dam (J), and E_1 is the final energy of the debris flow after overflowing past the check dam (J).

Because the initial energy E_0 was constant, the energy output by the debris flow downstream was the minimum when the dissipation energy was the maximum, that is, the check dam was able to optimally regulate the energy of the debris flow. We can thus assess the regulatory effects of different check dams by comparing the dissipation energy generated by them. However, due to constraints imposed by different types of debris flow, the shape of the check dam, and the characteristics of the material, no accurate means of measuring the dissipation energy is currently available. Some researchers have defined the ratio of the pore water pressure behind the dam to its normal stress (Hübl et al., 2003; Tian et al., 2017) during the interaction between it and the debris flow as the liquefaction coefficient. This can be indirectly used to characterize the magnitude of the dissipation energy. The liquefaction coefficient is calculated as follows in Equation 2:

$$L = \frac{\sigma_w}{\sigma_t} = \frac{\sigma_w}{\rho_0 g h \cos\theta} \times 100\% \tag{2}$$

where L is the liquefaction coefficient (%); σ_w is the pore water pressure behind the dam (kPa); σ_t is the normal stress behind the dam (kPa), ρ_0 is the initial density (g/cm^3); h is the height of mud

TABLE 3 Median particle diameter of deposits behind each dam.

Soil sample type	Initial soil sample	Dam-I	Dam-II	Dam-III	Dam-IV	Dam-V
d_{50} (mm)	0.98	2.61	2.82	2.65	2.71	2.21

Note: d_{50} denotes median particle diameter.

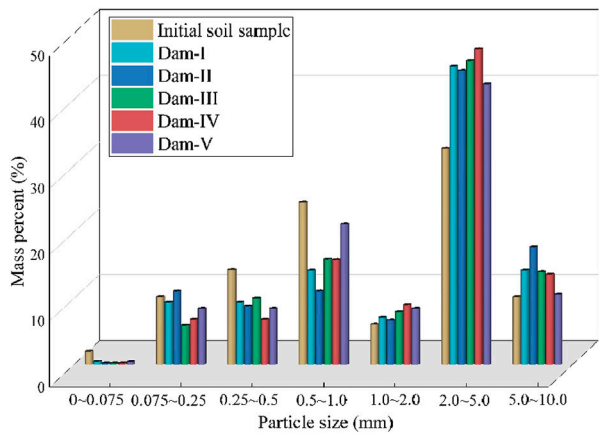


FIGURE 13
Particle size distribution of deposits.

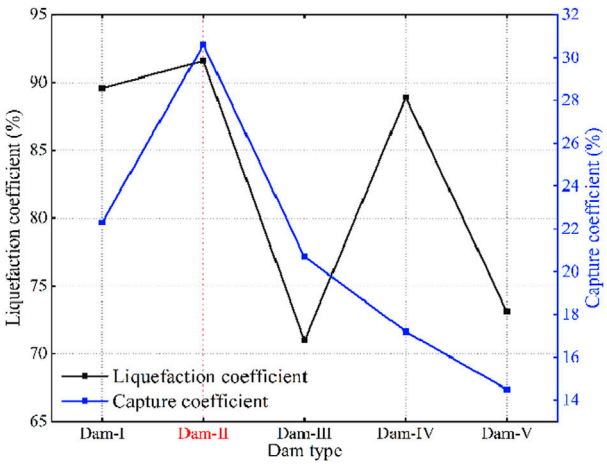


FIGURE 14
Liquefaction coefficient and capture coefficient.

behind the dam, and is taken as its maximum accumulated height (cm); g is the gravitational acceleration (m/s^2); and θ is the slope of the channel bed, which was set to 9° in this paper.

By comparing the liquefaction coefficients of check dams with different opening ratios, their regulatory effects on the energy of the debris flow can be quantitatively evaluated. The curve of the relationship between check dams with different opening ratios and their liquefaction coefficients is plotted in Figure 14. It is evident from it that the liquefaction coefficient of Dam II was the highest, 91.6%. That is, the interaction between this check dam and the internal debris flow was the most intense, generated the maximum dissipation energy and had the best effect in terms of energy dissipation on the debris flow. This may also be why the quality of the body of deposit behind dam II was the highest and its particles were the coarsest: A large number of solid particles in the debris flow collided and rubbed behind the dam, and finally the energy was completely dissipated causing the deposit to tend towards stillness. Following this, as the opening ratio increased, the liquefaction coefficient decreased rapidly, the effect of dissipation in the energy of the debris flow due to the check dam weakened, the debris flow developed better penetrability, and thus the maximum height of deposition behind the dam decreased significantly compared with that in case of dam II (Figure 10).

6.2 Relationship between check dams with different opening ratios and their regulatory effect on solid material in debris flow

A core function of check dams is to retain solids in the debris flow. The capture coefficient is commonly used to quantitatively evaluate their effects on solids in the debris flow (Hübl et al., 2003):

$$T = \frac{M_i}{M_0} \times 100\% \tag{3}$$

where T is the capture coefficient (%), M_0 is the total mass of solid matter in the debris flow (kg), and M_i is the mass of solid matter in the debris flow that is retained by the check dam (kg).

In our experiments, the body of the deposit in the flume was scoured and entrained into the debris flow by the incoming water. Some of the solid matter was transported downstream over the check dam along with the debris flow, while the remainder was captured by the check dam to form the deposit behind it. Therefore, the capture coefficient under different conditions of the dam was calculated by using Equation 3, and the curve of the relationship between the capture coefficient and the opening ratio of the dam was plotted, as shown in Figure 14. It shows that the curve exhibited an overall "single-peak" trend of change. The capture coefficient was the maximum at 30.6% for dam II, in which case the effect of retaining solid materials was the best. Subsequently, the capture coefficient continued to decrease as the opening ratio increased.

6.3 Overall evaluation of regulatory effects of debris flow by check dams with different opening ratios

The regulatory effects of check dams on debris flows are mainly related to two aspects: regulating energy and solid matter (Lin et al.,

2017). Moreover, the safety of check dams is also an indispensable factor in prolonging their service life (De Haas et al., 2015). A balance must be achieved between reducing the energy of debris flow and the removal of solid matter from it, and the safety of the dam during the construction of check dams (Chen et al., 2015). Figure 14 shows that better results were obtained when the coefficient of capture of the check dam was greater than its liquefaction coefficient. Because the benefits brought about by such retention could compensate for some of the damage to the check dam caused by the impact of debris flows, it is suitable to set an opening ratio in the range of 4.2%–6.3%, as shown in Figure 14. At the same time, the opening ratio of check dams should be reasonably selected according to the specific conditions of debris flow on-site.

For example, if local debris flows have a high frequency of occurrence and there is a large number of loose deposits in the ditch, dam II (opening ratio, 4.2%) is the most appropriate choice for regulating the energy and materials of debris flows. But this imposes stringent requirements on the strength of the dam, the service life of which can be extended by building groups of check dams. If local debris flows have a low frequency of occurrence, dam III (opening ratio, 6.3%) is the best choice. While ensuring minor damage to the dam itself such that it has a longer service life, this choice can help retain solids from the debris flow.

7 Conclusion

In this paper, five check dams with different opening ratios (ranging from 2.1% to 10.4%) were designed and tested based on field investigation data. Changes law of volumetric water content, pore water pressure, deposit morphology, and particle size distribution were analyzed to explore the control effect of check dams on the debris flow from the perspective of matter and energy. The following conclusions can be drawn:

(1) As the opening ratio of the check dam increased, the volumetric water content and peak pore water pressure of the body of deposits behind the dam exhibited a trend of first decreasing and then stabilizing. When the opening ratio increased to 6.3%, the parameters of the soil and water reached stable values, indicating that further increasing the opening ratio had little influence on the parameters of debris flow.

(2) Check dams with different opening ratios all had a good effect in terms of retaining the coarse and sluicing the fine. The average particle size of the deposits behind the dam was coarsened by 2.65 times, mainly by increasing the ratio of particles in the range of sizes of 2–5 mm. Of the five types of dams considered, dam II (opening ratio, 4.2%) yielded the maximum degree of coarsening.

(3) The range of opening ratios of 4.2%–6.3% was the optimum interval for controlling debris flow. Dam II (opening ratio, 4.2%) yielded the best control effects in terms of both the energy and the material of the debris flow.

Many factors influence the layout of openings in check dams. Quantitative parameters such as the slopes of different channels, maximum particle size, and unit weight of debris flow materials should be considered in future research to further refine the open holes in check dams and enhance their performance. Opening discharge culverts are also weak points in the design of check dams that can lead to their failure (Chen et al., 2017). Therefore, researchers should also consider protecting the open holes in check dams. Their shape can be optimized to this end, and flexible materials should be used in their manufacture to minimize the damage sustained by check dams due to impact with debris flow.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JH: Writing–original draft, Writing–review and editing. XL: Funding acquisition, Writing–original draft, Writing–review and editing. ZZ: Methodology, Writing–review and editing. JZ: Resources, Writing–review and editing. YM: Formal Analysis, Writing–review and editing. QL: Methodology, Writing–review and editing. YW: Methodology, Writing–review and editing. YA: Writing–review and editing, Supervision, Validation, Investigation.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Spatial distribution prediction of landslide susceptibility based on integrated particle swarm optimization

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Landslide sensitivity prediction relies on multiple environmental factors, making it difficult to obtain accurate prediction results. In order to improve the prediction accuracy of regional landslide sensitivity, a landslide sensitivity spatial distribution prediction method based on integrated particle swarm optimization was studied in Lianhe Village, Jianfeng Town, Shizhong District, Leshan City, Sichuan Province. Based on the determination coefficient, the sensitivity of landslide influencing factors was analyzed, and the weights of the influencing factors were determined. A landslide sensitivity spatial distribution prediction model was established based on support vector machine. By introducing simulated annealing and mutation operations into the particle swarm algorithm, an integrated particle swarm algorithm was obtained to extract high weight features of landslide sensitivity space and generate landslide sensitivity prediction results. The experimental results show that the cumulative value (ACU) of this method for predicting landslide sensitivity is 0.91, which can accurately predict the spatial distribution of landslide sensitivity in the study area and has practical value.

KEYWORDS

integrated particle swarm optimization, support vector machine, landslide susceptibility, space distribution, application value

1 Introduction

A landslide is a highly destructive geological disaster. It is sudden and unpredictable. Every time it occurs, there will be a huge loss of life and property. This has a far - reaching impact on the infrastructure of human society, residents' lives and the natural environment (Zhu et al., 2023). The weakness of geological structure provides a potential sliding surface for the formation of landslides. Topography and water system distribution directly affect the triggering conditions and movement path of landslides (Chen et al., 2023; Zhu et al., 2024). Meteorological conditions, especially extreme rainfall, earthquakes and other natural disasters, often become the direct cause of landslides. In addition, with the intensification of human activities, the erosion and instability of the earth's surface have been further aggravated, making the risk of landslide disasters significantly increased (Zeng et al., 2023; Wei et al., 2024). In the vast territory of China, the distribution of landslide disasters shows obvious regional characteristics (Luo, 2023). Due to the limited ability to predict the impact of landslide disasters, early warning resources (such as monitoring instruments, warning information release platforms, etc.)

often find it difficult to achieve comprehensive coverage and efficient utilization. In this situation, if there is a lack of spatial distribution prediction of landslide susceptibility, disaster response departments will not be able to identify high-susceptibility areas and focus on monitoring and warning them, resulting in an unreasonable allocation of warning resources and the inability to take effective preventive measures before disasters occur, such as reinforcing mountains and carrying out engineering treatment. Therefore, it is particularly important to carry out spatial distribution prediction of landslide susceptibility.

In recent years, many scholars have carried out research and have achieved some research results. Literature (He et al., 2023; Qiu et al., 2022) takes Weixin County, a mountainous area in Northeast Yunnan, as the research object. Firstly, a comprehensive evaluation index system is established, and then the factors are classified by using the woe model. Finally, the multi-scale support vector machine model is established, and the landslide susceptibility grade map is established by using Geographic Information System (GIS) technology. The selection of Support Vector Machine (SVM) model parameters has a great impact on the results, and the generalization ability of its model is not enough to achieve the ideal evaluation effect. Reference (Zou et al., 2023) proposed an evaluation method of landslide susceptibility in eastern Tibet Based on the frequency ratio and the Analytic Hierarchy Process (AHP) model. This method first selects the Digital Elevation Model (DEM) and its derived data (slope, aspect), faults, formation lithology, seismic points and other factors, then normalizes each factor, calculates the relative importance of each factor using the Factor Rating (FR) method, and finally calculates the weight of impact factors to build an evaluation model. The FR method used in this method can intuitively reflect the relationship between factors and landslide occurrence frequency. However, it ignores the complex non-linear relationship between factors and landslide occurrence, as well as the coupling between factors, which further exacerbates the complexity of the AHP model and leads to poor prediction accuracy. In literature (Yang et al., 2023; Wang et al., 2022), Yushe County is taken as the research area. Firstly, based on the GIS platform, five influencing factors of slope and slope height are selected as evaluation indexes through cluster analysis. Then, the information value of each factor is calculated using the Weighted Information Value (WIV) method. Finally, the weighted sum is obtained to evaluate the results of geological disaster susceptibility. Although the WIV method can effectively integrate multi-source information, its results are sensitive to weight allocation and do not fully consider the spatial correlation between factors, resulting in the need to improve its application prediction accuracy. In reference (Wang et al., 2023), a landslide hazard susceptibility evaluation method based on an information model is proposed. In this method, Chongqing, a city with serious landslide disasters, is taken as the research area. Firstly, based on the historical landslide data, 10 evaluation indexes, including slope and aspect, are selected. Then, the contribution of each factor to landslide occurrence is calculated using the information model. Finally, the contribution is ranked, and the landslide susceptibility distribution map of the research area is obtained. Although the information model can reflect the contribution of various factors to landslide occurrence, it may overlook some potential non-linear landslide influencing factors, which may affect the evaluation results and lead to poor prediction accuracy.

In view of the problem that the above method is affected by the landslide influencing factors and the prediction accuracy is insufficient, the prediction of landslide susceptibility spatial distribution based on integrated particle swarm optimization is carried out. Innovatively analyze and extract potential, non-linear landslide impact factors; analyze the spatial correlation between influencing factors based on the deterministic coefficient; complete the sensitivity analysis of landslide influencing factors; and reduce the impact of factor weight allocation on the prediction results. Considering the complex non-linear relationship between influencing factors and landslide occurrence, as well as the coupling between factors, simulated annealing and mutation operations are simultaneously introduced into the particle swarm algorithm to optimize the ensemble particle swarm algorithm and improve its generalization ability. Solve the effective spatial high factor weight characteristics of landslide susceptibility, simplify the prediction model, and obtain distribution prediction results.

2 Overview of the study area

2.1 Geological environment analysis

The study area is Lianhe village, Jianfeng Township, Shizhong District, Leshan City, Sichuan Province. The survey area is located in a deep-seated hilly area extending in a beaded shape from the Northeast, and location and general situation of the study area is shown in Figure 1.

As shown in Figure 1, the landslide is developed on the slope on the north side of the dome, with the direction of the slope in the West and North, a width of 80–130 m, and a slope of 10°–17°; The lower section is a steep slope with a length of 60–150 m and a slope of 30°–55°; The gentle slope area is a long and gentle slope, with a slope of 10°–20°. Most residential houses are located on this slope. The stratum above the hill scarp is the sandstone of the upper Cretaceous Jiaguan formation, locally intercalated with thin mudstone. The slope at the foot of the slope is composed of silty mudstone and argillaceous siltstone of the lower hill 3, members of the Penglaizhen formation of the upper Jurassic system. The Neogene Holocene collapse (residual) diluvium in this area is sporadically distributed. The present talvium in the landslide area is mainly composed of gravel. The geological structure of this area is adjacent to the Xinqiao fault of the NNE trending fault, which is located in the Northeast (hanging wall) of the fault. It is affected by the pull bending folds of the two walls and is about 350 m away from the fault. The rock occurrence in this area is 315°, ∠12, which is a monoclinic structure. Compressed by geological structure, the rock mass fissure is developed, mainly including two groups of 80°∠78° and 133°∠75°. The landslide area is a typical clockwise slope terrain. On this basis, follow-up research was carried out.

2.2 Analysis and extraction of landslide impact factors

The causes of landslides are complex and can be attributed to two categories of influencing factors: controlling factors and inducing and promoting factors. The controlling factor is the basic

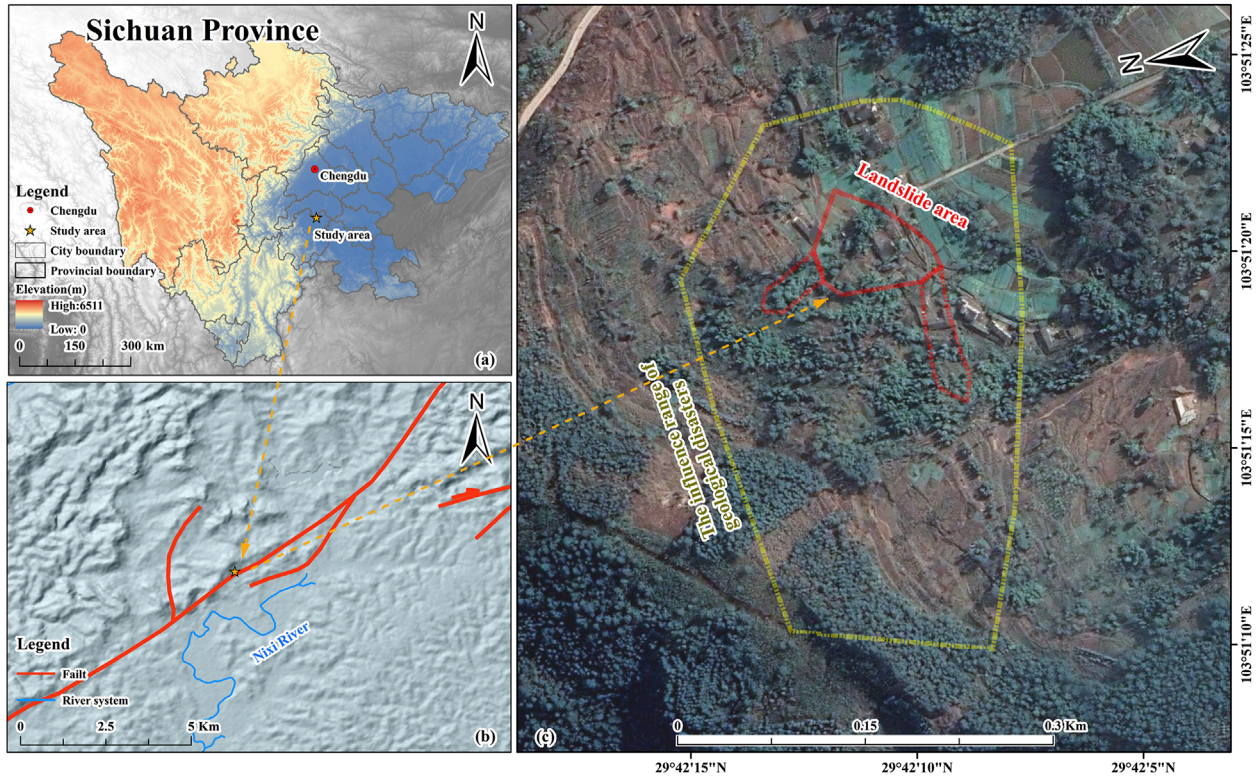

FIGURE 1
Location and general situation of the study area.

condition of landslide occurrence and plays a decisive role in the formation of landslides. The inducing and promoting factors further stimulate or accelerate the landslide process on the basis of the controlling factors (Duan et al., 2023).

2.2.1 Control factor analysis

1) Geomorphic factors: These factors jointly shape the topographic background of landslide occurrence, such as steep slope, unfavorable slope direction (such as towards the direction vulnerable to erosion) and complex topographic relief, increasing the risk of landslide.
2) Geological factors: Rock combinations of different lithologies have different resistance to landslides. The stability of slope structure directly affects the occurrence of landslides, while the fault distance reflects the potential impact of regional geological structure on landslides (Anand et al., 2023a).
3) Hydrological factors: Hydrological conditions are very important for triggering landslides, especially rainfall, which is one of the most common triggering factors for landslides.

2.2.2 Analysis of inducing and promoting factors

1) Surface coverage: The type, thickness and stability of surface vegetation, soil layer and other coverings have an important impact on landslides. The bare surface without vegetation coverage is more likely to be washed by rain, accelerating the landslide process (Chang et al., 2023).
2) Seismicity: The propagation and energy release of seismic waves in rock mass will cause damage to the structural integrity of rock mass, lead to slope instability and induce landslides.
3) Human activities, such as farming, deforestation, urban construction, and road construction, can have negative impacts on natural slopes, thereby increasing their landslide risk. In addition, unreasonable excavation, stacking and other behaviors are also direct causes of landslides (Fan et al., 2022).

In summary, this paper extracted 18 influencing factors, including elevation, slope gradient, slope orientation, slope length, terrain curvature, terrain undulation, engineering rock formation, slope structure, fault distance, water system distance, watershed area, flow path length, Landslide Susceptibility (LS) coefficient, Melton strength, terrain humidity index, rainfall, land use, and road distance for further research. The impact of these 18 influencing factors on landslide occurrence is as follows: Elevation factor: Elevation affects climate, vegetation, and indirectly affects landslide occurrence. Generally speaking, high-altitude areas may have lower temperatures, frequent freeze-thaw cycles, severe rock weathering, and an increase in the amount of loose material. Meanwhile, vegetation growth conditions in high-altitude areas are relatively poor, and the reinforcement effect of vegetation roots on soil is weak, making landslides prone to occur. Slope factor: Slope is one of the key factors affecting landslide occurrence (Melati et al., 2024). A steeper slope will subject the rock and soil mass to greater gravitational forces, increasing the sliding force and affecting the runoff velocity and infiltration of surface water. When the slope

exceeds a certain limit, the stability of the rock and soil mass will significantly decrease, making it prone to landslides. Slope aspect factor: Slope aspect affects conditions such as light, temperature, precipitation, and vegetation growth. The sunny slope receives more solar radiation, with higher evaporation and relatively lower soil moisture content (Li et al., 2023). The vegetation type and coverage may differ from the shady slope. On shady slopes, the humidity may be high, and in some cases, excessive soil moisture can increase the risk of landslides. Slope length factor: When the slope length is long, the runoff distance of surface water on the slope increases, and the erosion and scouring ability of runoff is enhanced. It is easy to carry away loose materials on the slope, reduce the stability of the slope, and easily form gullies, which can lead to geological disasters such as landslides. Terrain curvature factor: Terrain curvature reflects the degree of curvature of the terrain. At the curvature of normal terrain (convex terrain), the rock and soil mass are easily subjected to tensile stress, leading to internal structural damage to the rock and soil mass. In areas with negative terrain curvature (concave terrain), it is easy to accumulate water, increase soil moisture content, reduce the shear strength of rock and soil mass, and increase the possibility of landslides. Terrain undulation factor: A large terrain undulation means a large height difference, and the gravity effect on the rock and soil mass varies greatly, which can easily lead to stress concentration. Meanwhile, areas with large terrain undulations are often accompanied by complex geological structures and different lithological combinations, increasing the potential risk of landslides. Engineering rock formation factor: Different engineering rock formations have different physical and mechanical properties, such as hardness, weathering resistance, permeability, etc. Weak rock formations (such as shale, mudstone, etc.) are prone to weathering, have low strength, and are prone to deformation and damage when subjected to external forces, leading to landslides. Slope structure factor: Slope structure includes the bedding structure of rock and soil, the development of joints and fissures, etc. If the bedding tendency of the rock and soil mass on the slope is consistent with the slope inclination, and the inclination angle is smaller than the slope inclination angle, this forward slope structure is more prone to sliding under the action of gravity (Di et al., 2023). The integrity of the rock and soil mass with developed joints and fissures is destroyed, and the shear strength is reduced. The rock and soil mass along the slope are prone to sliding along the bedding plane, causing landslides. Fault distance factor: The rock and soil mass near the fault is strongly affected by crustal movement, resulting in rock fragmentation, crack development, and damage to the integrity and stability of the rock and soil mass. The closer to the fault, the stronger the impact and the higher the risk of landslides. Water system distance factor: Areas close to water systems have higher groundwater levels and higher soil moisture content. Meanwhile, lateral erosion of the water system may weaken the support force at the foot of the slope, causing the rock and soil mass to lose balance and leading to landslides. Watershed area factor: A larger watershed area means more catchment areas, resulting in larger runoff during rainfall. A large amount of surface water runoff will increase the erosion and scouring ability of the slope, reducing the stability of the slope. Flow path length factor: When the flow path length is long, the energy accumulation of water flow in the slope or valley is greater, and the erosion and scouring ability is enhanced. Long flow paths may also lead to more slope material being transported, affecting the stability of the slope. Length Slope (LS) coefficient: the LS coefficient comprehensively considers the effects of slope length and slope gradient on soil erosion and landslides. It reflects the comprehensive effect of terrain on the erosion force of water flow and the stability of rock and soil mass. The larger the coefficient, the greater the potential impact of terrain on landslides. The LS coefficient is relatively high, making landslides more likely to occur under triggering factors such as rainfall. Melton intensity factor: Melton intensity is an indicator that measures the relationship between terrain humidity conditions and potential landslide risks. A higher Melton strength indicates a higher terrain humidity, which increases the likelihood of soil being supersaturated and reduces the shear strength of the rock and soil mass, thereby increasing the risk of landslides. Terrain moisture index factor: The terrain moisture index reflects the influence of terrain on soil moisture distribution. It comprehensively considers the relationship between terrain slope, slope orientation, slope length, and soil moisture. A higher terrain moisture index indicates a high soil moisture content, which reduces the shear strength of the rock and soil mass and makes it prone to landslides (Oyda et al., 2024). Rainfall factor: Rainfall is one of the main triggering factors for landslides. On the one hand, rainfall increases the weight of the rock and soil mass, and increases the sliding force. On the other hand, rainwater infiltration into the rock and soil mass will reduce its shear strength, making it easier for the rock and soil mass to slide. Land use factor: Different land use methods have varying impacts on landslides. For example, forest vegetation can improve the stability of soil and rock through root system stabilization, interception of rainfall, and other methods. Construction land (such as building construction, road construction, etc.) may damage the original terrain and soil structure, increasing the risk of landslides. Road distance factor: In areas close to the road, excavation, filling, and other engineering activities during road construction can alter the stress state and hydrological conditions of the rock and soil mass. The drainage system of the road may also affect the soil moisture content in the surrounding area. The closer to the road, the more obvious these effects are, and the higher the risk of landslides.

3 Sensitivity analysis of landslide influencing factors based on deterministic coefficients

After completing the extraction of landslide impact factors, the deterministic coefficient theory is introduced to conduct a sensitivity analysis of landslide impact factors. Sensitivity analysis of influencing factors helps determine which influencing factors are closely related to landslides (He et al., 2022; Ji et al., 2022). The formula for calculating the determination coefficient of landslide impact factors is as follows:

$$CF = \begin{cases} \dfrac{PP_a - PP_s}{PP_a(1 - PP_s)}, PP_a \geq PP_s \\ \dfrac{PP_s - PP_a}{PP_s(1 - PP_a)}, PP_s \geq PP_a \end{cases} \quad (1)$$

In the formula, PP_a represents the probability of landslide being affected by factor a; PP_s represents the probability of landslide

TABLE 1 Classification and grading information of certainty coefficient.

Number	Coefficient range	Describe	Stability partition
1	−0.1 > CF ≥ −1	There is very little certainty of geological hazards occurring, and it is basically impossible for geological hazards to occur	Stabilize
2	0.1 > CF ≥ −0.1	The possibility of geological disasters is difficult to determine	Indeterminacy
3	0.4 > CF ≥ 0.1	Potential for geological hazards to occur	Less stable
4	0.7 > CF ≥ 0.4	There is a high possibility of geological disasters occurring	Instability
5	1 > CF ≥ 0.7	Geological disasters are highly prone to occur	Extremely unstable

occurrence in the study area, and its calculation method is as follows:

$$PP_a = \frac{S_{pa}}{S_a} \tag{2}$$

$$PP_s = \frac{S_p}{S} \tag{3}$$

In the formula, S_a represents the area of landslide occurrence in a; S_{pa} represents the area of data class a; S_p represents the area where landslides occur within the region; S represents the total area of the region (Guo et al., 2022).

According to Equations 1–3, it can be seen that the maximum and minimum values of the coefficient of certainty for the landslide impact factor are 1 and −1, respectively. When the coefficient of certainty is greater than 0, it indicates a high degree of certainty that a landslide will occur in the area. When the coefficient of certainty is equal to 1, it indicates that a landslide will inevitably occur, with a probability of 100%; When the coefficient of certainty is less than 0, it indicates that the certainty of landslide occurrence is low, and the probability of landslide occurrence in the evaluation unit at the location is low; When the coefficient of certainty is equal to −1, it indicates that the unit is stable and will not experience landslides; When the coefficient of certainty is approximately equal to 0, it indicates that there is no correlation between the event occurrence and the evaluation unit, and it is impossible to determine whether it is prone to landslides (Zhou et al., 2022). The classification and grading information of the determination coefficient is shown in Table 1:

Next, calculate the determination coefficients of the influencing factors and combine the determination coefficients of different factors using the following formula to obtain the factor weights:

$$Z = \begin{cases} x + y - xy, xy > 0 \\ \dfrac{x + y}{1 - \min(|x|, |y|)}, xy < 0 \end{cases} \tag{4}$$

In the formula, x represents the susceptibility factor of landslides; y represents the frequency of regional landslides under the influence of influencing factors. According to Equation 4, merge the deterministic coefficient values of each factor to complete the factor weight calculation. To prevent multicollinearity caused by multiple influencing factors, calculate the Pearson correlation coefficient between each pair of features. If the absolute value of the correlation coefficient is greater than the threshold of 0.7, it is considered that these two features have strong collinearity. When collinearity is found, priority is given to retaining factors with higher weight values and discarding another factor.

4 Construction of spatial distribution prediction model for landslide susceptibility

The geological structure, soil type, rock properties, and other factors vary significantly in different regions, and the availability and quality of landslide historical data, geological survey data, etc., directly affect prediction. The PSO (particle Swarm Optimization) algorithm is used to optimize the parameters of the SVM model. Introduce an insensitive loss function and set the parameters of the particle swarm reasonably, such as particle number, inertia weight, and acceleration coefficient. Find the optimal parameter combination, select and extract effective features, and predict the spatial distribution of landslide susceptibility.

4.1 Construction of prediction model based on sensitivity and SVM

SVM is a supervised machine learning algorithm based on statistical learning theory. The occurrence of landslides is a complex geological process that is influenced by multiple factors. It is not easy to collect sufficient data points on landslide occurrence and non-occurrence comprehensively. SVM has good generalization ability in small sample situations. It separates samples of different categories by finding the optimal classification hyperplane rather than relying excessively on a large amount of sample data to fit the model like other algorithms. In addition, the susceptibility of landslides is influenced by numerous factors, which form a high-dimensional feature space. When constructing prediction models, it is necessary to consider the comprehensive impact of these factors simultaneously. SVM can effectively process high-dimensional data by mapping the original high-dimensional data to a higher dimensional feature space through kernel functions, and finding the optimal classification hyperplane in this high-dimensional space. There will be no "curse of dimensionality" due to the increase in data dimensions, thus accurately capturing the complex relationship between various factors and landslide susceptibility. Therefore,

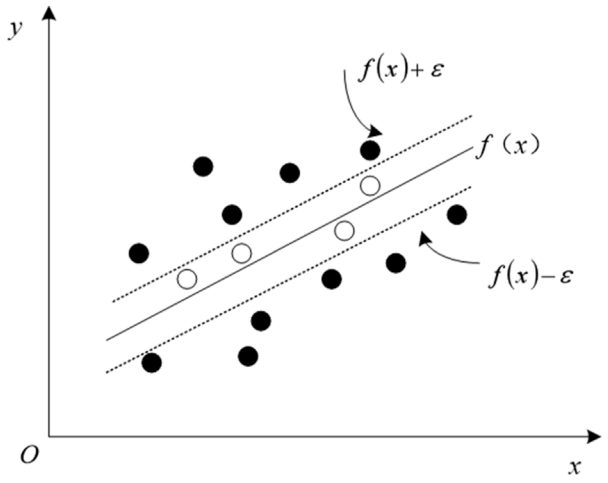

FIGURE 2
Schematic diagram of support vector machine.

SVM is used to construct the prediction model. In the process of constructing a landslide susceptibility spatial distribution prediction model based on SVM, a core issue is to optimize the position of the hyperplane to ensure the maximization of the classification interval between different categories, namely, landslide points and non-landslide points, while minimizing the error of misclassification of training samples (Wang et al., 2022). This challenge requires finding the optimal balance between maximizing classification interval and minimizing classification error. To achieve this goal, an insensitive loss function is introduced, which defines an error tolerance range ε. When the difference between the predicted value f(x) and the observed value y is less than ε, the prediction is considered accurate, meaning no loss occurs at that point. The principle is shown in Figure 2.

From Figure 2, it is evident that support vector machines fit all sample points by finding a regression equation. Assuming dataset (x_i,y_i), x_i represents the influencing factor data, and y_i represents the coefficient of determination of the factor (Nirbhav et al., 2023b), a prediction model is constructed as follows Equation 5:

$$F = \min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i - \xi_i') \quad s.t.\begin{cases} -\varepsilon - \xi_i \le y_i - f(x) \le \varepsilon + \xi_i' \\ \xi_i' \ge 0 \end{cases} \tag{5}$$

In the formula, ω represents the weight vector orthogonal to the hyperplane, ξ_i represents the relaxation variable, and C represents the penalty parameter; ε represents the insensitive loss function (Bui et al., 2023). By analyzing the sampling points, a new kernel function is proposed and solved, resulting in the following regression as follows Equation 6:

$$f(x) = Z\sum_{i=1}^{n}(\alpha_i - \alpha_i')e^{-\gamma\|x_i - y_i\|^2} + Fb \tag{6}$$

In the formula, α_i represents the regression factor; γ represents the nuclear parameter; b represents distance deviation. Thus, the construction of a landslide susceptibility prediction model is completed.

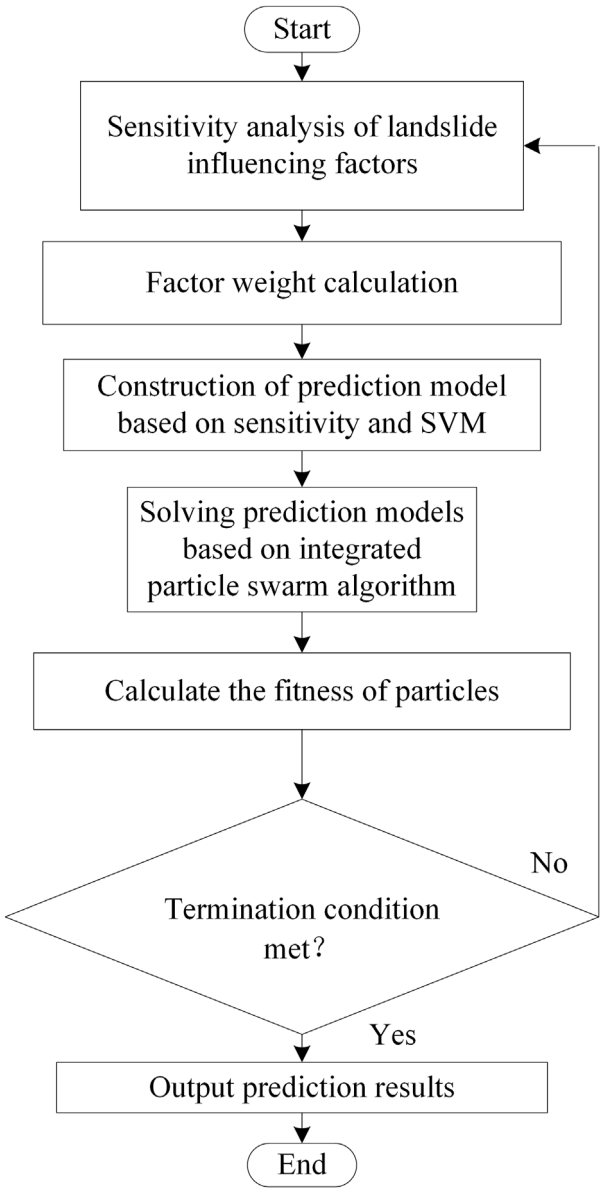

FIGURE 3
The overall prediction process of the prediction model.

4.2 Deep optimization solution of prediction model based on integrated particle swarm algorithm

Due to the lack of precise and unified methods for selecting the penalty coefficient C and kernel parameter γ in support vector regression (SVR), the choice of model parameters has a direct and significant impact on the generalization performance of SVR. In addition, if all the influencing factors of the landslide point are indiscriminately used as input values for the SVR model, not only will increase the computational complexity of the model due to the inevitable redundancy of information between each factor, but the complex non-linear relationship between these factors and landslide occurrence, as well as the coupling between factors, will

TABLE 2 Information on data sources and types in the research area.

Data base	Data sources	Data type
Landslide point disaster data	Sichuan Provincial Geological Environment Monitoring Center	Scalar quantity
DEM model	Geospatial data cloud	30 m × 30 m grid
Geological environment data	Leshan city 1:50,000 geological map data	Complexor
Rainfall data	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	1 km × 1 km grid
Landsat TM Image data	Geospatial data cloud	30 m × 30 m grid
River network road data	Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences	Complexor

further exacerbate the complexity of the model. Therefore, it needs to be deeply optimized and solved. Due to the complex non-linear relationship between landslide influencing factors and landslide occurrence, and the coupling between factors, the prediction model may have multiple local optimal solutions (Zhang et al., 2023). Traditional optimization algorithms may easily fall into local optima, resulting in the inability to find globally optimal model parameters. The particle swarm algorithm has good global search capability. It searches for the optimal solution in the solution space through a group of particles, and each particle continuously adjusts its position based on its own experience and the collective experience. This search method can cover most of the solution space, making it more likely to find the global optimal solution and improving the accuracy of landslide prediction models, even in complex non-linear relationships and factor coupling. In addition, when dealing with complex models such as landslide prediction, the model becomes complex due to multiple influencing factors and coupling relationships. However, the particle swarm optimization algorithm has relatively fewer parameters, which makes it more convenient to optimize and solve complex landslide prediction models, reducing the complexity of the optimization algorithm itself. Therefore, the particle swarm optimization algorithm is used to solve the prediction model. This process involves introducing simulated annealing and mutation operations into the particle swarm algorithm simultaneously, and the training process seeks the optimal model parameters to maximize the model's generalization ability, thereby achieving an effective prediction of the spatial distribution of landslide susceptibility. In this optimization, the particle swarm optimization algorithm was selected as the main optimization-solving tool (Yang and Zhu, 2021).

The integrated particle swarm algorithm is applied to solve the problem, and the specific process is as follows:

(1) Initialize particles and related parameters, set the particle swarm size to n, maximum iteration times to K, simulated annealing probability threshold to δ_d, mutation probability threshold to δ_m, and inertia weights to $\omega_{\max}$ and $\omega_{\min}$ (Xiong et al., 2022).

(2) Calculate the fitness value of particles according to the Equation 7:

$$d_{ik} = \min\left\{\left\|x_{i,k} - x_{j,k}\right\| : i \neq j\right\} \tag{7}$$

In the formula, d_{ik} represents the closest distance of particle i in the k dimension; $x_{i,k}$ represents the position of the i particle in the k dimension; $x_{j,k}$ represents the position of the j particle in the k dimension; $\left\|x_{i,k} - x_{j,k}\right\|$ represents the Euler distance between particles i and j in k dimensions. Assign a random number between (0,1) to the i particle. If the random number is less than δ_d, perform simulated annealing algorithm. If not, execute (3). On this basis, first generate a new position for the particle based on its current position and velocity, and calculate its fitness at the new position; For a particle, if its fitness is better than its original optimal solution d_{best}, it is set as d_{best}; Calculate the overall maximum value D_{best} by taking the maximum value d_{best} of each particle; Update the velocity of the particles according to Equation 8 and limit it to within $V_{\max}$; According to Equation 9, update the current position of the particle, which is limited to region $X_{\max}$; Calculate the change in fitness value between two positions, i.e., ΔE; If ΔE is less than the allowed deterioration range of the objective function and ΔE<0, keep the value; otherwise, discard the value.

$$V_{id}^{k+1} = f\left(\omega V_{id}^{k}\right) + c_1 r_1\left(d_{ik} d_{id}^{k} - X_{id}^{k}\right) + c_2 r_2\left(d_{gd}^{k} - X_{id}^{k}\right) \tag{8}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{9}$$

In the formula, ω is the inertia weight, k is the number of iterations, V_{id} is the particle velocity, X_{id} is the particle position, and c_1, c_2 is the acceleration coefficient; r_1, r_2 represents a random number within [0,1]; V_{id}^{k+1}, V_{id}^{k} represents the iteration rate of particle i through $k+1$ and k; Among them, d_{id}^{k} represents the best position of particle i in history; d_{gd}^{k} is the best choice for all d_{id}^{k}; X_{id}^{k+1}, X_{id}^{k} represents the position of i during $k+1$ and k iterations.

(3) d_{best} comparison was made between the suitability of particles and their optimal value A. If the current value is better than d_{best}, then set d_{best} to the current value and use d_{best} as the current position in the D dimension.

(4) A comparison was made between the fitness of particles and the optimality of the population. If the current value is better than D_{best}, then set D_{best} as the fitness of the current particle.

(5) Update the direction and step size of particle motion, generate a new population, and verify whether its velocity and position are outside the interval.

(6) Perform mutation operation. Assign a random number to the i particle within the range of [0,1]. When the random number is smaller than δ_m, a variable operation is performed.

(7) Continue $k = k_1 + 1$ until the termination condition is met.

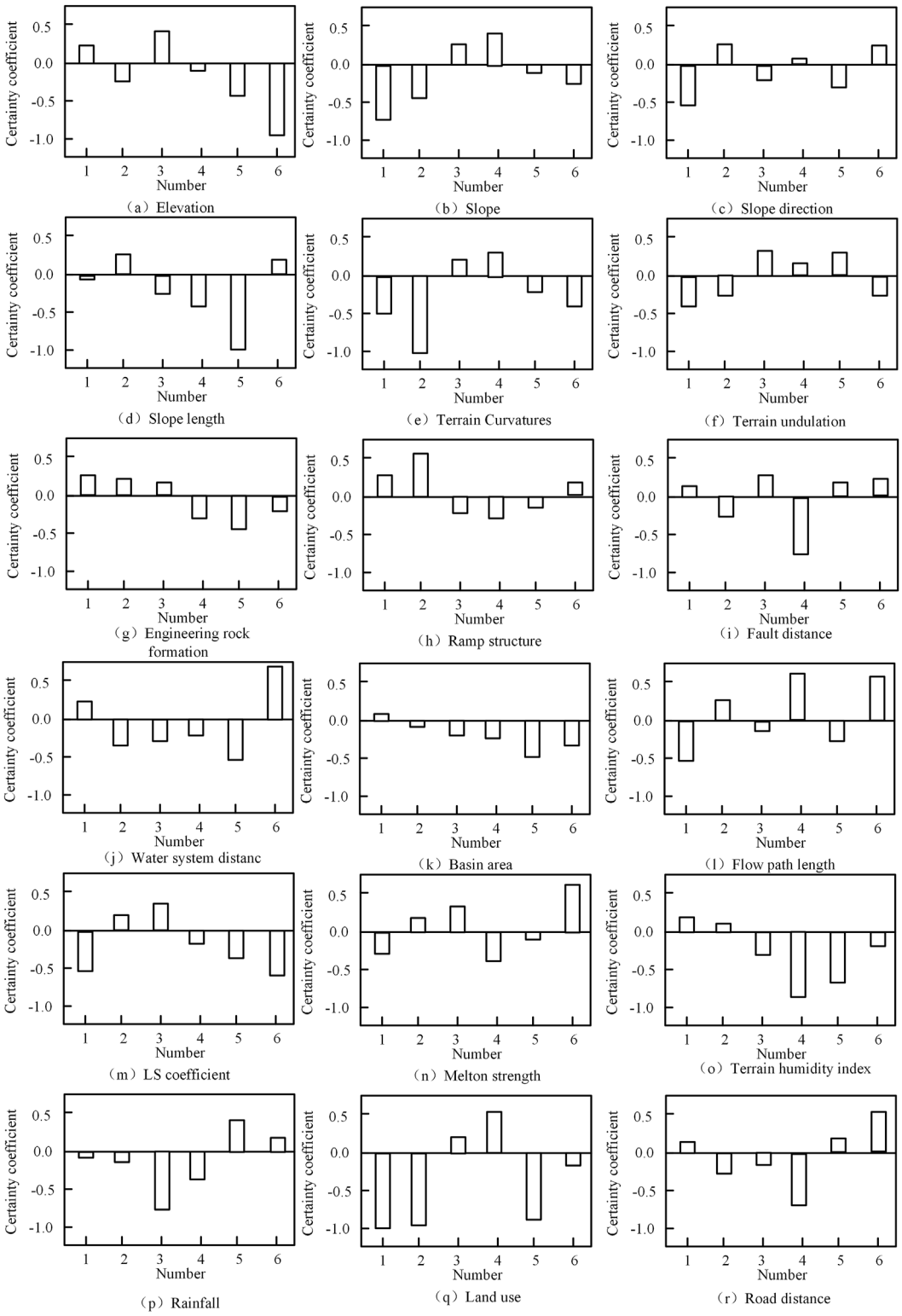

FIGURE 4
Determination coefficient calculation results of influencing factors.

By combining SVM, a powerful classification algorithm, with regression tools and integrated particle swarm optimization algorithms, the spatial distribution characteristics of landslide susceptibility can be solved. By selecting the features that have the greatest impact on landslide susceptibility, such as slope, elevation, rainfall, etc., as landslide influencing factors, the spatial distribution of landslide susceptibility can be predicted. The overall flow chart of the predictions described above is shown in Figure 3.

TABLE 4 Comparison of spatial distribution prediction results of landslide susceptibility by three methods.

Method	Predisposing zoning	Zoning area/km 685.89^2	Area ratio/%	Disaster point/place	The proportion of disaster points is/%	Disaster point density/ (location/100 km^2)	Disaster density
The landslide prediction method	High prone	523.18	19.71	113	75.81	21.8	3.95
	Higher predisposition	548.96	25.20	28	18.82	4.12	0.72
	Middle prone	515.40	19.10	7	5.37	1.42	0.25
	Lower predisposition	548.96	20.18	0	0	0.00	0.00
	Low prone	426.80	15.81	0	0	0.00	0.00
The Landslide prediction method based on information model	High prone	516.82	23.79	116	77.85	20.3	3.87
	Higher predisposition	555.71	25.58	25	16.78	4.12	0.72
	Middle prone	498.29	22.94	8	5.37	1.42	0.25
	Lower predisposition	524.12	24.13	0	0	0.00	0.00
	Low prone	431.92	19.89	0	0	0.00	0.00
The proposed method	High prone	400.94	14.85	111	74.32	27.44	5.01
	Higher predisposition	506.51	18.76	28	18.92	5.53	1.01
	Middle prone	459.20	17.01	5	3.38	1.09	0.20
	Lower predisposition	589.33	27.56	5	3.38	0.85	0.12
	Low prone	589.33	21.83%	0	0.00%	0.00	0.00

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5 Example validation and result analysis

5.1 Data sources

The dataset used in this study includes landslide hazard data, geological environment data, Landsat TM image data with a resolution of 30 m × 30 m, and river network road data in the study area. The specific data sources and types are shown in Table 2.

In the research area, a total of 148 landslide disaster points were identified and recorded. To evaluate the application effectiveness of the proposed method scientifically, the dataset was divided in a 7:3 ratio. Study the geographic information data of the research area, such as topography, geological structure, rainfall, vegetation coverage, soil type, etc., as influencing factors for landslide susceptibility prediction. 104 landslide points were selected as the training dataset, while the remaining 44 landslide points were used as the validation dataset. The processing method for the above data is as follows: clean the landslide point data, remove duplicate or erroneous records, and convert the coordinates uniformly to the UTM (Universal Transverse Mercator Projection) coordinate system. Digitize the geological map and encode geological information such as lithology according to classification standards to ensure consistency in data format. Perform radiometric calibration on Landsat Terrain Modeling (TM) image data, convert the original digital quantification value (DQ) value into radiance value, and then perform atmospheric correction to eliminate the influence of atmospheric scattering and absorption on the image, obtaining surface reflectance data. Register all data (landslide disaster data, geological environment data, Landsat TM image data, river network road data) to the same spatial reference frame UTM coordinate system to ensure spatial consistency of the data. The spatial resolution of different data is inconsistent, and bilinear interpolation is used to resample low resolution data to match high-resolution data in spatial resolution. Use clipping tools in ArcGIS to manipulate the boundary vector data of the study area as the clipping range.

The initial penalty parameter is 10, the kernel function is 0.1, 30 particles are set, the inertia weight is 0.7, and the learning factors are set to 2.05 and 2.05, respectively, which affect the speed at which particles learn from individual and global optima. Adopting a dynamic adjustment strategy, the initial value is set to 0.9 and gradually decreases as the number of iterations increases. The maximum number of iterations is 400.

Construct a grid with an ε value, such as $\varepsilon \in [0.01,1]$, and take values at a certain step size (such as 0.01). For each ε value, train an SVM regression model and calculate the evaluation metric R2 coefficient on the test set The closer R2 is to 1, the better the model fit, and the final determination of the optimal ε value for the evaluation index is taken as the error tolerance range. The error tolerance range determined in this paper is ±0.5.

TABLE 3 Weight information of influencing factors.

Influencing factors	Weight	Influencing factors	Weight
Altitude	0.10	Water system distance	0.12
Slope	0.15	Basin area	0.08
Slope direction	0.05	Flow path length	0.13
Slope length	0.10	LS coefficient	0.12
Terrain Curvatures	0.07	Melton strength	0.11
Terrain undulation	0.08	Terrain humidity index	0.07
Engineering rock formation	0.10	rainfall	0.15
Ramp structure	0.08	land use	0.05
Fault distance	0.10	Road distance	0.05

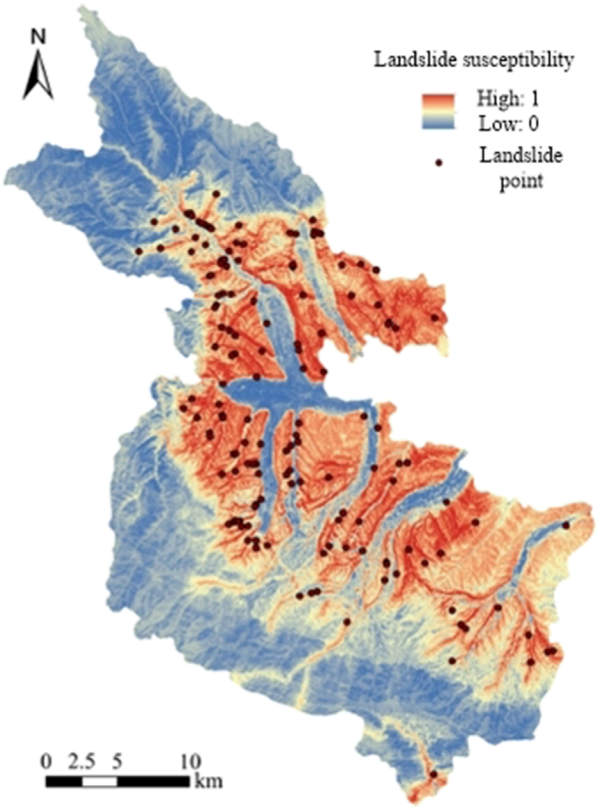

FIGURE 5
Prediction results of landslide susceptibility spatial distribution.

5.2 Prediction function verification

Simulate annealing operation on particles with a probability of 0.1 (e.g.,), accept a certain range of poor solutions to escape from local optima; Perform mutation operation on particles with a probability of 0.05 (e.g.,) The proposed method was applied to extract landslide influencing factors, and the determination coefficient of the influencing factors was calculated. The results are shown in Figure 4.

As shown in Figure 4, six samples of the 18 influence factors were greater than-1 and less than 0.5. Normalize the determination

coefficients of each influencing factor in Figure 4, calculate the entropy and difference coefficients of each determination coefficient, and finally normalize the difference coefficients to obtain the weight values of each influencing factor as shown in Table 3.

The experiment conducted collinearity analysis on 18 influencing factors and calculated the Pearson correlation coefficients between each pair of influencing factors, such as slope and aspect, using the following Equation 10:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (10)$$

In the formula, n is the number of influence factor samples, x_i and y_i is the i observation of slope x and slope direction y, $\bar{x}$ and $\bar{y}$ the observed mean of slope x and slope direction y, respectively.

The Pearson correlation coefficient calculation results of the 18 influencing factors do not conform to values greater than 0.7 or less than −0.7, indicating that there is no linear correlation between all influencing factors. Therefore, 18 influencing factors were retained.

The spatial distribution prediction of landslide susceptibility was completed, and the results are shown in Figure 5.

From the analysis of Figure 5, it can be seen that the high and relatively high prone areas of landslide disasters in the study area are mainly concentrated on both sides of the valley and the low mountain and hilly areas adjacent to the town, with a total area of 907.45 km^2, accounting for 33.61% of the total area of the study area. The terrain and landform conditions in this area are particularly complex, with crisscrossing gullies and significant river erosion, resulting in relatively sparse vegetation coverage and severe soil erosion problems. In addition, the risk of geological disasters is further exacerbated by the influence of rainfall factors. Research has shown that there are a total of 138 landslide hazards in the area, accounting for 93.24% of the total number of landslides in the region. The density of disaster points is 15 per 100 km^2, making it a typical geological hazard-prone area. Landslide disasters are mainly distributed in the border areas between high mountains and low hills, with an area of 459.20 km^2, accounting for 17.01% of the total area. Although the number of geological hazard points in this area is relatively small, with only 5 landslide hazard points investigated, accounting for 3.38% of the total number of landslides, the density of hazard points has also reached 1 per 100 km^2, indicating that we still need to be vigilant about the occurrence of geological hazards.

The low landslide-prone areas and lower landslide-prone areas are widely distributed in the middle and high mountain areas above 3,000 m altitude and the towns and plain areas below 2,500 m altitude, with a total area of 1,178.66 km^2, accounting for 49.39%. Among them, 5 landslide disaster points were found in the low-risk area, accounting for 3.38% of the total number of landslides, while no landslide disaster occurred in the low-risk area. Specifically, the mountainous area in the north and south of the river is a middle and high mountain area eroded by tectonic erosion. The area is mainly composed of old bedrock mountains, with good vegetation coverage and relatively superior geological environment conditions. However, due to the steep terrain, some rocks are damaged by geological structures, resulting in landslides and other geological disasters. Although the area is generally stable and the probability of geological disasters is low, its potential risk is still worth noting.

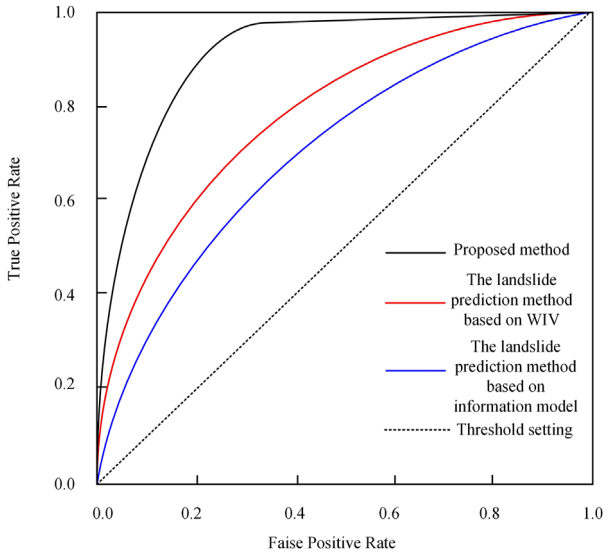

FIGURE 6
ROC curve of three methods.

TABLE 5 Comparison of three methods for predicting the spatial distribution of landslide susceptibility over time/ms.

Number of landslide points/one	The landslide prediction method	The landslide prediction method based on information model	The proposed method
10	32	45	16
20	57	51	19
30	62	58	21
40	74	67	28

The geomorphic type of town and farmland plain area is an erosion accumulation plain, and the stratum is mainly composed of Quaternary gravel pebbles and loess. Although the intensity of human activities is high, the threat to villagers' houses and farmland is low due to the flat terrain and relatively scattered geological disasters such as landslides. However, this does not mean that the risk of geological disasters in the region can be completely ignored, and monitoring and prevention still need to be strengthened.

In conclusion, the proposed method can be used to predict the spatial distribution of landslide susceptibility in the study area. Through the investigation and analysis of landslide disaster points in the study area, combined with multiple data such as topography, geological structure, meteorology and hydrology, different types of areas with high, high, medium, low and low landslide disasters can be identified. This spatial distribution prediction result is helpful in understanding the potential risk of landslide disasters, and the application effect is good.

5.3 Comparison performance verification

Taking the landslide prediction method based on WIV (Yang et al., 2023) and landslide prediction method based on information model (Wang et al., 2023) as the comparison method, the spatial distribution of landslide susceptibility in the study area is predicted with the proposed method. Thus, the comparison results are shown in Table 4 below.

It can be seen from Table 4 above that the three methods can predict the spatial distribution of landslide susceptibility in the study area, and all have certain functionality. This time, the ROC curve is used to compare the prediction accuracy of the three methods. Using this method to detect the susceptibility map mainly means judging the area under the curve (AUC). If the AUC value is larger, the evaluation result is better. Thus, the comparison results are shown in Figure 6.

The AUC in the figure represents the region surrounded by the intersection of the two ends perpendicular to the dashed line. As shown in Figure 6 above, the AUC values of the landslide prediction method (Yang et al., 2023), the landslide prediction method based on information model (Wang et al., 2023) method and the proposed method are 0.74, 0.81 and 0.91, respectively. The test results show that the proposed method has higher accuracy and better application effect in the spatial prediction of landslide geological hazard susceptibility in the study area. This is because this paper considers the complex non-linear relationship between influencing factors and landslide occurrence, as well as the coupling between factors. Using a simulated annealing algorithm and mutation operation to optimize the generalization ability of the particle swarm algorithm avoids getting stuck in local optimal solutions and obtains higher prediction accuracy.

Due to the real-time requirement of landslide prediction, the prediction efficiency of the three methods was further tested based on the prediction accuracy. The prediction time of the three methods is shown in Table 5.

According to Table 5, for 40 landslide locations, the prediction time of our method is less than 28 ms, while the prediction time of other methods is higher than 60 ms, indicating that the prediction efficiency of our method is higher. This is because this paper uses an optimized particle swarm optimization algorithm to solve the landslide prediction model, reducing the complexity of the coupling model of influencing factors and thus reducing the prediction time.

6 Conclusion

1. In order to strengthen the scientific and effective management of regional landslide disaster risks, this paper takes Lianhe Village, Jianfeng Township, Shizhong District, Leshan City, Sichuan Province as the research object, and studies a landslide susceptibility spatial distribution prediction method based on integrated particle swarm optimization.
2. The innovative content of the paper is the introduction of simulated annealing and mutation operations to improve the traditional particle swarm algorithm, proposing an integrated particle swarm algorithm to more accurately quantify the contribution of various factors to landslide occurrence.
3. The focus of this study is to apply integrated particle swarm optimization algorithm to support vector machine parameter optimization, improve its ability to avoid local optima, and make accurate predictions.
4. After verification, this method has high prediction accuracy and efficiency. The application of integrated particle swarm optimization algorithm and support vector machine in predicting the spatial distribution of landslide sensitivity enriches the theoretical framework system of landslide disaster prediction and provides a new approach to improve landslide warning and prevention capabilities. In the future, while exploring more innovative technologies and methods, it is expected that this method can be promoted to more regions, continuously improving the ability to predict and prevent geological disasters, and contributing to the construction of a safer and more harmonious living environment.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

QZ: Conceptualization, Investigation, Methodology, Resources, Writing–original draft, Writing–review and editing.

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Formation mechanism of climate warming-induced landslides in permafrost along the Qinghai-Tibet Engineering corridor

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The Qinghai-Tibet Plateau (QTP) has undergone substantial warming, resulting in extensive permafrost degradation and a pronounced increase in landslide frequency. However, the causal link between climate warming and permafrost landslide occurrences remains poorly understood. A comprehensive inventory of permafrost landslides along the Qinghai-Tibet Engineering Corridor (QTEC) from 2016 to 2022 was compiled through remote sensing and field verification, along with an analysis of landslide triggering factors based on data from 5 weather stations, 4 active layer thickness observation sites, and 3 precipitation stations. From 2000 to 2020, the mean annual air temperature (MAAT) showed an increase of 0.5°C per decade, while precipitation remained relatively stable. A notable peak occurred in 2016, with MAAT and mean annual surface ground temperature rising sharply by 0.59°C and 0.41°C, respectively, from the previous year. In the same year, active layer thickness across observation sites increased by an average of 18.5 cm, exceeding the average thickening rate. This substantial deepening of the active layer suggests that a portion of the underlying permafrost, potentially ice-rich near the permafrost table, thawed during the warm season. Laboratory experiments further reveal a three-stage reduction in soil strength as temperatures approach 0°C, with the most pronounced decline at −1°C. Interpretation of landslide data shows that landslide frequency in 2016 significantly increased, reaching approximately 1.3 times the historical total. This suggests that a thawed interlayer forming at the active layer-permafrost interface plays a dominant role in landslide initiation. The thawed layer acts as a weak zone, enabling the downward movement of the overlying active layer and contributing to slope instability. These findings provide robust evidence linking temperature rise to permafrost-related landslides, offering new insights into the mechanisms of temperature-induced slope instability in high-altitude regions.

KEYWORDS

climate warming, permafrost degradation, landslides, Qinghai-Tibet Engineering corridor, Qinghai-Tibet plateau

1 Introduction

Permafrost, defined as ground (soil or rock, including ice and organic material) that remains at or below 0°C for at least two consecutive years, is significantly influenced by climate warming (Dobinski, 2011; Hu et al., 2022). The Qinghai-Tibet Plateau (QTP), encompassing 1.06×10^6 km^2 of permafrost, represents the largest permafrost region in low-latitude areas and commonly referred to as the "Third Pole" and the "Asian Water Tower" (Yao et al., 2012; Zhang et al., 2022; Zou et al., 2017). The warming rate in the QTP, surpassing the Northern Hemisphere average (Kuang and Jiao, 2016), causes permafrost degradation characterized by elevated ground temperatures, deepening active layers, and a reduction in area, which subsequently results in surface subsidence, slope instability, accelerated rock glaciers movement, and significant alterations in hydrological processes (Krautblatter et al., 2013; Etzelmüller et al., 2020; Haberkorn et al., 2021; Marcer et al., 2021). In recent years, there has been a significant increase in both the frequency and spatial extent of landslides in the permafrost region of the QTP, particularly along the Qinghai-Tibet Engineering Corridor (QTEC) (Luo et al., 2019; Niu et al., 2015; Xia et al., 2022). The types of landslides associated with permafrost include active layer detachment (ALD), retrogressive thaw slump (RTS), retrogressive thaw flow, soil slope deformation, soil creep, and solifluction (Couture and Cruden, 2010; Hungr et al., 2013; Mao et al., 2024). ALD and RTS are the two most common types of landslides on the Qinghai-Tibet Plateau (Swanson, 2021).ALD predominantly occurs in warm season when the thawing of surface soils induces sliding of the active layer over the underlying permafrost (Lewkowicz and Harris, 2005). This phenomenon is typically characterized by shallow sliding, with the slip plane located between the active layer and permafrost interface. RTS is initiated by the exposure of subsurface ice due to natural or anthropogenic factors, resulting in seasonal thawing that causes the overlying mass to collapse. This cyclical process of ice exposure and subsequent collapse drives the progressive retreat of the headwall (Lacelle et al., 2015; Lewkowicz and Way, 2019).

Variations in precipitation intensity and frequency are critical triggers for landslides (Handwerger et al., 2022; Kirschbaum et al., 2020), with higher temperatures exacerbating soil moisture evaporation and altering its structure (Andresen et al., 2020; Fatichi et al., 2020), thereby increasing landslide susceptibility (Marino et al., 2020; Nefros et al., 2023). Human activities, such as urbanization, deforestation, and infrastructure development, further disrupt natural hydrological cycles, intensify soil erosion, and destabilize slopes, heightening landslide risk (Nanehkaran et al., 2022; Quevedo et al., 2023). Integrated models combining climate data, topography, and soil characteristics provide a comprehensive assessment of landslide risks and mechanisms (Cemiloglu et al., 2023; Mao et al., 2024; Nanehkaran et al., 2023b). Studies across diverse regions show considerable disparities in landslide sensitivity to climate change: in mountainous areas, increased landslides are linked to snowmelt and precipitation changes (Liu et al., 2021), while extreme rainfall events drive landslides in tropical regions (Amarasinghe et al., 2024; Nanehkaran et al., 2023a). Although global research has illuminated the relationship between landslides and climate change, the response of landslide mechanisms to rising temperatures and changing precipitation on the QTP remains understudied. Research on the plateau has primarily focused on creep characteristics, morphological features, and landslide spatiotemporal distribution (Mu et al., 2020; Sun et al., 2017). Advanced remote sensing and Geographic Information Systems (GIS) have facilitated large-scale monitoring of landslide dynamics. For instance, Xia et al. (2022) compiled an inventory of 875 landslides along the QTEC, mapping their spatial distribution but without detailed temporal analysis. The temporal landslide evolution in the Beiluhe region revealed significant increases in landslide scale and frequency in recent years (Luo et al., 2019; Yang et al., 2023), linking this trend to rising temperatures (Luo et al., 2019). However, the causal mechanisms through which temperature elevations trigger landslides in permafrost of QTP remain unclear and require further exploration.

The objective of this study is to investigate the causal relationship between rising temperatures and permafrost landslides along the QTEC. We first analyzed meteorological and geothermal data from multiple stations to assess changes in air temperature, ground temperature, and active layer thickness over the past decade. Subsequently, we compiled a detailed landslide frequency inventory from 2016 to 2022 by visually interpreting multi-temporal satellite images. We quantified the changes in the number of landslides during this period and performed a comparative analysis of the correlations between variations in air temperature, ground temperature, and the observed increase in landslide occurrences.

2 Study area/data/test method

2.1 Study area

The study area is located in the permafrost region of the Qinghai-Tibet Plateau (QTP) (Ran et al., 2012). It extends from Xidatan in the north to Naqu in the south, covering a length of approximately 550 km and an area of 8×10^4 km^2. Since 1950, the region has experienced significant warming (Li et al., 2023), resulting in permafrost degradation and a reduction in vegetation cover and species (Jin et al., 2020). These changes have contributed to increasing slope instability in the area (Jin et al., 2008; Wu et al., 2012).

2.2 Data

The study area, primarily characterized by alpine meadows and alpine steppe, exhibits pronounced differences in color and texture in landslide-affected regions compared to the surrounding undisturbed landforms. Additionally, the progressive expansion traits of permafrost-related landslides can be distinctly identified through the analysis of multi-temporal high-resolution satellite imagery. The high-resolution images used are Planet images (https://www.planet.com/) of every July from 2016 to 2022 with a resolution of 3 m, which completely cover the study area. July was chosen as it is the ground surface of the study area was completely free of snow cover compared to May and June. Despite being time-consuming compared to automated identification, manual detection offers high accuracy and enables the addition of attributes

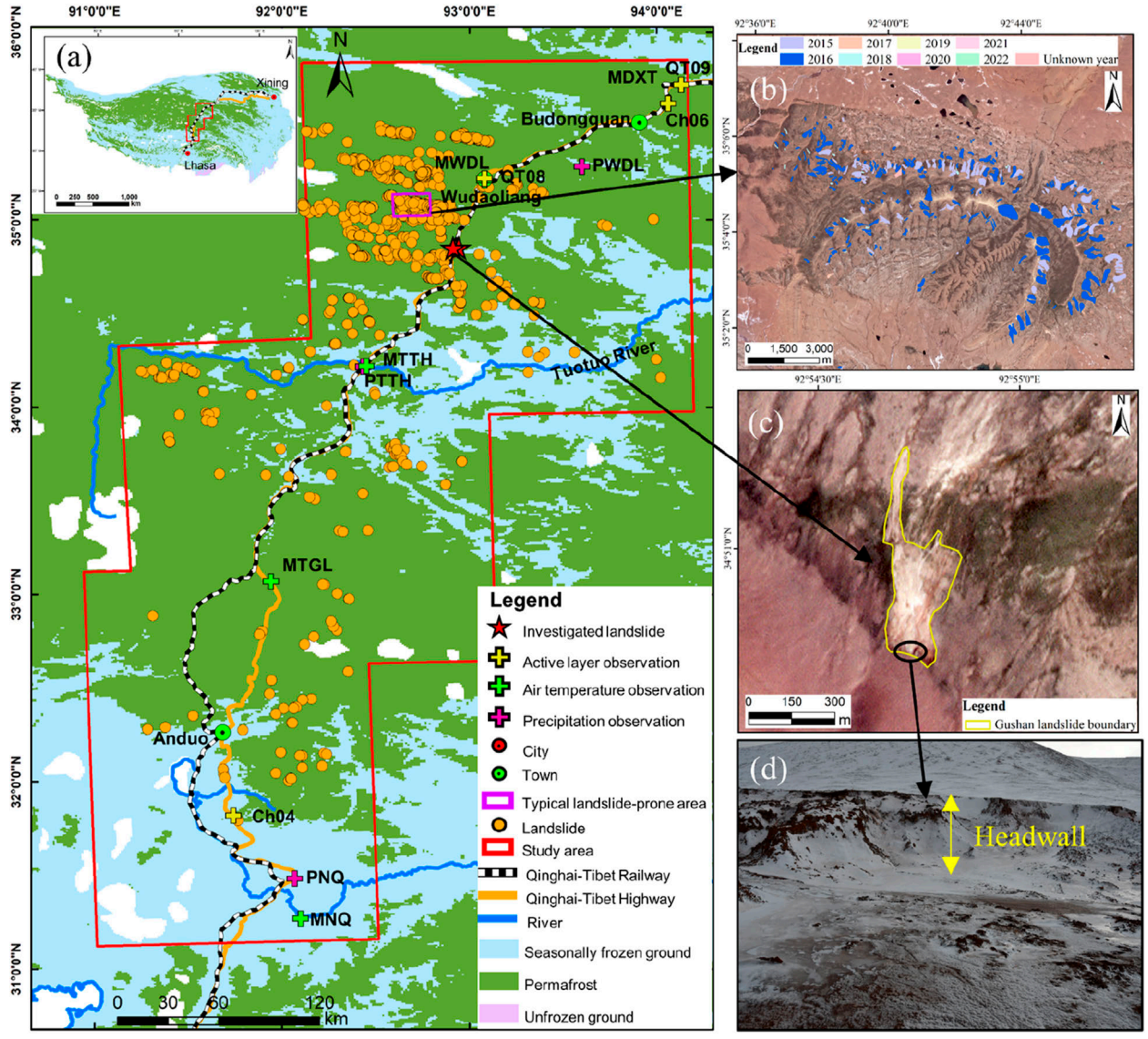


FIGURE 1
(A) Study area location, permafrost monitoring network, and landslide distribution. The permafrost monitoring network includes 4 automatic temperature stations, 3 precipitation stations, and 5 active layer observation stations along the QTEC in natural settings. A total of 1,298 landslides are distributed on both sides of the QTEC. **(B)** Landslide distribution in the typical landslide-prone area, with different colors indicating various initial failure years. **(C)** Satellite image of a representative Gushan landslide in July 2022. **(D)** Field photograph of the Gushan landslide in October 2023.

during the identification process. In addition to assessing the whole study area, a typical landslide-prone sub-area was chosen for detailed spatiotemporal assessment (Figure 1). In addition to delineating landslide boundaries, a critical component of image interpretation involves categorizing landslide types. Landslides identified for the first time in a given image, when compared to the preceding temporal image, are classified as new landslides. Active landslides are those that show expansion and an increase in area relative to the most recent image (2022). It is noteworthy that for the earliest available image, such as the 2016 dataset for the entire study area, no prior image exists for comparative analysis. Consequently, landslides identified in this initial image are designated as pre-existing landslides without further classification. These pre-existing landslides serve as a foundational dataset for tracking and analyzing landslide occurrences and expansion in subsequent time periods.

To ensure the accuracy of the landslide inventory, field surveys were conducted in the study area in April and October 2023. Due to the largely uninhabited nature and limited accessibility of the region, surveys were restricted to a 3-km corridor on either side of the QTEC. On-site verification successfully confirmed all 5 landslides previously identified in satellite imagery. For instance, the Gushan landslide (Figures 1C, D) was initially identified in satellite imagery and subsequently confirmed through field verification. An unmanned aerial vehicle (UAV) was utilized to capture high-resolution aerial photographs of representative landslides, which were then processed to generate a digital orthophoto map (DOM) and a digital surface model (DSM) of these landslides.

A comparative analysis of landslide areas derived from UAV and satellite imagery for selected landslides indicated that the area discrepancy between the two sources was less than 5%. This variance could be attributed to differences in the resolution of the imagery sources, or it may reflect ongoing landslide expansion between 2022 and 2023.

The air temperature and ground temperature data were provided by the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/). The meteorological stations indices include daily air temperature, precipitation, humidity, wind speed gradient observation, and radiation balance. However, it is important to note that certain data points may be missing due to variations in the construction time of each station or other factors. The daily ground temperature of the active layer observations was measured at different depths below the permafrost table from the ground surface between 2002 and 2018. The precipitation data was obtained from the China Meteorological Data Service Centre (http://www.cma.gov.cn/). There are 3 precipitation stations evenly distributed in the northern, middle, and southern parts along the QTEC.

2.3 Test method

To investigate the geological characteristics of the active layer, we excavated a 2-m-deep observation trench at the headwall of the Zilrama landslide (Figure 2A). To obtain undisturbed soil samples, the trench was positioned to avoid areas with pronounced fissures at the headwall and maintained a minimum distance of 0.5 m from any cracks. As shown in Figure 2B, the active layer, excluding the top organic-rich layer, was divided into three distinct sub-layers. Soil samples from each sub-layer were carefully collected using a ring cutter for laboratory testing of soil physical properties (Figure 2C). Additionally, approximately 50 kg of soil from each layer was gathered to prepare artificial samples for mechanical properties testing. Table 1 presents the physical properties of the soil layers, measured through a variety of tests, including sieving, Malvern particle size analysis, moisture content, specific gravity, and liquid and plastic limit tests. Figure 3 shows the grain size distribution curves. The results indicate that the active layer soil in permafrost landslide areas predominantly comprises fine-grained material, with particle size decreasing closer to the permafrost table. Field observations revealed substantial pore ice within the frozen soil of the active layer, while moisture content tests confirmed saturation of the soil in this layer (Figures 2D, E).

The landslide headwall height is approximately 2 m; hence, soil from the third layer was selected for low-temperature triaxial testing to evaluate the mechanical properties. Testing was conducted using a thermo-mechanical triaxial compression apparatus (UL200/60 SH) manufactured by Wille, Germany, with a maximum axial load capacity of 60 kN, confining pressure up to 4 MPa, and temperature control from −30°C to 60°C with 0.1°C precision (Figure 4). Sample dimensions were 70 mm in diameter and 140 mm in height. To ensure sample consistency, particle size was restricted to below one-tenth of the sample diameter. Particles exceeding 10 mm, comprising 1% of the sample mass, were excluded without impacting the mechanical analysis. Before preparation, soil samples were dried at 105°C for 24 h. The target dry density was set to 1.7 g/cm^3, matching field values, with a 10% moisture content achieved by combining 916 g of soil particles with 91.6 g of water. The mixture was sealed and allowed to equilibrate for 24 h (Figure 5A). To ensure uniformity, the mixture was divided into 28 mm segments and compacted in 5 layers, with each layer compacted to a designated height and the surface leveled before adding the next layer. Once prepared (Figure 5B), the specimen was wrapped in a latex membrane and mounted onto the triaxial apparatus (Figure 5C). Saturation was achieved through back-pressure saturation, with gradual increases in confining and back pressure over 6 h to prevent soil structural damage. A pore water pressure coefficient (B-value) exceeding 0.95 indicated full saturation (Figure 5D). The temperature control system then lowered the coolant to the target level, maintaining it for 6 h to ensure thermal equilibrium within the sample. An unconsolidated undrained (UU) shear test was conducted to assess temperature effects on soil strength under shallow landslide conditions. The confining pressure was set to 50 kPa, and the temperature maintained between −6°C and 0°C. Loading was applied at a constant strain rate of 0.7 mm/min, ceasing at 20% axial strain. After testing, the failure characteristics were documented, and the sample was weighed, oven-dried, and reweighed to determine post-saturation moisture content.

3 Results

3.1 Changes in hydrothermal disaster-prone environments

The air temperature in the permafrost region of the central QTP has consistently risen from 2000 to 2020, as indicated by all meteorological stations (Figure 6A). On average, the temperature has been increasing at a rate of 0.5°C per decade. Among these stations, the NQ station, located at the lowest altitude of 4452 m above sea level, has experienced the fastest increase rate at an annual average rate of 0.7°C per decade (Table 2). On the other hand, the TGL station, situated at the highest altitude of 5,044 m above sea level, has observed the slowest increase rate, with an annual average rising rate of 0.3°C per decade. The annual change patterns are highly consistent across all meteorological stations. It is evident that the MAAT in 2016 was considerably higher compared to the historical average (Figure 6A). During 2010–2020, The MAAT reached its peak value in 2016, followed by a downward trend then. The MAAT from the four meteorological stations in 2016 increased by 0.59°C compared to 2015, surpassing the average rising rate observed in recent decades. This alignment with global climate change is in line with the fact that 2016 was recorded as the hottest year in some regions of the planet, partly due to a powerful El Niño (Witze, 2023). On the other side, the data from two northern and central stations along the QTEC indicate that the rainfall in 2016 was even lower than the average annual precipitation (Figure 6B). Interestingly, although the rainfall at the southern precipitation monitoring station in the study area increased significantly in 2016 compared to 2015, there were no significant occurrences of landslides in the southern study area. Furthermore, the precipitation at the northern station in the study

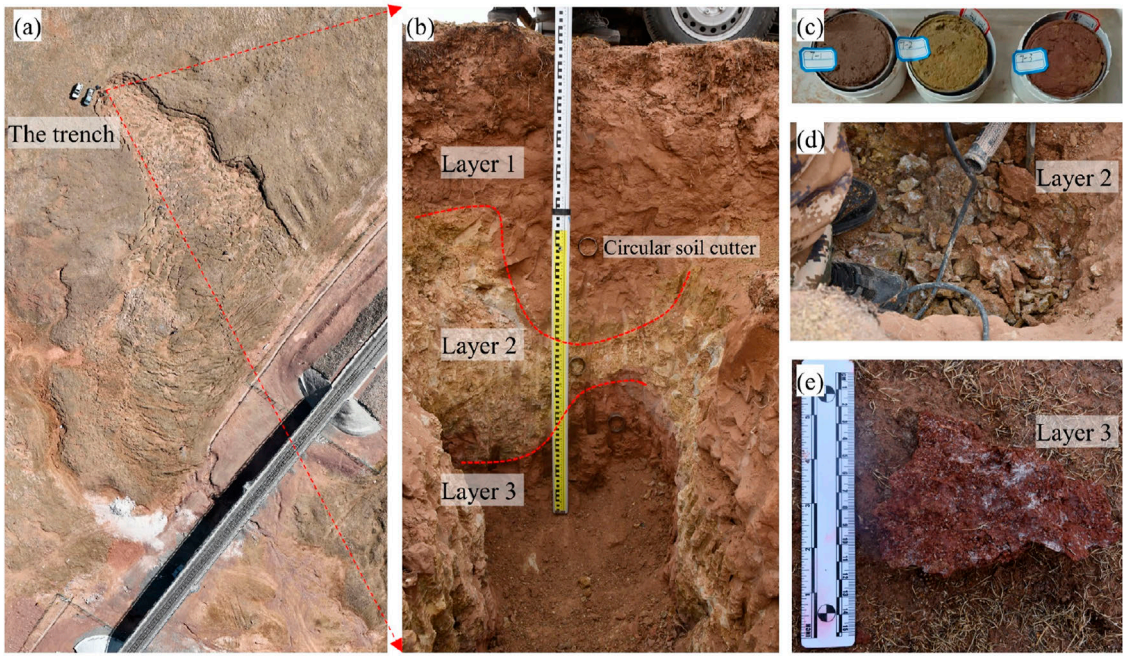
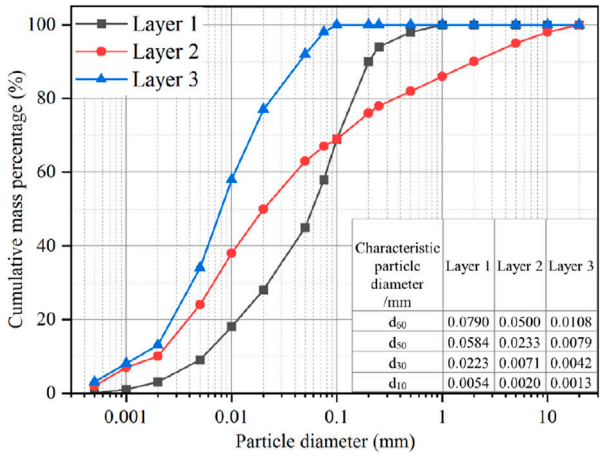


FIGURE 2
(A) DOM of the Zilrama landslide and the specific location of the trench. **(B)** Geological characteristics of the active layer. **(C)** Ring cutter samples from various layers. **(D)** and **(E)** Pore ice within active layer soil.



Characteristic particle diameter /mm	Layer 1	Layer 2	Layer 3
d_{60}	0.0790	0.0500	0.0108
d_{50}	0.0584	0.0233	0.0079
d_{30}	0.0223	0.0071	0.0042
d_{10}	0.0054	0.0020	0.0013

FIGURE 3
Grain size grading curve of soil samples from different layers.

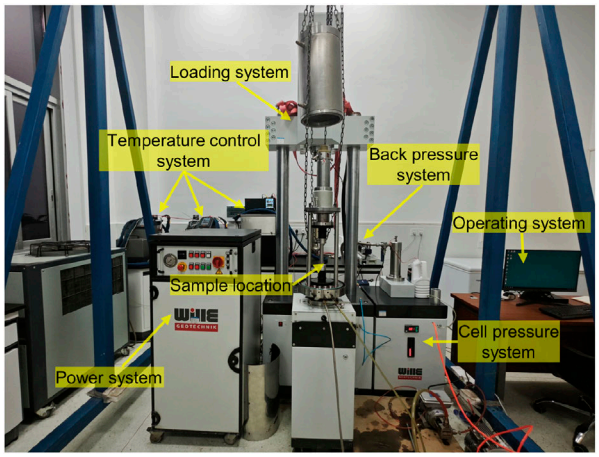


FIGURE 4
Low-temperature triaxial shear testing apparatus, including loading system, back-pressure system, temperature control system, cell pressure system, and temperature control system.

area showed a significant increase after 2016, while the precipitation at the central and southern stations remained relatively stable after that year.

The thermal state of permafrost is primarily controlled by climate, with influences from land surface characteristics such as vegetation, snow cover, soil physical properties, and geological conditions including organic-layer thickness and ground ice content (Smith et al., 2022). When these surface and subsurface conditions remain stable over a short period of time, the thermal state of shallow permafrost is mainly determined by air temperature. During 2011–2018, the maximum mean monthly air temperature and the maximum mean monthly ground temperature exhibit an identical varying pattern (Figure 6C). Annually, the highest air temperature is observed in August, which corresponds to the peak ground temperature in the shallower layers. However, in the deeper layers, the maximum mean monthly ground temperature has a delayed response to air temperature,

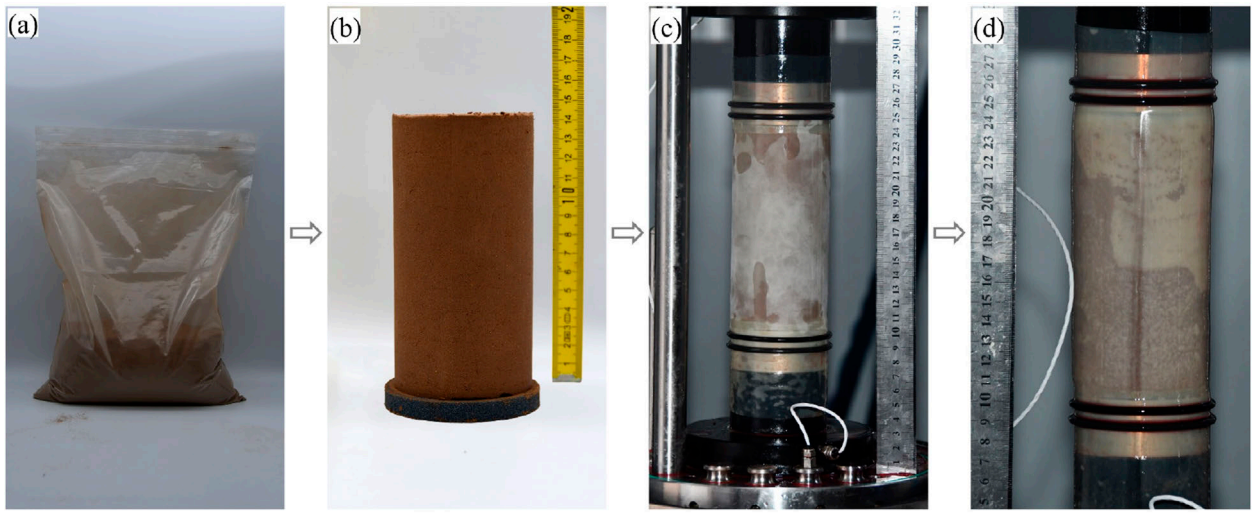


FIGURE 5
Specimen preparation procedure. **(A)** Oven-dried soil particles, **(B)** Soil sample, **(C)** and **(D)** Sample before and after saturation.

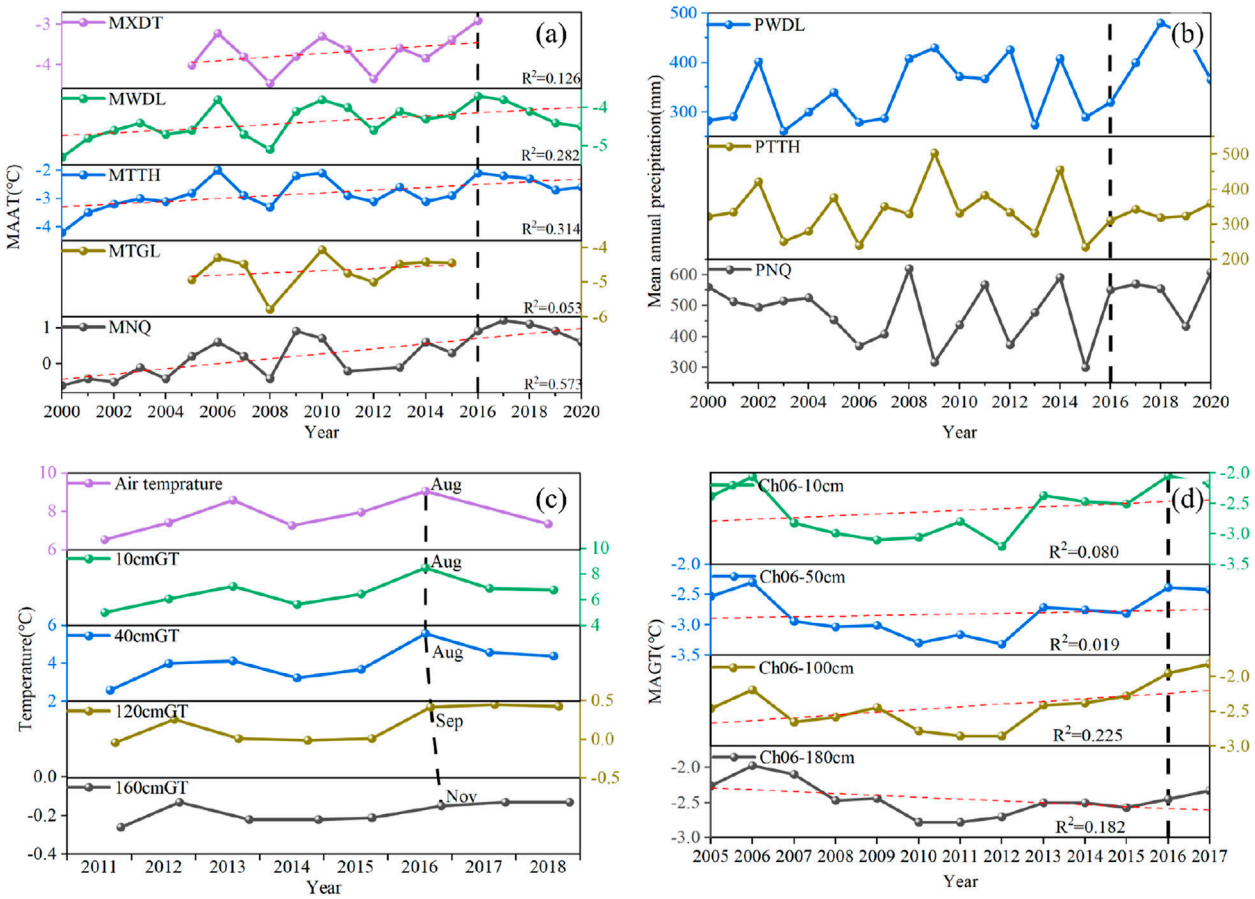


FIGURE 6
(A) The mean annual air temperature (MAAT) from five meteorological stations located along the QTEC from 2000 to 2020. **(B)** The mean annual precipitation of 3 precipitation monitoring stations along the QTEC from 2000 to 2020. **(C)** The month with the highest mean monthly air temperature and ground temperature at various depths of the station (QT09). **(D)** The mean annual ground temperature (MAGT) from different depths at the Ch06 active layer observation site.

TABLE 1 Physical properties of the tested material.

Sample	Mass moisture content (%)	Natural density (g/cm^3)	Dry density (g/cm^3)	Specific gravity	Saturation (%)	Liquid limit (%)	Plastic index
Layer 1	24	2.04	1.64	2.62	106.7	22.6	6.2
Layer 2	25	2.02	1.62	2.66	102.3	31.3	12.4
Layer 3	21	2.06	1.70	2.64	101.0	38.4	20.4

TABLE 2 The information of meteorological stations along the QTEC.

Site name	Altitude (°)	Longitude (°)	Elevation (m)	Average MAAT (°C)	MAAT in 2016 (°C)	Increasing rate (°C/year)	Increasing in 2016 compared to 2015 (°C)
MXDT	35.72	94.13	4,448	−3.697	−2.9	0.045	0.5
MWDL	35.21	93.08	4,623	−4.362	−3.7	0.037	0.5
MTTH	34.22	92.45	4,547	−2.800	−2.1	0.049	0.8
MTGL	33.07	91.94	5,044	−4.662	—	0.032	—
MNQ	31.27	92.10	4,452	0.275	0.9	0.070	0.6

Represents missing data for the year.

which emerged until October or November. This indicates that air temperature is the primary factor influencing the thermal state of permafrost in permafrost regions. The temperature of the near-surface ground closely follows the annual cycle of air temperature, while the temperature variation decreases with depth.

The range of temperature at different depths in various observations varies greatly. However, the mean annual ground temperature (MAGT) consistently showed an upward trend, except for the deep ground of CH06 (Figure 6D). On average, the surface ground (10 cm or 15 cm below the surface) at all observations experienced a rising rate of 0.87°C per decade, which is higher than the rate of air temperature increase. The fastest rate of surface ground temperature rise was observed at QT09, with a rate of 2°C per decade. On the other hand, the average rate of temperature increase near the permafrost table across all observations was 0.40°C per decade, which is lower than that of the surface ground. The highest rate of increase near the permafrost table was still observed at the QT09 site, with a rate of 0.9°C per decade. This can be attributed to the fact that QT09 is located at the edge of the continuous permafrost region. Table 3 presents the average rate of increase at different depths for each observation, as well as the magnitude of temperature rise in 2016 compared to 2015. Similar to the air temperature, the mean annual surface ground temperature in 2016 rose sharply by 0.41°C per year compared to 2015, which was significantly higher than the average rate of surface temperature increase.

3.2 Strength decreasing response to the different temperature zones

The stress-strain curve is a widely used method for assessing soil deformation and strength. In the permafrost region of the Qinghai-Tibet Plateau, the failure behavior of saturated clay undergoes significant changes with temperature under low confining pressure. At soil temperatures of −3°C or lower, the soil exhibits pronounced brittle failure. On the other hand, at temperatures higher than −2°C, the soil shows significant plastic damage (Figure 7A). When the soil temperature is approximately −2°C, the transition from brittle to plastic failure occurs. In the case of plastic failure, the deformation increases with the applied stress. Therefore, the deviator stress corresponding to a strain of 20% is considered the strength or failure stress of the sample. At soil temperatures below −1.6°C, the soil strength exceeds 2 MPa and increases as the temperature decreases. However, when the soil temperature is slightly higher than −1.6°C but still below −1.0°C, the strength rapidly decreases to less than 500 kPa. As the soil temperature continues to rise to 0°C, the strength experiences a slight decrease to 200 kPa (Figure 7B).

The Figure 7C illustrates the variation of soil strength in the negative temperature range under low confining pressure, which can be divided into three zones. In the first zone, as the temperature rises, the strength gradually decreases. The second zone is characterized by a sharp decrease in strength as the temperature continues to increase. In the third zone, as the temperature approaches 0°C, the strength decreases at a slower rate. Typically, 0°C is considered the

TABLE 3 The information of active layer observations along the QTEC.

Site name	Altitude (°)	Longitude (°)	Elevation (m)	Depth (cm)	MAGT (°C)	Increasing rate (°C/year)	Increasing in 2016 compared to 2015 (°C)
QT09	35.72	94.13	4,448	10 40 120 160	−0.88 −1.07 −1.20 −1.21	0.199 0.160 0.011 0.091	0.59 0.52 0.35 0.27
Ch06	35.62	94.06	4,747	10 50 100 180	−2.62 −2.82 −2.43 −2.45	0.029 0.012 0.039 −0.027	0.46 0.43 0.33 0.12
QT08	35.22	93.08	4,621	10 40 200 240	−1.30 −1.28 −1.14 −1.23	0.051 0.064 0.066 0.059	0.27 0.32 0.12 0.07
Ch04	31.82	91.74	4,805	15 50 95 120	0.95 −0.35 −0.64 −0.65	0.075 0.062 0.027 0.057	0.32 0.26 −0.11 −0.25

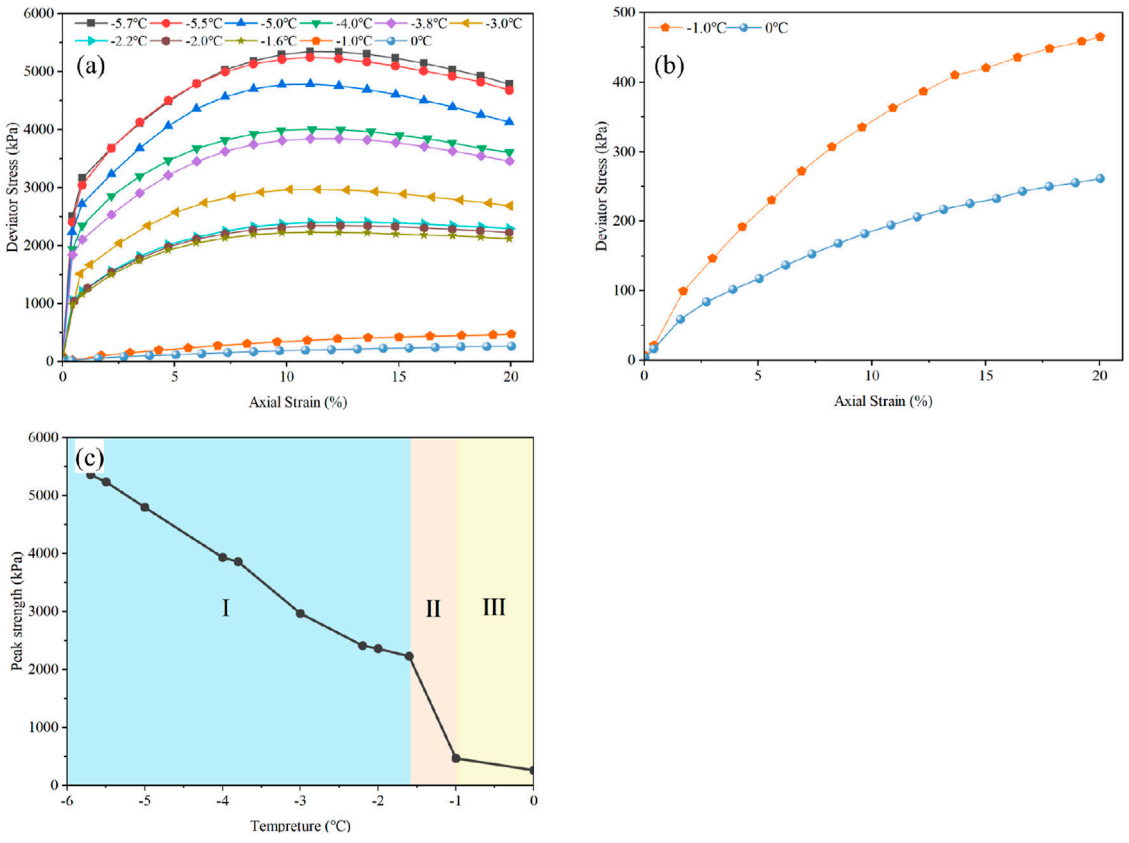


FIGURE 7
(A) The stress-strain curve of saturated soil at various temperatures under a confining pressure of 50 kPa. **(B)** The stress-strain curve at −1°C and 0°C. **(C)** Peak strength of soil under different negative temperatures.

standard for defining frozen soil from a thermal state (Dobinski, 2011). However, from the viewpoint of frozen soil physics and mechanics, the definition of freezing temperature T_f should be lower than 0°C. For clay in the permafrost region of the Qinghai-Tibet Plateau, a standard of −1°C should be set. At this temperature, the failure mode is already similar to that at normal temperature, and the strength also decreases significantly, leading to a sharp decline in slope stability. This change in macroscopic physical and mechanical properties is attributed to the reduction in pore ice or the increase in unfrozen water content during the soil thawing process.

3.3 Active-layer thickness increased as climate warming

The active layer is a ground layer in permafrost regions that undergoes annual thawing and freezing, with its thickness (ALT) being an essential characteristic of permafrost environments (Dobiński, 2020). The freeze-thaw index is an important parameter associated with permafrost. It serves as a significant indicator for assessing the current state and long-term fluctuations of permafrost, as well as the spatial and temporal variations in active layer thickness (Riseborough, 2003; Smith et al., 2009). Thawing index refers to the cumulative value of positive temperature over time (Wu et al., 2015). ALT can be determined by applying a modified version of the Stefan solution that incorporates the thawing index (Nelson and Outcalt, 1987; Nixon and McRoberts, 1973).

$$X = 416\sqrt{\frac{k}{L}}\sqrt{\mathrm{TISG}}$$

where X is ALT (m), and TISG is the annual thawing index of surface ground (°C·d) ,k is the diffusivity of soil [cm^2/s]; L is the volumetric latent heat of the soil [Cal/cm^3]. ALT is an increasing function of TISG, and with the increase of TISG, ALT will also show an upward trend.

It is worth noting that the thawing index of surface ground may vary across different active layer observations. The average value of the thawing index at QT09 is 601.02°C·d, while at QT05 it is as high as 1,494.89°C·d. Although there is significant variation in the specific values of all the observations, the rising and falling trends of the thawing index in different years are generally consistent. The thawing index of the surface ground (TISG) in all active layer observations exhibited an upward trend. The index experienced a substantial increase and nearly reached its highest point in 2016, after which it began to decline in the following years (Figure 8A). Consequently, there was a significant deepening of the active layer thickness in 2016, nearly reaching the maximum value observed in recent years.

ALT is also estimated by using linear interpolation of ground temperatures above and below 0°C, calculated from semimonthly temperature data obtained through daily ground temperature measurements (Frauenfeld et al., 2004; Wu and Zhang, 2010b). ALT along the QTEC has shown a significant upward trend in the past 10 years. The average thickness of the active layer, based on all observations, is 197 cm. The maximum thickness of 309.5 cm was recorded at QT05, while the minimum thickness of 113.7 cm was observed at Ch04. The average rate of increase in the active layer thickness at the four stations was 1.5 cm/year, with slight variations among the different stations. In 2016, there was a significant increase in the thickness of the active layer at each station, which can be attributed to a considerable rise in temperature along the QTEC during that year. In comparison to 2015, the thickness of the active layer at all stations increased by an average of 18.5 cm in 2016, surpassing the average rate of increase (Figure 8B). Notably, Ch04 experienced an increase of 42.83 cm in 2016, reaching the highest value observed in recent decades. Interestingly, measurements from the Circumpolar Active Layer Monitoring network in 2016 indicated that the ALT at all Arctic sites was either at or close to the maximum level recorded in the past 18–21 years (Zhao et al., 2020).

3.4 Landslide frequency increasing

The K3035W landslide (Figure 9A) occurred in late September 2010 (Niu et al., 2015). The QT03 observation, located 20 km away from the landslide, indicated that the active layer thickness (ALT) reached its highest value in 2010 (Figure 9B), with the deepest thawing occurring in late September (Figure 9C). A Google Earth image from October, 2010, clearly shows intact wheel ruts behind and on the sliding area of the landslide (Figure 9A), providing evidence that the landslide moved as a whole. This type of landslide is known as active-layer-detachment and is caused by the thawing of materials near the permafrost table. Active-layer-detachment typically occurs during late summer when the active layer reaches its greatest depth. The headwall of the landslide continued to retreat from 2011 to 2013 (Niu et al., 2015). Following the active-layer-detachment, the failure progressed into a retrogressive thaw slump due to the thawing of ice-rich permafrost or the exposure of ground ice.

The failures mainly initiated or expanded during the thawing season between August and November (Luo et al., 2022), so we collected satellite images of every July in the study area. Figure 10A illustrates that a single landslide took place in July 2016, suggesting that the landslide occurred prior to 2016. In July 2017, 6 landslides transpired within the same region, indicating that 5 new landslides emerged between August and October of the preceding warm season in 2016 (Figure 10B). The combined area of these 6 landslides in July 2017 amounted to 266,141 m^2. Over the subsequent years, the landslides continued to expand, resulting in an area of 430,189 m^2 by July 2022 (Figures 10C, D). This signifies a 61.6% increase in landslide area over the course of 5 years. Just like the K3035W, the typical landslides initially failed in the form of overall active layer detachment, and then the landslides continued to expand backward in the form of retrogressive thaw slump in the next few years.

The initiation of failures was concentrated in a specific year and month, rather than occurring steadily. Our inventory includes 1,298 landslides along the QTEC. Statistical analysis revealed that there were only 428 failures before 2016. However, in 2016, 621 new failures emerged, constituting 56.6% of the total number of landslides. In 2017 and 2018, only 55 and 130 failures formed, respectively. From 2019 to 2021, there were only 16 new landslides (Figure 11).

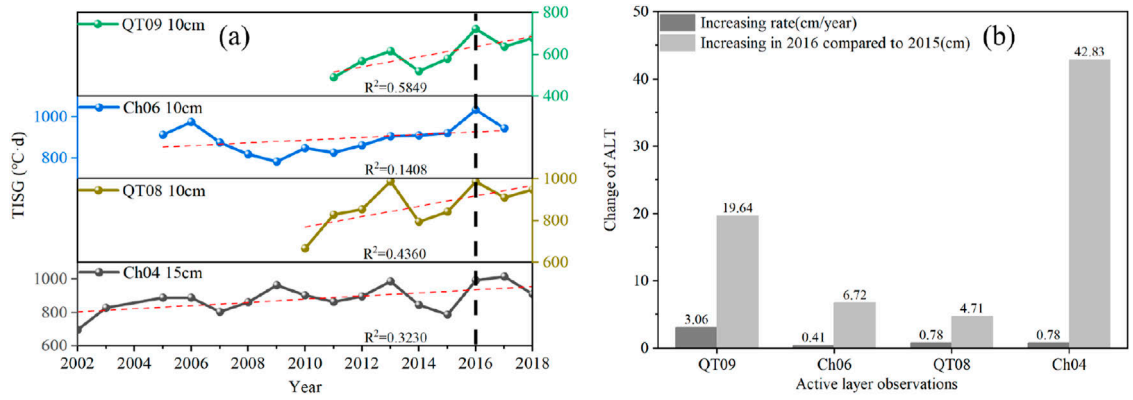


FIGURE 8
(A) The thawing index of surface ground at different active layer observations along the QTEC. **(B)** The changing of active layer thickness at four stations along the QTEC.

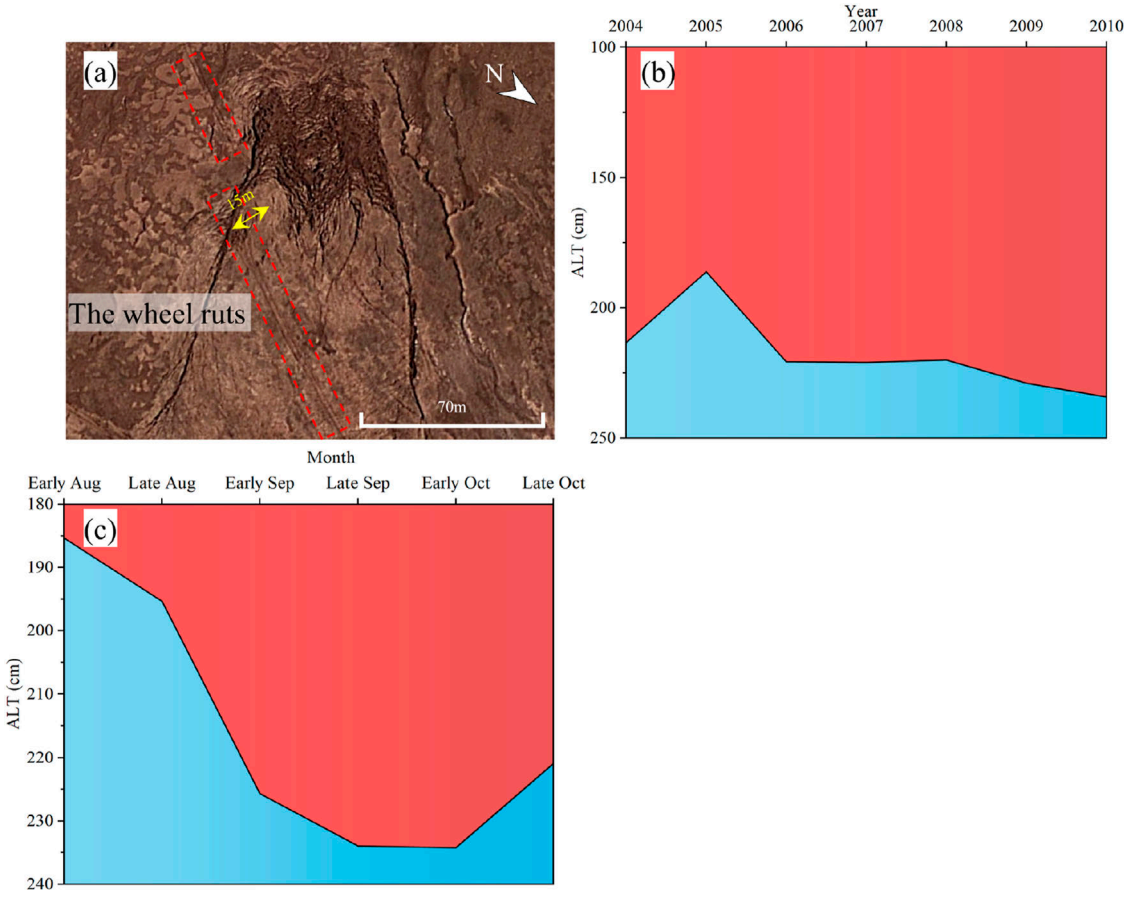


FIGURE 9
(A) Satellite image of the landslide K3035W on October 2010 (acquired from Google Earth). **(B)** Annual changes in active layer thickness at the QT03 from 2004 to 2010. **(C)** Monthly change of active layer thickness at the QT03 in 2010.

4 Discussion

Permafrost is formed due to a long-term negative heat exchange between the ground and the atmosphere, with the concentrated reflection of this process being the permafrost surface. The air temperature along the QTEC has shown a significant increase over the past decade. The MAAT in 2016 reached nearly its highest value from 2010 to 2020. The trend of surface ground temperature

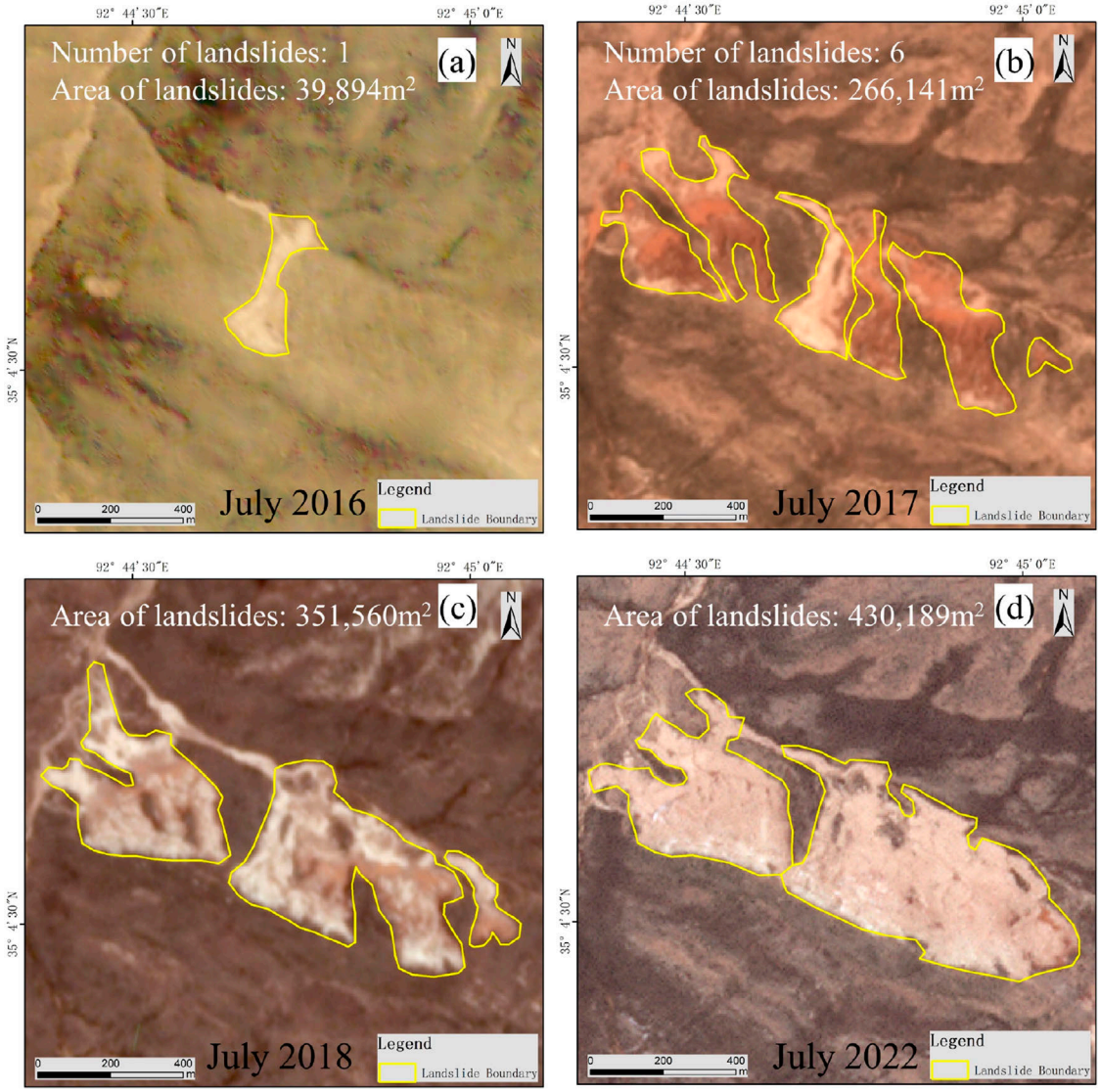


FIGURE 10
The evolution process of landslides in a typical area. **(A)** A typical landslide initiated before 2016 **(B)** Five typical landslides occurred in 2016 **(C)** and **(D)** The landslides continued to expand in the following years.

change closely aligns with the air temperature, suggesting that the near-surface air temperature is the primary factor influencing the surface ground temperature. As the atmospheric temperature rises, it inevitably leads to an increase in the temperature of the surface soil. The surface temperature of permafrost along the QTEC has risen significantly in the past decade, with a slightly higher rate of increase compared to the air temperature. Similarly, the increase in mean annual ground temperature (MAGT) in 2016, compared to 2015, was much higher than the average rate of increase. The temperature near the active layer and the permafrost also exhibited a rising trend, although the rate of increase was slightly lower than that of the surface ground. Therefore, the observed changes in permafrost thermal conditions are generally consistent with the increasing air temperature. Data from active layer observations along the QTEC also show that the thickness of the active layer has been on the rising over the last decade and increased significantly in 2016. The above phenomenon are concrete manifestations of permafrost degradation. As permafrost undergoes gradual degradation, substantial alterations in soil moisture and thermal conditions significantly influence vegetation growth and distribution. In the study area, over 70% of landslides occur within alpine meadow regions, with alpine meadows comprising 72.4% of areas exhibiting a significant decreasing trend in vegetation (Jin et al., 2020). The root systems of alpine meadows play a crucial role in stabilizing the soil, enhancing its cohesion and structural integrity. However, as the area of these meadows diminishes, the stabilizing function of the roots weakens, resulting in a loosening of soil particles and an increased susceptibility to landslides. Furthermore, the vegetation within these meadows demonstrates effective water regulation capabilities, facilitating the absorption of precipitation and the reduction of surface runoff. The ongoing degradation of permafrost contributes to the decline of alpine meadows, thereby diminishing

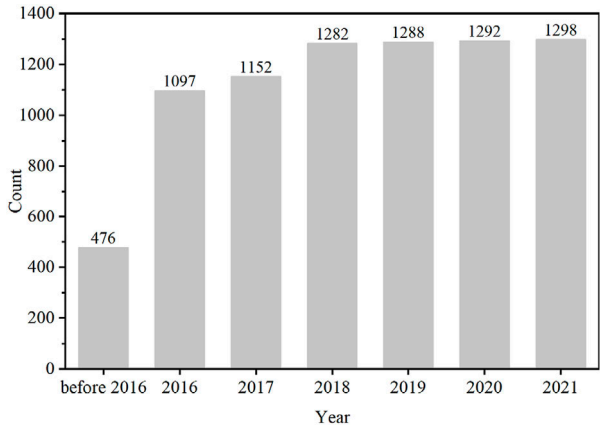


FIGURE 11
Number of landslides along the QTEC from 2016 to 2021.

their water regulation capacity and leading to increased surface water accumulation and saturation in the upper soil layers. This accumulation ultimately results in a reduction of the soil's shear strength. Additionally, the absence of vegetation cover exposes the soil to direct solar radiation, accelerating permafrost melting and inducing frequent cycles of expansion and contraction that compromise soil stability. Collectively, these factors engender an unstable soil water-thermal cycle, further undermining the soil's resistance to sliding.

The significant deepening of the active layer thickness beyond the historical average indicates a change in soil temperature near the permafrost table, transitioning from permanently negative to positive during the warm season. Typically, the soil's freezing temperature (T_f) is below 0°C. Therefore, a more accurate understanding of soil freezing and thawing should be based on T_f. As the temperature rises, the active layer and permafrost start to move downwards, causing the original permafrost to melt and form a thawed interlayer. Although the deepened portion of the active layer may not entirely align with the thawed interlayer, the deepening of the active layer implies the melting of some perennial frozen soil near the permafrost table in the warm season.

The K3035W landslide occurred in September 2010. It is important to note that observations of the active layer 20 km away from the landslide site indicated that the ground temperature and active layer thickness reached their highest levels in 2010. Additionally, the active layer thickness significantly increased compared to 2009, and in late September, the depth of the thawing ground reached its maximum. This suggests that in late September 2010, the perennial frozen soil on the permafrost table thawed, forming a thawed interlayer, which was the main factor contributing to the landslide. Initially, the landslide involved the detachment of the active layer, followed by continuous collapse and retreat of the headwall, resulting in a retrogressive thaw slump. In 2016, the air temperature along the QTEC experienced a sharp rise, reaching a historical high. However, there was no significant increase in rainfall during that year. In the northern and central regions where landslides were predominantly located, the rainfall in 2016 was even lower than the average annual precipitation. Between 2008 and 2018, no earthquakes exceeding magnitude 4 were recorded in the study area (https://www.usgs.gov/programs/earthquake-hazards). Moreover, remote sensing analysis indicated that 99.8% of identified landslides were located at least 1 km away from areas of human activity and rivers. Notably, the thickness of the active layer in 2016 increased significantly compared to 2015, resulting in the formation of a thicker thawed interlayer. Among the 1,298 landslides in the synthesis dataset, nearly half occurred in 2016, reinforcing the hypothesis that the development of a thawed interlayer at the active layer permafrost interface, driven by rising temperatures, is the primary cause of landslides. Extreme temperatures serve as the direct triggering factors for landslides in permafrost region. Nevertheless, this study does not explore the potential trends of landslides in permafrost area under future climate change scenarios. To address this limitation, future research should incorporate numerical analysis or physical modeling techniques to validate the findings of this study and evaluate how projected climate changes may affect landslide occurrences in permafrost region. (Fang et al., 2023).

Rising temperatures and the consequent deepening of the active layer increase the likelihood of slope destabilization, posing potential risks to the structural integrity of infrastructure along the QTEC. As the active layer thickens and the thawing index escalates, substantial ground deformation may occur, diminishing the soil's load-bearing capacity and potentially compromising foundational stability. Given these risks, future infrastructure planning along the QTEC should integrate designs that are resilient to permafrost degradation. Key measures include reinforcing foundations, implementing monitoring systems for early detection of ground instability, and considering alternative construction materials and techniques that account for dynamic freeze-thaw cycles. Long-term, continuous monitoring, alongside proactive mitigation strategies, will be essential for adapting to the evolving permafrost landscape in this region.

5 Conclusion

This study systematically investigates the temporal relationship between rising air temperatures and landslide occurrences in permafrost regions.

1) Highest recorded value of air temperature in 2016: Over the past several decades, the permafrost areas along the QTEC have experienced a steady rise in air temperature, with the mean annual air temperature (MAAT) in 2016 approaching its highest recorded value. In contrast, annual precipitation has remained relatively stable, and in 2016, rainfall was even below the mean annual levels in the northern and central regions where landslides are predominantly concentrated. Air temperature emerges as the most critical factor influencing the thermal state of the surface ground. Both ground temperature and active layer thickness (ALT) have shown significant upward trends, with the ALT at each

monitoring station increasing by an average of 18.5 cm in 2016 compared to 2015.
2) Concentration of landslides in 2016: Analysis of the landslide dataset along the Qinghai-Tibet Engineering Corridor (QTEC) reveals that nearly 50% of the landslides occurred in 2016 and the landslide frequency in 2016 significantly increased, reaching approximately 1.3 times the historical total.
3) Climate warming as the primary inducing factor: The significant increases in temperature and the concentrated occurrence of landslides in 2016 indicate that climate warming is the principal factor inducing landslides in permafrost regions.

The findings of this study provide robust empirical evidence linking climate warming to increased landslide activity in permafrost regions. They offer valuable insights into the mechanisms and processes by which rising temperatures and permafrost thaw contribute to slope instability. However, this research does not extensively explore the physical mechanisms underlying temperature-induced slope instability. Future studies should focus on investigating these physical processes and assessing the impact of landslide events on permafrost degradation. Such research would provide a scientific foundation for the prediction and prevention of landslides in permafrost regions.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://data.tpdc.ac.cn/zh-hans/data/789e838e-16ac-4539-bb7e-906217305a1d.

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Backward erosion piping mechanism in dike foundations with and without landside blanket layers: numerical simulation of size effects

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Introduction: This study investigates the backward erosion piping mechanism and its dependency on model size through both experiments and numerical simulations. The objective is to understand how different model dimensions affect the hydraulic gradients and piping behavior in dike systems.

Methods: Numerical simulations were performed using the finite element method (FEM), where the dike foundation was modeled in 3D and seepage flow was simulated under various hydraulic gradients. Physical experiments were also conducted using small-scale dike models to verify the numerical results and study the effects of model size.

Results and Discussion: The results show that in dikes without blanket layers, hydraulic gradients increase steadily as the piping channel develops, leading to upstream erosion and failure. In contrast, dikes with a blanket layer exhibit a stabilizing effect: the hydraulic gradient initially decreases before increasing, leading to a self-healing phenomenon that halts further channel progression. The study further reveals that the size effect—indicated by hydraulic gradients—diminishes with larger model dimensions and becomes negligible beyond a certain threshold. Additionally, the interaction between model width and depth significantly influences the progression of piping. These findings offer valuable insights for designing more resilient dike systems and improving flood protection strategies.

KEYWORDS

backward erosion piping, size effect, mechanism, development mode, dike foundations

1 Introduction

Dike systems play a critical role in flood protection, yet they are persistently threatened by backward erosion piping—a process where seepage-induced soil particle removal leads to the formation and progression of subsurface channels. This phenomenon, if left unchecked, can cause catastrophic dike failures and widespread flooding, rising

the water level, posing significant risks to communities and infrastructure (Qiu et al., 2024; Zhu et al., 2024). Previous studies, such as those by (Van Baars and Van Kempen, 2009), have emphasized the significant role of seepage and piping mechanisms in dike failures, highlighting that inadequate understanding of these processes can lead to catastrophic breaches. Their work underscores the critical need for effective mitigation strategies to address the challenges posed by backward erosion piping in flood protection systems. Similarly, Schmocker (2011) further contributes to this understanding by illustrating how dike material heterogeneity and foundation conditions are pivotal factors influencing the risk of erosion and failure. Additionally, The integration of geosynthetics into dike systems has been shown to significantly enhance resilience by controlling water-soil interactions, as highlighted by (Heibaum, 2014). Understanding these mechanisms is crucial for improving dike resilience and enhancing flood management strategies.

Furthermore, the structure of dike foundations plays a pivotal role in mitigating these risks. Dikes are typically built upon varying foundation types, which can influence the propagation of backward erosion piping. A key feature that significantly affects this process is the landside blanket layer—an impermeable or low-permeability layer that is placed between the dike core and the foundation. For dikes without this layer, once the piping channel begins, it tends to propagate unabated upstream, as there is no barrier to halt the erosion process. In contrast, the inclusion of a landside blanket layer provides a stabilizing effect. As shown by (Yao, 2014) and others, the presence of this layer initially reduces the hydraulic gradient at the piping tip, creating a self-stabilizing phenomenon that slows or even halts the channel's progression temporarily. Over time, as the hydraulic gradient increases, the piping process resumes, but this phenomenon demonstrates a crucial difference in the erosion dynamics when compared to dikes without the blanket layer.

Numerous studies have investigated various aspects of backward erosion piping. For instance, Bersan et al. (2018) evaluate distributed temperature measurements for early detection of piping, linking hydraulic head variations to seepage-induced instability. On this basis, Akrami et al. (2021) provide insights into piping development in silty dike foundations, addressing mitigation through coarse sand barriers. Moreover, Bonelli (2013) analyze hydraulic head differentials as a trigger for backward erosion in dams and levees, offering a framework for geotechnical safety. Vandenboer et al. (2017) highlight the impact of leakage length on piping initiation and its implications for countermeasure effectiveness. Pol et al. (2019) analyze progression rates of backward erosion piping through laboratory experiments. Their study presents data from 45 controlled experiments and reliability analysis to refine models of erosion. Finally, Wewer et al. (2021) propose a transient backward erosion piping model using laminar flow transport equations. Gragnano et al. (2023) model innovative natural-based solutions for countering backward erosion piping, emphasizing sustainability. This study bridges experimental results and predictive modeling, enhancing understanding of piping initiation and development. These studies collectively enhance our understanding of the phenomenon, aiding in the development of more effective flood mitigation strategies.

However, there are few researches focusing on the size effect of the experiment models. A notable observation in backward erosion piping research is the profound impact of model size on the critical hydraulic head. Larger-scale models often exhibit lower critical heads, highlighting the scale dependency of piping phenomena. Further, the piping mechanism and the mode of channel propagation vary significantly across different foundation types, adding another layer of complexity to its study. For instance, Yao (2014) emphasized that the propagation patterns and critical conditions for piping differ in foundations with and without a landside impermeable blanket layer. In the absence of such a blanket layer, once a piping channel initiates, the erosion process continues relentlessly upstream without reaching equilibrium, ultimately leading to dike failure. This persistent propagation contrasts starkly with the equilibrium state often observed in experiments on foundations equipped with landside blanket layers, as reported by (Sellmeyer, 1988; Mao et al., 2004; Yao et al., 2007).

The three-dimensional finite element method (FEM) based on stable seepage theory provides new insights into the role of size-dependent mechanisms in the formation of piping, and elucidates the role of impermeable blanket layers in mitigating the backward erosion piping process. These simulations performed on homogeneous dike foundations both with and without landside impermeable blanket layers, have shed light on the size-dependent mechanisms driving piping. For example, Peng and Rice (2020) used FEM to analyze laboratory data, advancing our understanding of erosion mechanisms under controlled conditions. Similarly, Robbins et al. (2021) applied random FEM to model stochastic variations in piping progression, emphasizing the interplay between soil properties and hydraulic gradients. Wang et al. (2024) extended these approaches to temporal modeling, offering insights into the dynamic evolution of erosion pipes over time. The results underscore the interplay between dike geometry, seepage dynamics, and soil heterogeneity, which together govern the onset and progression of piping channels. These findings have significant implications for the design of resilient dike systems, especially in regions vulnerable to high seepage gradients.

While advancements in experimental and numerical methods have deepened our understanding of backward erosion piping, several questions remain unanswered. For example, what are the precise scaling laws governing the critical hydraulic head in large systems? How can foundational characteristics be optimized to resist persistent channel propagation in the absence of blanket layers? Addressing these questions is vital for developing effective countermeasures and predictive models for dike safety. The following sections delve into the experimental findings, computational analyses, and theoretical frameworks that collectively form the foundation of our current understanding of backward erosion piping.

2 Methods and implementation

2.1 Theoretical basis for numerical simulation of dike foundation piping

Understanding the theoretical framework underpinning numerical simulations is critical for accurately modeling backward erosion piping phenomena in dike foundations. Numerical simulations, particularly those employing the finite element method (FEM), offer a robust approach to analyze complex seepage and

erosion interactions. These methods leverage governing equations of steady-state seepage and soil mechanics, incorporating factors such as anisotropic permeability and boundary conditions to replicate real-world conditions, the details are shown in the follows:

The continuous differential control equation of steady seepage in heterogeneous anisotropic porous media is:

$$\sum_{i=1}^{3}\frac{\partial}{\partial x_i}\left(\sum_{j=1}^{3}k_{ij}\frac{\partial H}{\partial x_j}\right)=0 \tag{1}$$

The Factor k_{ij} is the permeable coefficient tensor, H is the total water head, and $x_i(i=1,2,3)$ is the rectangular axes. This equation reflects the relationship between the seepage flow in different directions, where the permeability varies with direction due to soil heterogeneity.

The boundary conditions for backward erosion piping in dike foundations consist of the water head and the flow boundary conditions. The water head boundary condition is as shown in Equation 2:

$$\Gamma_1 \quad H|_{\Gamma_1}=H_0(x_i) \tag{2}$$

The flow boundary condition is:

$$\Gamma_2 \quad \sum_{i=1}^{3}\left(\sum_{j=1}^{3}k_{ij}\frac{\partial H}{\partial x_j}\right)n_i=q(x_i) \tag{3}$$

$H_0(x_i)$ is the known water head function at the boundary Γ_1. $q(x_i)$ is the known discharge at the boundary Γ_2, when $q(x_i)=0$, Equation 3 corresponds to an impermeable boundary condition at that time.

The FEM Galerkin was used to discretize the governing Equation 1 and the equation can be derived as Equation 4:

$$KH=F \tag{4}$$

where K is the permeability matrix, H is the total water head vector, and F is the load vector of the seepage area relatively. The equation represents the balance between the forces generated by the permeability and the external forces (such as hydraulic gradients) acting on the system.

The equivalent permeability k_n in backward erosion piping area is defined as Equation 5, which is referred to the former study (Liuqian et al., 2007).

$$k_n=\frac{8Rg}{\lambda V} \tag{5}$$

The factor λ is the friction factor of head loss of the piping channel, V is the mean flow rate in the channel, R is the hydraulic radius of the piping channel, and g is the acceleration of gravity.

2.2 Implementation of numerical simulation method for dike foundation piping

Firstly, the FEM is chosen for the numerical calculation based on the steady seepage theory, and the model is dispersed by 20-node hexahedral element, and appropriately increase the mesh around the pipe outlet and pipe channel to enhance the accuracy of the numerical simulation in regions where critical physical phenomena, such as erosion and seepage, are occurring. In this case, the pipe outlet and the developing piping channel are areas where high gradients in hydraulic head and rapid changes in flow can occur, making them more susceptible to errors when modeled with coarse meshes. The minimum mesh size is 1.25 cm in length, 1.25 cm in width, and 1 cm in height. Taking a model with a width and thickness of 50 cm as an example, based on the symmetry of the model, a model with half the width is taken for modeling calculation, that is, the model has a width of 25 cm and a depth of 50 cm, a total of 63,333 nodes, and 14,280 mesh cells are divided, as shown in Figure 1A.

The numerical calculation was performed on the backward erosion piping respectively in dike foundations without- and with-landside blanket layer (Figures 1B, C). The parameters of sand are the same with the model tests by (Yao, 2014). 8 different model widths and 7 different model depths are set for the size effect study. The values of width are respectively 2.5 cm, 5 cm, 10 cm, 20 cm, 30 cm, 50 cm, 75 cm and 100 cm, and the values of depth are respectively 1 cm, 5 cm, 11.5 cm, 20 cm, 30 cm, 50 cm and 75 cm. The width and depth of piping channel are fixed 2.5 cm and 1 cm respectively. The seepage field of each size model with setting the length of piping channels as different present values under the fixed hydraulic head is analyzed. The permeability of the piping channel is simplified as 1,000 times of the sand matrix without piping (Liuqian et al., 2007). The numerical calculation model for dike foundation piping without- and with-landside cover (Figures 1B, C) have the same model length (70 cm), seepage length (50 cm) and the length of the piping channel taken as 1.25 cm, 5 cm, 10 cm, 20 cm, 30 cm and 40 cm. The summery of the model implementation is shown in Table 1.

The physical model is a closed box with dimensions of 0.5 m, 0.3 m, and 0.1 m in length, width, and height, respectively. The sample diameter length is controlled at 0.35 m. The body of the model slot is made of PVC board, and the top surface of the model slot is covered with organic glass board. The bottom of the organic glass board is coated with silicone gel (to increase the friction between the sand particles and the glass board, and to ensure close contact between the sand particles and the glass board with the elasticity of silicone gel). The glass board and the slot body are sealed with water stop strips and screws, as shown in Figure 1D.

The experimental model tank without landside cover layer has a closed top cover plate, which is blocked and fixed by upstream filter plates and downstream baffles. The upstream filter plate adopts a method of sandwiching geotextile between two layers of steel plates filled with small holes to ensure smooth water flow into the sand sample and prevent the sand sample from flowing into the upstream inlet part. The downstream baffle is slightly lower than the height of the sample to form a smaller slope on the downstream side of the sand sample, simulating the seepage outlet. The upstream inflow enters the sand sample through the opening on the right side of the model slot connected by a water pipe, passing through the upstream inflow part and the filter plate. The downstream outflow flows from the sloping seepage outlet to the downstream outflow part through the opening on the left side of the model box connected by a water pipe, as shown in Figures 1D,E.

The difference between the experimental model slot with landside cover layer and the model slot without landside cover

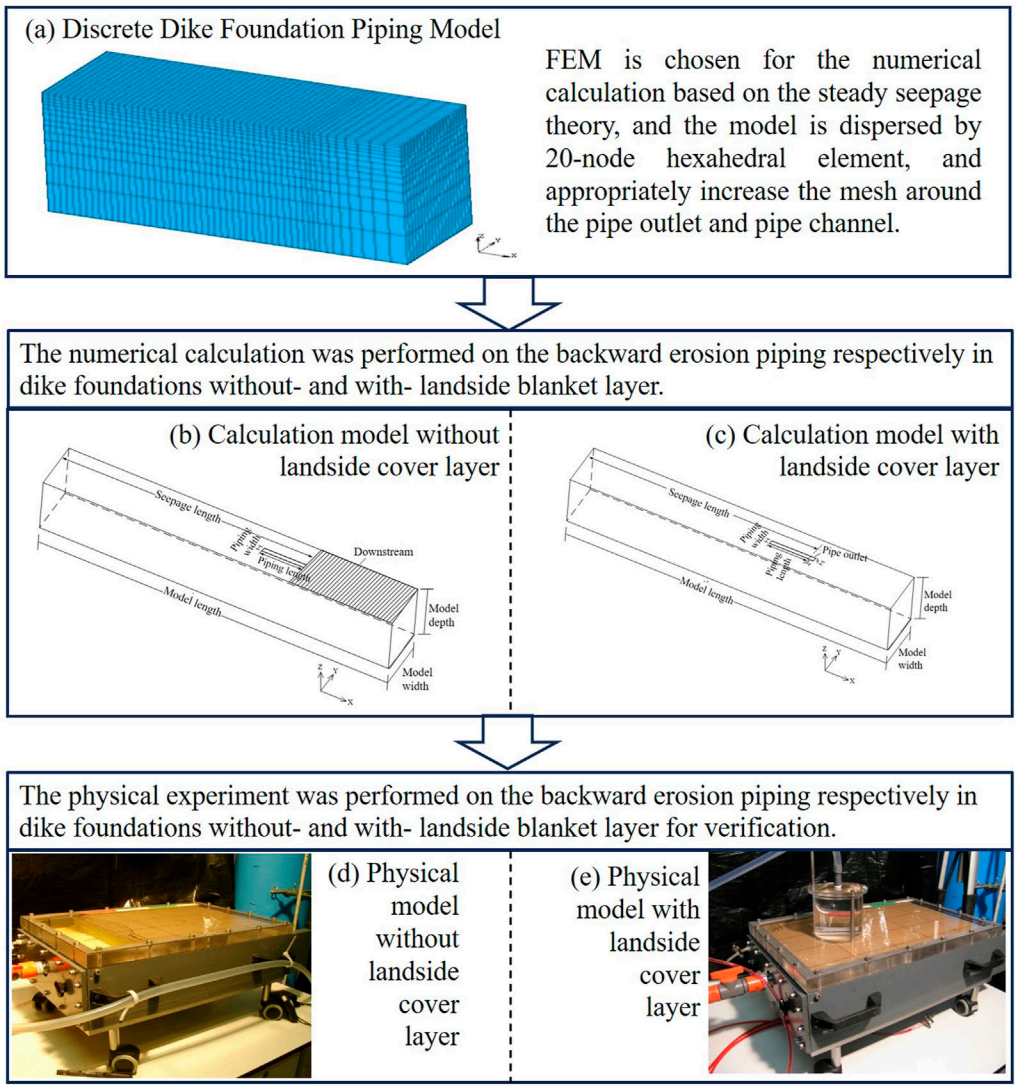

FIGURE 1
Research roadmap. **(A)** Discrete Dike Foundation Piping Model. **(B)** Calculation model without landside cover layer. **(C)** Calculation model with landside cover layer. **(D)** Physical model without landside cover layer. **(E)** Physical model with landside cover layer.

layer lies in the design of the seepage outlet. For the model with a landside cover layer, a 6 mm diameter circular hole (Notice: the circular hole is an idealized representation, used for simplicity in the physical model. We have also emphasized the limitations of this approach and suggested that real-world leakage is more complex and irregular, influenced by factors such as soil heterogeneity, dike material defects, and variable hydraulic gradients) is pre-drilled in the centerline of the glass plate covering the top, 0.35 m from the upstream inlet, to simulate the outflow from a piping hole. The outflow of seepage water is designed to be retained by the upstream filter plate and the end of the model tank, with the tank being closed and the downstream side of the model tank sealed, allowing outflow only through the pre-drilled circular hole on the top. A transparent cylinder is installed above the hole, with a water pipe connected to the top of the cylinder, allowing seepage water to flow out through the hole, the cylinder, and the water pipe, as shown in Figure 1E.

Two piezometers are installed on the side of the model tank to reflect the variation process of the water head inside the embankment foundation and to verify any abnormalities in the water head during the experiment. A digital camera is fixed and suspended above the model tank, set to take timed automatic photos and store them on a server. The digital camera can capture the entire surface of the sand sample, allowing for continuous tracking of the development of piping channels on the sand surface. Additionally, another digital camera is available for capturing local piping phenomena at any time.

3 Result and discussion

For both homogeneous dike foundations with and without land cover layer, the distribution patterns of seepage fields under different model widths and thicknesses will be analyzed to reveal the variation

TABLE 1 Model implementation.

Item	Description
Element type	20-node hexahedral element
Mesh size	Minimum: 1.25 cm (length), 1.25 cm (width), 1 cm (height)
Sand parameters	Same as model tests by (Yao, 2014)
Model length	70 cm
Seepage length	50 cm
Size effect study	8 different model widths, 7 different model depths
Width values	2.5 cm, 5 cm, 10 cm, 20 cm, 30 cm, 50 cm, 75 cm, 100 cm
Depth values	1 cm, 5 cm, 11.5 cm, 20 cm, 30 cm, 50 cm, 75 cm
Length of piping channel	1.25 cm, 5 cm, 10 cm, 20 cm, 30 cm, 40 cm
Piping channel dimensions	Width: 2.5 cm, Depth: 1 cm
Permeability of piping channel	1,000 times of sand matrix without piping

in hydraulic gradient at the front end of the piping channel. This analysis aims to investigate the impact of model width and thickness on the embankment piping process and study the size effect of embankment piping models.

3.1 Backward erosion piping in dike foundations without landside blanket layer

In order to select reasonable boundary conditions, the influence of the upstream and downstream head difference on the hydraulic gradient of the pipe tip is analyzed. Select two models with different width and depth for analysis: (a) model with 30 cm width and 1 cm depth, (b) model with 50 cm width and 30 cm depth. Apply water head to the upstream and downstream of the models, gradually increasing the water head to simulate the development process of piping phenomenon. The water head gradually increases from 1 cm to 50 cm, with each increase being 1 cm. For the convenience of comparison, the hydraulic gradient of the pipe tip calculated at a water head of 1 cm is taken as the reference, and the ratio of the hydraulic gradient of the pipe tip calculated at different pipe channel lengths under each level of water head to the hydraulic gradient at 1 cm (hereinafter referred to as the relative hydraulic gradient of pipe tip) is compared with it.

Figure 2 shows the calculation results under different water head conditions. From the figure that under the same level of water head conditions, the relative hydraulic gradient of different lengths of pipe tip is the same, and this relative value increases linearly with the change of water head. Therefore, the distribution law of hydraulic gradient at the pipe tip under different head difference conditions is the same. Therefore, it is only necessary to study the distribution law of hydraulic gradient at the pipe tip under a certain head difference condition. This article takes the upstream and downstream head difference of 5 cm for calculation and analysis.

The numerical calculations are performed on backward erosion piping in dike foundations without landside blanket layer with models of different widths and depths. The hydraulic gradients of the tip of the piping channel are acquired and their variation trends with the piping channel length increase are shown with different model widths and depths (Figure 3).

Figure 3 shows the variation of the hydraulic gradient of the pipe tip with the length of the piping channel. As shown in Figure 3 that when the piping channel is relatively short, i.e., when the piping channel begins to form, the smaller the model width, the smaller the hydraulic gradient at the front of the piping channel. Therefore, under the same critical condition for the initial formation of the piping channel at the dike foundation, a model with a smaller width requires a higher head to reach the initial conditions for piping compared to a model with a larger width. It can also be seen that as the piping channel develops upstream and the length of the piping channel increases, the hydraulic gradient at the front of the piping channel increases under all width and depths conditions, showing a monotonous upward trend. Therefore, once the piping channel begins to form, the hydraulic gradient at the pip tip will continue to increase, indicating that once the piping channel forms, it cannot be stopped and will continue to develop upstream until scour damage occurs when it connects with the upstream. This also implies that under the model conditions, the initial gradient at the formation of the piping channel at the dike foundation represents the critical gradient for piping failure.

Additionally, in Figure 3, subfigures (a) to (g) illustrate an increase in model depth from 1 cm to 75 cm. Despite this variation, the patterns observed in each subfigure remain similar. This similarity suggests that, when the model width is kept constant, the gradient of the pipe tip also increases with the length of the piping channel. Consequently, both model width and model depth appear to have minimal impact on the observed phenomenon: once the pipe initiation occurs, it continues unabated until it reaches the upstream, as previously reported in model tests (Yao, 2014; Yao et al., 2013).

The observations from Figure 3 regarding the influence of model depth on the hydraulic gradient are further supported by the data presented in Figure 4, which examines the variation of the hydraulic gradient with model width and depth. In both cases, it is evident that the dimensions of the model, whether depth or width, play a similar role in determining the hydraulic gradient at the pipe tip.

As shown in Figure 4, the variation trend of the hydraulic gradient of the piping face with model width under different piping channel lengths. From the graph, it can be observed that under the same piping channel length, when the model width is small, the hydraulic gradient on the pipe tip differs significantly for different model widths. As the model width increases, the difference gradually becomes smaller, and once the model width reaches a certain size, the hydraulic gradient on the piping face becomes nearly identical, approaching a constant value. This indicates that when the model width is small, the hydraulic gradient at the pipe tip has a significant impact, thus affecting the critical gradient for piping failure. Once the model width reaches a certain size, the difference diminishes as the model width increases, and the

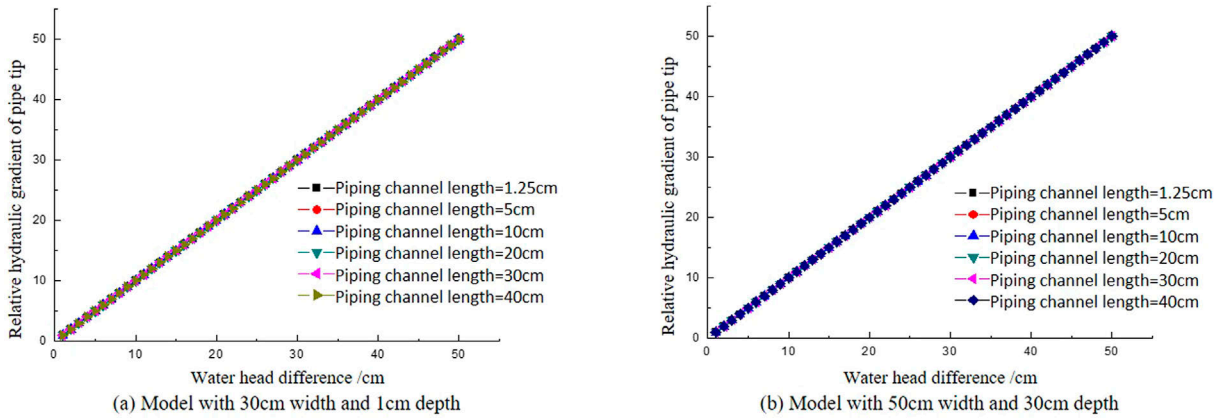

FIGURE 2
The relationship between hydraulic gradient and boundary conditions in the pipe tip. **(A)** Model with 30 cm width and 1 cm depth. **(B)** Model with 50 cm width and 30 cm depth.

influence of model width on the piping development process can be considered negligible. The similar situation can be observed in all model depths in Figures 4A–G, indicating that the effect of model depths has the same pattern with model widths.

Based on the benchmark of calculating the hydraulic gradient at the pipe tip when the maximum model width is 100 cm, analyze the relative value of the hydraulic gradient $|(J-J_{100})/J_{100}|$ at the pipe tip with varying model depths for different piping channel lengths. A tolerance error of 5% is taken for the relative value of the hydraulic gradient at the pipe tip, the widths that can let model reach the tolerance error is shown in Figure 5.

From Figure 5, it can be observed that the model width required to achieve the tolerance error is not a single value but is related to the model depths. The smaller the model depth, the smaller the model width required to achieve the tolerance error; conversely, the larger the model thickness, the larger the model width required to achieve the tolerance error.

Based on the benchmark of calculating the hydraulic gradient at the pipe tip when the maximum model depth is 75 cm, analyze the relative value of the hydraulic gradient $|(J-J_{75})/J_{75}|$ at the pipe tip with varying model widths for different piping channel lengths. A tolerance error of 5% is taken for the relative value of the hydraulic gradient at the pipe tip, the depths that can let model reach the tolerance error is shown in Figure 6.

From Figure 6 reflects the depth of the model required to tolerate errors is not significantly related to the width of the model. The required model depth decreases with increasing pipeline channel length.

3.2 Backward erosion piping in dike foundations with landside blanket layer

In order to select reasonable boundary conditions, the influence of the upstream and downstream head difference on the hydraulic gradient of the pipe tip is analyzed. Select two models with different width and depth for analysis: (a) model with 100 cm width and 75 cm depth, (b) model with 100 cm width and 1 cm depth, (c) model with 2.5 cm width and 75 cm depth. Apply water head to the upstream and downstream of the models, gradually increasing the water head to simulate the development process of piping phenomenon. The water head gradually increases from 1 cm to 50 cm, with each increase being 1 cm. For the convenience of comparison, the hydraulic gradient of the pipe tip calculated at a water head of 1 cm is taken as the reference, and the ratio of the hydraulic gradient of the pipe tip calculated at different pipe channel lengths under each level of water head to the hydraulic gradient at 1 cm (hereinafter referred to as the relative hydraulic gradient of pipe tip) is compared with it.

Figure 7 shows the calculation results under different water head conditions. The figure shows that under the same level of water head conditions, the relative hydraulic gradient of different lengths of pipe tip is the same, and this relative value increases linearly with the change of water head. Therefore, the distribution law of hydraulic gradient at the pipe tip under different head difference conditions is the same. Therefore, it is only necessary to study the distribution law of hydraulic gradient at the pipe tip under a certain head difference condition. This article takes the upstream and downstream head difference of 5 cm for calculation and analysis.

It is different with the calculation results of backward erosion piping in dike foundations without landside blanket layer, the values of hydraulic gradient of the pipe tip do not increases monotonically but decrease firstly and then increase with the pipe length increasing in dike foundations with landside blanket layer (Figure 8). As shown in Figure 8, the variation of the hydraulic gradient on the pipe tip with changes in the piping channel length, it can be observed that under the condition of equal upstream and downstream head differences, when the piping channel length is relatively short, the smaller the model width, the smaller the corresponding hydraulic gradient on the pipe tip. As a result, models with smaller widths require a higher head difference to reach the same initial conditions for piping formation compared to models with larger widths. In other words, models with larger widths require a lower head difference to form a piping channel. And that is the same as the dike foundations without landside blanket layer.

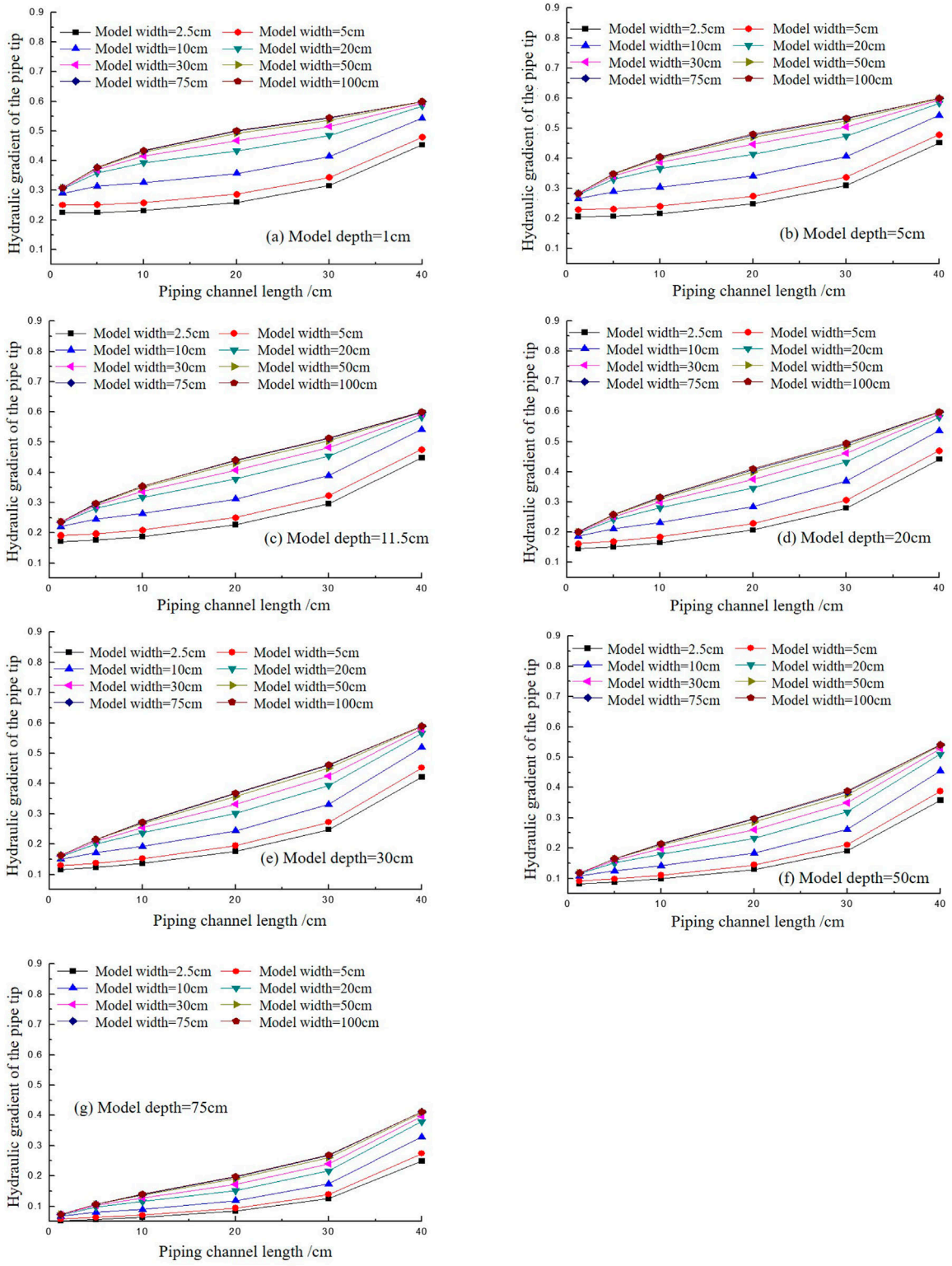

FIGURE 3
The variation of the hydraulic gradient with the pipe length increasing in different model widths and depths in dike foundations without landside blanket layer. **(A)** Model depth-1 cm. **(B)** Model depth-5 cm. **(C)** Model depth-11.5 cm. **(D)** Model depth 20 cm. **(E)** Model depth-30 cm. **(F)** Model depth-50 cm. **(G)** Model depth-75 cm.

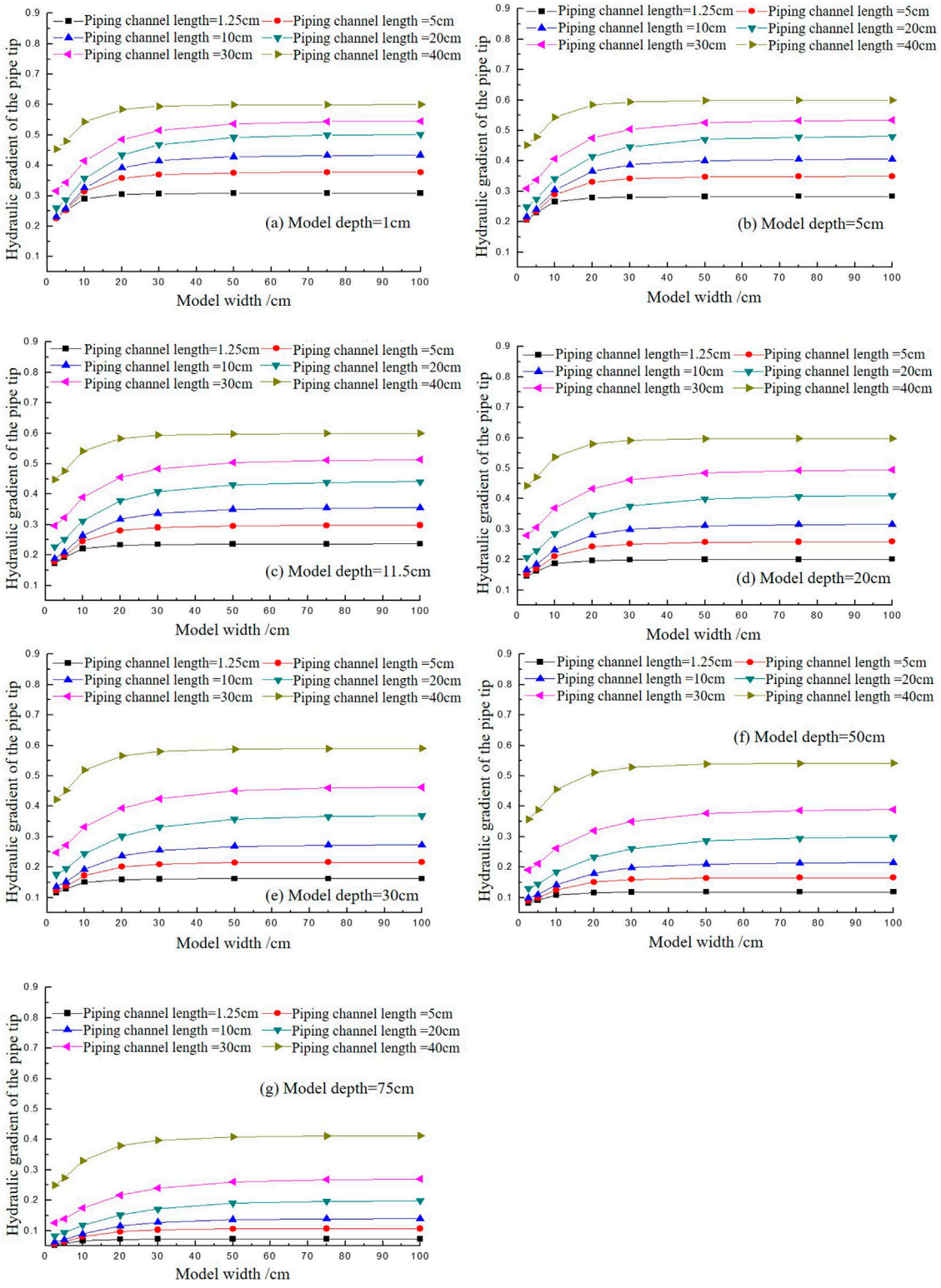

FIGURE 4
The variation of the hydraulic gradient of the pipe tip with the increase of model width and depth with different piping channel lengths. **(A)** Model depth=1 cm. **(B)** Model depth-5 cm. **(C)** Model depth-11.5 cm. **(D)** Model depth-20 cm. **(E)** Model depth-30 cm. **(F)** Model depth 50 cm. **(G)** Model depth-75 cm.

	1cm	5cm	11.5cm	20cm	30cm	50cm	75cm
1.25cm	11.00	12.00	14.00	15.00	15.00	16.00	14.00
5cm	21.00	22.00	24.00	28.00	27.00	28.00	28.00
10cm	30.00	30.00	33.00	40.00	38.00	40.00	42.00
20cm	40.00	40.00	42.00	47.00	44.00	47.00	49.00
30cm	33.00	35.00	40.00	46.00	41.00	45.00	46.00
40cm	17.00	17.00	17.00	22.00	20.00	23.00	27.00

FIGURE 5
The model widths that can reach the tolerance error (without landside blanket layer).

	2.5cm	5cm	10cm	20cm	30cm	50cm	75cm	100cm
1.25cm	61.00	61.00	62.00	62.00	62.00	62.00	62.00	62.00
5cm	60.00	60.00	60.00	60.00	60.00	60.00	60.00	60.00
10cm	57.00	57.00	58.00	58.00	58.00	57.00	57.00	58.00
20cm	49.00	49.00	49.00	49.00	50.00	49.00	49.00	49.00
30cm	36.00	36.00	35.00	37.00	37.00	37.00	36.00	36.00
40cm	16.00	14.00	12.00	11.00	9.00	9.00	9.00	9.00

FIGURE 6
The model depths that can reach the tolerance error (without landside blanket layer).

When the model width is small and the model depth is also small (as shown in Figure 8A with a model depth of 1 cm, and widths of 2.5 cm, 5 cm, 10 cm, 20 cm, and in Figure 8B with a model depth of 5 cm, and widths of 2.5 cm, 5 cm), as the piping channel length increases, the hydraulic gradient on the pipe tip gradually increases, showing a monotonically rising trend. Moreover, the rate of increase becomes more significant, indicating that during the upstream development of the piping, it follows an unstoppable trend. Once the piping channel forms, it quickly connects the upstream and downstream. This condition is only used for comparison between different sizes and simulates an extreme situation.

When the model width is small but the model depth is sufficiently large (as shown in Figures 8C–G), the hydraulic gradient on the pipe tip, as the piping channel length increases, no longer follows a monotonically increasing trend. Instead, it initially decreases before increasing, creating a concave-up curve. This trend suggests that during the early stage of piping channel formation, the hydraulic gradient on the pipe tip decreases, potentially dropping below the critical gradient. As a result, the piping channel halts its development and reaches a stable equilibrium. As the head increases, the piping channel extends upstream to a certain length, and the hydraulic gradient increases, surpassing the critical value, breaking the equilibrium and causing the piping to continue its development. The calculation results show that, under conditions with a landside blanket layer, there is a self-healing phenomenon during the development of the channel. This is consistent with the phenomenon observed in (Guo et al., 2024).

As shown in Figure 9, the variation trend of hydraulic gradient on the pipe tip with the model width under different piping channel lengths. Figure 9 shows that under the same piping channel length conditions, when the model width is relatively small, the hydraulic gradient on the pipe tip with different model widths varies greatly. As the model width gradually increases, the difference tends to flatten. When the model width reaches a certain size, the hydraulic gradient on the pipe tip almost does not differ much and tends to a constant value. This indicates that when the model width is small, it has a greater impact on the hydraulic gradient of the front end of the piping channel, and therefore has a greater impact on the critical gradient of piping failure. After the model reaches a certain width, as the model width increases, this difference gradually approaches zero, and the influence of model width on the development process of piping can be basically ignored. This trend can be observed in all sub-figures (a-g) in Figure 9, indicating that the effect of model depth has the same pattern with model width. So, in dike foundations with landside blanket layer, it is consistent with

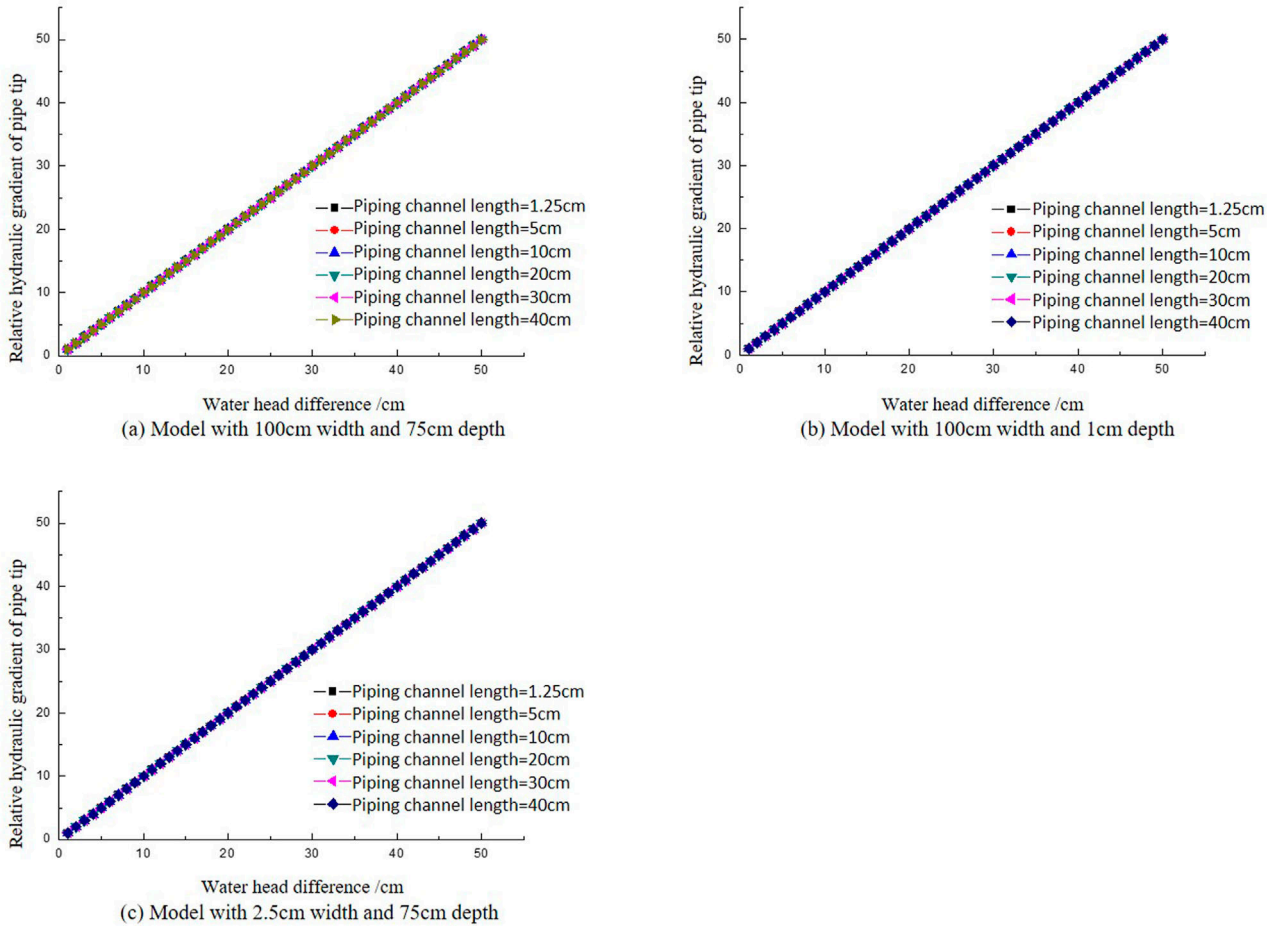

FIGURE 7
The relationship between hydraulic gradient and boundary conditions in the pipe tip. **(A)** Model with 100 cm width and 75 cm depth. **(B)** Model with 100 cm width and 1 cm depth. **(C)** Model with 2.5 cm width and 75 cm depth.

calculation analysis of the size effect on backward erosion piping in dike foundations without landside blanket layer that the model influence is decreasing and going to be zero when the model size reaches to large enough (Figure 4).

Based on the benchmark of calculating the hydraulic gradient at the pipe tip when the maximum model width is 100 cm, analyze the relative value of the hydraulic gradient $|(J-J_{100})/J_{100}|$ at the pipe tip with varying model depths for different piping channel lengths. A tolerance error of 5% is taken for the relative value of the hydraulic gradient at the pipe tip, the widths that can let model reach the tolerance error is shown in Figure 10.

As shown in Figure 10, the model width required to achieve the tolerable error generally falls between 70 cm and 90 cm. Therefore, when the model width is set at 1.8 times the seepage path, its impact can be largely ignored.

Based on the benchmark of calculating the hydraulic gradient at the pipe tip when the maximum model depth is 75 cm, analyze the relative value of the hydraulic gradient $|(J-J_{75})/J_{75}|$ at the pipe tip with varying model widths for different piping channel lengths. A tolerance error of 5% is taken for the relative value of the hydraulic gradient at the pipe tip, the depths that can let model reach the tolerance error is shown in Figure 11.

As shown in Figure 11, the depth of the model with landside blanket layer required to tolerate errors is not significantly related to the width of the model. The required model depth decreases with increasing pipeline channel length. This is consistent with the model without landside blanket layer.

3.3 Physical experiment for verification

A small-scale physical model is used to conduct experimental verification on the piping of dike foundations with homogeneous permeable layers under the conditions of no landside cover layer and with landside cover layer. The physical properties of sand samples are listed in Table 2.

The particle size distribution curve of the experimental sand sample is shown in Figure 12:

The sand samples of dike foundation piping are globally photographed and tracked, and the required water head for each typical stage are shown in Table 3.

According to Table 3, for the dike foundation without landside cover, the ratio of ratio of formation to failure water head is the highest at 95% and for the dike foundation with landside cover,

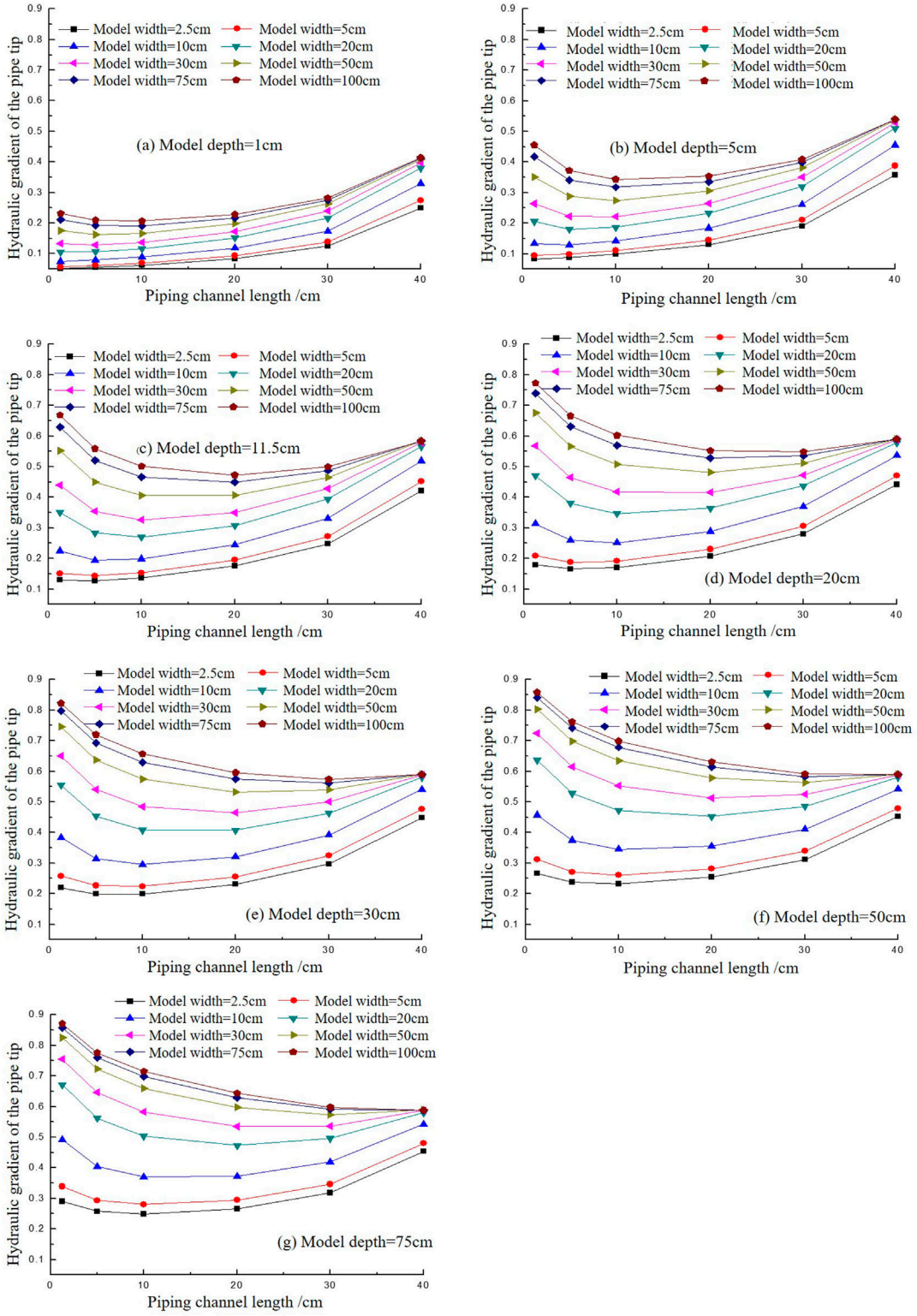

FIGURE 8
The variation of the hydraulic gradient with the pipe length increasing in different model widths in dike foundations with landside blanket layer. **(A)** Model depth-1cm. **(B)** Model depth-5 cm. **(C)** Model depth-11.5 cm. **(D)** Model depth = 20 cm. **(E)** Model depth = 30 cm. **(F)** Model depth 50 cm. **(G)** Model depth = 75 cm.

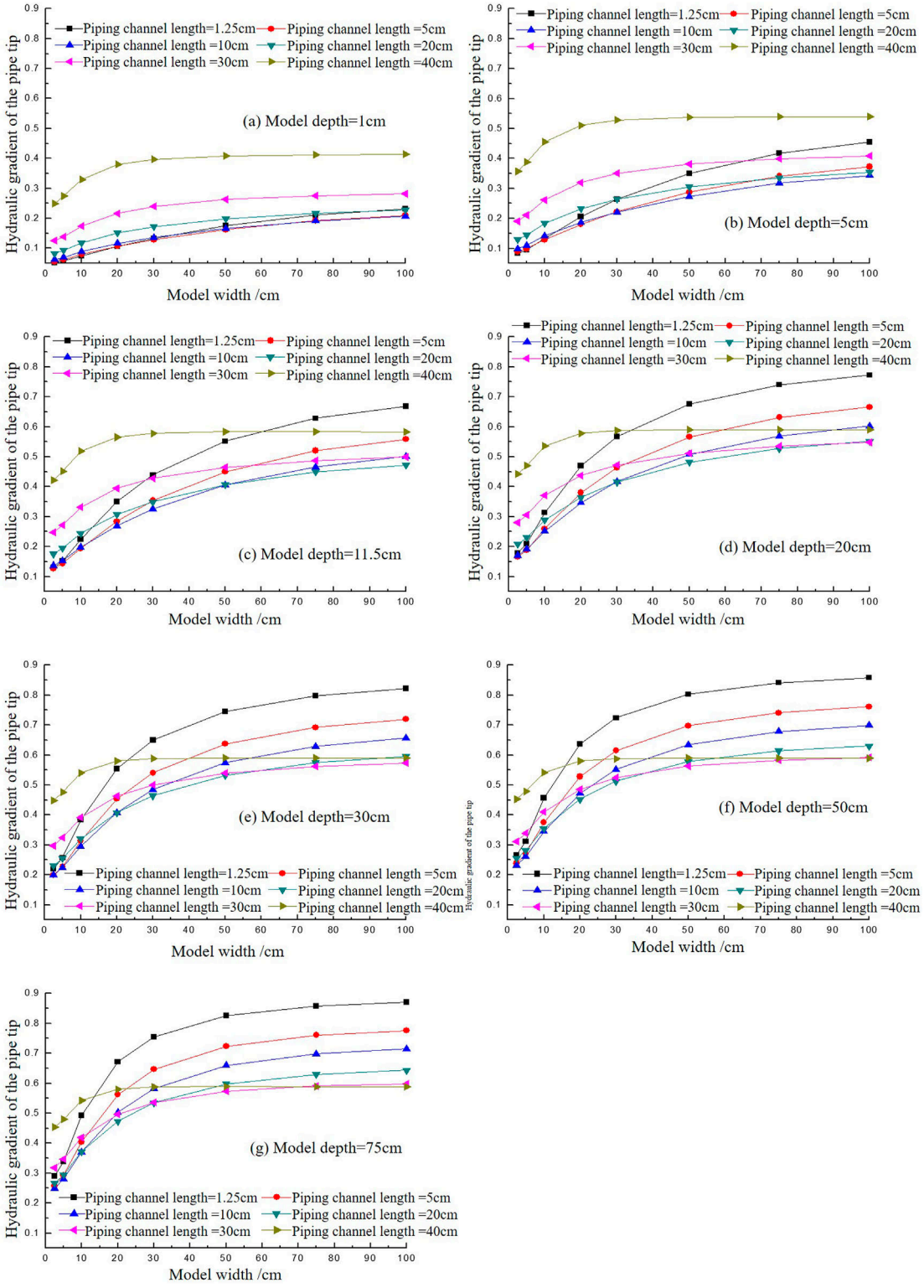

FIGURE 9
The variation of the hydraulic gradient of the pipe tip with the increase of model width with different piping channel lengths. **(A)** Model depth = 1 cm. **(B)** Model depth = 5 cm. **(C)** Model depth = 11.5 cm. **(D)** Model depth 20 cm. **(E)** Model depth-30 cm. **(F)** Model depth-50 cm. **(G)** Model depth-75 cm.

the ratio of ratio of formation to failure water head is the lowest at 57%. The experimental results show that the dike foundation without landside cover will not form obvious piping channels before reaching the critical water head. Even if piping channels are formed, their scale is very small and cannot be strictly called piping channels. At the critical head, there will only be a significant upward development

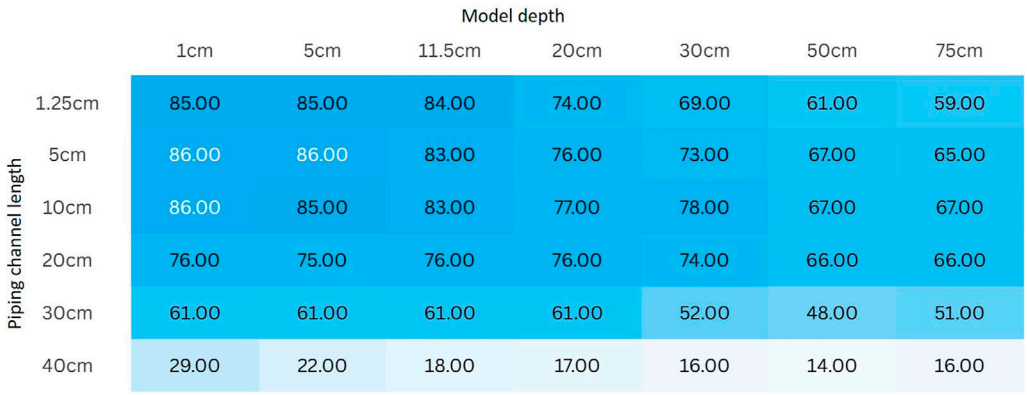

FIGURE 10
The model widths that can reach the tolerance error (with landside blanket layer).

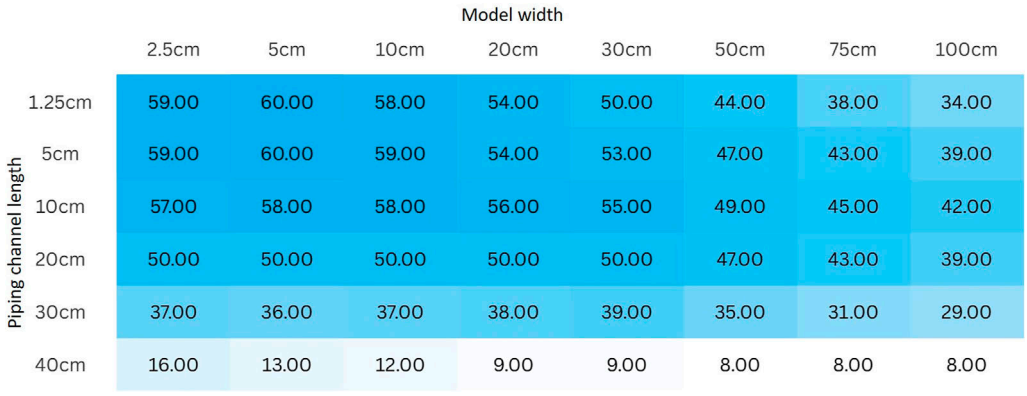

FIGURE 11
The model widths that can reach the tolerance error (with landside blanket layer).

TABLE 2 Physical properties of sand samples.

	d_{50} (μm)	d_{60} (μm)	d_{70} (μm)	d_{60}/d_{10}	Permeability coefficient m/s (Dr≈85%)	Min porosity (%)	Max porosity (%)
Sand B	132	142	154	1.6	5.58E-05	34.0	46.9
Sand C	355	420	430	1.5	2.82E-04	34.0	44.5
Sand E	220	262	300	2	3.5E-05	32.2	42.25

of the piping channel. Once it appears, it will not stop until it is connected to the upstream and experiences erosion damage. As observed in earlier experiments (Yao, 2014), these channels continued to propagate upstream without any self-regulation, leading to eventual failure of the dike foundation. And this is consistent with the numerical simulation results showed in Figure 3 that as the piping channel develops upstream and the length of the piping channel increases, the hydraulic gradient at the front of the piping channel increases under all width and depths conditions, showing a monotonous upward trend.

Compared to the situation without landside blanket layer, under the test conditions with landside blanket layer, the ratio of the water head formed by the piping channel to the critical water head for piping failure is slightly lower, with the highest ratio being 88% and the lowest being 57%, as shown in Table 3. In the initial stage of destruction, after the formation of the piping channel, there is a "self-healing" phenomenon of stop and go before falling below the critical water head, but the length of the channel is still limited, only a few centimeters. This pattern is consistent with the self-stabilizing effect of impermeable layers observed in the numerical

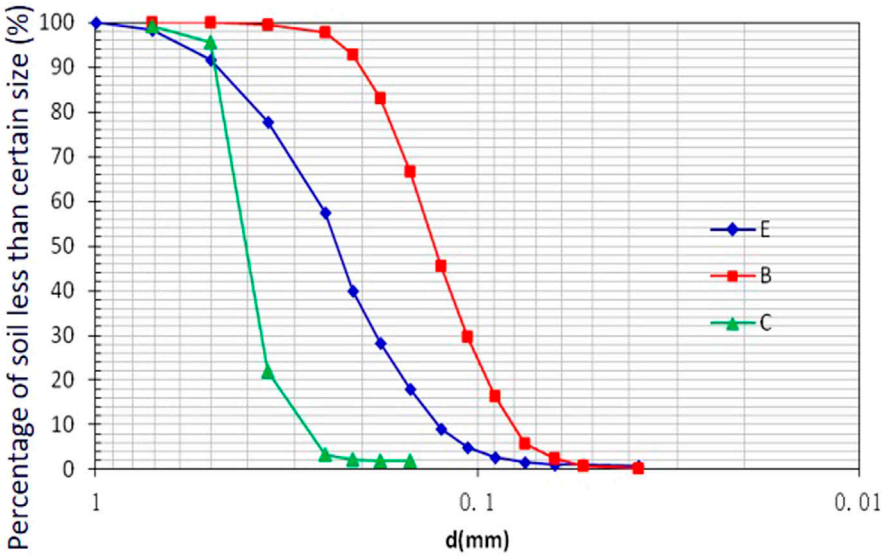

FIGURE 12
Percentage of soil mass smaller than a certain particle size.

TABLE 3 The required water head for each typical stage.

Sand sample	Landside layer	Penetration deformation begins to occur	Formation of piping channels	Piping failure	Ratio of formation to failure water head (%)
E	No	4	9	14	64
B	No	—	19	20	95
B, C	No	9	12	13	92
B, C	YES	3	4	7	57
B	YES	4	7	8	88
B	YES	2	7	8	88

model results showed in Figure 8 that during the early stage of piping channel formation, the hydraulic gradient on the pipe tip decreases, potentially dropping below the critical gradient, as a result, the piping channel halts its development and reaches a stable equilibrium.

While the general trends aligned well, there were some differences between the numerical and physical results, such as the sand sample E without landside blanket layer, the physical experiment result in Table 3 which should be similar to the sand sample B without landside blanket layer according to the numerical model. This can be attributed to several factors: Firstly, the numerical model made certain simplifications to reduce computational complexity. For instance, assumptions such as isotropic soil permeability or simplified boundary conditions (e.g., neglecting transient effects or small-scale heterogeneities) may not fully represent the real-world behavior observed in the physical experiments. Secondly, in the physical experiments, inflow and outflow conditions were controlled more directly, but minor variations in the experimental setup (such as slight differences in soil compaction or water head application) could introduce deviations. In contrast, the numerical model simulated a more uniform flow distribution based on idealized boundary conditions, which may not always match the complex flow dynamics seen in the physical setup.

4 Conclusion

This research provides a comprehensive analysis of the backward erosion piping mechanism and its size effects in dike foundations, incorporating numerical simulations, experimental validations, and theoretical interpretations. It reveals several critical conclusions.

1. The study demonstrates that the dimensions of experimental models significantly influence the critical hydraulic gradients

and the progression of piping channels. Smaller widths and depths necessitate higher hydraulic heads to initiate piping, while larger dimensions mitigate these effects, with the influence diminishing when the model reaches a sufficiently large size.

2. The physical experimental results show that dike foundations without a landside cover form piping channels only after reaching the critical water head, with the channels propagating upstream without self-regulation, leading to eventual failure, consistent with the numerical simulations showing an increasing hydraulic gradient as the piping channel develops. For dikes with a landside blanket layer, the formation of piping channels occurs at a lower water head, with a "self-healing" phenomenon observed in the early stages, where the hydraulic gradient decreases, halting channel development temporarily, which is consistent with the numerical model results that during the early stage of piping channel formation, the hydraulic gradient on the pipe tip decreases, potentially dropping below the critical gradient.
3. The findings underscore the need to consider size effects in laboratory tests and the design of mitigation strategies for backward erosion piping. Recommendations include scaling experimental models appropriately and incorporating landside blanket layers to enhance dike stability.

Although the research offers significant insights into the backward erosion piping mechanism and its size effects in dike foundations, it acknowledges certain limitations. Despite the meticulous design of the experimental setup to emulate real-world conditions, achieving perfect replication of natural environments remained challenging. Minor inconsistencies in outcomes were observed, attributed to uncontrollable variations in water head application and soil compaction. To build upon these findings, future studies could enhance the Finite Element Method (FEM) approach by integrating transient seepage dynamics and accounting for soil heterogeneity and multi-phase flow. This would involve considering both water and air phases within piping channels, providing a more realistic portrayal of time-dependent processes. Additionally, incorporating nonlinear permeability models machine learning methods (Wei et al., 2024) and random field methods to simulate variable soil properties would further bolster the FEM model's robustness and applicability to real-world dike foundations, where dynamic flow conditions and soil variability are prevalent.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

QY: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. XY: Data curation, Formal Analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing–review and editing. ZW: Formal Analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing–review and editing. HH: Formal Analysis, Investigation, Methodology, Software, Supervision, Validation, Writing–review and editing. MM: Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Writing–original draft.

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Conflict of interest

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A new IoT low-cost bi-directional wire extensometer for landslide monitoring

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The monitoring of slopes' dynamics is essential to ensure the safety of infrastructures exposed to landslide risk and to develop mitigation strategies. However, it is not always possible to perform proper and slope-distributed monitoring due to the high cost of professional instruments. In this context, we developed a low-cost Arduino©-based wire extensometer for landslide monitoring. This instrument is capable of measuring the bi-directional distance between two fixed points, which is useful in landslide areas to observe linear displacements over time. Traditional wire extensometers are equipped with potentiometers, which allow measuring only finite displacements. Instead, our low-cost extensometer exploits a capacitive rotary encoder, which is able to measure infinite displacements. In addition, the new instrument can measure both wire lengthening and shortening, thanks to a spring-loaded winding system. Furthermore, the instrument's settings can be modified to reach a millimetric resolution. The device - developed on an Internet of Things (IoT) project - is equipped with an online data transmission system and with a data-log system for local data storage. Laboratory and field tests were carried out with the aim of evaluating the instrument's accuracy and reliability. Preliminary results demonstrate the great potential of this low-cost sensor for displacement measuring in the field of landslide monitoring.

KEYWORDS

landslide monitoring, capacitive rotary encoder, wire extensometer, low-cost sensors, Arduino©, Internet of Things (IoT)

1 Introduction

The monitoring of slopes' dynamics is essential to ensure the safety of facilities exposed to landslide risk and to develop mitigation activities. The availability of spatially and timely distributed information about a mass movement (Kjekstad and Highland, 2009; Winter et al., 2016; Cruden, 1991) is a key factor for hazard management. In the last decades, the widespread use of new technologies had a key role in modern solutions developing in the field of landslides monitoring (Thirugnanam et al., 2022; Casagli et al., 2023), although their use is often limited by the high costs of commercial equipment (Dei Cas et al., 2021). Nowadays, low-cost solutions for slope monitoring can represent a solid alternative to professional systems (Fang et al., 2024).

Among the measurable parameters involved in slope instability, surface deformations are crucial to assess the activity of a landslide and related risk management. For this purpose - among the different monitoring systems - wire extensometers (Dunnicliff, 1993; Dei Cas et al., 2021) can be a valid solution when shear surfaces outcrop

(Corominas et al., 2005; Intrieri et al., 2012; Guerriero et al., 2017; Pasquaré Mariotto et al., 2021). Generally, professional wire extensometers are equipped with potentiometers (Li and Meijer, 1998; Zhang et al., 2005) - namely, analogic sensors - which are able to measure a defined displacement value along a unique direction. These features - combined with the high costs of these systems (~EUR 1000) - represent a limiting factor for their widespread use.

To address these shortcomings, (Guerriero et al., 2017), developed and tested a low-cost wire extensometer, which, however, in a few days of experiment, reached the maximum measurable displacement, showing the main drawback of the potentiometric sensor using. Different authors (Afandi et al., 2018; Setiono et al., 2023) tested wire extensometers based on the optical rotary encoder technology, finding that this kind of device has a low-speed limit for displacement measuring.

This technical note presents a new low-cost bi-directional wire extensometer that, unlike the previous systems, is based on the capacitive rotary encoder technology (Zheng et al., 2015). This sensor is able to measure infinite displacements along two directions. The prototype - developed on an Internet of Things (IoT) project - is equipped with an online data transmission system and a local storage data-log system. The device was firstly assessed in a climate-controlled environment through laboratory tests and successively was installed at the Grillo landslide (Southern Italy) with the aim to evaluate - through the comparison with multi-temporal Global Navigation Satellite System (GNSS) measurements performed - the reliability of the instrument in field conditions.

2 Materials and methods

2.1 The device

The device is composed of several modules: (a) rotary encoder, (b) data processing-storage-transmission system, (c) measuring system, and (d) power supply accommodated into a frame composed of a double waterproof plastic box (Supplementary Figure S1).

All the electronic components are fixed in the inner box (20 × 15 × 8 cm), while on the outer box (30 × 22 × 14 cm), a pulley is inserted in the rotary encoder's housing and kept in position by a bearing. This solution allows the reinforcement of the overall structure and protects the vulnerable parts against weathering.

2.1.1 Rotary encoder

The rotary encoder is a digital sensor that is able to turn mechanical motion into electrical waves. The encoder's rotation generates two electrical square waves that generally are 90° out of phase, allowing to determine the rotation's direction and the linear displacement. This sensor allows counting infinite displacements, and - because of its capacity to turn clockwise and counterclockwise - it is able to measure along two directions.

Rotary encoders can be equipped with several technologies, such as optical, magnetic and capacitive. In this study, a CUI DEVICES AMT 10 capacitive rotary encoder was chosen (Supplementary Figures S2A, B). This type of encoder is composed of a rotor, a fixed transmitter and a fixed receiver. The motion of the rotor compared to the transmitter generates electric signals used to determine the position and the rotation direction of the encoder. The sensor's resolution can be set by changing the number of electric pulses generated by the encoder for each revolution (PPR, "Pulses Per Revolution"). The resolution can range from 48 PPR to 2048 PPR simply by acting on 4 DIP switches housed in the encoder's case (Supplementary Figure S2A).

The chosen rotary encoder - characterized by lightweight, stiffness, simple structure and low power consumption - presents a high reliability if compared with the optical (Afandi et al., 2018; Setiono et al., 2023) and magnetic technologies (Shuanghui et al., 2009). Thanks to this innovative technology, the power demand for capacitive encoders is reduced to about 10% of optical and magnetic technologies, resulting in important power savings that are essential in harsh conditions. In addition, capacitive technology is widely used for motors' rotational speed measurements, allowing low and high-speed displacement observations (up to 15.000 revolutions per minute), in contrast with optical encoders, which can measure lower-speed displacements. Capacitive technology requires less maintenance than optical ones, which need to be periodically cleaned from dirt and dust to avoid accuracy losses over time. Moreover, magnetic technology has several limitations, such as electromagnetic field interferences, lower resolutions and accuracies and narrower working temperature ranges.

2.1.2 Data processing-storage-transmission system

The system for data processing, storage and transmission (Supplementary Figure S1) is composed of a series of modules, in particular: a power controller that sets the voltage of the input current; a Real Time Clock (RTC) with a 3 V coin cell battery backup (it allows the system to pick up data with specific timing and consequently to associate date and time to them); a micro SD card slot for the local data storage; a SIM 800l GPRS GSM module that provides to send the data online thanks to a SIM card; an Arduino electronic board with the task to manage the entire system and communicate with the rotary encoder. An Arduino Nano Every board was chosen for the compact size and the low price: this miniature-sized module is powered by an ATMega 4809 AVR processor and an ATSAMD11D14A ARM Cortex M0+ to act as a bridge between USB and the main AVR processor (https://docs.arduino.cc).

The device has been programmed using the Arduino IDE (Integrated Development Environment), an open-source software. The programming code is composed of a series of blocks (Supplementary Figure S3) that create a cyclic scheme of commands. The first one is the "GENERAL SETUP" block, which allows the system to start and check all the electronic components. After this, the system goes into the "IDLE" block, where it is able to read the rotary encoder's measurements. In the "WRITE" block, the Arduino board stores the measurements in the micro SD card. Then, there is the "CONNECTION STARTUP" block, where the device's internet connection is enabled. In the "FILE LIST" block, it is checked if some files are written and waiting for the online transfer. If it is true, it enters the "FILE TRANSMISSION" block, which is dedicated to sending files online. This part of the workflow ends when all the files on the waiting list are sent online. At the end of the transmission, the system turns off the internet connection ("END OF CONNECTION" block) and returns to the "IDLE" block. The data transmission block is programmed to send the data to a web

server (PHP protocol). The code was developed to collect all the editable parameters (ID sensor, sending data frequency, web server address, encoder functions) in a single window to facilitate setup activities, especially for field operations.

An error management section was developed in the programming code to enhance systems' reliability, especially for data transmission architecture. When the device starts, the Arduino board is programmed to check the GSM module's correct functioning by waiting for its "OK" message: if the GSM module does not send it immediately (broken module or cables disconnected), malfunction is detected and the system goes into "offline mode", where only local data storage is enabled. In this way, unnecessary power consumption is avoided, preserving the system until the operator's technical assistance. If Arduino receives the "OK" message, "online mode" is enabled, and the GSM module starts a series of 30 network connection attempts. Once it completes 30 attempts without succeeding in network connection, the system goes again into "offline mode" and only local data storage is enabled until the operator's manual reset is done.

If the device is powered, the local data storage function is always enabled: observed data remain stored in a micro SD card after malfunction eventualities (connection failure or even system shutdown).

This system is suitable for areas where telephone network coverage is sufficient to guarantee data transmission. Alternatively, it is possible to use a radio transceiver that provides to send data to a GSM modem router installed on the nearest network-covered site.

2.1.3 Measuring system.

The infrastructure of the measuring system (Figure 1) is composed of (a) two steel tubular poles, (b) the pulley and (c) the winding system.

The two steel poles are linked by a special wire made of invar. This metal alloy - composed of 36% of nickel, 64% of iron and small amounts of carbon and manganese - is characterized by a very high corrosion resistance and a negligible thermal expansion coefficient (around 0.5 x 10^{-6}°C between 20°C and 50°C) (https://lkalloy.com).

The pulley is 3D printed in plastic material and accommodates the invar wire with the function to rotate when a linear displacement variation occurs between the two poles; this rotation is transferred from the pulley to the rotary encoder, which is capable of turning it into a certain number of electric pulses per each pulley's revolution. Finally, the Arduino board reads these electric pulses and turns them into the real linear displacement. The number of electric pulses per revolution (PPR) generated by the encoder can be set in a range that goes between 48 and 2,048 PPR by changing the position of DIP switches located on the encoder's case. By changing the number of the encoder's PPR and modifying the pulley's diameter, the resolution of the extensometer can be set. In this case, a 48 PPR setting and a 70 mm diameter pulley were chosen, leading the system to a resolution of 4.58 mm. The Arduino board was programmed to directly provide 4.58 mm of displacement per each electric pulse detected, guaranteeing a prompt data analysis without using any other kind of data processing or algorithms. A constant tension on the wire is required for the correct operation of the extensometer; this is provided by a handmade, low-cost spring-loaded winding system. It is composed by an internal metal spring housed in a rotating drum, that accommodates the invar wire. Thanks to the metal spring's tension, this system allows measurements of both wire lengthening and shortening to be performed, without the need to make any further changes to the infrastructure.

2.1.4 Power supply

Considering the open-field installation, a solar system was chosen to power the device. The power supply is composed of a 30 W solar panel linked to a 12 V, 10 Ah battery. A 12 V, 10 Amp solar charge controller was used to manage the power supply unit. To operate safely, the Arduino board needs a voltage lower than 12 V; for this purpose, a DC-DC converter was used to set and stabilize the power line at around 7 V. The device's power consumption was bench-tested using a FUTURA ELETTRONICA AL3005 power supply unit. A maximum absorption peak of 0.14 A at 12.5 V was observed during the online data transmission process, and 0.06 A at 12.5 V was recorded the rest of the time ("IDLE" function). Considering an average absorption of 0.10 A, the overall current drainage is 30 Wh. The 30 W solar panel and the average local solar radiation of 4.6 h per day can provide 138 Wh per day: this amount of energy, well over the device's request, is enough to keep the battery charged over time. In case of solar panel failure, the 10 Ah battery could guarantee an autonomy of around 100 h with the average device's current drainage. If more autonomy is required, a second battery linked in parallel to the first one can be added without making any other changes to the system. Past field applications showed that this kind of power supply architecture, in the presence of similar current absorptions, can last for several years without problems (no need to replace batteries, solar panels or charge controllers).

2.2 Laboratory tests

The potential effects of the temperature and humidity variation on the device's electronic components were tested through a climatic chamber (Supplementary Table S1). This equipment is capable of testing electronic devices by simulating field conditions (Van Geel et al., 2015; Ruzza et al., 2018). The device was left in the zero-millimeter position the whole time.

The device's electronic components (rotary encoder and data processing-storage-transmission system) were directly exposed to temperature and humidity variations by removing them from their protective external frame (double waterproof plastic box) to maximize the effectiveness of the tests. In particular, the components were carefully placed on the electrically insulated racks of the climatic chamber, and they were powered during tests by getting the cables across the chamber's dedicated silicone plugs. A step-by-step procedure of laboratory tests is reported in Supplementary Figure S4.

First of all, a thermal efficiency experiment was conducted (Figure 2): the device was tested in a −10°C + 80°C range. A temperature of −10°C was reached in the first part of the test. Then, the components were heated to reach a maximum temperature of about 80°C. The total test duration was 40 min, and the sampling rate was set to provide measurements every 2 s.

Then, a humidity test was performed (Figure 3). The climatic chamber was set to increase the humidity levels from about 30% (laboratory humidity levels) to a maximum of approximately 98%. Then, it was left in these conditions overnight, performing 14 h of testing. Measurements were collected every 5 s up to 11 min - during the increase in humidity stage - and every 60 s for the rest of the experiment.

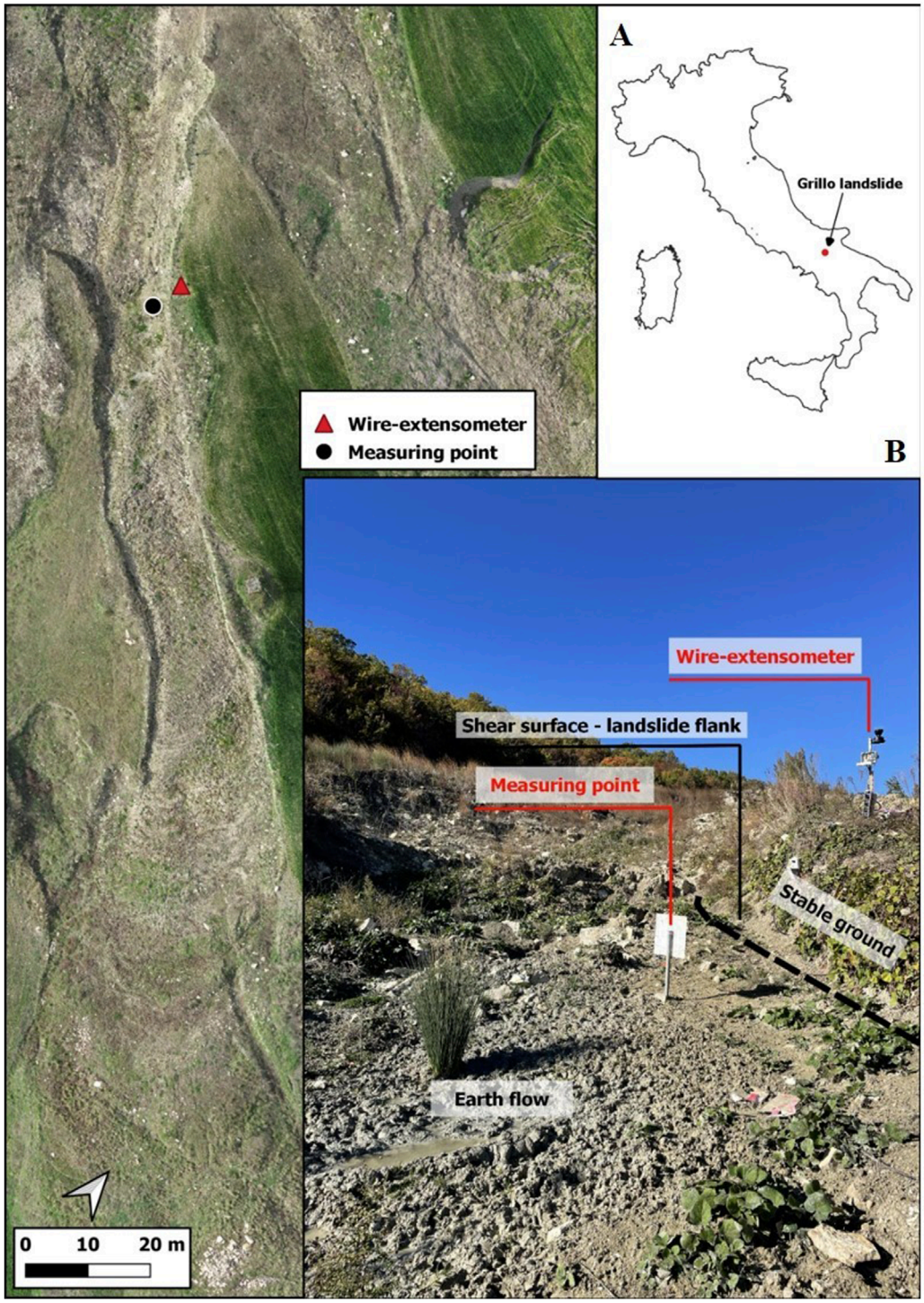

FIGURE 1
(A) Overview of the Grillo earth flow and its location in Southern Italy **(B)**; Installation setting and landslide local condition.

Subsequently, an 80-gram bag of silica gel desiccant was placed in the device's box. In addition, polyurethane foam was sprayed on the interior walls of the plastic box, and a handmade cover composed of extruded polystyrene panels was used for the outside of the box to reduce the thermal excursion and consequently, the risk of internal condensate formation. Then, a further humidity test - following the same workflow as the first one - was carried out.

2.3 Field test

The bi-directional wire extensometer was successively installed at the *Grillo* landslide (41°14′32″ N, 15°15′51″ E) in Montaguto municipality, Southern Italy (Figure 1). This mass movement - classified as an earth flow (Hungr et al., 2014) and involving clay flysch material (Pinto et al., 2016; Mazza et al.,

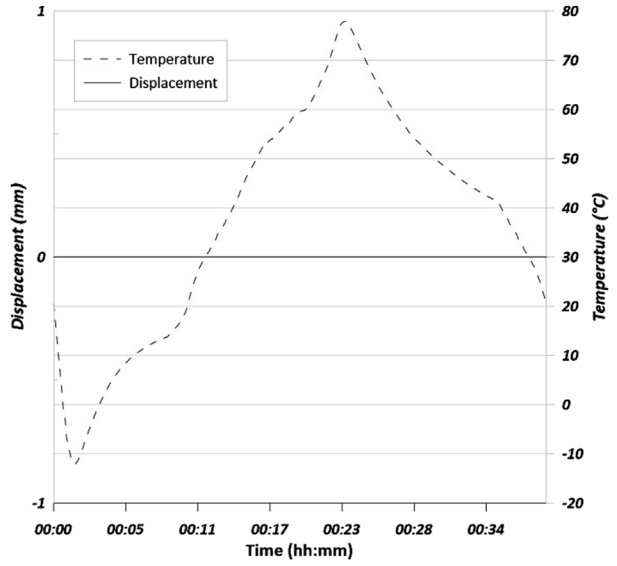

FIGURE 2
Correlation between the linear displacement measured and temperature values recorded during the thermal efficiency test.

2023a) - exhibited relevant movements between April 2022 and June 2023 (Mazza et al., 2023b).

The device was installed along the left flank of the earth flow - where a well-defined shear surface outcrops (Figure 1B) - using two 2 m long and 5 cm diameter steel tubular poles driven into the ground for a depth of at least 50 cm, and stabilized by metallic tie rods. The first one was installed in the transport zone, while the second one was placed outside the landslide perimeter, in a stable area. They were linked using a 6-meter-long invar wire. The position of these elements was defined with the aim of measuring the landslide's main direction movement.

The monitoring campaign started on 06 December 2023 and ended on 03 March 2024 with an acquisition frequency of 6 h. The data recorded were compared with multi-temporal Global Navigation Satellite System (GNSS) measurements, performed using a mobile GNSS station (Supplementary Table S2). This station was mounted on a 2 m high pole and the measurements were carried out by a local area correction, recording the position of the transport zone's steel tubular pole for each campaign survey, being careful to put of the lower end of the instrument on a predefined spot, in contact with the steel pole (Supplementary Figure S5). A total of 6 survey campaigns were performed.

- 6 December 2023.
- 13 January 2024.
- 18 January 2024.
- 26 January 2024.
- 7 February 2024.
- 3 March 2024.

3 Results and discussion

3.1 Laboratory tests

Figure 2 shows the results of the thermal efficiency experiment. In particular, during the cooling stage, the temperature was brought from +20°C (starting point) to −10°C (at minute 3): 0 mm of linear displacement were measured. Then, during the heating stage, the temperature was brought from −10°C (at minute 3) up to +80°C (at minute 25): also in this stage, 0 mm of linear displacement were read. Therefore, this experiment showed that the device was not affected by thermal drift in the observed range, reporting a total linear displacement of 0 mm from start to finish.

Figure 3 shows the device's behavior during the humidity test before and after the device's insulation upgrades. Focusing on the test performed before the insulation's upgrades (Figures 3A, B), during the increase in humidity stage (from minute 0–11) that brought the moisture from 30% up to about 98%, it is possible to observe that the device was perfectly stable. When 98% of moisture was reached, the graph showed a stepwise pattern of increasing linear displacement, measuring a total of 1,653 mm at the end of the test. Thus, the data acquired from this experiment reveal a clear correlation between linear displacement and humidity levels, showing that this climatic parameter can negatively affect the device's correct functioning.

This sensitivity to the wet conditions observed in the laboratory test is probably dependent on the capacitive technology of the rotary encoder.

The results of the humidity test after the device's insulation upgrades (Figures 3C, D) show that no more correlation between moisture and linear displacement was found: 0 mm were observed during the entire experiment. This behavior demonstrates the efficiency of the solutions adopted on the device in terms of moisture insulation, which allowed it to solve the capacitive technology issues in wet conditions. Therefore, even in the presence of significant levels of field humidity (90% or higher), the bi-directional wire extensometer's proper functioning was not compromised.

3.2 Field test

Data comparison resulting from the device's field test is shown in Figure 4. The bi-directional wire extensometer measured a maximum displacement value of 32 mm, while the GNSS measurements showed a value of 38 mm, resulting in an overall 6% difference between the two data sets. In particular, for the first 3 GNSS surveys, a displacement of 0 mm was measured by the two systems: this coherence showed the device's measurements stability, proving that the insulation technique adopted was able to solve the sensor's moisture drift. Observing the GNSS survey campaign performed on 07 February 2024, the device was able to measure 9.16 mm of linear displacement, which, compared to 12 mm of the GNSS system, results in a difference of 16% between the two techniques. The last measurements (03 March 2024) showed a displacement of 32.1 mm for the wire extensometer and 38 mm for the GNSS technique, resulting in a difference of 13% between the two data sets. Thus, a slight underestimation trend was detected by using wire extensometer measurements. However, considering

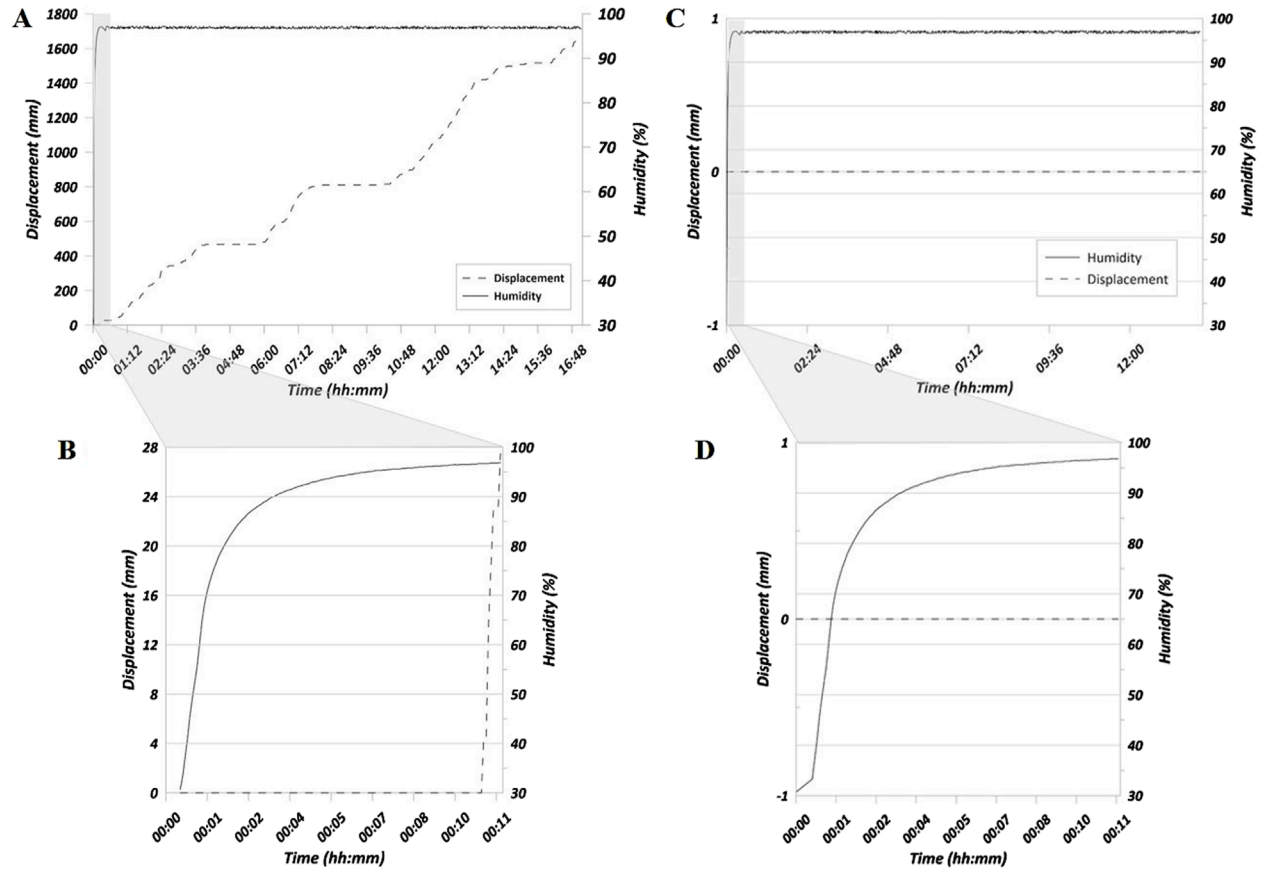

FIGURE 3
(A) Correlation between the linear displacement measured and humidity values recorded during the humidity test before the device's insulation upgrades; **(B)** focus on the increase in humidity stage (from minute 0–11); **(C)** Correlation between the linear displacement measured and humidity values recorded during the humidity test successively the device's insulation upgrades; **(D)** focus on the increase in humidity stage (from minute 0–11).

the test covered a short period (around 3 months), merely prolonged observations could evaluate the device's stability in the long term.

Moreover, it is worth noting that all the tests were performed using a resolution of 4.58 mm. However, this value - suitable for landslide monitoring applications - can be changed by choosing the diameter of the pulley and by acting on 4 DIP switches housed in the rotary encoder's case. These switches set the number of electric pulses generated by the encoder for each revolution (PPR, "Pulses Per Revolution"). Therefore, considering that the number of PPR can range from 48 to 2,048, our device could be able to measure displacements with even higher resolutions. This capability could represent a relevant innovation for this kind of monitoring system, extending its use for structural health monitoring. In addition, unlike wire extensometers based on potentiometric technology, the capacitive rotary encoder allows counting infinite displacements along two directions. Indeed, our device - being equipped with a handmade spring-loaded winding system that guarantees constant tension on the extensometer's wire-could be able to measure both lengthening and shortening without the need to make any further changes to the system. Exploiting this feature, our wire extensometer could be easily installed in all geo-structural settings, both in distensive and compressive kinematic contexts.

Furthermore, by implementing a "do-it-yourself approach", our bi-directional wire extensometer's overall cost is around 400 euros (Supplementary Table S3), considerably cheaper than professional solutions (starting from around 1,500 euros to almost 10,000 euros). Thus, with the average cost of a single professional device, we can produce at least three low-cost wire extensometers. However, low-cost components are more susceptible to failure and a small budget for more frequent assistance could be necessary. In particular, periodic inspections of the device's components should be performed: a checklist and a spare parts list to bring for eventual quick repairs are provided in Supplementary Table S4 for on-field inspections. For this purpose, the device's electronic parts were developed to be easily replaceable in case of failure.

4 Conclusion and future improvements

A low-cost bi-directional wire extensometer - based on Arduino© technology and equipped with a capacitive rotary encoder - was developed for landslide monitoring.

The tests showed that a proper insulation technique can solve the device's moisture drift. In addition, laboratory tests assessed

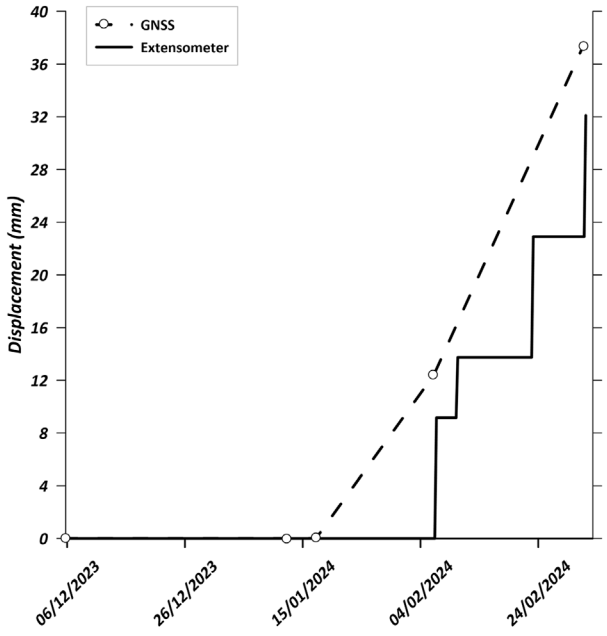

FIGURE 4
Comparison between wire-extensometer and GNSS displacement data.

the device's correct functioning in a temperature range from −10 to +80°C and for more than 90% humidity, guaranteeing proper functioning in extreme environmental conditions. Combining the stability and the low-cost features, the bi-directional wire extensometer can be considered a valid alternative to professional devices, especially in large-scale monitoring contexts where a network of multiple installations is required. In addition, the spring-loaded winding system - which also allows the bi-directional wire extensometer to perform shortening measurements without the necessity of any other adjustment - could be tested and used for future installations in compressive contexts.

Nevertheless, although our solution to mitigate the sensitivity of the device to the wet conditions appeared to be resolutive, some improvements - such as the use of a little electric fan installed on the device's box with the function to create a continuous air circulation - can be studied and applied for further laboratory and field tests with the aim to increase the durability of the system. Additional power consumption could be limited by programming the device to turn on the electric fan only for short intervals during the day. Moreover, information about power supply voltage could be integrated into online data transmitted to monitor the system's functioning and, in case of problems, perform technical assistance before total power failure.

A further improvement could be represented by experimentation with a sensors' network linked to an online platform capable of applying machine learning and IA for predictive analysis. Using linear displacement data collected on landslide's strategic points, this technology could be able to predict future scenarios by learning from historical data collected, leading to a faster decision-making process.

Finally, the bi-directional wire extensometer was tested for a short period (around 3 months): very small displacement data were recorded, and prolonged observations are required to evaluate the device's stability in the long term.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

DC: Conceptualization, Investigation, Methodology, Software, Writing–review and editing, Resources. DM: Conceptualization, Data curation, Methodology, Software, Writing–review and editing. FG: Supervision, Writing–review and editing. PR: Supervision, Writing–review and editing, Funding acquisition.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Flash flood simulation based on distributed hydrological model in future scenarios

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Extreme rainfall events are frequent, particularly in economically underdeveloped hilly areas, where conventional hydrological models struggle to accurately simulate the formation of flash floods. Therefore, this study focuses on the Daxi River Basin in Guangdong Province. First, CMIP6 precipitation data is utilized to analyze the future precipitation variations on interannual and monthly scales. Compared to the baseline period, the annual precipitation increases under all three scenarios. Next, design storms with a return period greater than 2 years are allocated into rainfall patterns. By combining the accumulated precipitation with the soil moisture content, different distributed hydrological models are applied to calculate the corresponding flood discharges for different rainfall events. The results indicate that: 1) Precipitation under the SSP5-8.5 scenario is generally higher than under the SSP1-2.6 and SSP2-4.5 scenarios, with the SSP1-2.6 scenario showing the mildest increase. 2) The peak flood simulated by the CREST model are relatively low, at 235.4 m^3/s, with fewer precipitation events covered, which is significantly lower than the simulation accuracy of the CNFF model. 3) The Daxi River Basin has a low probability of experiencing flash flood disasters exceeding the 10-year return period in the period from 2026 to 2070. The above research results will provide important references for flash flood disaster prevention in similar basins.

KEYWORDS

flash flood, CREST, CMIP6, future scenario, daxi water Basin

1 Introduction

In recent years, climate change has triggered changes in the state of the hydrological cycle. In particular, the frequency of extreme precipitation events has increased the probability of flood risk (Fowler et al., 2021; Zhou et al., 2021). According to the sixth Assessment of Intergovernmental Panel on Climate Change (IPCC), the increase in temperature over the next 20 years will be 1.5°C or more,and precipitation has increased, but with spatial and temporal variability (Zhu et al., 2024) (i.e., In 2021, summer and fall precipitation led to severe flooding in many places in the north of China. From July 29 to 1 August 2023, torrential to heavy rainfall occurred in most parts of Beijing and the central southern region of Tianjin and Hebei, with extraordinarily heavy

rainfall in some areas, and the maximum rainfall reached 1,003 mm) The frequent occurrence of extreme precipitation induces severe flooding (Ma et al., 2024). Flash floods belong to a kind of flood disaster, which refers to stream and river floods, mudslides, landslides and other disasters triggered by heavy rainfall in a small area (usually within a few hundred km^2) of a hilly area (Hong et al., 2013), which is sudden, difficult to forecast and warn, and seriously hazardous. Therefore, for the defense of flash floods, the prediction of flash flood trends under future climate scenarios is an important reference.

Future flash flood prediction is one of the research hotspots in the field of climate change (Zhang et al., 2023), and General Circulation Models (GCMs) can better simulate climate characteristics at annual or seasonal scales, and they are the main tools for studying future climate change. The Coupled Model Intercomparison Projec (CMIP), initiated and organized by World Climate Research Programme's Working Group on Coupled Modelling (WGCM) in 1995, has achieved a series of research results in climate numerical simulation and shared data. Many scholars at home and abroad use CMIP simulation results to conduct climate change research for the next 5–10a, which provides important data support for predictions in the directions of climate extremes, food security, and sea level rise (Wu and Xin, 2019). Among them, CMIP6 corrects the long-standing problems of model bias and poor quantification of radiative forcing in CMIP5 (Song et al., 2021; You et al., 2021). Ridder et al. (2021) found that the CMIP6 model simulated the combined events of precipitation and strong winds, drought and heat waves and their return periods over North America, Europe and Eurasia well. Kim et al. found that the CMIP6 model was able to capture the global and regional extreme temperature patterns compared to the CMIP5 model (Kim et al., 2020). Additionally, precipitation intensity simulations have been improved in terms of reducing drought bias. Based on precipitation and temperature from 1985 to 2014, Wu et al. (2023) used 20 CMIP climate patterns to conduct a comprehensive assessment of the water conservation area of the Yellow River Basin and verify that its simulation effect is the best. Dong and Dong. (2021) used CMIP6 and CMIP5 to simulate and evaluate extreme precipitation in Asia, finding the polarization of CMIP6's simulation performance was severe, but its simulation performance was good. Dai et al. combining the CMIP6 multi-model averaged data, found that temperature and precipitation of the Shiyang River Basin in the period of 2023–2,100 showed an increasing trend (Dai et al., 2023). Xu et al. used CMIP6 to predict future extreme precipitation changes in China. Under the SSP2-4.5 and SSP5-8.5 scenarios, total precipitation, maximum 5-day precipitation, and the number of extremely heavy precipitation days are expected to increase significantly. However, the drought risk caused by precipitation anomalies is expected to be alleviated (Xu et al., 2022). With the continuous development of GCMs, CMIP6 improves the spatial resolution as well as the simulation capability, and its temperature characteristics are better than the precipitation characteristics. Meanwhile, different models exhibit varying simulation capabilities, providing valuable references for mitigating future disaster risks at local spatial and temporal scales.

The simulation accuracy of hydrological models is the core technology for flash flood disaster prevention. Many research on the mechanism of flash flood runoff mostly focuses on the aspects of precipitation-infiltration-runoff (Liu and Huang, 2020; Liu et al., 2019). Due to the differentiated topography and hydrometeorological conditions in different study areas, coupled with frequent extreme weather and significant urbanization effects, Hydrological mechanisms such as Underlay surface and rainfall infiltration have changed, resulting in the complexity and randomness of hydrological processes such as runoff generation and confluence, which has caused problems such as calculation bias in the two-dimensional numerical simulation of flash floods, so the models targeting different spatiotemporal characteristics in the same area have been developed and used successively (Li et al., 2023). Model calculation methods mainly include statistical quantification and hydrological and hydrodynamic methods. The statistical quantification method is relatively simple, but requires a large amount of data and is not suitable for small watersheds in remote mountainous areas prone to flash floods. hydrodynamic methods can consider the physical formation process of runoff and require higher accuracy (Wang et al., 2022). It can predict flash floods in watersheds without data (Chen et al., 2022; Li et al., 2024; Hao et al., 2023). Hydrological and hydrodynamic models take into account dynamic characteristics such as motion waves and diffusion waves, and can better express the spatiotemporal characteristics of slope runoff. Among them, distributed hydrological models such as MIKE SHE and SWAT have strong physical foundations and can be extended to small watersheds Region (Chen et al., 2022). HEC-HMS and TOPMODEL models are commonly used in semi-distributed hydrological models, and their parameter determination is relatively simple. Distributed hydrological models have been applied and verified in many mountainous watersheds at home and abroad, showing certain effectiveness and superiority. For example, Simulation of Spatiotemporal Variable Sources Mixed Runoff Model and China Flash Flood Hydrological Model (CNFF), the former is suitable for flash flood simulation in small mountainous watersheds with diverse topography and complex runoff mechanisms, and the latter uses modular modeling technology to integrate various nonlinear runoff generation and confluence models (He et al., 2024). The algorithm satisfies the simulation of flood processes in small watersheds in different mountainous areas. The Coupled Routing and Excess Storage model (CREST) is a grid-based distributed hydrological model, mainly used for real-time hydrological simulation, and is suitable for multi-watershed or small- and medium-scale watershed simulation at high resolution (Kan et al., 2017). All in all, selecting appropriate models for different watersheds is of great significance for improving the simulation and prediction of hydrological processes.

Under the background of global warming, coupled with the impact of human activities, extreme precipitation occurs frequently. The responses of different underlying surfaces to changes in different climate elements have regional differences, so using appropriate hydrological models to accurately simulate flash flood processes can minimize the risk of flash flood disasters. This paper analyzed the temporal and spatial variation patterns of future precipitation based on the CMIP6 precipitation data. Then selected different distributed hydrological models, comprehensively considered the previous influencing rainfall, conducted simulation comparisons, and then predicted the changes in flash flood disaster risks under different future climate scenarios. The aim is to obtain more

accurate flash flood simulation results to provide a reference for regional disaster prevention. In recent years, numerous studies have explored the impacts of climate change on extreme precipitation and associated flash floods, highlighting the increasing frequency and intensity of these events. Research has shown that extreme rainfall is closely linked to secondary disasters such as landslides, debris flows, and slope failures, particularly in mountainous regions with complex topography (Wei et al., 2024; Qiu et al., 2024). The combination of high-intensity rainfall and human-induced changes to the landscape exacerbates flood risks. Advances in CMIP6 data and hydrological models, such as MIKE SHE, SWAT, and CREST, have significantly improved the simulation of these extreme events, yet challenges remain in accurately predicting secondary hazards. Addressing these gaps is critical for enhancing regional flood preparedness and disaster risk management. The structure of this study is as follows: following the introduction in Section 1, Section 2 presents the data and methods employed in this research. It begins with a description of the study area and proceeds to an overview of data preprocessing, methodologies, and research framework. Section 3 provides a detailed explanation and discussion of the research results. Finally, Section 4 concludes the article and offers prospects for future work.

2 Data and methods

2.1 Study area

Lianping County is located in Heyuan City, Guangdong Province, with mountains, hills and basins accounting for more than 90% of the total area of the county, and is a typical mountainous county (Figure 1). The climate belongs to the subtropical monsoon climate, the precipitation season is obvious, concentrated in April to September, the precipitation is more, the average annual is more than 1,000 mm, and at the same time, it is affected by the Pacific typhoon, and there are many heavy rains and floods. The topography of Lianping County is inclined from north to southeast and southwest, with an average altitude of 693.5 m. The permanent population is 285,200, and the GDP of Lianping County in 2023 will be 1062035 million yuan, a year-on-year increase of 4.6%. The Daxi Water Basin is located in Lianping County and flows into the Xinfeng River, the largest tributary of the Dongjiang River system. In this paper, the upper reaches of the Daxi River are mainly selected, with latitude and longitude from 114°32′25″ to 114°42′38″ east longitude and 24°26′26″ to 24°35′12″ north latitude, with a basin area of 175.95 km^2. The topography of the basin is high around the periphery, low in the middle and the drop is large. The outlet of the basin is located in the southwest. The basin belongs to the subtropical monsoon climate, and the precipitation is concentrated from April to September, with an average annual precipitation of more than 1,000 mm. From May 21 to 23, 1989, the county suffered a flash flood caused by heavy rainfall, causing 86,800 people to be affected and eight people died; on 23 April 1992, Lianping County was hit by a heavy rainstorm not seen in a century, with a rainfall of 223.5 mm in just over 2 hours. On 10 June 2019, a catastrophic flood occurred in Daxishui, affecting more than 50,000 people and killing 11 people.

2.2 Data preprocessing

The data in this paper mainly include the basic data (DEM, river network and small watershed data) and monitoring station data of the Daxi River Basin, the measured precipitation and flow data from 2019 to 2023, and the EC-Earth3 model data from CMIP6 that is suitable for regional temperature and precipitation simulation in China is selected (Liu and Huang, 2020; Liu et al., 2019; Li et al., 2023; Wang et al., 2022). Including the future daily precipitation data for 2026–2,100 include historical precipitation data from 1961 to 2014, low radiative forcing scenarios under moderate development (SSP1-2.6), moderate radiative forcing scenarios under local or inconsistent development (SSP2-4.5), and high radiation forcing scenarios under high fossil fuel consumption development (SSP5-8.5) (SSP1-2.6 scenarios for EC-Earth3 model data lack precipitation data for 2,100). Firstly, the CMIP6 data were evaluated and corrected using the CN05.1 dataset (China Meteorological Forcing Dataset, version 5.1) from the Climate Change Research Center of the Chinese Academy of Sciences, along with the daily meteorological data from the corresponding historical period (1950–2014) as observation data (Hao et al., 2023; He et al., 2024). The data is a grid dataset based on the interpolation of daily precipitation and temperature data from 2,472 surface meteorological observation stations of the National Meteorological Information Center, with a resolution of 0.5°×0.5° (Kan et al., 2017). To ensure data accuracy, outliers in historical datasets were removed, and spatial interpolation methods were applied to fill missing values. Due to the different resolutions of the two datasets, spatial downscaling is required. Considering that the area of the Daxi water basin is slightly small, the basin station was selected for data processing. Furthermore, the validation of downscaled data was performed by comparing it with observed station data within the study area to ensure reliability and consistency. See Table 1 for details of the study area data.

2.3 Methods

In this study, China Flash Flood hydrological model (CNFF) and the Coupled Routing and Excess Storage model (CREST) were selected. Based on the attributes of natural small watersheds, CNFF adopts the concept of modularization and hierarchical architecture, and takes the clusters considering the topological relationship of the basin water system, high-precision topographic and geomorphological data as the unit, and is compatible with the production and confluence characteristics of different climate types, and constructs a model library of multiple processes of the water cycle. The model is mainly aimed at the research of flash flood prevention in small watersheds, and solves the problems of nonlinear production and confluence simulation and calculation of high timeliness under the conditions of short duration and heavy precipitation. In a certain sense, CNFF is a generalized distributed hydrological model of river basins, and its hydrological units mainly include seven categories: river basins, river sections, nodes, water sources, water division, reservoirs, and depressions. The calculation process mainly includes five modules: meteorology, runoff, confluence, river flood evolution, and water conservancy facility regulation,

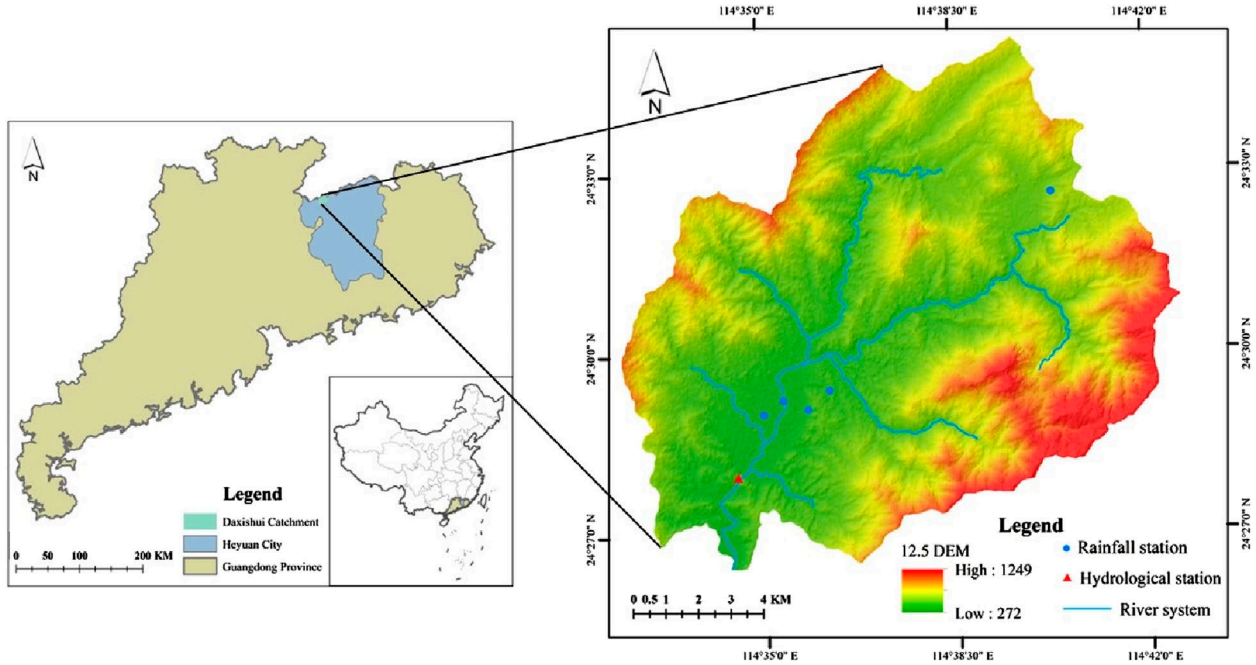

FIGURE 1
Location map of study area.

TABLE 1 Data source.

Data type	Source	Remark
DEM	Chinese Academy of Sciences Resources and Environmental Science Data Center (https://www.resdc.cn/)	The resolution is 12.5m
River network data		
Small watershed data		
Station data		It includes 1 hydrological station and 6 rainfall gauge stations
Design storm grid data		The resolution is 1km
Precipitation data		
Slope data		Extracted from DEM elevation data
Population density data		
Land use type data		The resolution is 12.5m
Soil type data	Chinese Academy of Sciences Resources and Environmental Science Data Center (https://www.resdc.cn/)	The resolution is 12.5m
CN05.1	National Meteorological Information Center (http://data.cma.cn/)	Daily precipitation data from 1961 to 2014
CMIP6	Earth System Grid Federation (https://esgfnode.llnl.gov/projects/cmip6/)	Daily precipitation data from 1961 to 2014 and 2026 to 2100 under SSP1-2.6, SSP2-4.5 and SSP5-8.5 of EC-Earth3 models

and each module selects different algorithms according to the characteristics of the river basin. Among them, the runoff generation mainly includes vegetation interception, evapotranspiration, soil moisture, etc.

The CREST (the Coupled Routing and Excess Storage) model, jointly developed by the Remote Sensing Hydrometeorology Laboratory of the United States Weather Service and the University of Oklahoma, USA, is a grid-based distributed hydrological model, which is mainly used for global and regional real-time hydrological simulations, which can be used for multi-basin simulations while maintaining relatively high computational efficiency, and is also very suitable for small- and medium-scale watershed simulations at high resolution. The CREST model divides the study area into regular grids, and the resolution of the grid is defined by the user, and on this basis, the temporal and spatial variability of surface water and groundwater storage and energy is simulated, which can be applied to multiple scales. The model uses the variable permeability curve to calculate the runoff generation, uses the multilinear reservoir to simulate the grid-by-grid surface and groundwater confluence, and reproduces the surface and groundwater flow process by coupling the runoff generation elements and the grid-by-grid confluence structure. The model can be used for both multi-basin simulation and small- and medium-scale watershed simulation at high resolution, and has relatively high computational efficiency. The input data of the model mainly include hydrological data and basic data (such as DEM, flow direction, flow pool, slope, etc.), in which the gridded rainfall data and potential evapotranspiration (PET) are used as the driving force of the model. Output data (e.g., soil moisture, surface runoff, subsurface runoff, etc.) can be distributed output with a grid as a unit or output separately for selected study sites.

Compared to CNFF, which is designed specifically for small watersheds and excels in simulating nonlinear hydrological processes under short-duration and high-intensity precipitation events, CREST focuses more on larger-scale or long-term hydrological simulations with a higher degree of computational efficiency. The modular parameter settings of CNFF allow for detailed customization and higher accuracy in flash flood simulations, but they come with higher data and computational demands. CREST, with its grid-based structure, simplifies parameterization and is better suited for real-time applications, though it may sacrifice precision in small, topographically diverse basins.

At the same time, the Nash-Sutcliffe efficiency coefficient was selected to quantitatively evaluate the effect of hydrological simulation. The NSE is particularly suitable for assessing flash flood simulations due to its ability to compare the goodness of fit between simulated and observed discharge values over time. This metric is especially effective in identifying the degree of error during peak discharge events, which are critical in flash flood scenarios. By normalizing residual variance to observed flow variance, NSE emphasizes the performance of models in reproducing the variability of observed flows, making it a widely accepted metric in hydrology. The NSCE values can be divided into four intervals, representing four levels of hydrological simulation utility: NSCE ≤ 0.5 is poor, 0.50 < NSCE ≤ 0.65 is applicable, 0.65 < NSCE ≤ 0.75 is good, and 0.75 <NSCE ≤ 1.00 is excellent; The formula for calculating this parameter is given in Equation 1:

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{s,i} - Q_{0,i})^2}{\sum_{i=1}^{N}(Q_{0,i} - \bar{Q_0})^2} \quad (1)$$

In the formula: Qs, i is the simulated flow rate at the time of t = i, m^3/s; Qo, i is the measured flow rate at time i, m^3/s; Q_0 is the average measured flow rate, m^3/s.

The downscaling methods of Global Climate Model (GCMs) are divided into two categories, dynamic downscaling technique and Statistical downscaling technique. The computation cost of dynamic downscaling is large, and the information processing results for some small changes are poor (Lu et al., 2022). The statistical downscaling method is simple to calculate, and the statistical characteristics at different scales often have good invariance (Maria et al., 2024), and it has a wide range of applications. Delta downscaling is a type of empirical downscaling in statistical downscaling, which mainly superimposes the historical measured data and change characteristics (relative change or absolute change) of GCMs data in the same period to the future climate scenarios of the region, so as to obtain climate data under future scenarios after downscaling and deviation correction, which is relatively simple and computationally intensive, and can reduce the simulated values to specific observation stations (Keeble et al., 2021). The algorithms for temperature and precipitation are different in the delta downscale. For precipitation, the calculation method is to divide the precipitation in the future forecast period of GCMs by the precipitation in the historical period to obtain the absolute change rate of the two. Then, the actual precipitation data of each meteorological station in the historical period is multiplied by the absolute rate of change to obtain the precipitation in the future period of the meteorological station. The formula for calculating this parameter is given in Equation 2:

$$P_f = \frac{P_{Gf}}{P_{Go}} P_o \quad (2)$$

In the formula, P_f is the precipitation in the future forecast period of the downscaled climate model. P_{Gf} is the climate model of future precipitation. P_{Go} is the historical precipitation of the climate model. P_o is the historical measured precipitation of the meteorological station.

2.4 Research framework

This study introduces, evaluates, and corrects CMIP6 precipitation data, using the daily meteorological data from the CN05.1 dataset (1950–2014) as the baseline. Firstly, the study analyzes the characteristics of future precipitation changes on interannual and intramonthly scales, as well as the potential impacts of climate change on precipitation patterns. Subsequently, the CREST model was validated using observed flood data from 2019 to 2023, and a reasonable set of parameters suitable for the study basin was determined. The Nash efficiency coefficient

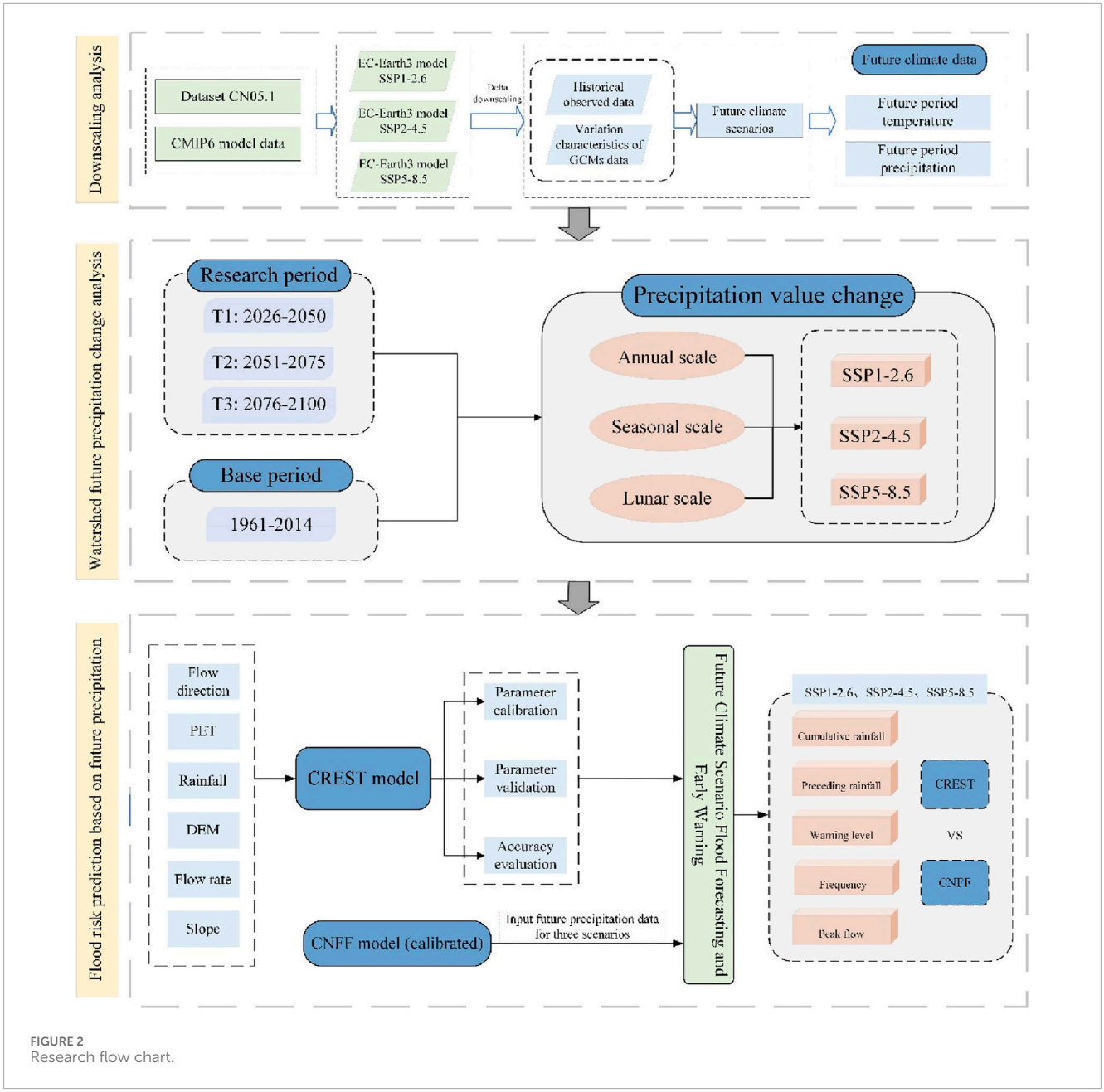

FIGURE 2
Research flow chart.

reached the "acceptable" range, meeting the accuracy requirements of the hydrological model. Next, future daily precipitation events exceeding the 2-year return period design storm were selected, and rainfall pattern allocation was conducted to characterize different types of precipitation patterns. On this basis, the CREST model was used to calculate the corresponding flood discharge, which was then compared with the results from the CNFF. This comparison was used to predict flash flood risk changes under the future climate scenarios. The specific technical approach is shown in Figure 2. This process integrates the use of the CREST model to compute flood discharges, followed by a comparison with results from the CNFF Model. The final goal is to predict the changes in flash flood disaster risk under future climate scenarios.

3 Results and discussion

3.1 Analysis of future precipitation changes

The average annual precipitation from 1961 to 2014 was 1717.2 mm, showing a fluctuating downward trend, and the trend rate was −12.4/10a. The annual average value of simulated precipitation was 1,488.9 mm, which was 13.3% lower than the observed value, and the trend rate was −20.6/10a. After Delta downscaling and deviation correction, the annual mean of model precipitation was 1717.1 mm, and the trend rate was −33.2/10a. The correction effect is obvious, as shown in Figure 3. Obviously, the bias-calibrated model simulations deviate from the observations with little deviation and the trend is consistent with the observations,

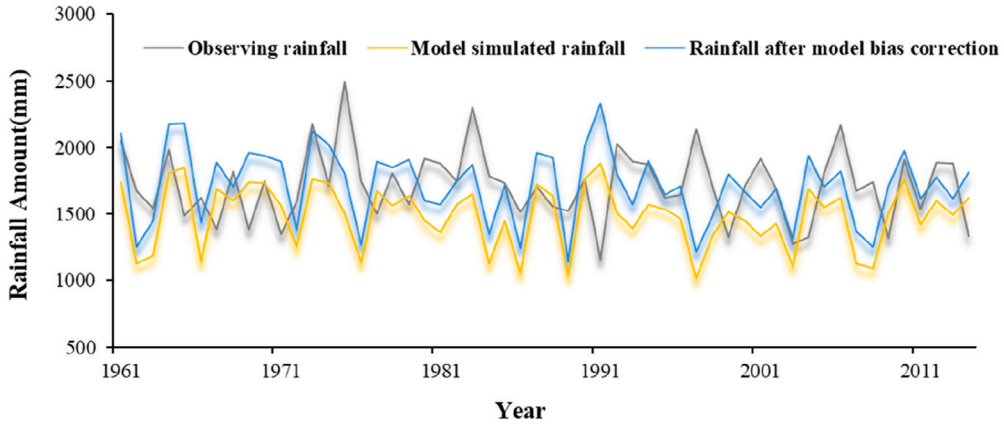

FIGURE 3
Annual precipitation from observations and simulations from 1961 to 2014.

which can be used to describe precipitation characteristics on a time scale.

In order to explore the variation characteristics of future precipitation on the annual and monthly scales under the three scenarios of climate models SSP1-2.6, SSP2-4.5 and SSP5-8.5, the study period 2026–2,100 was divided into three stages: T1 (2026–2050), T2 (2051–2075) and T3 (2076–2,100), and the changes of precipitation values in different stages under the three scenarios compared with the base period (1961–2014) were calculated.

Under the three scenarios of SSP1-2.6, SSP2-4.5 and SSP5-8.5, the average annual precipitation showed an increasing trend, and its annual average values were 1828.89 mm, 1817.60 mm and 2024.14 mm, respectively, which increased by 6.5%, 5.8% and 17.9% compared with the base period. The increase rates were 0.6 mm/10a, 19.8 mm/10a and 88.1 mm/10a, respectively. The increase of interannual precipitation was the largest under the SSP5-8.5 scenario. The increase trend of interannual precipitation was the most moderate under the SSP1-2.6 scenario, that is, the probability of future extreme precipitation under the SSP5-8.5 scenario was higher than that under the SSP2-4.5 and SSP1-2.6 scenarios, which also indicated that the high pollution concentration caused by high fossil fuel consumption led to enlarge the growth in precipitation. As shown in Figure 4, the probability of a minimum value of precipitation in the SSP1-2.6 scenario is higher than that in the SSP2-4.5 scenario. Therefore, in the next 75 years, although the precipitation increases in the SSP1-2.6 scenario compared with that in the base period is larger than that is in SSP2-4.5 scenario, the trend rate in the SSP1-2.6 scenario is smaller than that of the SSP2-4.5 scenario. SSP1-2.6. In the SSP1-2.6 scenario, there are more peaks and troughs of precipitation, while in the SSP2-4.5 scenario, the upper and lower ranges of the precipitation threshold fluctuate less, and its growth trend is relatively stable.

Figure 5 shows the monthly changes of precipitation in each period under the future scenario, and the average annual precipitation in the three stages of SSP1-2.6, SSP2-4.5 and SSP5-8.5 all showed an increasing trend, ranging from 3.3% to 32.5%. The smallest increase is in the period 2026–2050, when it is 56.4 mm under the SSP1-2.6 scenario. The SSP5-8.5 scenario had the largest increase in the 2076–2,100 period, which was 558.7 mm. In the future climate simulation data, the month with the most precipitation occurred in June during the T3 period under the SSP5-8.5 scenario, which was 519.7 mm. However, the largest monthly growth was 231.3% in November in the T1 period under the SSP2-4.5 scenario, and the precipitation in November in the other three stages showed a downward trend. Under the SSP1-2.6 scenario, the monthly precipitation in the T1 and T2 phases is mainly increased compared with the base period, and the decrease months are concentrated in November, December, January and February. The precipitation in the T3 stage is mainly decreasing, and the interannual precipitation in the T3 stage still shows an increasing trend, but compared with other stages, the increase is the smallest.

Under the SSP2-4.5 scenario, the monthly precipitation fluctuates most drastically, and the precipitation fluctuation in T1 is opposite to that in T2 and T3, and the T1 stage has the largest decrease in June, which is only 30.1 mm. Under the SSP5-8.5 scenario, the precipitation fluctuation in the T1 stage is relatively flat compared with the base period, the precipitation fluctuation in the T2 and T3 stages is upward, and the increase in the T3 stage is the largest. The precipitation in the three stages is also declining in February and November. Under the three scenarios, the precipitation in September exceeded the base period, and the increase rate was more than 17.2%. In the three scenarios, the precipitation in January February in the future will decrease compared with the base period.

Figure 6 shows the seasonal changes of precipitation in each period under the future scenario. In June, July and August (summer), the precipitation decreased only in T1 under the SSP2-4.5 scenario, while the rest showed an increasing trend and the precipitation in September, October and November (autumn) showed an increasing trend. Under the SSP2-4.5 scenario, the precipitation fluctuation in T1 was the largest, and the seasons with the largest increase and decrease were in this stage, which were −60.8% in summer and 144.3% in autumn, and extreme precipitation is more likely to occur during this period. The summer sum of the three phases of SSP1-2.6 and SSP5-8.5 increases the most.

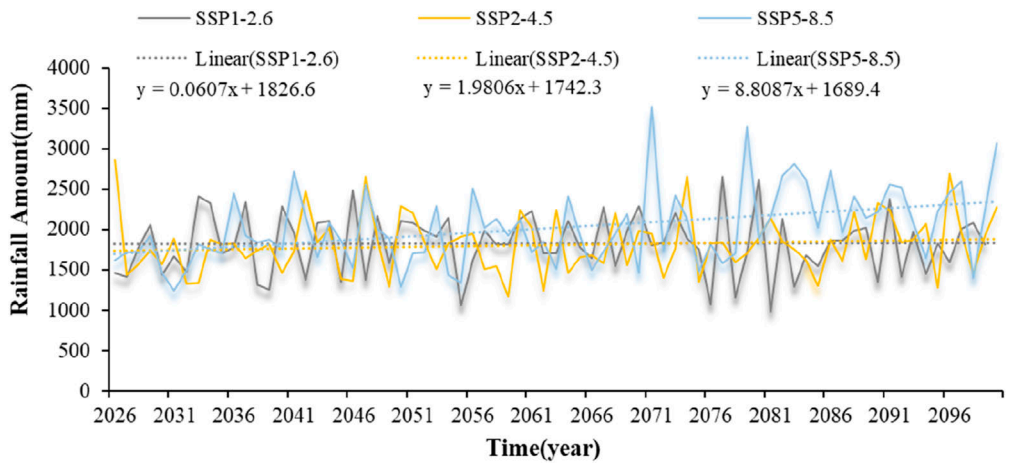

FIGURE 4
Future annual precipitation changes under three climate scenarios.

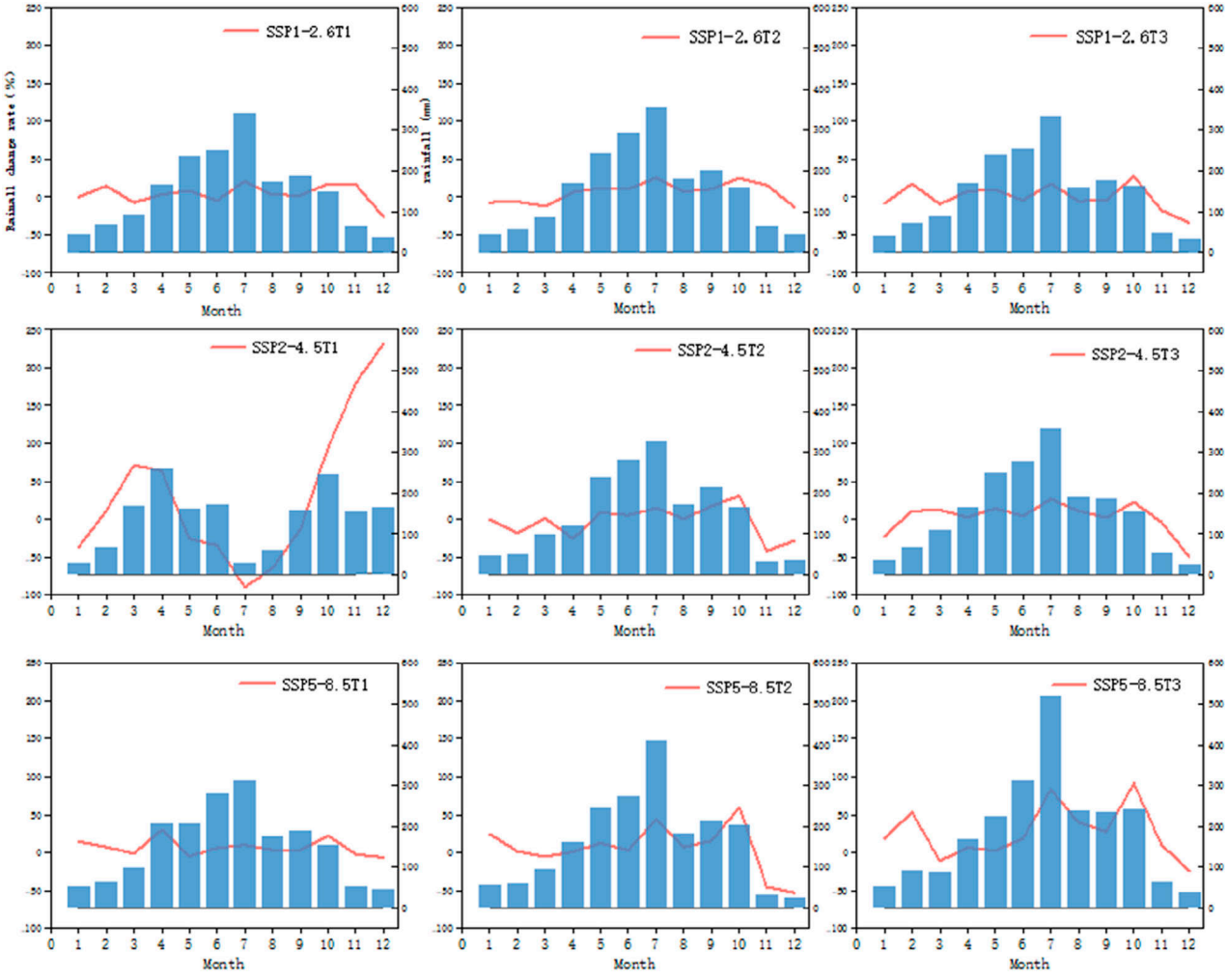

FIGURE 5
Monthly variation of precipitation in future periods.

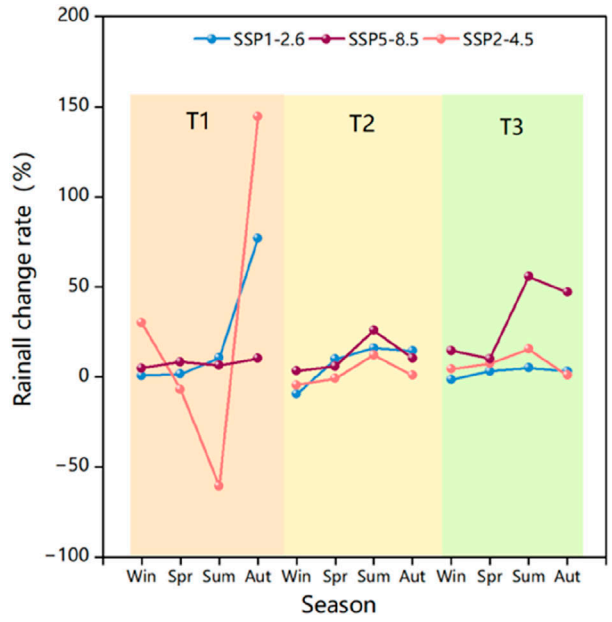

FIGURE 6
Seasonal changes in precipitation in future periods.

3.2 Flash flood prediction based on CNFF model

Taking the daily precipitation as the research scale, the 24-h precipitation of 2-year event (104.63 mm) or more was selected as the research object, and the precipitation was calculated according to the area of the Daxi water basin, and then the surface rainfall of the basin was obtained. The schedule of the sessions is allocated according to the maximum 1-day rainstorm pattern, and flood prediction and early warning under future climate scenarios are also carried out. According to statistics, there were 6, 7 and 35 events under the SSP1-2.6, SSP2-4.5 and SSP5-8.5 scenarios where the daily precipitation reached 2-year event. The 24-h rainfall pattern was used to distribute the rainfall, and the cumulative rainfall in the first 3 days of precipitation was calculated, and the soil moisture in the previous period was determined according to the accumulated rainfall in the previous period. In the SSP2-4.5 scenario, the 20960623 session and the 20960624 sessions will be calculated according to the same session due to the time continuity, and two peak flows will be obtained. Similarly, under the SSP5-8.5 scenario, 20710612–20710613, 20771029–20771030, 20820629–20820630-20820701 and 21000623–21000624-21000625 will be counted as the same session. Based on the design rainfall and the distribution of the maximum daily rainfall process in the region, the design flood discharges for six recurrence intervals were calculated, thereby determining the flood recurrence characteristics of the river reach. Specifically, the peak discharges for different recurrence intervals range from 120 m^3/s to 1,053.3 m^3/s, with a 2-year recurrence interval design flood discharge of 120 m^3/s, 5-year recurrence interval at 302.2 m^3/s, 10-year recurrence interval at 498 m^3/s, 50-year recurrence interval at 883.8 m^3/s, and 100-year recurrence interval at 1,053.3 m^3/s. According to the design flood discharges in ascending order, warning levels from I to VI were assigned to the six recurrence intervals. Subsequently, the China Hydrological Model was used to simulate and predict typical flood events.

In the previous stage, based on the measured precipitation and flow data from 2019 to 2023, the parameters of the CNFF were calibrated and verified, and the average Nash coefficients were obtained at 0.79 and 0.89 in the process of model calibration and validation, so as to verify the good applicability of CNFF. Figure 7 shows the early warning analysis of flood response under future climate scenarios (SSP1-2.6 and SSP2-4.5), in which 4 of the six precipitation events under the SSP1-2.6 scenario reached the warning level, which were I., II., I., and III., respectively, and the largest flood peak flow was 20820416, with a frequency of nearly 100-year event. Under the SSP2-4.5 scenario, three of the seven precipitation events reached the warning level, which were II., II., III., respectively, and the peak flow of 20960624 session can reach 10-year event. Under the SSP5-8.5 scenario, 19 of the 35 precipitation events reached the warning level, and grades I., II., III., and IV have 8, 9, 1, and 1 game, respectively, and the peak flood flow of 21000625 session reached 20–50-year event. Overall, the frequency of precipitation in the 35 sessions ranged from 2 to 20-year event, and the maximum precipitation was the 20940827 sessions of 20-year event, about 220.6 mm. However, the peak flood flow generated by it is only close to 5-year event; The maximum peak flow is 810.5 m^3/s at 21000623–21000624-21000625. In addition, if the continuous precipitation exceeds 2-year event, the frequency of the peak flood flow calculated by the same field has increased. Obviously, continuous precipitation increases the probability of flooding. The 26 flood peak flows reached the early warning level, and the floods reaching levels I and II were higher than those of III and IV, and the sensitivity of previous precipitation and early soil moisture to peak flood flow was significant. Under the scenarios of SSP1-2.6, SSP2-4.5 and SSP5-8.5, the number of sessions that reached the warning level mostly occurred in June, with a probability of 56%. In addition, the floods of 10-year event or more occurred in the T3 (1976–2,100) stage, which is consistent with the positive trend of annual precipitation change under the three scenarios. Therefore, from 2026 to 2070, there will be no 10-year flood disasters in the Daxi Water Basin, but attention should be paid to debris flows, landslides and other chain disasters caused by low-frequency floods. Under the SSP1-2.6 and SSP2-4.5 scenarios, the probability of flooding in April is higher, while in the SSP5-8.5 scenario, the probability of extreme disasters will be increased due to high pollution emissions, and the probability of flooding is much higher than that of the other two scenarios. Under the SSP5-8.5 scenario, flash flood flows triggered by extreme precipitation events can reach as high as 1,053.3 m^3/s. This not only leads to flooding disasters within the watershed but may also trigger a series of secondary disasters, such as landslides and mudslides. The combination of soil saturation caused by extreme precipitation and the scouring effect of flash floods reduces the stability of mountain slopes, making landslides more likely. Meanwhile, the rapidly moving mudslides further exacerbate the destruction risk in downstream areas. These secondary disasters are often sudden and destructive, posing significant threats to transportation, infrastructure, and the safety of residents' lives and property.

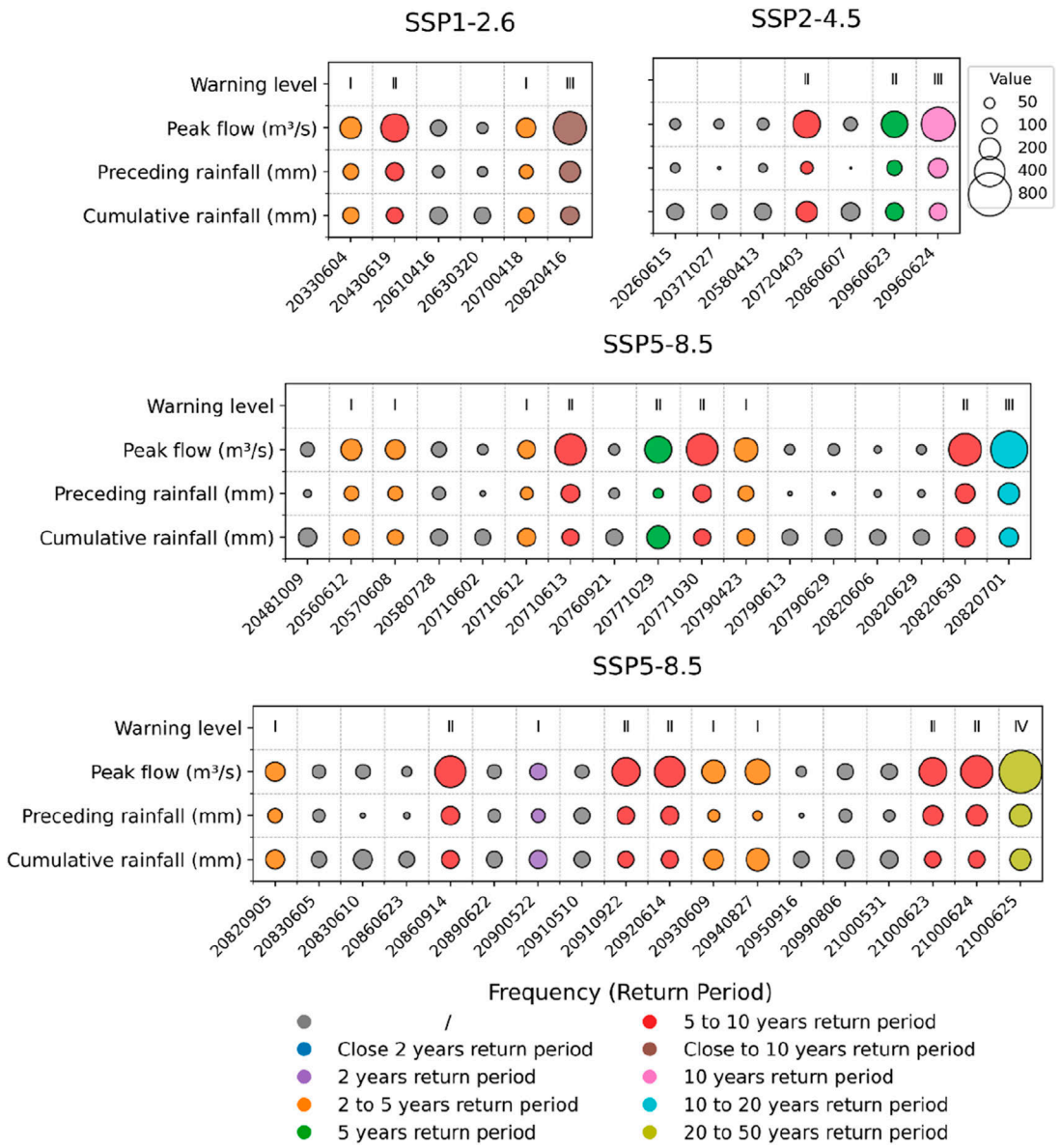

FIGURE 7
Analysis of flood response and early warning under future climate scenarios (SSP1-2.6、SSP2-4.5、SSP5-8.5) based on CNFF.

3.3 Flash flood prediction based on CREST model

The river flow data and precipitation data from 2021 to 2022 were selected for simulation, and the model parameters were calibrated from 9 April 2021 to 1 July 2022 according to the time series. Figure 8 shows the continuous flow process used for calibration, the Nash coefficient is in the "applicable" range, the simulated flow is smaller than the measured flow, especially the fitting of the peak is poor, the relative deviation between the simulated flow and the measured flow is 199% at the maximum, and the minimum is 0, and the peak time is advanced, but the change trend is more consistent. Using the data from July 2 to 1 September 2022 for simulation verification, the Nash coefficient is also in the "applicable" range, and the overall trend of simulated flow is consistent with that of measured flow, but the relative error of peak flow is large (Figure 9). Based on simulation and validation, the CREST model simulates the flow trend well in the long-term series simulation of small watersheds, while the error of the peak simulation is larger.

Combined with the calibrated and validated CREST model, the 24-hour precipitation of 2-year event (104.63 mm) or more was selected as the research object, and then the flood prediction and early warning under future climate scenarios were carried out. As shown in Figure 10 below, under the three scenarios, there were 11 sessions with flow exceeding the 2-year event, but no session with rainfall reaching the 5-year event. Under the SSP2-4.5 scenario, the flow of precipitation exceeded 120 m^3/s in two events, and the

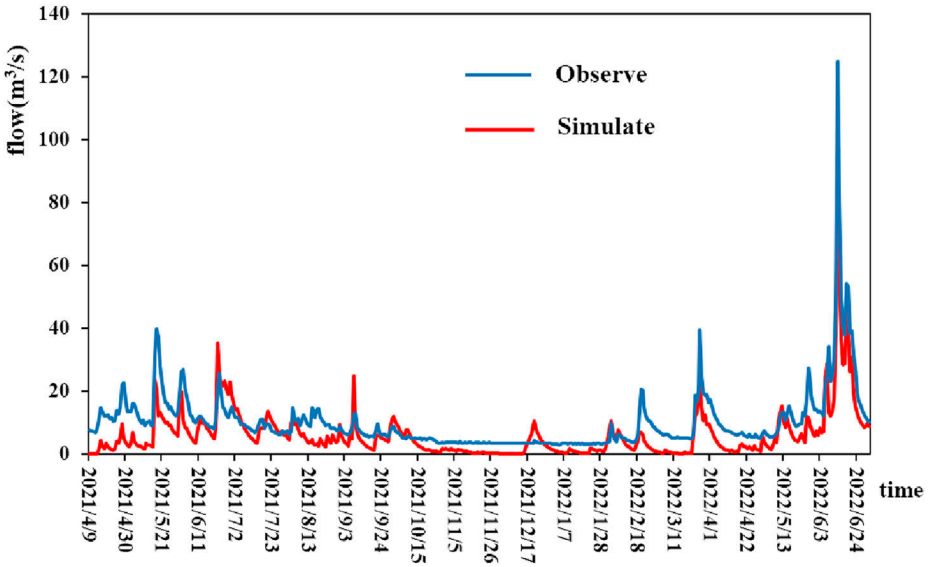

FIGURE 8
The continuous flow process of calibration period.

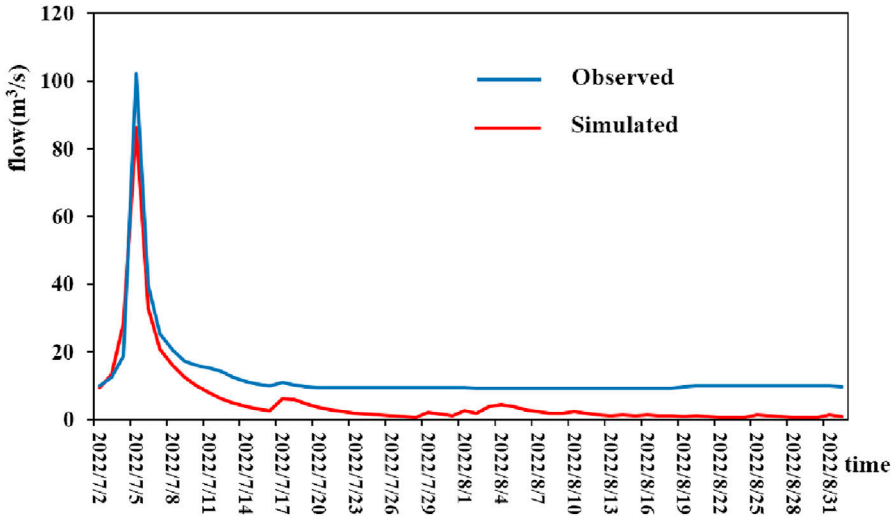

FIGURE 9
The continuous flow process of verification period.

peak flow of 20720403 was the largest. Under the SSP5-8.5 scenario, nine of the 35 precipitation events reached the warning level, and the maximum precipitation was 21000625, about 231 m^3/s. Under the SSP1-2.6, SSP2-4.5 and SSP5-8.5 scenarios, the probability of reaching the warning level is 23%, and most of the floods occurred in the T3 (1976–2,100) stage, which is consistent with the annual precipitation trend.

Combined with the above analysis, it can be seen that in the simulation of the two hydrological models, the relative error of 12 sessions is within 20%, and the overall gap is large, whilst the flow simulation value of CNFF model is higher than that of the CREST model, with the former reaching 810.5 m^3/s and the latter only 235.38 m^3/s. This may be due to the fact that CNFF model focuses on the simulation of flash floods in small watersheds, which is more advantageous in the simulation of short time series. In addition, the CREST model is primarily designed for long-term series simulations, where it performs reliably in capturing the overall flow trends over extended periods. However, its ability to accurately simulate peak flow in short-term or extreme precipitation events is limited, particularly when precipitation intensity and runoff responses are more localized and rapid. The CREST model fails to fully capture the complexity of hydrological dynamics in small watersheds during extreme events, which helps explain why it underestimates peak flows and shows significant differences

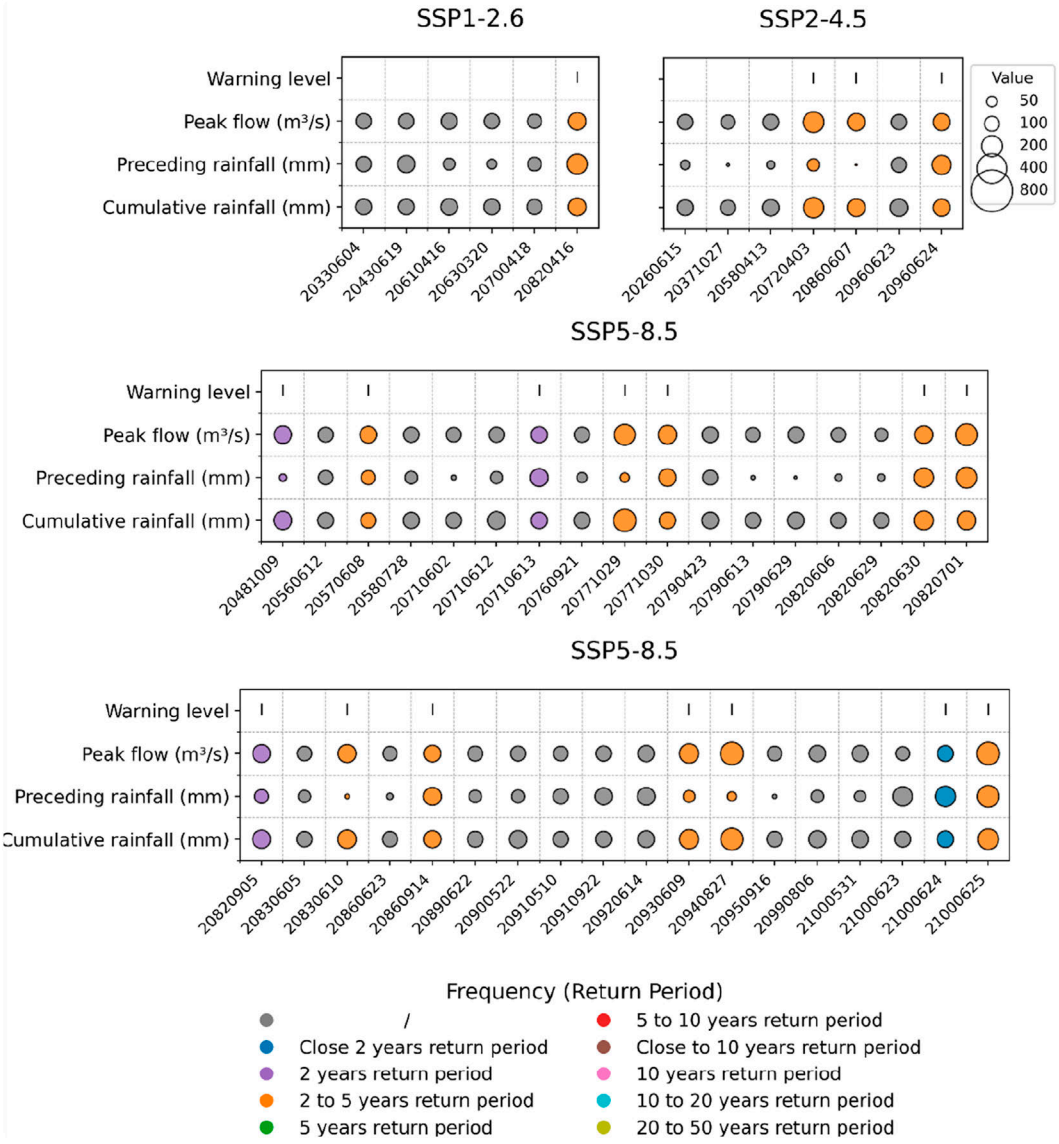

FIGURE 10
Analysis of flood response and early warning under future climate scenarios (SSP1-2.6、SSP2-4.5、SSP5-8.5) based on the CREST model.

compared to the CNFF model, which is specifically designed for flash flood simulations in small watersheds. Therefore, while the CREST model provides reliable results in long-term trend analysis, its performance in peak flood prediction is less accurate, necessitating the use of other models or optimized calibration to obtain more accurate short-term predictions.

4 Conclusion

Accurate simulation and risk prediction of flash flood cultural processes in future scenarios are crucial for flash flood defense. Based on CMIP6 precipitation data, this paper selects two distributed hydrological models, namely, CNFF and CREST, to predict the changes of flash flood disaster risk under different climate scenarios in the future. In the analysis of future precipitation trends, the precipitation under the SSP5-8.5 scenario is higher than that under the SSP1-2.6 and SSP2-4.5 scenarios. Compared with the SSP1-2.6 scenario in the base period, the annual rainfall increase is more than that in the SSP2-4.5 scenario, but the increase is the most modest.

According to CNFF, a total of 26 flood peaks reached the early warning level, amongst which the floods reaching levels I and II were higher than those of III and IV, and the sensitivity of previous precipitation and early soil moisture to the peak flood flow was significant, and the maximum peak flood flow occurred in 21000625 times, which was 810.5 m^3/s (20–50-year event).

Based on the CREST model, a total of 13 precipitation peaks reached the warning level, all of which were Level I. flood warnings, and the maximum number of simulated peak floods was 235.38 m^3/s. The simulation results of the two models are quite different, and only 12 sessions have a relative error of less than 20%,

which is mainly related to the model structure and data processing. Based on the results of this study, it is recommended to establish a dynamic flood early warning system in the basin, with a particular focus on enhancing monitoring and prevention efforts in June. At the same time, due to the limitations of time and data collection, multiple climate models, different downscaling methods, and high-resolution data can be used in follow-up research to further improve simulation accuracy.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

QL: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. NZ: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing–review and editing. LW: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Validation, Visualization, Writing–review and editing. KY: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Validation, Writing–review and editing. JWu: Formal Analysis, Investigation, Supervision, Validation, Writing–review and editing. JWa: Writing–review and editing. MM: Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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Integrating multi-source monitoring data and deep convolutional autoencoder technology for slope failure pattern recognition

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Introduction: Over the past few decades, China has vigorously advanced its strategy to build a powerful transportation network, constructing and maintaining numerous slope engineering projects. However, frequent major safety incidents caused by slope failures highlight the urgent need for automated identification of failure events during the operational phase of slopes.

Methods: This study integrates rainfall, surface displacement, and vertical displacement monitoring data, and proposes an automatic failure mode identification method based on deep convolutional autoencoder technology. The model is trained on monitoring data collected during the normal operational phase of slopes, extracting features from normal data to reconstruct the original data. The trained model is then utilized for structural anomaly detection by leveraging the characteristic that reconstruction errors for failure mode samples are significantly higher than for normal samples.

Results: A case study was conducted on a specific slope where, on 24 May 2024, the displacement development rate in some areas increased significantly, ultimately leading to collapse. The proposed model accurately identified the time and evolution of the landslide, demonstrating its capability to detect failure events effectively.

Discussion: Validation results confirm that the model can effectively distinguish previously unseen abnormal modes, offering significant practical value for identifying similar structural anomalies. This approach provides a reliable tool for slope monitoring and anomaly detection, enhancing safety in slope engineering projects.

KEYWORDS

multi-source data fusion, deep convolutional autoencoder, slope displacement, rainfall, health monitoring

1 Introduction

In recent years, slope safety issues have garnered widespread attention. Research has shown that the key factors influencing slope stability primarily include rainfall and groundwater levels (Zhang et al., 2011; Jiang et al., 2020; Yang and Zhang, 2024; Zhao et al., 2024). From the perspective of structural forces, the types of forces acting on slopes are relatively simple. Under normal circumstances, when the response remains within a stable range, it indicates that the slope is in a stable state. However, accidents caused by rainfall and changes in groundwater levels have become increasingly common (Arslan Kelam et al., 2024; Jing et al., 2024; Qin et al., 2024), making it imperative for managers to monitor the real-time operational status of critical slopes. Existing studies suggest that slope failure pattern identification methods can be broadly categorized into model-driven (Yuan et al., 2020; Wang et al., 2021; Liu and Wang, 2023; Chand and Koner, 2024; Garo et al., 2024; Huber et al., 2024; Shehadeh et al., 2024; Wang et al., 2024) and data-driven approaches (Bui et al., 2020; He et al., 2022; Alam et al., 2024). Model-driven techniques are limited by the specific characteristics of the studied objects, which restricts their applicability. To develop a more generalizable method for slope failure pattern recognition, health monitoring technology has been introduced. In recent years, the introduction of new monitoring technologies has significantly accelerated the rapid development of slope monitoring, such as the application of multi-field information monitoring technologies (Fang et al., 2023) and multi-smartphone photogrammetric monitoring systems (Fang et al., 2024). This technology provides an effective means of acquiring real-time data on slope environments and forces, enabling data-driven identification of slope failure patterns based on real-time monitoring data (Alam et al., 2024).

Extracting key indicators that characterize the operational status of slopes using observational data has become a focal point for researchers. For instance, mixed artificial intelligence models have been utilized to predict slope failure (Bui et al., 2020), and continuous random forests have been employed to automatically classify seismic signals related to slope instability (Wenner et al., 2020). A notable advantage of data-driven methods is their independence from specific structural forms, allowing for the exploration of the inherent features of the data based on structural characteristics, thereby yielding robust indicators with strong generalization capabilities to represent the structural operational status.

In recent years, artificial intelligence technologies have gained widespread attention in the field of data mining and have been applied in novel monitoring techniques. For example, the introduction of InSAR monitoring technology enables the acquisition of large-scale deformation data, and when combined with deep neural network techniques, it can predict the spatial and temporal trends of regional displacements (He et al., 2022; Lu et al., 2024). These monitoring techniques have also found successful applications in landslide monitoring (Anantrasirichai et al., 2020). Neural network technologies are widely used in various fields, such as object detection and natural language processing, and have achieved remarkable results in civil engineering, particularly in vision-based displacement monitoring. Drawing from these successful experiences, this study introduces deep convolutional autoencoder technology, which has been extensively used in the field of structural damage identification in civil engineering (Chen et al., 2024; Li et al., 2024; Teng et al., 2024). Compared to traditional methods that derive structural state indicators through theoretical analysis (Fan et al., 2024), deep convolutional autoencoders address the challenge of feature selection. Furthermore, this approach employs an unsupervised learning methodology, requiring only monitoring data from structures during their normal operational phase for model training. Once trained, the model can automatically identify abnormal patterns that differ from the normal operational state, effectively addressing the issue of data imbalance regarding abnormal patterns in civil engineering (Bao et al., 2019). Of course, there are many types of unsupervised learning methods, each suited to different application scenarios, such as the K-nearest neighbors algorithm (KNN) (Ramaswamy et al., 2000; Angiulli and Pizzuti, 2002), variational autoencoders (VAE) (Dong et al., 2018; Kim et al., 2018), and generative adversarial networks (GAN) (Schlegl et al., 2017). However, the deep convolutional autoencoder model (Cheng et al., 2018) employed in this study integrates both feature extraction and damage identification functionalities. With its end-to-end input-output structure, the model was selected for its compatibility with the specific characteristics of slope monitoring data and its strong modeling capabilities. The autoencoder excels at feature representation, effectively capturing both spatial and temporal patterns from multi-dimensional time series data, offering a deeper understanding of

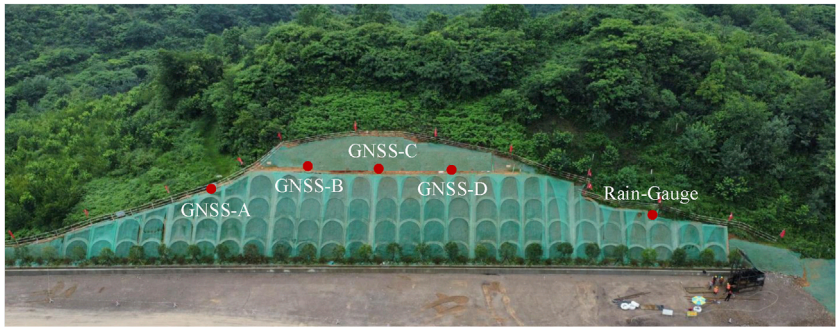

FIGURE 1
Slope site and sensor layout diagram.

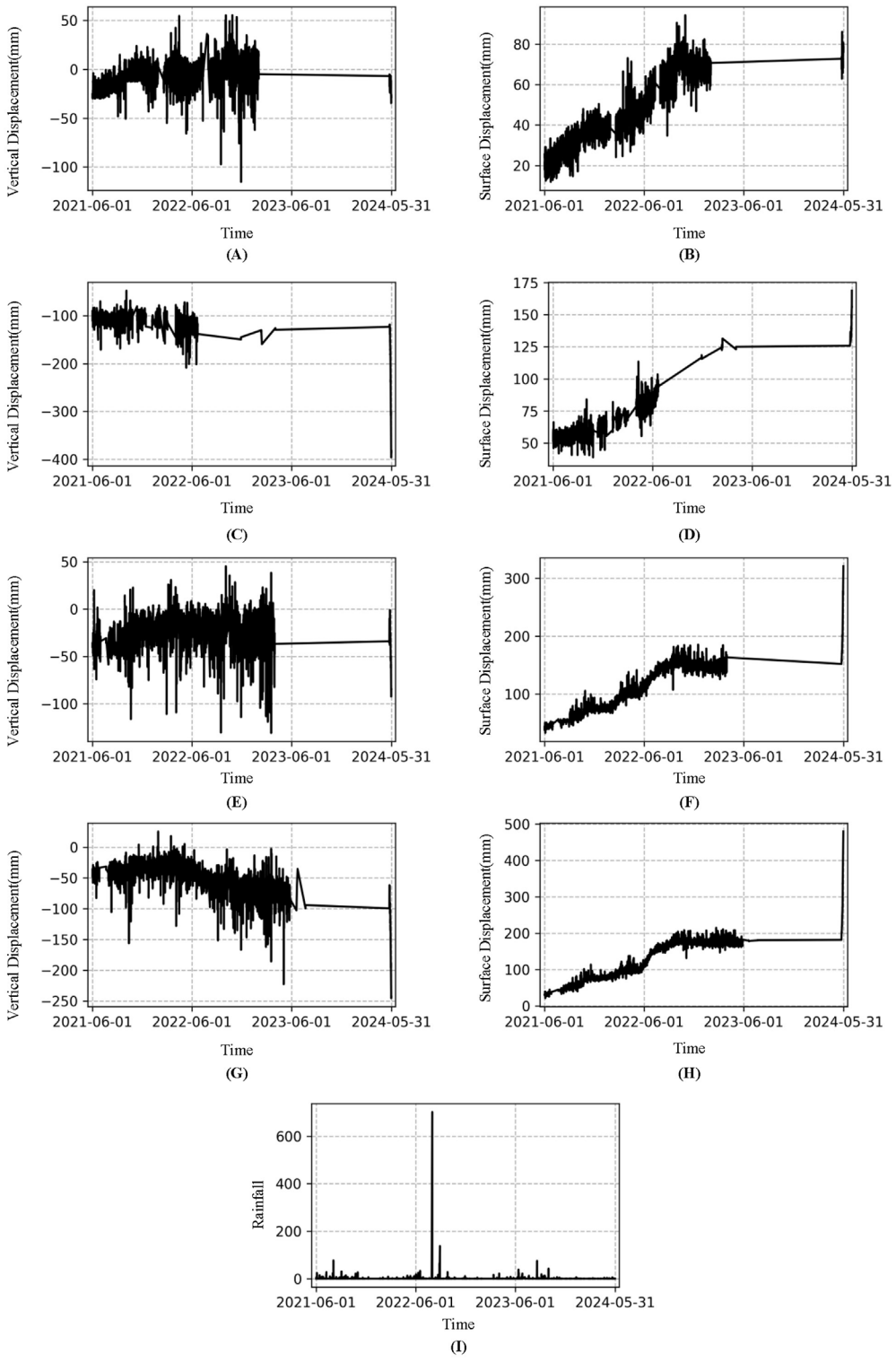

FIGURE 2
Time history of each sensor during the monitoring period. **(A)** Vertical displacement of GNSS-A. **(B)** Surface displacement of GNSS-A. **(C)** Vertical displacement of GNSS-B. **(D)** Surface displacement of GNSS-B. **(E)** Vertical displacement of GNSS-C. **(F)** Surface displacement of GNSS-C. **(G)** Vertical displacement of GNSS-D. **(H)** Surface displacement of GNSS-D. **(I)** Rain-Gauge.

slope dynamics compared to traditional methods that may focus solely on statistical or temporal features. Its built-in denoising capability enhances the robustness of anomaly detection, enabling the model to prioritize meaningful patterns while mitigating the influence of noisy measurements commonly found in slope monitoring datasets. Furthermore, the approach is highly scalable,

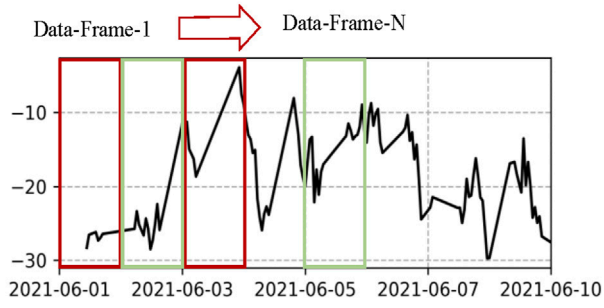

FIGURE 3
Data samples generated using a 24-h non-overlapping sliding window.

making it ideal for handling high-dimensional data, which is essential for complex monitoring scenarios.

Based on the aforementioned research, this paper employs deep convolutional autoencoder technology to integrate multi-source monitoring data of slopes, achieving precise identification of slope failure modes. The organization of this paper is as follows. Section 1 reviews the development history of abnormal pattern recognition in slopes and highlights the advantages of deep convolutional autoencoders. Section 2 introduces the engineering background, the characteristics of the monitoring data, the preprocessing methods used in this study, and the framework of the proposed method. Section 3 displays the results obtained from the study. Section 4 summarizes the findings of this paper.

2 Materials and methods

2.1 Data description and data preprocessing

2.1.1 Engineering overview

This study focuses on a cut slope located in a region characterized by tectonic erosion and hilly landforms. The slope has a height of approximately 15–20 m, with a natural gradient ranging from 20° to 50°. Based on borehole exploration and geological surveys, the surface layer of the slope is covered with Quaternary silty clay, with a thickness of 2–3 m and containing gravel, as shown in Figure 1. Beneath this layer, the bedrock belongs to the Cretaceous Jiangdihe Formation, consisting mainly of grayish-green silty mudstone and red mudstone, with localized intercalations of clay layers. The rock mass exhibits varying degrees of weathering, ranging from strong to moderate. It typically features relatively rough fractured textures and displays thin to medium bedding structures. The geological structure of this section is significantly influenced by tectonic activity, and the severe weathering of the rock mass results in the predominance of soil layers in the slope.

Based on the geological conditions and stability analysis of the slope, combined with engineering analogies, the first level of the slope is supported using an arched skeleton structure. Within the skeleton, a combination of sprayed anchor mesh and grass planting is employed to provide protection, enhancing both the stability and ecological sustainability of the slope.

After the completion of the slope support structure construction, manual inspection revealed significant displacement and deformation trends at the designated measurement points. Consequently, four surface displacement monitoring points were set up. Additionally, to monitor the impact of rainfall on slope displacement development, a rain gauge was installed in an open area. To monitor the long-term stability of the slope, this study introduced GNSS monitoring and rainfall monitoring, establishing 4 GNSS measurement points and 1 rainfall measurement point, as shown in Figure 1. The sampling frequency for the GNSS measurement points is 1/1,800 Hz, while the sampling frequency for the rainfall measurement point is 1/3,600 Hz. The GNSS measurement points can monitor three-dimensional spatial displacements, and through conversion, both surface displacement (denoted as “dxy” in the following text) and vertical displacement (denoted as “dz” in the following text) at the measurement points can be obtained. This study selected monitoring data from 1 January 2022, to 31 May 2024, as the research object, with the time-series curve illustrated in Figure 2.

2.1.2 Data preprocessing

As mentioned above, the sampling rates of the GNSS monitoring points and rainfall monitoring points are not consistent, and during the monitoring period, different sensors did not achieve synchronized data collection. To align the data from various sensors, we assume that the data between two observation points follow a linear relationship. Therefore, linear interpolation is used to estimate the data at any given time point. Based on the timestamps of the sampled data, we interpolate to obtain the hourly sample values within the selected time range, thereby completing the data alignment for all monitored variables.

For the purposes of model training and testing described later, the data is grouped into time frames of 24 h each. The timestamps of the monitoring data across 9 channels are aligned, and then the data from these 9 channels within the same time frame are taken together to form a single sample, with a sample size of 9 × 24, as shown in Figure 3. After removing missing data, a total of 710 samples were obtained over the entire monitoring period. Of these, 70% (497 samples) were used as the training set, 10% (71 samples) as the validation set, and 20% (142 samples) as the test set.

To visually demonstrate the differences in monitoring data before and after the landslide, this paper employs parallel coordinate visualization. In this approach, each monitoring channel is represented by a vertical axis, and the changes at each channel over time are displayed based on the magnitude of the monitored data. This allows for the identification of correlations between various monitored quantities at the same timestamp. By analyzing the results from multiple sensors, it becomes apparent that during the landslide event, significant displacement changes occurred in GNSS-B, GNSS-C, and GNSS-D, while no significant rainfall was observed during the period of large displacement changes. As shown in Figure 4, the correlation between rainfall and displacement is relatively weak, but the displacement correlation among the measurement points is relatively strong.

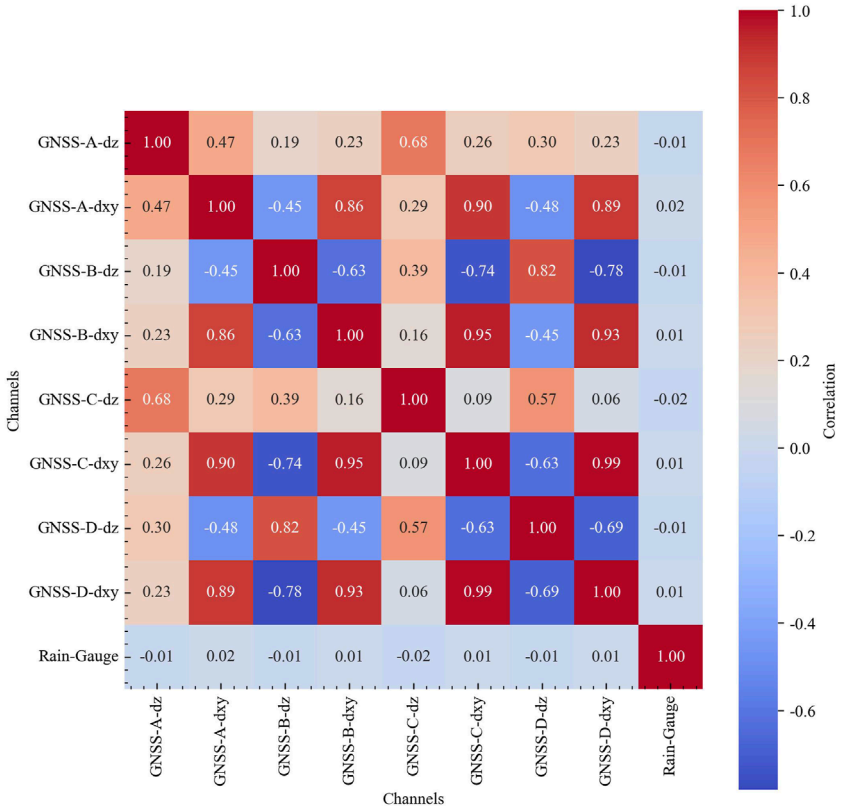

FIGURE 4
Correlation heatmap of slope monitoring sensors across different channels.

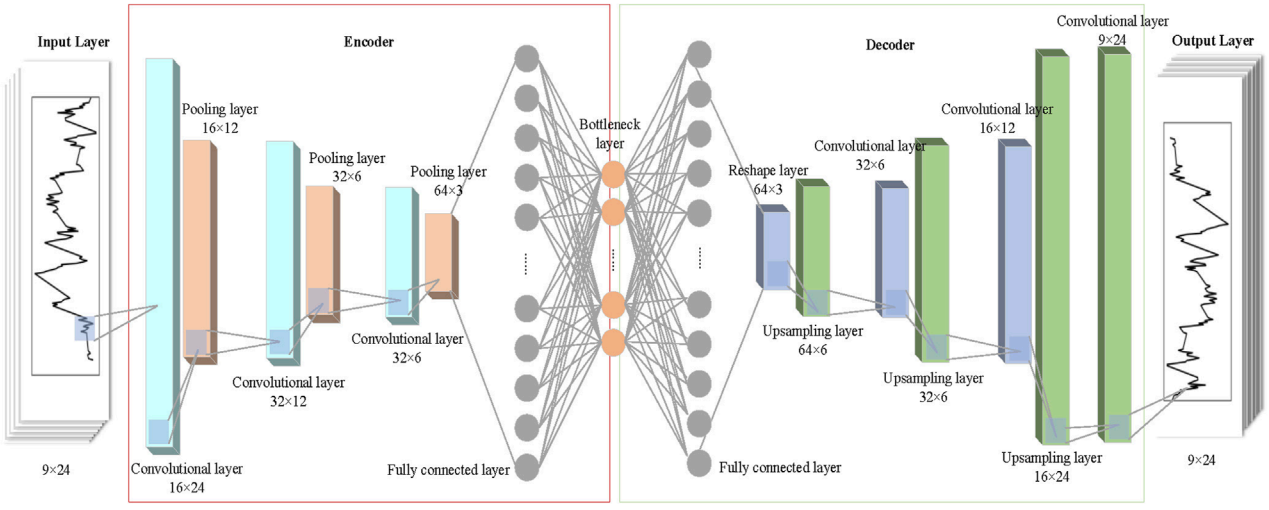

FIGURE 5
Model architecture diagram of the deep convolutional autoencoder.

2.2 Methods

2.2.1 Framework of the proposed method

Based on the characteristics of the monitoring data described in the previous section, it can be observed that during the period of slope failure, the displacement of the monitored slope shifts rapidly, while the rate of displacement change remains relatively slow during normal operation. Leveraging this phenomenon, this paper proposes a slope failure mode identification method based on a deep convolutional autoencoder. The method utilizes monitoring

TABLE 1 Deep convolutional autoencoder configuration.

Network layer	Input dimension	Output dimension	Parameter	Activation function
Input layer	9 × 24			
Convolutional layer	9 × 24	16 × 24	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Pooling layer	16 × 24	16 × 12	Kernel size: 2 × 1 Stride: 2	
Convolutional layer	16 × 12	32 × 12	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Pooling layer	32 × 12	32 × 6	Kernel size: 2 × 1 Stride: 2	
Convolutional layer	32 × 6	64 × 6	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Pooling layer	64 × 6	64 × 3	Kernel size: 2 × 1 Stride: 2	
Flatten layer	64 × 3	192		
Fully connected layer	192	48		
Fully connected layer	48	192		
Reshape layer	192	64 × 3		
Upsampling layer	64 × 3	64 × 6	Scale factor: 2	
Convolutional layer	64 × 6	32 × 6	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Upsampling layer	32 × 6	32 × 12	Scale factor: 2	
Convolutional layer	32 × 12	16 × 12	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Upsampling layer	16 × 12	16 × 24	Scale factor: 2	
Convolutional layer	16 × 24	9 × 24	Kernel size: 3 × 1 Stride: 1 Padding: 1	ReLU
Output Layer	9 × 24			

data from the normal operation period as the training set, where the deep convolutional autoencoder extracts features corresponding to the normal operating state. Specifically, the encoder compresses high-dimensional monitoring data to capture the essential features of the slope's normal behavior, while the decoder reconstructs the original data from these compressed features. After training, the model is applied to slope failure mode identification, where anomalies are detected by analyzing the residuals between the reconstructed data and the original data.

This approach falls under unsupervised learning algorithms, which means that the model does not require prior knowledge of any failure modes during the training process. It effectively addresses the issue of insufficient failure samples commonly encountered in civil engineering. By learning from normal operating data, the trained model can directly identify abnormal data features that deviate from the normal state, demonstrating strong generalization capabilities. The architecture of the model is shown in Figure 5.

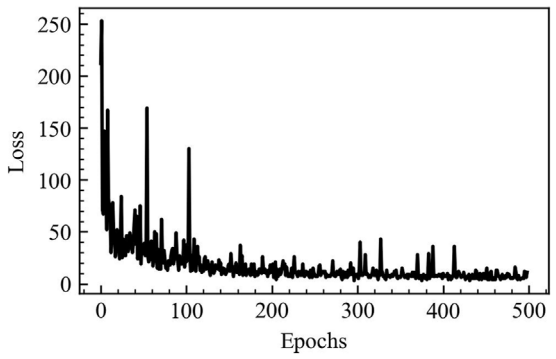

FIGURE 6
Mean squared error of the deep convolutional autoencoder model over 500 epochs.

The input to the model is a 9 × 24 matrix, where 9 represents the 9 monitoring channels: GNSS-A-dz, GNSS-A-dxy, GNSS-B-dz, GNSS-B-dxy, GNSS-C-dz, GNSS-C-dxy, GNSS-D-dz, GNSS-D-dxy, and Rain-Gauge, while 24 indicates that each data frame contains 24 sampling points. After processing through the encoder, the input reaches the bottleneck layer and is then reconstructed by the decoder. Given the relatively small input dimensions, this study employs a convolution kernel size of 3 to reduce the number of parameters while preserving local features of the data. A stride of 1 is used to retain as much data detail as possible. Various architectures with 3, 4, and 5 convolutional layers were tested. While deeper architectures slightly reduced training error, a 3-layer design was ultimately chosen to balance computational efficiency and parameter reduction. The structure of the encoder and decoder is shown in Table 1. The encoder utilizes the ReLU activation function, employs max pooling with a kernel size of 2 and a stride of 2; the upsampling layer has a scaling factor of 2, and all convolutional kernels have a size of 3 × 1, with a stride of 1 and padding of 1.

2.2.2 Performance evaluation

The unsupervised model used in this study for the identification of abnormal patterns in slopes can be viewed as a binary classification model, determining whether a structure is in a normal or abnormal state. Therefore, the model's classification results can be evaluated using metrics such as accuracy, precision, recall, and F1 score. Accuracy measures the overall correctness of the model by dividing the number of correct predictions (true positives and true negatives) by the total number of predictions. Precision indicates how many of the positively predicted samples were actually correct. It focuses on the correctness of positive predictions. Recall measures how well the model can identify actual positive cases. It calculates the proportion of true positives out of all actual positives. The F1 score is the harmonic mean of precision and recall. It provides a balanced measure when you want to consider both false positives and false negatives. The calculation formulas are shown as Equations 1–4.

$$accuracy = \frac{TP + TN}{TP + FN + FP + TN} \times 100 \quad (1)$$

$$precision = \frac{TP}{TP + FP} \times 100 \quad (2)$$

$$recall = \frac{TP}{TP + FN} \times 100 \quad (3)$$

$$F_1 = 2 \times \frac{precision \times recall}{precision + recall} \times 100 \quad (4)$$

Where TP represents the count of samples that are genuinely positive and accurately classified as positive by the model. TN refers to the number of genuinely negative samples that the model correctly identifies as negative. FP indicates the count of samples that are truly negative but mistakenly classified as positive by the model. FN refers to the number of truly positive samples that the model incorrectly labels as negative.

2.2.3 Model training

In this study, 497 samples were used as the training set, 71 samples as the validation set, and 142 samples as the test set. The model was trained for 500 epochs with a batch size of 8. The loss function adopted was the mean squared error (MSE) loss, and the optimization algorithm used was Adam, with an initial learning rate of 1e-3 and a weight decay of 1e-5. The training loss during the process is shown in Figure 6. As observed, starting from the 100th epoch, the training loss stabilized. The final model parameters were selected based on the epoch where the sum of the training and validation losses was minimized. The model was trained on a machine equipped with a 6-core CPU, 16 GB of memory, and a GTX1650 GPU, completing the process in 5 min and 12 s. Built using PyTorch, the model can be deployed in engineering applications by creating a web-based microservice using the Flask framework. Real-time data can be processed by invoking the microservice, enabling the model to determine whether structural anomalies are present.

3 Results

3.1 Anomaly pattern identification methods and results

The trained model was applied to the test dataset to identify slope failure patterns. The test dataset contains 134 samples from the slope's normal operational state and 8 samples from the failure development or failure stage. To use the model's reconstruction error for identifying slope failure patterns, the mean and standard deviation of the reconstruction error from the training samples were calculated to establish a threshold evaluation system. The prediction results of the trained model on both the training and validation datasets were collected and visualized using a bar chart, as shown in Figure 7A. It can be observed that the frequency distribution of errors resembles the shape of a normal distribution. A quantile-quantile (Q-Q) plot was further used to assess the deviation of the error distribution from a normal distribution, as depicted in Figure 7B. Apart from the data at both ends, most points lie approximately on a straight line, supporting the assumption that the errors follow a normal distribution. Based on this, the mean of the error samples plus three times the standard deviation was used as the threshold to determine whether data anomalies exist, enabling the identification of abnormal patterns in slopes.

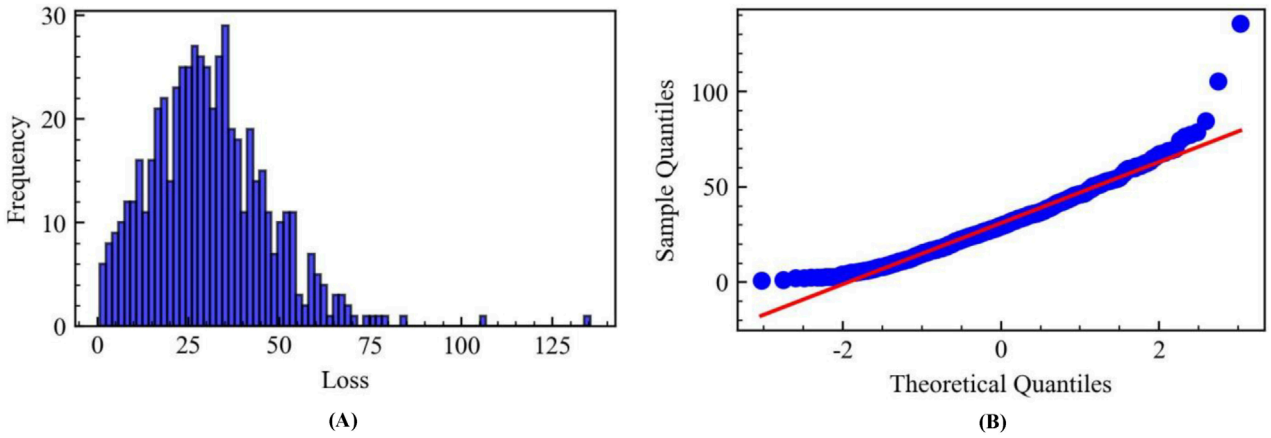

FIGURE 7
Frequency distribution and quantile-quantile plot of reconstruction loss for training and validation datasets. **(A)** Frequency distribution. **(B)** quantile-quantile plot.

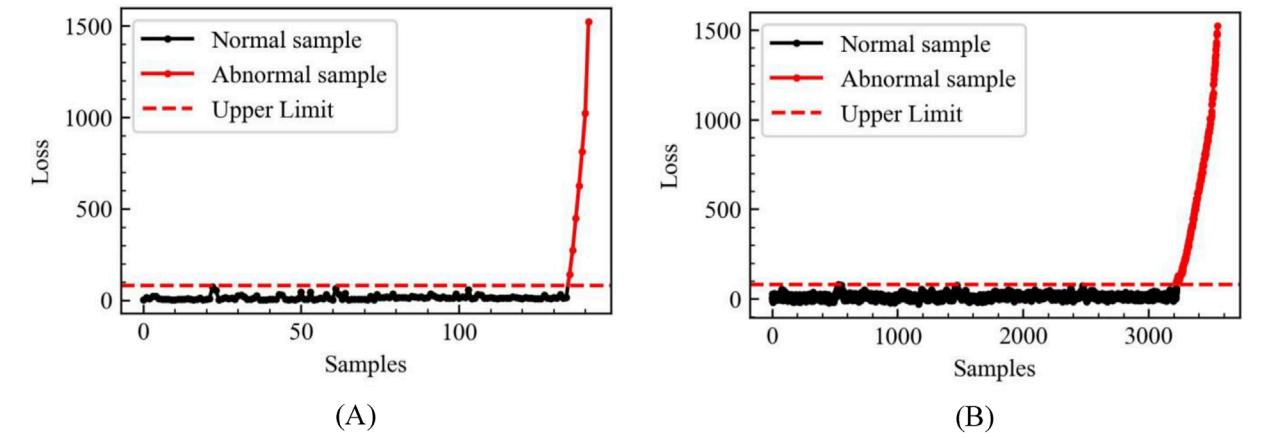

FIGURE 8
Slope anomaly pattern recognition results based on threshold and deep convolutional autoencoder reconstruction error. **(A)** Test sample recognition results with non-overlapping sliding window. **(B)** Test sample recognition results with overlapping sliding window.

In the test dataset, the 8 abnormal samples were derived from the monitoring data collected between 24 May 2024, and 31 May 2024. During these 8 days, the slope displacement gradually increased, with the rate of change accelerating each day. Using the anomaly detection method proposed in this study to determine whether the slope exhibited abnormal behavior, the model was able to accurately identify both the progression of the slope failure and the final failure event, as shown in Figure 8A. The site of the slope failure is shown in Figure 9. However, in the early stages of failure, specifically on 24 May 2024, when the displacement change was minimal, the model failed to detect the anomaly accurately. This is primarily because, in the early stages of a landslide, not all sensors are affected, and the mean squared error (MSE) metric inherently lacks sensitivity to early-stage anomalies. To enhance the timeliness of warnings, it is recommended to use a deep autoencoder as a feature extraction model, utilizing the features from its bottleneck layer as input to build an anomaly detection model that is more sensitive to fused features. For instance, an anomaly detection model based on Support Vector Machines (SVM) or a Gaussian Mixture Model (GMM) could be employed to address the insensitivity of MSE, which relies on averaging operations, to early-stage anomalies.

According to the performance evaluation metrics, the prediction accuracy in this case reached 99.30%, with a high accuracy for alarms, as shown in Table 2. With limited data, this study applies L1 regularization in the loss function by adding a regularization term to constrain the number of model parameters. Additionally, the Adam optimizer and weight decay mechanism are used to minimize the impact of overfitting. It should be noted that the most effective approach remains increasing the data volume. In the future, the dataset will be further expanded to establish a standardized anomaly detection sample set, providing a solid data foundation for training similar models.

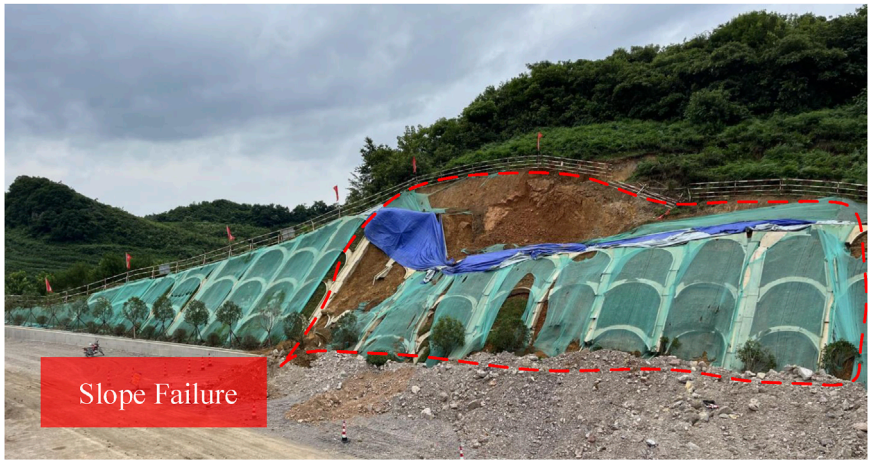

FIGURE 9
The on-site real image of the final slope collapse.

TABLE 2 Performance evaluation metrics of the model on the test set with non-overlapping sliding window.

Performance evaluation metrics	Result
Precision	100.00%
Recall	87.50%
F_1	93.33%
Accuracy	99.30%

Results demonstrate that the model can accurately detect unseen data anomalies. This unsupervised learning algorithm has broad applicability, requiring only normal data samples for training. It effectively addresses the issue of insufficient anomalous data samples in structural monitoring.

3.2 Further improving the timeliness of anomaly pattern identification

To further enhance the timeliness of anomaly detection, the non-overlapping sliding window was replaced with an overlapping sliding window, as shown in Figure 10. The sliding step was set to 1 h, allowing a new sample to be constructed whenever new data arrived for the model to evaluate for anomalies. Validation on the test dataset using this approach revealed that the previous non-overlapping sliding window mode struggled to accurately detect anomalies due to small displacements on the first day, requiring 48 h to identify anomalies. In contrast, the overlapping sliding window mode successfully detected anomalies within 30 h, significantly reducing the anomaly detection time and improving the potential for practical engineering applications. The test set, constructed using overlapping sliding windows, contains a total of 3,385 samples, of which 192 samples correspond to monitoring data during the landslide occurrence process, while the remaining samples represent the normal operational stage of the slope. The model accurately classified 3,356 samples, while the remaining 29 samples, belonging to the early development stage of the landslide, were not correctly identified as landslide anomaly patterns. The classification results of the samples are detailed in Figure 8B, and the evaluation metrics are presented in Table 3. Since the sliding window includes more monitoring data from the early stages of landslide occurrence, which were not accurately identified, the accuracy, F1 score, and recall of the model have decreased compared to previous results.

4 Discussion

In this study, a deep convolutional autoencoder-based unsupervised failure mode recognition algorithm is proposed to identify and alert slope failure modes. This algorithm integrates surface displacement, vertical displacement, and rainfall monitoring data from the slope. By training the model with normal operation phase data, it assesses the proximity of the structure to failure by comparing the reconstruction error between the reconstructed and observed data. Validation through a slope case study revealed that the model can accurately identify the development stages of slope failure, achieving a recognition accuracy of 99.30%. However, this method has certain limitations. First, the current monitoring data contains many missing values, leading to insufficient model training. Further data collection is needed to establish a standardized dataset. Second, early detection of slope failure remains a challenge, largely due to the reliance on reconstruction error as the main assessment method. Future research will focus on using the bottleneck layer features of the model for anomaly recognition to further improve the accuracy of failure mode identification.

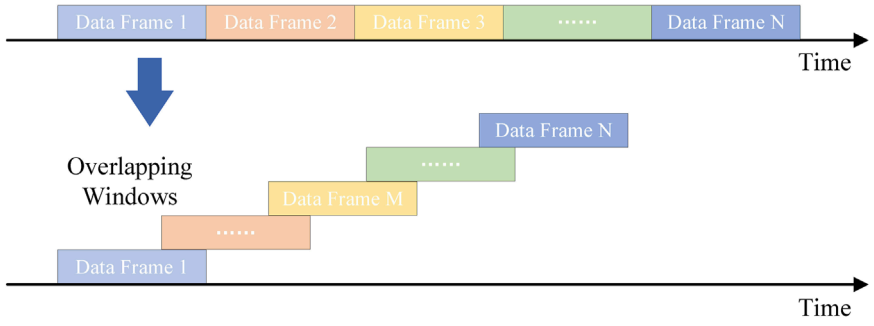

FIGURE 10
Schematic diagram of non-overlapping and overlapping windows.

TABLE 3 Performance evaluation metrics of the model on the test set with overlapping sliding window.

Performance evaluation metrics	Result
Precision	100.00%
Recall	84.90%
F_1	91.83%
Accuracy	99.14%

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

NH: Conceptualization, Writing–original draft, Methodology, Investigation, Validation, Visualization, Writing–review and editing. WM: Resources, Writing–review and editing. ML: Resources, Writing–review and editing. MM: Writing–review and editing. QH: Resources, Writing–review and editing. LD: Writing–review and editing. JT: Writing–review and editing.

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Conflict of interest

Authors WM and QH were employed by Guizhou Transportation Planning Survey and Design Academe Co., Ltd. Author ML was employed by Guangxi Communications Design Group Co., Ltd. Author JT was employed by Yunnan Provincial Transportation Planning and Design Institute Co. Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2025.1531857/full#supplementary-material

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A cooperative search algorithm-based flood forecasting framework: application across diverse Chinese catchments

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Flood forecasting is crucial for disaster mitigation, particularly in regions prone to flash floods. This study introduces a novel flood forecasting framework by coupling the Geomorphological Instantaneous Unit Hydrograph (GIUH) with the Xinanjiang model and optimizing parameters using the Cooperation Search Algorithm (CSA). Applied across six diverse Chinese catchments, the framework significantly improved computational efficiency and accuracy. Key findings demonstrate that: 1) CSA achieved high Nash-Sutcliffe Efficiency (NSE >0.9) with only 16 optimization trials on average, outperforming the SCE-UA algorithms; 2) The model performed exceptionally in data-sparse regions, achieving NSE values >0.9 even with minimal datasets; and 3) Enhanced runoff routing via GIUH enabled accurate simulation of extreme rainfall events. These results highlight the framework's potential for operational flood forecasting and disaster management globally. Future research will expand validation datasets and explore applications across varied hydrological and climatic conditions.

KEYWORDS

flood forecasting, geomorphological instantaneous unit hydrograph (GIUH), cooperation search algorithm, parameter optimization, diverse catchment

1 Introduction

Flood forecasting plays a crucial role in water resource management and disaster risk reduction, particularly in catchments prone to flash floods. These catchments, characterized by steep terrain and rapid hydrological responses, are highly sensitive to intense rainfall events, making them vulnerable to severe flooding (Ragettli et al., 2017, Qiu et al., 2024). Accurate and efficient flood forecasting models are essential for mitigating the impacts of such events. However, achieving reliable simulations is challenging due to the variability in hydrological conditions and

the scarcity of observational data in many regions (Addor et al., 2017; Singh et al., 2014). Accurate and efficient flood forecasting systems are critical for mitigating these impacts.

Flood forecasting frameworks now integrate hydrological models, data analytics, and machine learning to provide accurate predictions and timely warnings for flood mitigation. The literature on this topic spans a range of methodologies, from traditional hydrodynamic models to cutting-edge artificial intelligence and geospatial data analysis (Wei et al., 2024). Rostami et al. (2024) introduced a framework using data from VIIRS water fractions to improve flood predictions, focusing on dynamic inundation models for flood-prone regions. Zhou (2024) demonstrated the application of big data and deep learning in hydrological modeling, leading to improved accuracy in flood prediction systems. Chen et al. (2024) explored Bayesian models for analyzing spatial extremes, which are critical for understanding flood risks in varied geographical settings. Belcore et al. (2024) applied geoinformatics within early warning systems, enhancing flood resilience in regions like the Sahel. Lo et al. (2024) investigated combining conformer models with rainfall-runoff simulations to increase the reliability of hydrological forecasts. Porter et al. (2024) emphasized the importance of future population and socioeconomic scenarios in assessing flood exposure under varying conditions. Duraisekaran et al. (2024) implemented a framework that combines simulation and optimization for effective flood management, particularly in conservation reservoirs. Chang et al. (2025) proposed a multi-step correction framework to refine runoff forecasts using ensemble methods. Feng et al. (2025) showcased a framework that leverages digital twin technology for real-time flood forecasting and resource management. Flood forecasting frameworks are transitioning toward data-centric and AI-driven approaches, integrating geospatial and probabilistic models for enhanced accuracy. These frameworks are critical for disaster preparedness and risk mitigation, particularly in the face of climate change.

Traditional flood forecasting models (Zhu et al., 2024; Feng et al., 2025), such as hydrodynamic and statistical methods, have been widely applied. However, their effectiveness is often limited by high computational demands, inadequate representation of hydrological processes, and challenges in calibrating parameters under data-scarce conditions (Singh et al., 2014). These limitations underscore the necessity of developing innovative frameworks that integrate physical realism, computational efficiency, and adaptability to varying hydrological scenarios.

Recent advancements in hydrological modeling and optimization techniques offer new opportunities to address these challenges. Metaheuristic algorithms, such as the Cooperation Search Algorithm (CSA), have emerged as powerful tools for efficient parameter optimization. Unlike traditional methods such as the Shuffled Complex Evolution University of Arizona (SCE-UA) algorithm, CSA leverages collaborative behavior to explore complex solution spaces and achieve faster convergence (Feng et al., 2021). Meanwhile, integrating geomorphological insights through the Geomorphological Instantaneous Unit Hydrograph (GIUH) enhances the physical representation of runoff processes, particularly in ungauged or data-scarce catchments (Moussa, 2008).

This study bridges these advancements by coupling GIUH with the Xinanjiang model (Zhao and Wang, 1988), a widely used hydrological model that accounts for soil moisture dynamics, and optimizing its parameters using CSA. The proposed framework is applied to six representative catchments across China, encompassing diverse climatic and hydrological conditions. The objectives of this research are: 1) to evaluate the efficiency and accuracy of CSA compared to SCE-UA for parameter optimization; 2) to assess the performance of the GIUH-enhanced Xinanjiang model in data-scarce and data-rich catchments; and 3) to contribute to the development of a robust and scalable flood forecasting framework that addresses the challenges of varying data availability. By addressing these objectives, this study advances the field of flood forecasting by offering a computationally efficient and adaptable framework with significant potential for disaster preparedness and water resource management.

2 Material and data

2.1 Study area

Six representative catchments are in Six different Chinese provinces (Figure 1): Anhui, Fujian, Hainan, Henan, Hunan and Jiangxi, and each catchment has different weather, soil types and vegetation. All study catchments have in common that winters are dry and flash floods occur after intensive summer rainstorms. Catchment areas range between 105.3 and 722.0 km^2 (Table 1), and the average area of catchments is 272.3 km^2. Meteorological data are available from 37 rain gauges located within or in the close vicinity of the 6 catchments provided by the China Meteorological Data Service Center (http://data.cma.cn.). Data from rain gauges and hydrological stations are available only for the summer storm events, which includes hourly rainfall and hourly observed discharge data (provided by China Institute of Water Resources and Hydropower Research). The county weather stations provide the information about daily rainfall amounts outside of the storm events and daily air temperature data.

2.2 Catchment properties

The attributes have been selected for their potential to affect catchment hydrology (e.g., Addor et al., 2017; Berghuijs et al., 2014; Singh et al., 2014) and are available for whole China. The attributes are extracted from the following data sets.

2.2.1 Elevation

Topographical attributes such as altitude, aspect or slope are extracted from digital elevation model (DEM) data, and the resolution of the DEM is 30 m, which was provided by the Geospatial Data Cloud site, the Computer Network Information Center, and the Chinese Academy of Sciences (http://www.gscloud.cn).

2.2.2 Soil texture

Information about soil is provided by the Soil and Terrain database (SOTER) for China, version 1.0, at scale 1:1 million, compiled by the Institute of Soil Science, Chinese Academy of Science (ISSAS) and ISRIC-World Soil Information (Dijkshoorn et al., 2008). The soil texture was resampled to 30 m with the same resolution as DEM in this study.

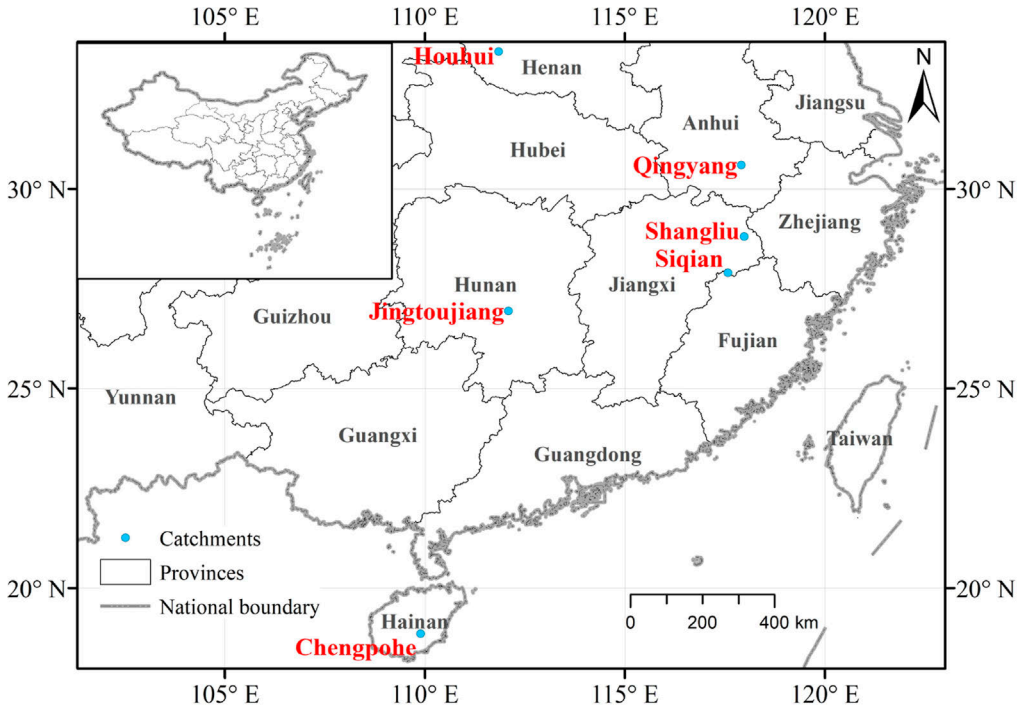

FIGURE 1
Map of study area showing the position of six catchments.

TABLE 1 Summary of study catchments.

Name	Province	Area (km^2)	River length (km)	No. of flood events	Annual precipitation (mm)	Annual air temperatures (°C)	Number of rainfall station
Qingyang	Anhui	122.5	24.8	19	1,368.2	16.4	4
Siqian	Fujian	134.7	31.1	58	1,871.8	18.5	4
Chengpohe	Hainan	722.0	177.1	1	2,395.3	22.9	13
Houhui	Henan	394.3	100.8	4	849.7	15.2	14
Jingtoujiang	Hunan	155.0	30.3	50	1,324.2	18.3	1
Shangliu	Jiangxi	105.3	35.9	1	1,820.7	17.7	1

2.2.3 Landuse and vegetation

Landuse and vegetation information is provided by the 2009 Global Land Cover Map (GlobCover) (Bontemps et al., 2011). The land cover map has a resolution of 300 m. For this study, it was resampled to 30 m with the same resolution as DEM.

3 Methodology

3.1 Flood forecasting framework

This study adopts a systematic approach to develop and validate a novel flood forecasting framework by integrating hydrological modeling with advanced optimization techniques. The flood forecasting framework comprising two main components (Figure 2): 1) Hydrological Model Development: The Xinanjiang model is enhanced with the Geomorphological Instantaneous Unit Hydrograph (GIUH) to improve runoff routing accuracy. This integration aims to account for geomorphological characteristics derived from Digital Elevation Models (DEMs), providing a robust representation of the hydrological processes in diverse catchments. 2) Parameter Optimization: The Cooperation Search Algorithm (CSA) is applied for efficient parameter optimization. CSA's collaborative and population-based mechanism ensures fast convergence to optimal solutions, addressing challenges like data scarcity and model complexity. We compared the performance of CSA with the Shuffled Complex Evolution University of Arizona (SCE-UA) algorithm to highlight its advantages.

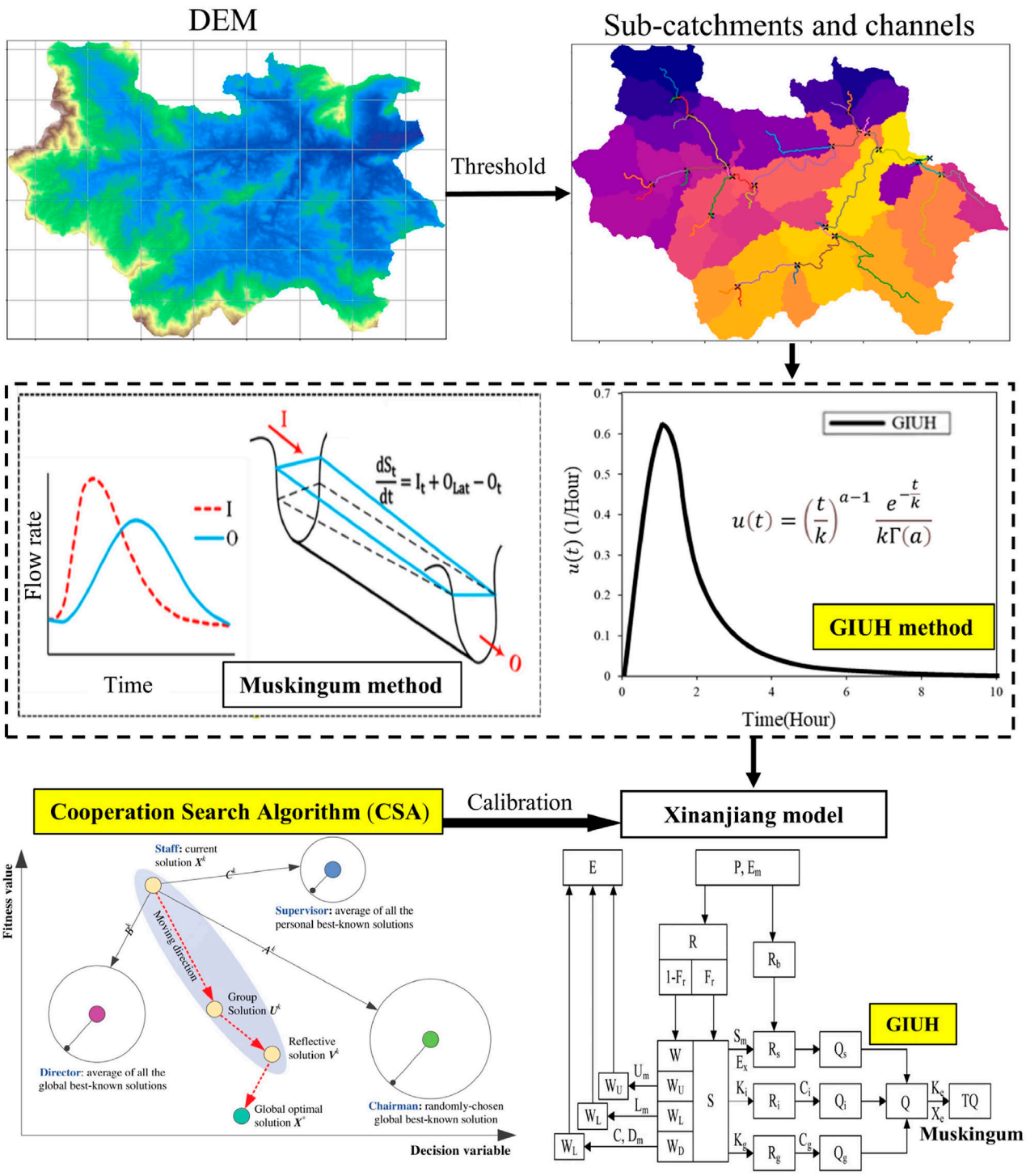

FIGURE 2
Flowchart of the cooperative search algorithm-based Flood Forecasting Framework.

3.1.1 Hydrological model

The Xinanjiang model was developed to forecast flows to the Xinanjiang reservoir by Zhao and Wang (1988). The main hypothesis used in the model development is the concept of runoff formation on repletion of storage. The original Xinanjiang model includes a runoff generating component and a runoff routing component. It has 6 parameters that include seven runoff generating component parameters (U_m, L_m, D_m, B, I_m, K, C) and 8 runoff routing parameters (S_m, E_x, K_g, K_i, C_g, C_i, K_e, X_e). The 15 parameters are abstract conceptual representations of non-measurable watershed characteristics that have to be calibrated by an optimization method. This is mainly because the manual

calibration can be a rather tedious and time-consuming task. The physical descriptions of these parameters are listed in Table 1. The value of each parameter is usually within a certain range according to physical and mathematical constraints, information about watershed characteristics, and from modeling experiences.

The geomorphological instantaneous unit hydrograph (GIUH, Bamufleh et al., 2020; Lei et al., 2023) is used for the routing of runoff from the overland flow plane to the river channel. GIUH based on Nash model, the equation for GIUH, which is a function of Horton ratios, is given by gamma distribution as (Nash, 1960). The formula for calculating this parameter is given in Equation 1:

$$u(t) = \left(\frac{t}{k}\right)^{a-1} \frac{e^{-\frac{t}{k}}}{k\Gamma(a)} \tag{1}$$

Where $u(t)$ is the ordinates of the GIUH, t is the time in hours, and $\Gamma(a)$ is the gamma function for argument a. a and k are called the shape and scale parameters respectively can be calculated from DEM (Lei et al., 2023). And the Muskingum method (McCarthy, 1938) is used for the channel flow routing process.

3.1.2 Parameter calibration method

This paper applies two parameter optimization algorithms, shuffled complex evolution of the University of Arizona (Duan et al., 1994) and Cooperation Search Algorithm (CSA, Feng et al., 2021), for the hydrological model parameter optimization, and compares the efficiency of the two optimization algorithms. SCE-UA algorithm, as a global search algorithm, was compared against the multi-start simplex (MSX) method and the adaptive random search (ARS) method on watershed model calibration problems (Duan et al., 1994). The results showed that SCE-UA was a much superior method than MSX and ARS method. The SCE-UA has been widely used in various watershed model calibrations (Sorooshian et al., 1993; Duan et al., 1994; Luce and Cundy, 1994; Gan and Biftu, 1996; Yapo et al., 1996; Cooper et al., 1997; Kuczera, 1997; Franchini et al., 1998; Abdulla et al., 1999; Thyer et al., 1999; Eckhardt and Arnold, 2001). Recently, the SCE-UA has also been applied with success to Soil and Water Assessment Tool (SWAT) for hydrologic parameters (Eckhardt and Arnold, 2001) and hydrologic and water quality parameters (van Griensven and Bauwens, 2003). Cooper et al. (2007) applied the global optimization SCE-UA method with the established hydrologic process-based constraints to calibrate the Tank Model. It is found that performances of the SCE and GA are better than simulated annealing. More recently, the SCE, simple genetic algorithm (SGA) and micro-genetic algorithm (μGA), are applied in the parameter calibration of a grid-based distributed rainfall-runoff model (GBDM) and their performances are compared (Wang et al., 2010). Goswami and O'Connor (2007) applied SCE-UA to calibrate SMAR model parameters. These studies demonstrate that the SCE-UA method is a robust, effective and efficient search algorithm.

The Cooperation Search Algorithm (CSA) is a novel metaheuristic optimization algorithm proposed by Feng et al. (2021). This algorithm is inspired by the collaborative behavior of modern corporate teams and is characterized by strong optimization ability and fast convergence. The objective function Nash-Sutcliffe efficiency (NSE) was used for parameter calibration. The CSA primarily consists of four stages: Team building phase, Team communication operator, Reflective learning operator, and Internal competition operator.

3.1.2.1 Team building phase

In this stage, all the staff members in the team are randomly assigned according to Equation 2. After evaluating the performance of all the solutions, $M \in [1, I]$ leader solutions will be selected from the initial swarm to form the external elite set.

$$x_{i,j}^{k} = \emptyset\left(\underline{x}_j, \overline{x}_j\right), i \in [1, I], j \in [1, J], k = 1 \tag{2}$$

where I is the number of solutions at the current swarm. $x_{i,j}^{k}$ is the j th value of the i th solution at the k th cycle. $\phi(L, U)$ is the function to generate a random number uniformly distributed in the range of $[L, U]$, $\underline{x}_j$ and $\overline{x}_j$ are the lower and upper limits of the j th variable. J is the number of decision variables.

3.1.2.2 Team communication operator

Each staff member can gain new information by exchanging knowledge with the chairman, as well as with the board of directors and supervisors. As shown in Equation 3, the team communication process involves three components: the chairman's knowledge A, the collective knowledge B from the board of directors, and the collective knowledge C from the board of supervisors. The chairman is randomly selected from the board of directors to simulate a rotating mechanism, while all members of the board of directors and supervisors are treated equally when calculating B and C.

$$u_{i,j}^{k+1} = x_{i,j}^{k} + A_{i,j}^{k} + B_{i,j}^{k} + C_{i,j}^{k}, i \in [1, I], j \in [1, J], k \in [1, K] \tag{3}$$

$$A_{i,j}^{k} = log(1/\emptyset(0,1)) \cdot \left(gBest_{ind,j}^{k} - x_{i,j}^{k}\right)$$

$$B_{i,j}^{k} = \alpha \cdot \emptyset(0,1) \cdot \left[\frac{1}{M}\sum_{m=1}^{M} gBest_{m,j}^{k} - x_{i,j}^{k}\right]$$

$$C_{i,j}^{k} = \beta \cdot \emptyset(0,1) \cdot \left[\frac{1}{I}\sum_{i=1}^{I} pBest_{i,j}^{k} - x_{i,j}^{k}\right]$$

where $u_{i,j}^{k+1}$ is the j th value of the i th group solution at the $k+1$ th cycle. $pBest_{i,j}^{k}$ is the j th value of the i th personal best-known solution at the k th cycle. $pBest_{ind,j}^{k}$ is the j th value of the ind th global best-known solution from the beginning to the kth cycle. ind is the index randomly selected from the set of $\{1, 2, \ldots, M\}$. $A_{i,j}^{k}$ denotes the knowledge gained from the chairman randomly chosen from the external elite set. $B_{i,j}^{k}$ and $C_{i,j}^{k}$ are the mean knowledge gained from M global best-known solutions found by far and I personal best-known solutions, respectively. α and β are the learning coefficients to adjust the influence degrees of $B_{i,j}^{k}$ and $C_{i,j}^{k}$.

3.1.2.3 Reflective learning operator

Aside from learning from the leader's solutions, the staff can also gain new knowledge by reflecting on their own experiences in the opposite direction, which can be expressed as follows:

$$v_{i,j}^{k+1} = \begin{cases} r_{i,j}^{k+1} \, if\left(u_{i,j}^{k+1} \geq c_j\right) \\ p_{i,j}^{k+1} \, if\left(u_{i,j}^{k+1} < c_j\right) \end{cases}, i \in [1, I], j \in [1, J], k \in [1, K]$$

$$r_{i,j}^{k+1} = \begin{cases} \emptyset\left(\underline{x}_j + \overline{x}_j - u_{i,j}^{k+1}, c_j\right) if\left(\left|u_{i,j}^{k+1} - c_j\right| < \emptyset(0,1) \cdot \left|\overline{x}_j - \underline{x}_j\right|\right) \\ \emptyset\left(\underline{x}_j, \underline{x}_j + \overline{x}_j - u_{i,j}^{k+1}\right) otherwise \end{cases}$$

$$p_{i,j}^{k+1} = \begin{cases} \emptyset\left(c_j, \underline{x}_j + \overline{x}_j - u_{i,j}^{k+1}\right) if\left(\left|u_{i,j}^{k+1} - c_j\right| < \emptyset(0,1) \cdot \left|\overline{x}_j - \underline{x}_j\right|\right) \\ \emptyset\left(\underline{x}_j + \overline{x}_j - u_{i,j}^{k+1}, \overline{x}_j\right) otherwise \end{cases}$$

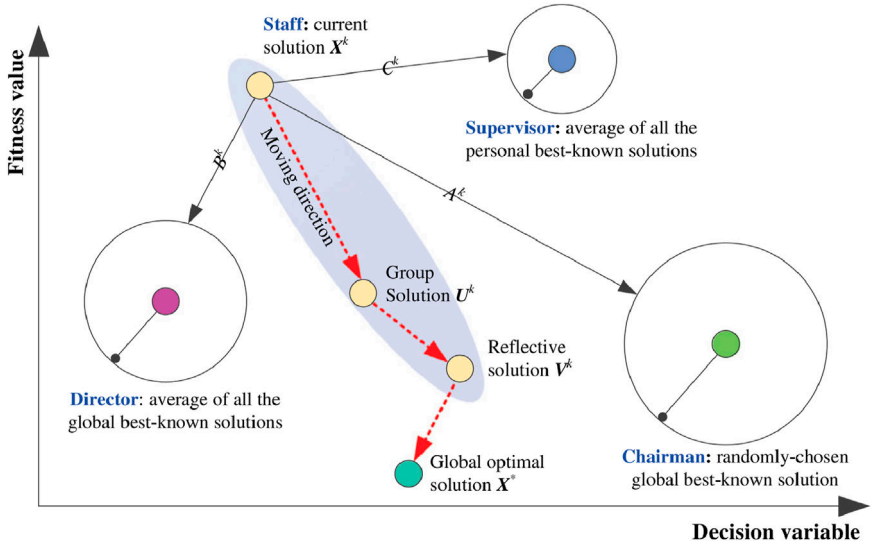

FIGURE 3
Sketch map of the CSA method.

TABLE 2 List of statistical metrics[a].

Statistical metrics	Unit	Equation	Perfect value
Nash-Sutcliffe efficiency (NSE)	NA	$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2}$	1
Absolute peak flood error (EQP)	%	$EQP = \lvert(Q_{oP} - Q_{sP})/Q_{oP}\rvert$	0

[a]Notation: T is total number of time step, Q_o^t is observed discharge at time t, Q_m^t is simulated discharge at time t, $\overline{Q_o}$ is average discharge of a flood event, Q_{oP} is the observed peak flow; Q_{sP} is the simulated peak flow.

$$c_j = \left(\underline{x}_j + \overline{x}_j\right) \cdot 0.5$$

where $v_{i,j}^{k+1}$ is the j th value of the i th reflective solution at the $k+1$ th cycle.

3.1.2.4 Internal competition operator

The team gradually enhances its market competitiveness by ensuring that all staff members with better performance are consistently retained, which can be expressed as follows:

$$x_{i,j}^{k+1} = \begin{cases} u_{i,j}^{k+1} \, if\left(F\left(\boldsymbol{u}_{i,j}^{k+1}\right) \le F\left(\boldsymbol{v}_{i,j}^{k+1}\right)\right) \\ v_{i,j}^{k+1} \, if\left(F\left(\boldsymbol{u}_{i,j}^{k+1}\right) > F\left(\boldsymbol{v}_{i,j}^{k+1}\right)\right) \end{cases}, i \in [1,I], j \in [1,J], k \in [1,K]$$

where $F(\boldsymbol{x})$ is the fitness value of the solution $\boldsymbol{x}$. To effectively multiple physical constraints, all the variables in $\boldsymbol{x}$ are firstly modified to the feasible zone by Equation 4, and then the penalty functions method in Equation 5 is used to obtain the fitness value $F(\boldsymbol{x})$ by merging the constraint violation value into the objective value $f(\boldsymbol{x})$. Then, for feasible solutions, all the constraints are well met so that the fitness value is equal to the original objective value; for infeasible solutions, the constraint violation value becomes positive so that the fitness value is larger than the objective value. In this way, the swarm can be guided to feasible search area as far as possible.

$$x_j = \max\left\{min\left\{x_j, \overline{x}_j\right\}, \underline{x}_j\right\} \tag{4}$$

$$F(\boldsymbol{x}) = f(\boldsymbol{x}) + \sum_{e=1}^{E} c_e^1 \cdot \max\left\{g_e(\boldsymbol{x}), 0\right\} + \sum_{f=1}^{F} c_f^2 \cdot \left|h_f(\boldsymbol{x})\right| \tag{5}$$

where x_j is the j th value in the solution $\boldsymbol{x}$ to be evaluated. c_e^1 is the penalty coefficient for the eth inequality constraint. c_f^2 is the penalty coefficient for the f th inequality constraint.

The pseudo-code of the CSA method is given as below:

Via the above carefully-designed operators, the CSA method in Figure 3 can effectively improve the quality of all the obtained solutions to approximate the global optima. Next, the traits of the CSA method are summarized as below.

1) Compared with individual-based methods, the population-based evolutionary mechanism used in CSA generates multiple solutions within the search space, which helps identify promising regions and escape from local optima.
2) The swarm achieves a balance between global exploitation and local exploration through the team communication and reflective learning operators, which increases the likelihood of approximating the global optimal solution.
3) With the internal competition operator, the best solutions discovered so far are stored and dynamically updated during the evolutionary process, which effectively ensures the global convergence of the population.
4) The optimization problem is treated as a black box, where the output depends only on specific inputs. As a result, the CSA method can theoretically be applied to any optimization problem. This allows the operator to focus on the modeling

TABLE 3 Parameters to be calibrated.

	Parameter	Physical description	Unit	Initial range
Runoff generating parameter				
1	K	Ratio of potential evapotranspiration to pan evaporation	[-]	0.1–0.2
2	U_m	Averaged soil moisture storage capacity of the upper layer	[mm]	10–30
3	L_m	Averaged soil moisture storage capacity of the lower layer	[mm]	10–60
4	D_m	Averaged soil moisture storage capacity of the deep layer	[mm]	10–80
5	C	Coefficient of the deep layer that depends on the proportion of the catchment area covered by vegetation with deep roots	[-]	0.1–0.3
6	B	Exponential parameter with a single parabolic curve, which represents the non-uniformity of the spatial distribution of the soil moisture storage capacity over the catchment	[-]	0.1–0.9
7	I_m	Percentage of impervious and saturated areas in the catchment	[%]	0.0–0.2
Runoff routing parameter				
8	S_m	Areal mean free water capacity of the surface soil layer, which represents the maximum possible deficit of free water storage	[mm]	5–50
9	E_x	Exponent of the free water capacity curve influencing the development of the saturated area	[-]	1.1–1.5
10	K_g	Outflow coefficients of the free water storage to groundwater relationships	[-]	0.1–0.8
11	K_i	Outflow coefficients of the free water storage to interflow relationships	[-]	0.1–0.5
12	C_i	Recession constants of the lower interflow storage	[-]	0.1–0.99
13	C_g	Recession constants of the groundwater storage	[-]	0.7–0.99
14	K_e	Parameter of the Muskingum method	[-]	1–3
15	X_e	Parameter of the Muskingum method	[-]	0.1–0.5

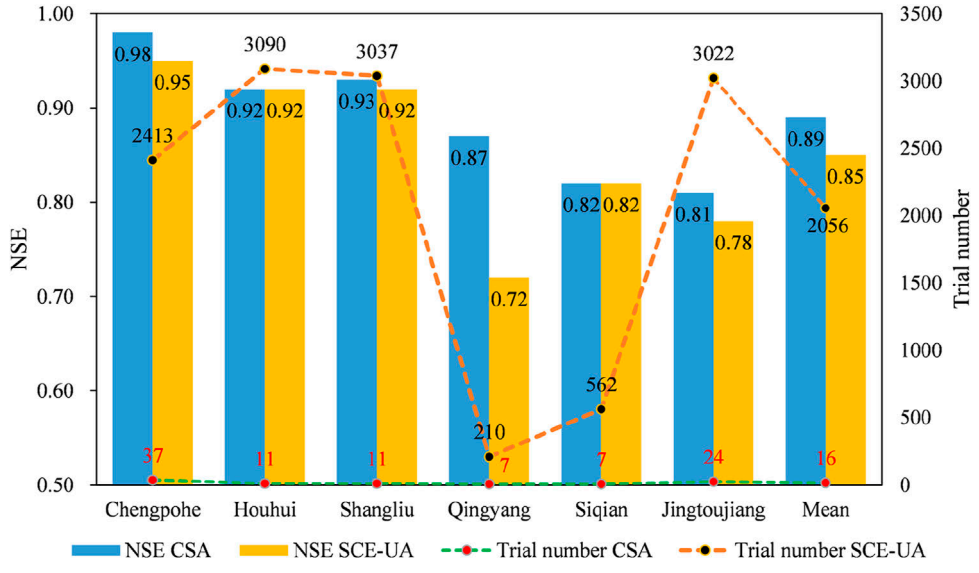

FIGURE 4
The parameter optimization trial number and objective function (NSE) graph of the CSA and SCE-UA algorithms.

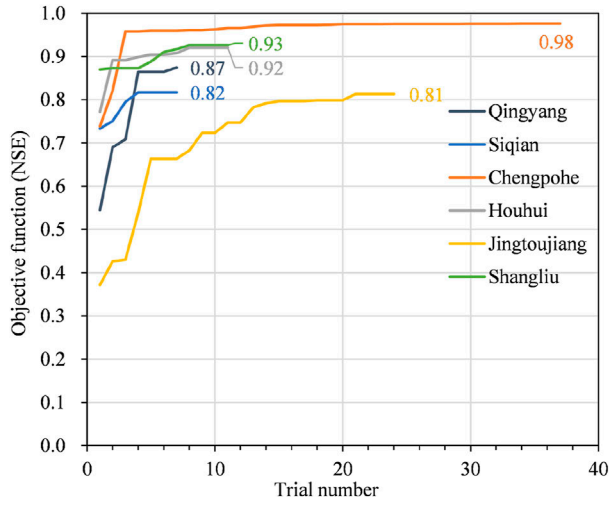

FIGURE 5
The parameter optimization trial number and objective function (NSE) the CSA algorithms.

process rather than the development of the optimization algorithm, thereby improving work efficiency.

5) In CSA, the original large swarm can be naturally divided into several small but independent subpopulations, which can be processed on multiple different computing units. In other words, developing a parallel version of CSA to improve execution time and solution quality in high-performance computing environments is straightforward.

3.2 Model evaluation

The evaluation of the model's performance focuses on two key aspects.

3.2.1 Overall streamflow fit

The model's ability to reproduce streamflow dynamics at the event scale is assessed using the Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970; Table 2) metric. This statistic evaluates how well the simulated streamflow matches observed data, providing an overall measure of model accuracy.

3.2.2 Streamflow extremes

The model's capability to accurately simulate critical flood characteristics, such as peak flow and peak timing, is evaluated using the Absolute Peak Flood Error (EQP, Table 2). These metrics are essential for effective flood warning and disaster management.

The evaluation of the model performance aimed to (1) assess the capacity of the model to reproduce an overall streamflow fit at the event scale and (2) evaluate its ability to accurately identify streamflow extremes, i.e., the peak flow and the peak time, which are important for flood warning. The Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe, 1970) metric is used to assess the overall streamflow fit, and the absolute peak flood error (EQP) is used to evaluate the performance of peak flow (Table 2).

4 Results

4.1 Comparison of optimization algorithms

Using the same initial parameter values and parameter optimization range (Table 3), the CSA and SCE-UA algorithms were applied separately to calibrate the parameters for the six catchments. Due to a little flood event in the Chengpohe, Houhui, and Shangliu catchments, only parameter calibration was performed for these three catchments. The calibration periods for the Qingyang, Siqian, and Jingtoujiang catchments are 1995–1997, 1971–1976, and 1994–1998, respectively. The validation periods are 1997–2013, 1971–1992, and 1998–2004, respectively. The resulting number of optimization trials and the optimal NSE values are shown in Figure 4. The results show that CSA required an average of 16 trials, compared to 2056 for SCE-UA, making it over 100 times more efficient while achieving higher NSE values.

Figure 5 shows the convergence process of the CSA during parameter optimization of the Xinanjiang model for various river catchments. The vertical axis represents the objective function (Nash-Sutcliffe Efficiency, or NSE), which is a measure of model performance. Higher NSE values indicate better model accuracy in simulating the observed data. The horizontal axis represents the trial number, which corresponds to the iteration count in the optimization process.

Each line in the plot represents a different river catchment (Qingyang, Siqian, Chengpohe, Houhui, Jingtoujiang, and Shangliu), and the progress of each line shows how the NSE value improves with each iteration. The results showed that: chengpohe Catchment (orange line): the CSA algorithm achieves rapid convergence for Chengpohe, reaching a high NSE value of 0.98 in the first few iterations and maintaining this performance, indicating effective optimization. Shangliu Catchment (green line): the optimization process for Shangliu also shows fast convergence, reaching an NSE of 0.93 after about 10 iterations. Houhui Catchment (gray line): Houhui reaches an NSE of 0.92 after around 10 iterations, with a stable performance afterward. Siqian Catchment (blue line): Siqian's optimization curve shows slower convergence compared to the catchments above but achieves an NSE of 0.82 within 5 iterations. Qingyang Catchment (dark blue line): Qingyang reaches an NSE of 0.87 after around 5 iterations, showing gradual improvement. Jingtoujiang Catchment (yellow line): This catchment shows the slowest convergence, gradually increasing to an NSE of 0.81 over 20 iterations. In summary, the CSA algorithm effectively converges to high NSE values for most catchments within a reasonable number of iterations, particularly for the Chengpohe, Shangliu, and Houhui catchments, which achieved NSE values above 0.9.

The rapid convergence of CSA is evident from the optimization curves shown in Figure 4, where most catchments reached high NSE values within a few iterations. For instance, the Chengpohe catchment attained an NSE of 0.98 within 37 trials, whereas SCE-UA required 2,413 trials to achieve a slightly lower NSE of 0.95. This efficiency highlights the advantages of CSA's population-based evolutionary mechanism, which balances global exploration and local exploitation to approximate optimal solutions effectively.

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TABLE 4 Calibrated parameters of Xinanjiang model with CSA.

Parameters	Qingyang	Siqian	Chengpohe	Houhui	Jingtoujiang	Shangliu
K	0.12	0.12	0.15	0.11	0.10	0.11
U_m	18.37	25.94	12.89	29.84	10.17	24.29
L_m	27.12	11.80	25.55	29.28	13.15	18.55
D_m	18.96	70.15	40.10	24.32	57.82	15.00
C	0.13	0.10	0.20	0.15	0.10	0.16
B	0.37	0.40	0.40	0.31	0.40	0.27
I_m	0.17	0.20	0.13	0.20	0.11	0.14
S_m	25.00	22.56	15.75	24.78	5.21	6.43
E_x	1.21	1.02	1.50	1.31	1.34	1.10
K_g	0.20	0.44	0.46	0.53	0.38	0.75
K_i	0.41	0.46	0.44	0.38	0.29	0.11
C_i	0.84	0.70	0.70	0.73	0.79	0.75
C_g	0.98	0.98	0.95	0.93	0.96	0.94
K_e	2.62	1.63	1.21	2.67	3.64	1.00
X_e	0.31	0.13	0.33	0.26	0.20	0.18

TABLE 5 Statistical metrics of six catchments.

	NSE		EQP (%)	
	Calibration	Validation	Calibration	Validation
Qingyang	0.87	0.84	2.12	2.32
Siqian	0.82	0.83	3.25	5.21
Chengpohe	0.98	—	0.22	—
Houhui	0.92	—	5.25	—
Jingtoujiang	0.81	0.84	5.54	4.54
Shangliu	0.93	—	3.63	—

Table 4 shows the calibrated parameters of the Xinanjiang model, optimized using the CSA for the various catchments. Each row represents a different parameter of the model, and the columns show the values of these parameters for different catchments. The values in Table 4 show that each parameter varies across catchments, which indicates that each catchment has unique hydrological characteristics that were captured during the optimization process by CSA. K values vary between 0.1 and 0.15, showing similar ratio of potential evapotranspiration to pan evaporation across catchments. U_m, L_m, D_m and S_m values vary significantly, indicating differences in soil moisture capacities and storages among catchments. Parameter K_e and X_e of Muskingum method vary significantly, indicating differences in topography, channel structure, soil characteristics, and storage capacity among the catchments, which affect how each catchment responds to rainfall and contributes to runoff.

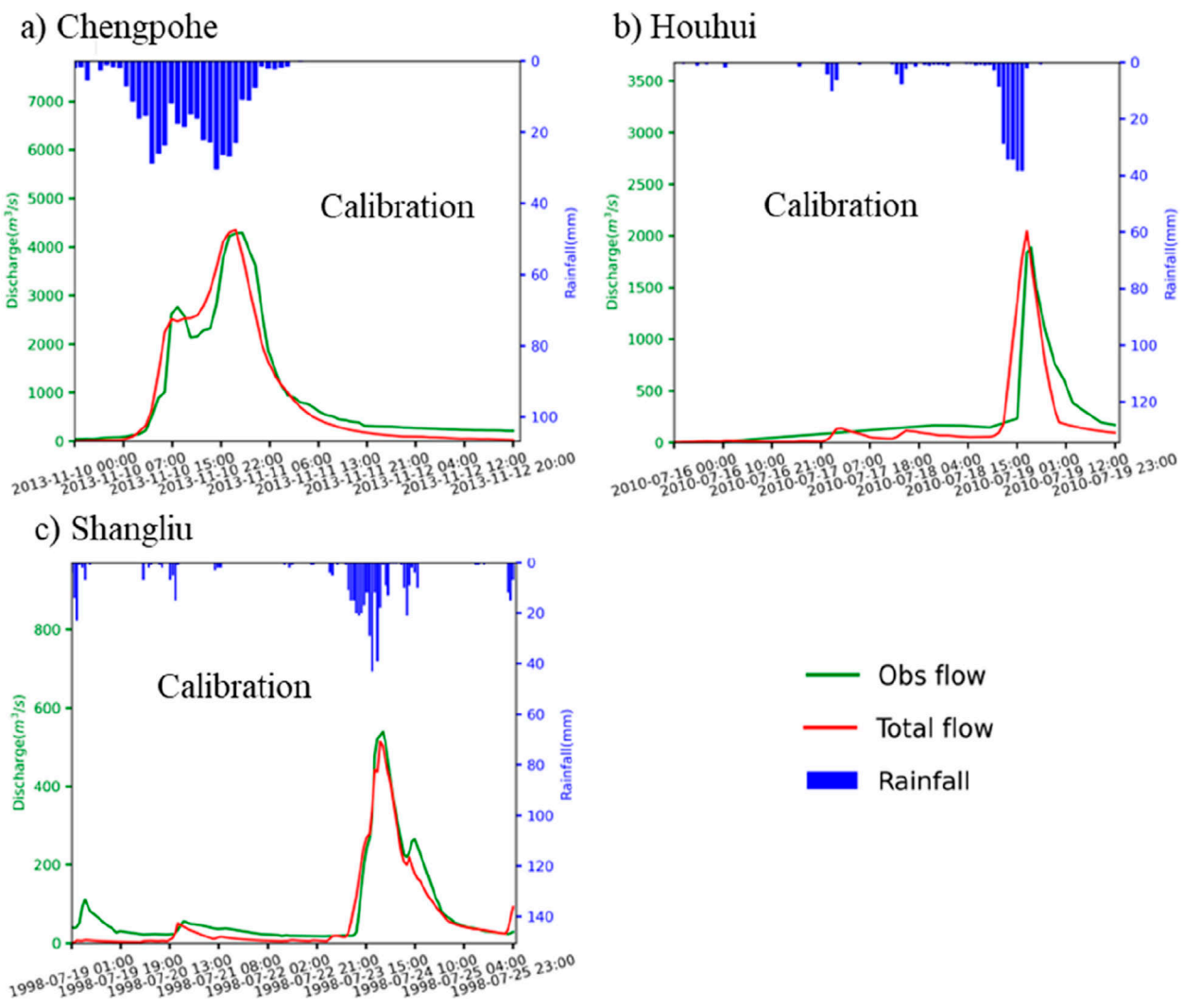

FIGURE 6
Flow hydrographs simulated by the flood forecasting framework for the three data-scare catchments (Obs flow: observed discharge; Total flow: simulated discharge; Rainfall: observed rainfall). **(A)** Chengpohe. **(B)** Houhui. **(C)** Shangliu.

4.2 Performance in data-scarce catchments

The Chengpohe, Houhui, and Shangliu catchments were calibrated using the CSA optimization method; however, their flood event records were insufficient to conduct a robust validation analysis. Despite this limitation, the model's calibration results in these catchments demonstrated exceptional performance, as reflected by the Nash-Sutcliffe Efficiency (NSE) values (Table 5). For Chengpohe, the NSE reached 0.98, indicating that the CSA achieved near-perfect alignment between the observed and simulated streamflows. Similarly, the Houhui and Shangliu catchments exhibited NSE values of 0.92 and 0.93, respectively, underscoring the algorithm's ability to optimize the Xinanjiang model parameters effectively.

The flow hydrographs (Figure 6) illustrate the CSA's capability to closely capture the temporal dynamics of streamflow during calibration. The simulated discharge in these catchments aligns well with the observed data, particularly in reproducing the peak flows and timing, which are critical for flood forecasting. The Chengpohe catchment, in particular, showcased the model's efficiency in simulating high-intensity flood events with a limited dataset. However, the lack of validation data in these catchments poses challenges for assessing the model's generalizability. It remains uncertain whether the parameters optimized using CSA would perform consistently under different climatic or hydrological conditions. This underscores the need for additional flood event records to validate the robustness and reliability of the CSA-optimized parameters. Future efforts should focus on expanding the dataset for these catchments to validate the model's robustness. Incorporating regional hydrological characteristics through parameter transfer techniques may also enhance model reliability in data-scarce regions.

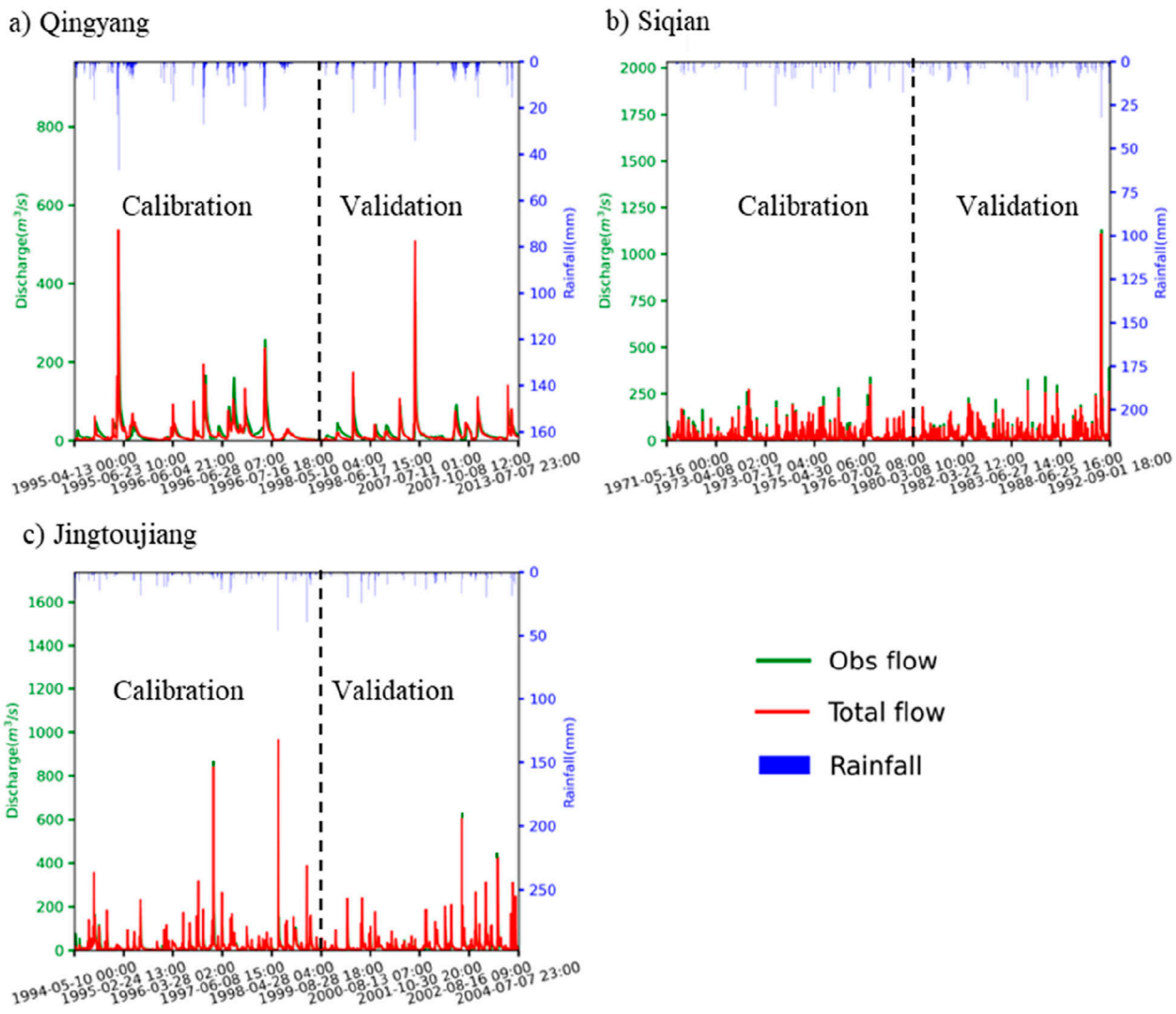

FIGURE 7
Flow hydrographs calibrated and validated by the flood forecasting framework for the three data-rich catchments (Obs flow: observed discharge; Total flow: simulated discharge; Rainfall: observed rainfall). **(A)** Qingyang. **(B)** Siqian. **(C)** Jingtoujiang.

4.3 Performance in data-rich catchments

In contrast, the Qingyang, Siqian, and Jingtoujiang catchments provided extensive datasets, allowing for both calibration and validation. The CSA-optimized parameters performed well, with NSE values of 0.87, 0.82, and 0.81 during calibration, and 0.84, 0.83, and 0.84 during validation (Table 5). Figure 7 demonstrates that the Xinanjiang model, calibrated using the CSA, simulates the flow hydrographs with a high degree of accuracy in these catchments. The model's ability to replicate the observed discharge, particularly during critical high-flow events, is evident, showcasing the CSA's effectiveness in parameter optimization.

The peak flow comparison in Figure 8 for the calibration period reveals that the model's predictions are in close agreement with the observed peak flows, indicating a strong capability to capture the extreme hydrological events. This is further supported by the flow process comparison in the calibration period, where the model's simulated hydrograph closely follows the observed hydrograph, suggesting a reliable representation of the catchment's response to rainfall.

The Qingyang catchment exhibited consistent performance across calibration and validation, with low Absolute Peak Flood Error (EQP) values of 2.12% and 2.32%, respectively (Table 5). This indicates reliable predictions of both magnitude and timing of peak flows. In the Siqian catchment, while the model performed well during calibration, it slightly underestimated extreme peak flows during validation, as shown in Figure 8. This discrepancy may reflect the catchment's complex hydrological response to extreme rainfall events.

The validation of the model's performance in these catchments is further reinforced by the statistical metrics provided in Table 2. The Nash-Sutcliffe Efficiency (NSE) values, as mentioned in this paper, are relatively high for these catchments, indicating a good overall streamflow fit. The Absolute Peak Flood Error (EQP) values are also within acceptable limits, demonstrating the model's accuracy in predicting peak flows, which is essential for flood warning systems.

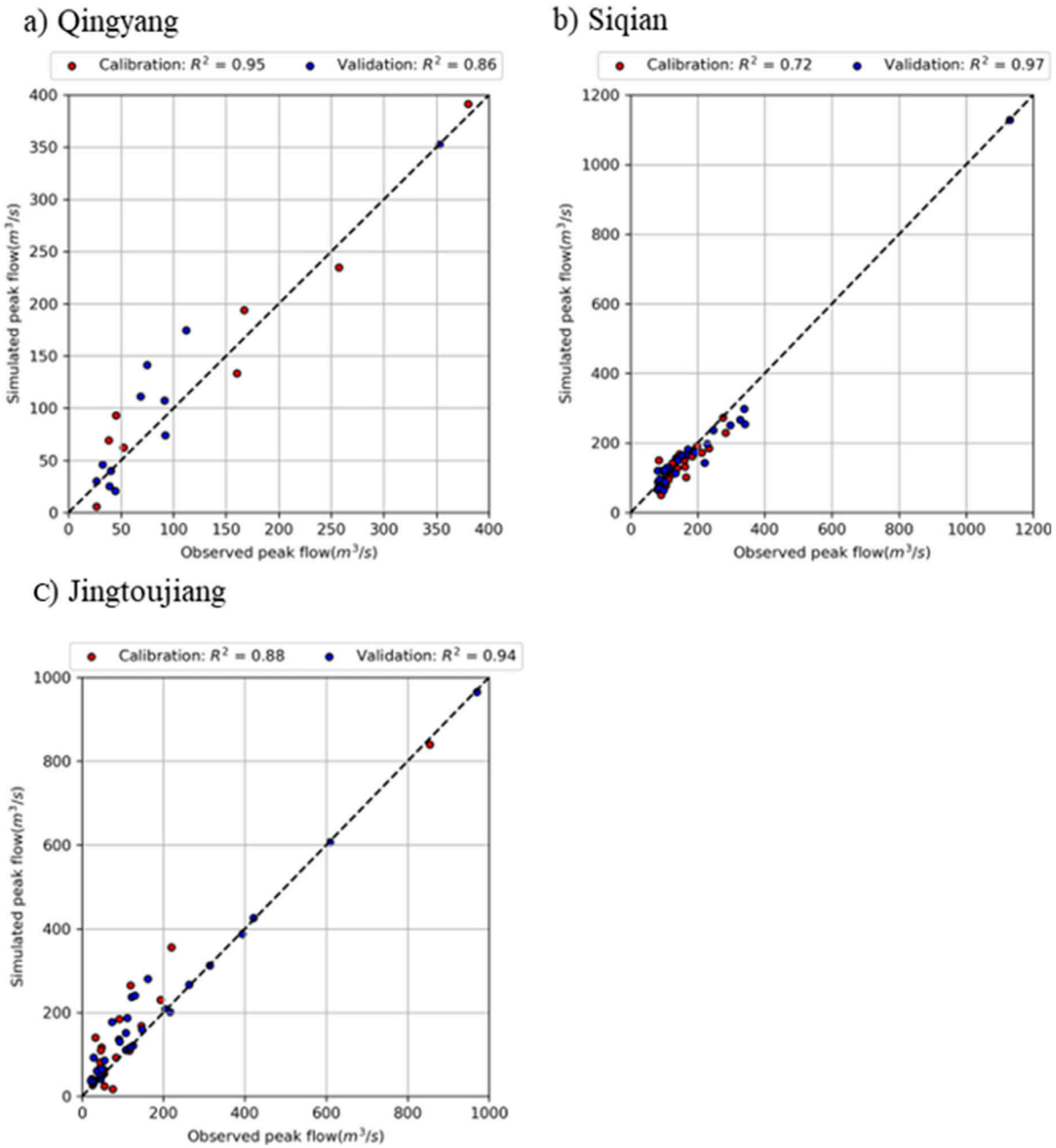

FIGURE 8
Comparison chart of observed and simulated peak flow. **(A)** Qingyang. **(B)** Siqian. **(C)** Jingtoujiang.

5 Discussion

5.1 General discussion on model performance and CSA's role in parameter calibration

The CSA-optimized flood forecasting framework demonstrated strong performance across all six catchments, achieving high NSE values and accurately capturing peak flows and timings. Notably, the framework excelled in data-scarce catchments, where traditional models often struggle due to limited historical data. For example, in the Chengpohe catchment, CSA achieved an NSE of 0.98 with only 37 optimization trials, significantly outperforming the SCE-UA algorithm, which required 2,413 trials to reach an NSE of 0.95.

This efficiency can be attributed to CSA's population-based evolutionary mechanism, which effectively balances global exploration and local exploitation. By retaining elite solutions through its internal competition operator, CSA converges quickly while avoiding local optima. These

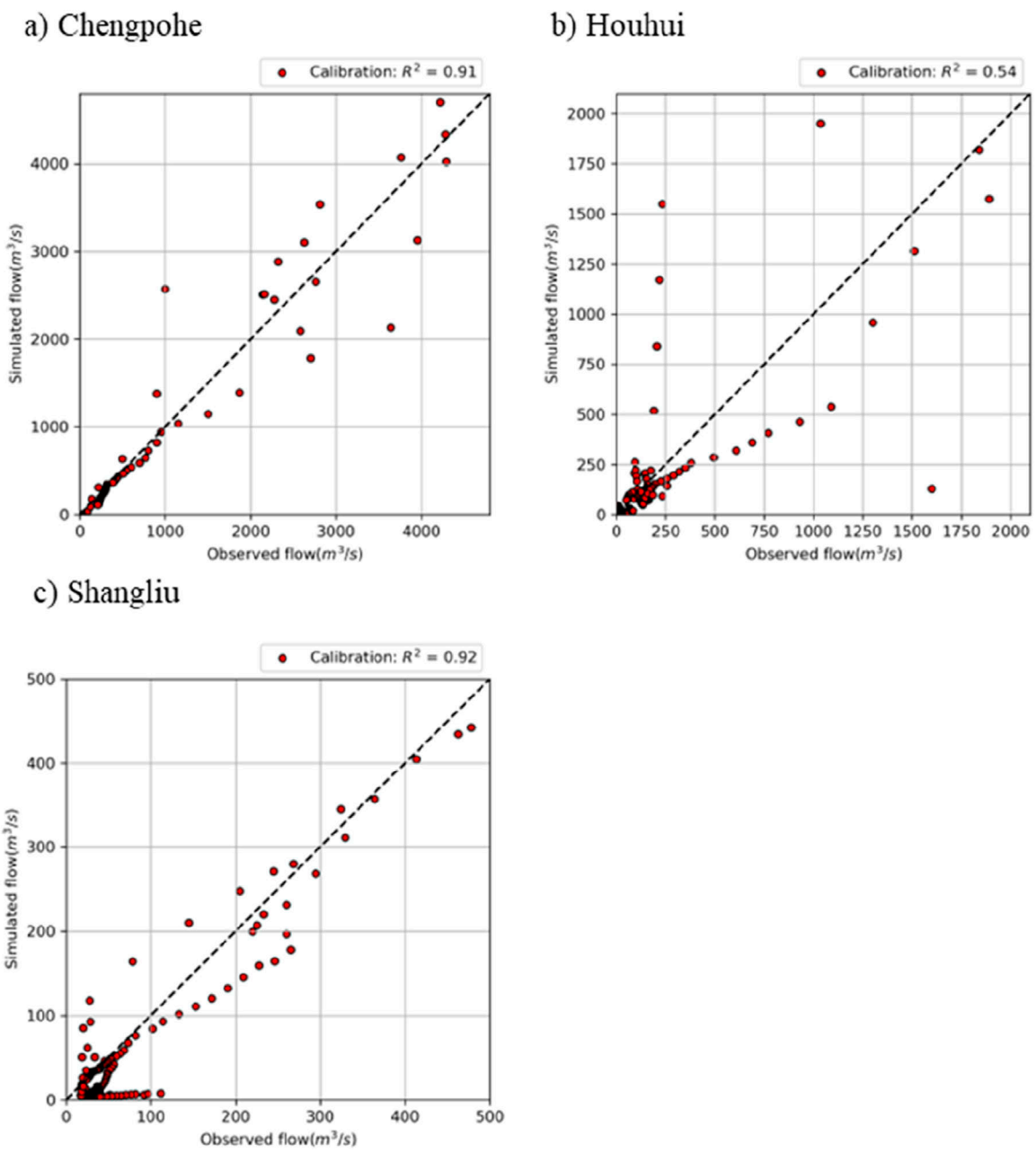

FIGURE 9
Comparison chart of observed and simulated flow process. **(A)** Chengpohe. **(B)** Houhui. **(C)** Shangliu.

characteristics make CSA particularly suitable for resource-constrained settings or time-sensitive applications like real-time flood forecasting.

However, the absence of validation datasets in data-scarce catchments such as Chengpohe, Houhui, and Shangliu limits the assessment of model generalizability. While the calibration results are promising, the lack of independent validation data poses challenges for assessing the robustness of the CSA-optimized parameters under different hydrological conditions.

5.2 General observations and implications for flood forecasting

Overall, the application of CSA to the flood forecasting framework significantly improved parameter optimization efficiency and simulation accuracy, particularly in the catchments with adequate calibration data. The CSA's rapid convergence to optimal parameter values (average trial number of 16 compared to 2056 for SCE-UA, Figure 4) is a key advantage, especially for catchments with complex hydrological characteristics like

Chengpohe. The high NSE values achieved during calibration demonstrate the algorithm's effectiveness in fine-tuning model parameters to match observed stream flows.

However, the validation results underscore the importance of a comprehensive dataset for model calibration and testing. The limited flood events in Chengpohe, Houhui, and Shangliu restrict the ability to fully evaluate the model's predictive capabilities (Figure 9). Figure 9B) showed that the correlation coefficient (R^2) between observed and simulated flow in the Houhui watershed is 0.54. Although the peak flow fits well, the overall flood process simulation is less accurate. While the validation results in Qingyang, Siqian, and Jingtoujiang suggest some sensitivity to varying hydrological conditions. This highlights the necessity of robust validation datasets and potentially the inclusion of regionalization techniques to enhance model performance in data-scarce catchments.

The CSA-optimized flood forecasting framework holds significant promise for improving flood forecasting capabilities in diverse catchments. Its ability to capture peak flows and timing is particularly valuable for flash flood warning systems. Future research should focus on extending the dataset for validation, integrating additional hydrological insights into the CSA framework, and exploring the model's applicability to other catchment types under varying climatic conditions.

Moreover, the ability to accurately predict peak flows and timing, as demonstrated in this study, makes the model well-suited for flash flood forecasting, where rapid responses are required. The framework's applicability to diverse climatic and hydrological conditions further enhances its potential as a global tool for flood management and early warning systems.

However, while the CSA-optimized model has shown promising results, its performance under real-time conditions should be further tested. Implementing the model in real-world flood forecasting systems would require continuous data assimilation and real-time calibration to ensure that the model adapts to rapidly changing conditions. Future research should focus on integrating the model with real-time data sources, such as satellite-based rainfall estimates and streamflow observations, to evaluate its performance in dynamic, operational settings.

5.3 Limitations and future directions

While the results demonstrate the robustness and efficiency of the CSA-optimized framework, several limitations must be addressed.

5.3.1 Dependence on high-quality DEMs

The accuracy of GIUH relies heavily on the resolution and quality of DEM data. In regions with low-resolution DEMs, the model's ability to simulate geomorphological processes may be compromised. Future research should explore the integration of satellite-based topographical data or machine learning techniques to enhance DEM quality and applicability.

5.3.2 Limited validation datasets

The absence of extensive flood event records in data-scarce catchments restricts the ability to fully validate the model's performance under diverse conditions. Expanding validation datasets through collaborative efforts or by employing parameter regionalization techniques can help address this limitation.

5.3.3 Real-time application challenges

Although the framework demonstrates strong performance, its real-time application requires integration with dynamic data sources such as satellite rainfall estimates or streamflow sensors. This would allow for continuous data assimilation and adaptive calibration, ensuring accurate predictions during rapidly changing flood conditions.

5.3.4 Generalizability across diverse climates

Testing the model across catchments with varied climatic and hydrological conditions will provide deeper insights into its scalability and robustness. For example, applying the framework to arid or snow-dominated regions may uncover additional parameter adjustments or methodological improvements. This will help assess the robustness and generalizability of the model, ensuring its applicability in diverse real-world flood forecasting scenarios. The integration of more advanced techniques, such as hybrid modeling or machine learning, could further enhance the model's predictive capabilities and adaptability.

6 Conclusion

This study successfully integrates the Geomorphological Instantaneous Unit Hydrograph (GIUH) with the Xinanjiang model, optimized by the Cooperation Search Algorithm (CSA), to develop an efficient and robust flood forecasting framework. Key findings include.

6.1 Efficient parameter optimization

The CSA significantly outperforms the Shuffled Complex Evolution University of Arizona (SCE-UA) algorithm, achieving higher Nash-Sutcliffe Efficiency (NSE) values with far fewer optimization trials (an average of 16 trials for CSA compared to 2056 for SCE-UA). This substantial improvement in computational efficiency makes CSA an ideal choice for resource-constrained regions.

6.2 Performance in data-scarce catchments

In catchments with limited flood event data, such as Chengpohe, Houhui, and Shangliu, the CSA-optimized model demonstrated exceptional performance, with NSE values exceeding 0.9. This highlights CSA's robustness in data-scarce settings and its potential to provide accurate flood forecasting even in regions with sparse hydrological data.

6.3 Validation in data-rich catchments

The model also showed strong performance in data-rich catchments (e.g., Qingyang, Siqian, and Jingtoujiang), accurately

simulating both streamflow dynamics and peak flows during calibration and validation. The low Absolute Peak Flood Error (EQP) values confirmed the model's ability to predict flood peaks and timings reliably.

6.4 Enhanced runoff routing

Integrating GIUH improved the model's ability to capture streamflow dynamics during extreme rainfall, showcasing the value of combining conceptual and geomorphological approaches.

6.5 Flood management and practical applications

The CSA-optimized model offers a computationally efficient and scalable tool for operational flood forecasting, with particular relevance to flash flood prediction. Its ability to simulate critical flood characteristics, such as peak flow and peak timing, makes it highly applicable for early warning systems in flood-prone regions. Moreover, the model's adaptability to different hydrological and climatic conditions suggests its potential for global use in flood risk management and disaster preparedness.

6.6 Future directions

Expanding datasets, refining optimization constraints, and testing across diverse climates and hydrological models are recommended to further enhance its robustness.

This study demonstrates the CSA-optimized framework's effectiveness, but further research is needed to validate its robustness by expanding flood event datasets, integrating real-time data, and testing it in diverse climatic conditions. In summary, the CSA-optimized Xinanjiang model, enhanced with GIUH, provides a powerful, efficient, and reliable approach for flood forecasting. This study contributes to advancing hydrological modeling techniques and offers practical tools for flood risk mitigation, with significant potential for improving disaster management and resilience in flood-prone regions worldwide.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JY: Writing–original draft. LW: Writing–original draft. JG: Writing–review and editing. YC: Writing–review and editing. YZ: Writing–review and editing. YW: Writing–review and editing. MM: Writing–review and editing.

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Conflict of interest

Author JY was employed by Shanxi Water Resources Research Institute Co., Ltd. Author YZ was employed by Shaoxing Designstitute of Water Conservancy and Hydro-Electric Power Co., Ltd.

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Utilizing deep learning for intelligent monitoring and early warning of slope disasters in public space design

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Introduction: The increasing frequency of slope disasters in urban and recreational public spaces, driven by climate change, presents significant risks to public safety and sustainable urban design. Conventional slope stability monitoring systems rely heavily on static models and manual interventions, often lacking adaptability and real-time predictive capacity. Earlier methods, including rule-based and empirical approaches, use fixed thresholds to assess risk factors such as soil moisture, slope angle, and seismic activity. Although machine learning models like decision trees and support vector machines have improved predictions using historical data, their scalability and adaptability remain constrained due to the need for intensive feature engineering and their limited ability to model complex nonlinear dynamics.

Methods: This study introduces a novel framework utilizing Deep Learning techniques to enable intelligent, real-time monitoring and early warning of slope disasters. The Adaptive Spatial Design Model (ASDM) incorporates real-time geospatial data, user behavior analytics, and environmental sensing to dynamically assess risk. It employs convolutional and recurrent neural networks for geo-hazard prediction, graph-theoretic optimization for decision-making, and adaptive spatial strategies to enhance model accuracy and responsiveness in changing environments.

Results: Experimental validation on real-world datasets shows that the proposed system effectively reduces false alarms and improves response times by 35% compared to traditional methods. The integration of neural network-based prediction with adaptive spatial planning enhances both the precision and timeliness of disaster warnings.

Discussion: This framework offers a transformative, safe, and functional approach to slope disaster management in dynamic public spaces. It advances sustainability and resilience by optimizing spatial design and human-environment interactions. The model's adaptability to environmental changes represents a significant improvement in urban design and disaster mitigation strategies.

KEYWORDS

slope disasters, adaptive design, deep learning, real-time monitoring, public space design

1 Introduction

Slope disasters, including landslides and rockfalls, pose severe threats to public safety and infrastructure, especially in urban and recreational environments where unstable terrains interact with human activities (Matthys et al., 2023). Effective monitoring and early warning systems are essential for mitigating these risks, ensuring both the protection of human lives and the sustainable design of public spaces. However, traditional monitoring approaches, which primarily rely on static models and manual inspections, often struggle with real-time adaptability, terrain complexity, and cost-effectiveness (Liu, 2022). Recent advances in artificial intelligence (AI), particularly deep learning, have paved the way for more robust and automated solutions for slope disaster monitoring. In this study, we investigate the evolution of AI-driven methods for slope disaster detection and prediction (Yusuff et al., 2023), focusing on the shift from conventional feature-engineered models to modern deep learning architectures. Despite these advancements, challenges remain in integrating multi-source geospatial data, improving interpretability, and enhancing real-time adaptability. To address these gaps, we propose a novel deep learning framework that leverages multimodal data fusion and adaptive optimization to enhance the accuracy and efficiency of slope disaster monitoring in dynamic public spaces.

The increasing frequency of slope disasters in urban and recreational public spaces, exacerbated by climate change, has been well documented in recent studies. Extreme precipitation events have intensified due to global warming, significantly increasing the likelihood of landslides in vulnerable regions. Global Fatal Landslide Occurrence from 2004 to 2016 Froude and Petley (2018) analyzed over 4,800 landslide events and found that rainfall-triggered slope failures have become more frequent, with a notable rise in urban and peri-urban environments. Deciphering the Effect of Climate Change on Landslide Activity: A Review Crozier (2010) highlights how rising temperatures contribute to permafrost degradation, reducing slope stability and increasing disaster risk. These findings underscore the urgent need for intelligent monitoring systems that integrate climate-adaptive design strategies to enhance public safety in urban environments.

Traditional approaches to slope disaster monitoring, such as symbolic AI and rule-based systems, rely on predefined thresholds for soil moisture, slope angles, and seismic activities to identify risks. While these methods provide interpretability and alignment with expert knowledge, they exhibit critical shortcomings in adaptability to dynamic terrains and real-time environmental changes Wei et al. (2024). Machine learning-based models, such as decision trees, support vector machines (SVMs), and random forests, have improved prediction accuracy by leveraging historical data, but they require extensive manual feature engineering and struggle to capture highly nonlinear relationships inherent in slope instability. Existing deep learning approaches, despite their success in satellite imagery analysis, often fail to integrate multimodal real-time sensor data effectively, limiting their applicability for early warning systems. To address these challenges, we propose the Adaptive Spatial Design Model (ASDM), which integrates multimodal data fusion, lightweight transformer-based architectures, and adaptive spatial optimization Zhao et al. (2025). By incorporating real-time geospatial data, user behavior analytics, and environmental sensing, ASDM dynamically assesses slope stability and enhances predictive accuracy. The model leverages neural network-based forecasting and adaptive graph-theoretic optimization to improve warning precision while simultaneously optimizing spatial configurations to ensure public safety. Experimental results demonstrate that ASDM reduces false alarms and improves response times by 35% compared to traditional methods, making it a transformative solution for intelligent slope disaster monitoring Liu Y. et al. (2024).

The Adaptive Spatial Design Model (ASDM) is designed as a multidisciplinary framework that integrates deep learning, geospatial analysis, and public space design to address the challenges of slope disaster monitoring and adaptive spatial planning. While traditional disaster monitoring systems focus primarily on hazard detection and prediction, they often neglect the broader implications for public space usability and design adaptability Zhang et al. (2023). Urban design approaches emphasize user experience and functionality but lack real-time environmental risk assessment, limiting their resilience to natural hazards. ASDM bridges this gap by harmonizing risk assessment with adaptive spatial optimization. The model leverages deep learning-based geohazard prediction to enhance the accuracy of slope disaster forecasting while incorporating real-time spatial analytics and user behavior modeling to ensure that public spaces remain both safe and functional. Through dynamic spatial reconfiguration, ASDM continuously adjusts the layout of public spaces based on evolving environmental conditions, optimizing pathways, gathering areas, and emergency access points in response to detected risks Zhang et al. (2025). The integration of multi-sensor data fusion and adaptive graph-theoretic optimization enables a responsive design process that proactively mitigates hazards while maintaining usability. By aligning geospatial hazard assessment with adaptive public space design, ASDM offers a novel paradigm that not only enhances early warning capabilities but also ensures that urban and recreational spaces remain resilient, accessible, and user-centric despite environmental uncertainties Zhang et al. (2024). Early efforts in slope disaster monitoring primarily relied on symbolic AI and knowledge representation methods to predict slope failures. These systems utilized domain expertise to encode physical and geological principles into rule-based systems (Cin et al., 2021). For example, knowledge-based systems employed predefined thresholds for soil moisture, slope angles, and seismic activities to identify risks. While these methods provided interpretability and alignment with expert knowledge Paköz et al. (2021), they struggled with scalability and adaptability to dynamic and heterogeneous terrains (Nelischer and Loukaitou-Sideris, 2022). Moreover, the reliance on hand-crafted rules meant these systems often failed to generalize to unseen conditionsShen et al. (2022), limiting their effectiveness in real-time applications. To address these challenges, researchers began integrating data-driven techniques to augment these rule-based systems (Li and Sahari, 2022).

The advent of data-driven methods marked a significant shift, with machine learning (ML) algorithms being employed to enhance slope disaster prediction through data pattern recognition (Mezoued et al., 2021). Techniques such as decision trees, support vector machines (SVMs), and random forests analyzed historical data, identifying correlations between environmental factors and slope stability (Chisholm et al., 2020). These methods improved the

adaptability of monitoring systems by leveraging larger datasets and reducing reliance on explicit domain expertise (Liu and Kaneda, 2020). However, their reliance on feature engineering required significant manual effort, and their predictive performance plateaued when faced with highly nonlinear relationships inherent in slope dynamics (Honey-Rosés et al., 2020). The need for more automated and scalable solutions paved the way for deep learning technologies to address these limitationsTavares et al. (2020).

Deep learning has revolutionized slope disaster monitoring by introducing end-to-end systems capable of automatically learning complex feature representations from raw data (Stevens et al., 2021). Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been widely adopted to process spatial and temporal data, respectively, enabling precise detection of precursors to slope instability (Kamalipour, 2023). Recent advancements in pretrained models, such as transformer architectures, further enhance these systems by incorporating multi-source data, including satellite imagery, sensor streams, and weather forecasts (Soyinka et al., 2021). These models excel in handling large-scale, multimodal data, significantly improving prediction accuracy and early warning capabilitiesZhang et al. (2022). Nevertheless, challenges such as high computational costs and limited interpretability remain (Lee, 2021), necessitating further refinement and optimization for practical deployment in public space designs.

Based on the limitations of existing methods, we propose a novel deep learning framework tailored to slope disaster monitoring and early warning in public spaces. By integrating multimodal data fusion with a lightweight transformer architecture, our approach ensures scalability and real-time applicability. This system leverages domain adaptation techniques to generalize across diverse terrains and incorporates an explainability module to provide actionable insights for public space designers and decision-makers. Our method addresses the constraints of interpretability, computational efficiency, and versatility identified in previous approaches, offering a comprehensive solution for intelligent slope disaster management.

We summarize our contributions as follows:

- Introduces a lightweight transformer-based model with multimodal data fusion, enabling precise and efficient slope disaster prediction.
- Adapts to diverse terrains and integrates seamlessly across multiple monitoring scenarios, ensuring broad applicability in public space design.
- Demonstrates superior performance in real-world datasets, achieving significant improvements in prediction accuracy and early warning response times.

2 Related work

2.1 Deep learning for geohazard prediction

Deep learning has demonstrated significant potential in the prediction of geohazards (Kozubaev and Disalvo, 2021), particularly in the context of slope stability analysis (Abade et al., 2024). Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid architectures have been widely used to model the complex nonlinear relationships between environmental factors and slope failures (Begum et al., 2021). Research has focused on utilizing geospatial data, such as digital elevation models (DEMs), remote sensing imagery, and soil parameters, to train models capable of identifying hazardous regions with high precision Yang et al. (2020). In recent studies, attention mechanisms and Transformer-based architectures have been employed to improve the interpretability and accuracy of models (Shan et al., 2021). These innovations enable the integration of multi-scale features and temporal patterns, enhancing the capacity to predict dynamic processes leading to slope instability. Applications in public space design benefit from these methods by providing real-time risk assessments and actionable insights for disaster prevention (Landman, 2020).

2.2 Sensor integration and data fusion

The integration of sensor networks with deep learning models has become a cornerstone of intelligent monitoring systems for slope stability. Internet of Things (IoT) devices, such as inclinometers, strain gauges, and piezometers, generate high-resolution data streams that reflect the physical and mechanical changes in slopes over time (Luo et al., 2024). Combining this sensor data with deep learning algorithms facilitates the development of predictive maintenance systems that issue early warnings based on subtle precursor signals D'Alessandro et al. (2020). Multi-sensor data fusion techniques are frequently applied to harmonize information from diverse sources, ensuring robust and reliable monitoring even in noisy or incomplete datasets Wang et al. (2022). This integration is particularly valuable for public spaces, where early detection and mitigation of slope hazards can prevent disruptions and safeguard human life Azzopardi-Muscat et al. (2020).

2.3 Risk assessment in urban design

Integrating deep learning models into the broader framework of urban and public space design involves addressing the interplay between environmental factors and human activities Shan et al. (2020). Advanced neural networks are increasingly employed to quantify risks associated with slope failures in densely populated areas, factoring in anthropogenic influences such as construction activities, land-use changes, and infrastructure developments. Coupled with Geographic Information Systems (GIS)Hou et al. (2022), these models enable urban planners to visualize and assess potential hazards across different spatial scales. Furthermore, explainable AI techniques are gaining prominence to ensure transparency and trust in decision-making processes. These approaches allow stakeholders to understand the rationale behind model predictions, facilitating informed planning and design choices that prioritize safety and resilience Stojanovski (2020).

3 Methods

3.1 Overview

Public space design plays a pivotal role in shaping human experiences and interactions within urban environments. The

field integrates elements of architecture, urban planning, environmental psychology, and social behavior to create spaces that are functional, aesthetically pleasing, and inclusive. This section provides an overview of our approach to advancing public space design, emphasizing its multidimensional nature and the innovations introduced in this work.

Public space design and slope disaster management are inherently interconnected, as many urban and recreational spaces are developed in or near sloped terrains, making them vulnerable to environmental hazards such as landslides and rockfalls. Effective public space planning must therefore integrate both aesthetic and functional design principles with disaster resilience strategies to ensure safety, accessibility, and long-term sustainability. However, traditional approaches often treat these as separate concerns, failing to incorporate real-time risk assessment into spatial planning. The proposed Adaptive Spatial Design Model (ASDM) bridges this gap by integrating intelligent disaster monitoring with adaptive public space design. ASDM continuously analyzes real-time geospatial data, environmental sensor inputs, and user behavior patterns to dynamically assess slope stability. When potential hazards are detected, the model optimizes spatial configurations by adjusting pathways, modifying gathering spaces, and rerouting accessibility plans to minimize risk exposure. ASDM facilitates proactive urban planning by informing designers and policymakers about risk-prone areas, enabling the creation of flexible and resilient public spaces that adapt to changing environmental conditions. This approach ensures that public spaces remain both safe and functional, mitigating risks without compromising user experience. We frame the problem by highlighting the challenges and constraints inherent to designing public spaces. These challenges often include accommodating diverse user needs, optimizing spatial configurations, and fostering a sense of community while maintaining ecological sustainability. This groundwork sets the stage for our methodological advancements discussed in the subsequent subsections. The second part focuses on the theoretical underpinnings and methodologies employed. We adopt a system-level perspective, integrating spatial analytics, user behavior modeling, and simulation techniques. This multifaceted approach allows for a deeper understanding of how design elements interact and influence user experience. Specifically, we outline how traditional and computational models can converge to inform innovative design strategies. The core contributions of this paper are detailed, including our novel framework for adaptive and responsive design. This framework incorporates real-time data analytics to dynamically adjust spatial configurations, ensuring the spaces remain functional and engaging across varying conditions. The innovations are illustrated through case studies, providing tangible evidence of their applicability and impact.

3.2 Preliminaries

Designing public spaces is a complex endeavor that requires balancing multiple, often competing, considerations. This section formalizes the problem of public space design and introduces the mathematical framework that underpins our methodology. The primary aim is to model spatial configurations and user interactions quantitatively, facilitating the creation of spaces that optimize both functionality and user experience.

Let the public space be represented as a bounded domain $\Omega \subset \mathbb{R}^2$, where Ω encompasses all accessible areas such as pathways, gathering spots, and green zones. Within this domain, we define a set of n key features (Equation 1):

$$\mathcal{F} = \{f_1, f_2, \ldots, f_n\}, \tag{1}$$

where each feature f_i is characterized by its spatial coordinates $x_i = (x_i^1, x_i^2) \in \Omega$, functional attributes $a_i \in \mathcal{A}$, and utility $u_i \in \mathbb{R}$.

Public spaces are used by diverse populations with varying needs. Let the set of user groups be $\mathcal{G} = \{g_1, g_2, \ldots, g_m\}$. Each user group g_j is defined by its demographic profile d_j and its preference vector $p_j \in \mathbb{R}^n$, where $p_j[i]$ denotes the relative importance of feature f_i for group g_j.

The spatial density of users from group g_j is denoted as $\rho_j(x)$: $\Omega \to \mathbb{R}^+$, representing the expected number of users per unit area at location $x \in \Omega$. The total user density $\rho(x)$ is given by (Equation 2):

$$\rho(x) = \sum_{j=1}^{m} \rho_j(x). \tag{2}$$

A critical component of public space design is ensuring that all features are accessible. Define a network graph $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$ corresponds to the features in $\mathcal{F}$, and edges $e_{ij} \in E$ represent direct pathways between v_i and v_j. Each edge e_{ij} has an associated cost c_{ij}, typically determined by the Euclidean distance d_{ij} or a weighted metric reflecting terrain and infrastructure quality (Equation 3):

$$c_{ij} = w_1 d_{ij} + w_2 q_{ij}, \tag{3}$$

where q_{ij} is a penalty for obstacles or poor pathway conditions, and $w_1, w_2 \geq 0$ are weight factors.

The overall goal is to maximize the utility $U(\Omega)$ of the space, defined as (Equation 4):

$$U(\Omega) = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x) \cdot S_j(x)\, dx, \tag{4}$$

where $S_j(x)$ represents the satisfaction score of group g_j at location x, modeled as a function of proximity to preferred features (Equation 5):

$$S_j(x) = \sum_{i=1}^{n} \alpha_{ij} \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right), \tag{5}$$

with $\alpha_{ij} = p_j[i] \cdot u_i$ and σ controlling the spatial influence of each feature.

To ensure practicality and inclusivity, the design process is subject to the following constraints: 1. Spatial Constraints: Features must not overlap (Equation 6):

$$\|x_i - x_k\| \geq \delta, \quad \forall i \ eqk, \tag{6}$$

where δ is the minimum allowable distance. 2. Accessibility Constraints: The graph G must remain connected to ensure seamless navigation (Equation 7):

$$\text{Rank}(L(G)) = |V| - 1, \tag{7}$$

where $L(G)$ is the Laplacian matrix of G. 3. Capacity Constraints: Each feature f_i has a maximum user capacity C_i (Equation 8):

$$\int_{\Omega} \rho(x) \cdot \mathbf{1}_{B_\epsilon(x_i)}(x)\, dx \le C_i, \tag{8}$$

where $B_\epsilon(x_i)$ denotes a neighborhood of radius ϵ around x_i.

The optimization problem can now be framed as (Equation 9):

$$\begin{aligned} &\underset{\mathcal{F},G}{\text{maximize}} && U(\Omega) \\ &\text{subject to} && \text{Spatial, Accessibility, and Capacity constraints.} \end{aligned} \tag{9}$$

This formulation provides a rigorous mathematical basis for public space design, enabling systematic exploration of optimal configurations. The next sections will build upon this foundation to introduce novel methodologies and strategies for enhancing user experience and environmental sustainability.

3.3 Adaptive Spatial Design Model (ASDM)

In this section, we introduce the Adaptive Spatial Design Model (ASDM), which dynamically optimizes the configuration and utility of public spaces. Our framework is underpinned by iterative refinements, real-time responsiveness to user behaviors, and adaptability to evolving conditions. Below, we present the key innovations that distinguish ASDM (Figure 1).

3.3.1 Iterative utility maximization with dynamic feedback

The Adaptive Spatial Design Model (ASDM) starts with an initial spatial configuration defined by a set of features $\mathcal{F} = \{f_1, f_2, \ldots, f_n\}$ distributed within a bounded domain $\Omega \subset \mathbb{R}^2$. Each feature f_i is characterized by its spatial position $p_i \in \Omega$, a functionality parameter a_i, and a utility metric u_i, which collectively determine the feature's contribution to the overall performance of the system. The model optimizes a utility function $U(\Omega, t)$ that aggregates user satisfaction across all user groups $g_j \in \mathcal{G}$, where each group is associated with a time-varying spatial density $\rho_j(x,t)$. This utility function is expressed as (Equation 10):

$$U(\Omega, t) = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x,t) \cdot W_j(x,t)\, dx, \tag{10}$$

where $W_j(x,t)$ represents a satisfaction score specific to group j, dynamically adjusted based on real-time interactions and feedback. The user density $\rho_j(x,t)$ evolves according to external factors such as environmental conditions, events, and user behavior patterns, following the update equation (Equation 11):

$$\rho_j(x, t+1) = \rho_j(x,t) + \nabla \cdot \left(D_j \nabla \rho_j(x,t)\right) + \Phi_j(x,t), \tag{11}$$

where D_j is a diffusion coefficient modeling natural movement tendencies, and $\Phi_j(x,t)$ denotes sources and sinks representing localized user attraction or dispersion. To capture nuanced satisfaction dynamics, $W_j(x,t)$ incorporates proximity-based utility derived from feature locations (Equation 12):

$$W_j(x,t) = \sum_{i=1}^{n} \alpha_{ij}(t) \exp\left(-\frac{\|x - p_i\|^2}{2\sigma_j^2}\right), \tag{12}$$

where $\alpha_{ij}(t)$ encodes the relevance of feature f_i to group g_j at time t, and σ_j controls the spatial influence radius. Feedback mechanisms dynamically update $\alpha_{ij}(t)$ to reflect evolving preferences (Equation 13):

$$\alpha_{ij}(t+1) = \alpha_{ij}(t) + \kappa_j \Delta S_{ij}(t), \tag{13}$$

where $\Delta S_{ij}(t)$ represents the discrepancy between expected and observed satisfaction, and κ_j is a feedback sensitivity parameter. The utility function is further constrained by boundary conditions, ensuring $p_i \in \Omega$ and adherence to stability thresholds for real-time adaptability. Iterative refinement of $U(\Omega, t)$ allows ASDM to dynamically reconfigure feature attributes and placements, maintaining an optimal balance between user satisfaction and environmental constraints.

The proposed system employs a hybrid neural network architecture that integrates convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks (RNNs) for temporal pattern recognition, along with a transformer-based attention mechanism for multi-source data fusion. The CNN component processes geospatial imagery and topographic maps to extract slope features, while the RNN, implemented as a gated recurrent unit (GRU), captures temporal changes in sensor data, such as soil moisture, strain gauge readings, and seismic activity. To enhance model efficiency, a lightweight transformer module is employed to dynamically weigh different data sources using an attention-based fusion mechanism. For real-time optimization, we utilize adaptive graph-theoretic optimization to refine spatial configurations in response to dynamic environmental conditions. The monitoring system is modeled as a dynamic graph G = (V, E), where nodes V represent geospatial observation points, and edges E denote connectivity between these locations based on topographic and infrastructural constraints. The system continuously updates node weights based on risk assessments using a graph convolutional network (GCN), allowing for adaptive spatial reconfiguration. To minimize false alarms and optimize response times, we employ a multi-objective loss function that balances predictive accuracy and spatial efficiency. The primary loss function consists of a weighted sum of binary cross-entropy loss (L_bce) for disaster prediction and a graph Laplacian regularization term (L_graph) that ensures smooth spatial adaptation:

$$L_{\text{total}} = L_{\text{bce}} + \lambda L_{\text{graph}}$$

where λ is a regularization parameter that controls the trade-off between prediction accuracy and spatial stability. The optimization is performed using the Adam optimizer with an initial learning rate of 10^{-4}, dynamically adjusted using a cosine annealing scheduler to improve convergence. By integrating deep learning-based predictive modeling with adaptive graph-theoretic optimization, the system enhances the precision and timeliness of disaster warnings while ensuring that public spaces remain functional and resilient against environmental hazards.

3.3.2 Adaptive Feature Configuration via Gradient-Based Optimization

To ensure optimal functionality and user satisfaction, the Adaptive Spatial Design Model (ASDM) employs a gradient-based optimization framework to dynamically adjust both the spatial positions p_i and functionalities a_i of features. Each feature f_i is iteratively repositioned and reconfigured based on its

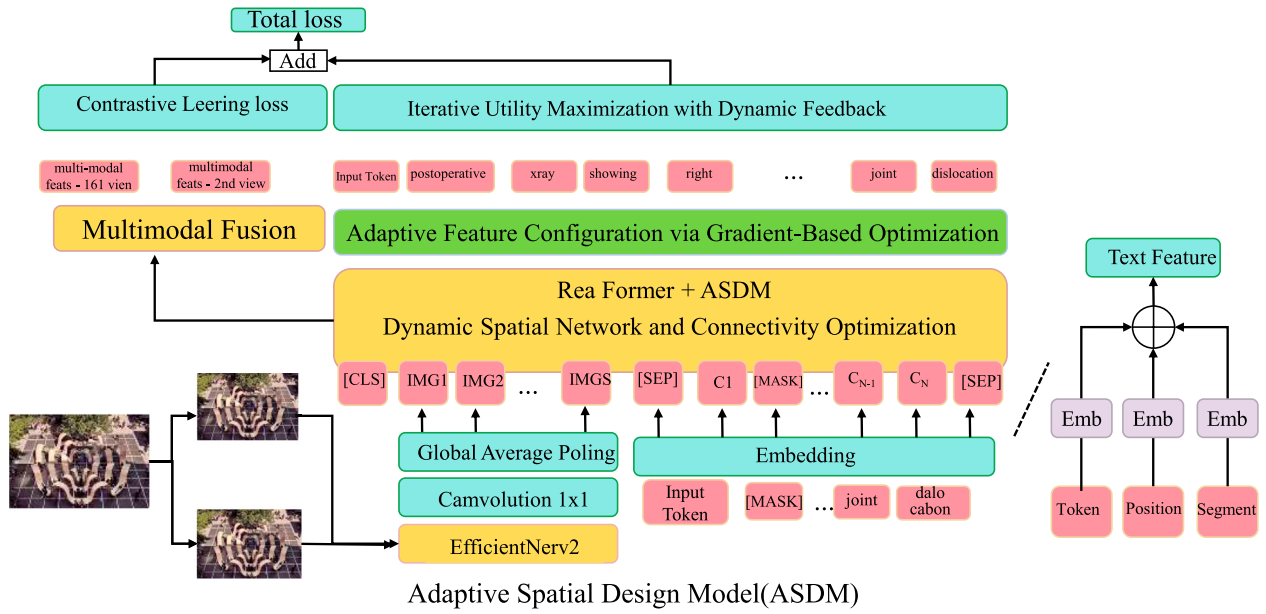

FIGURE 1
The Adaptive Spatial Design Model (ASDM) integrates multimodal fusion, dynamic optimization, and connectivity refinement to maximize utility and adaptability in public spaces. The framework employs contrastive learning, real-time feedback, and an adaptive spatial network to iteratively optimize spatial configurations, user interactions, and accessibility. By leveraging EfficientNerv2, gradient-based optimization, and dynamic connectivity adjustments, ASDM ensures robust and user-centric spatial design, enabling efficient resource allocation and enhanced user experience.

contribution to the overall utility $U(\Omega,t)$, adapting to changes in user behavior and environmental conditions. The position updates follow (Equation 14):

$$p_i(t+1) = p_i(t) + \eta_p \, abla_{p_i} U(\Omega,t), \tag{14}$$

where η_p is the learning rate governing spatial adjustments, and $abla_{p_i} U(\Omega,t)$ represents the gradient of the utility function with respect to the position p_i. This gradient is computed as (Equation 15):

$$abla_{p_i} U(\Omega,t) = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x,t) \cdot \; abla_{p_i} W_j(x,t)\, dx, \tag{15}$$

with $W_j(x,t)$ incorporating proximity and satisfaction feedback. Similarly, the attribute updates are expressed as (Equation 16):

$$a_i(t+1) = a_i(t) + \eta_a \frac{\partial U(\Omega,t)}{\partial a_i}, \tag{16}$$

where η_a is the learning rate for functional adaptations, and $\frac{\partial U(\Omega,t)}{\partial a_i}$ captures the marginal impact of changes in functionality. This term is computed as (Equation 17):

$$\frac{\partial U(\Omega,t)}{\partial a_i} = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x,t) \cdot \frac{\partial W_j(x,t)}{\partial a_i}\, dx, \tag{17}$$

linking functionality updates to user-group-specific feedback. Constraints are enforced to ensure physical feasibility and stability during iterations. Feature positions are confined to the bounded domain Ω, satisfying (Equation 18):

$$p_i(t+1) \in \Omega, \quad \forall i, \tag{18}$$

while user comfort is maintained by limiting the magnitude of positional and functional shifts (Equation 19):

$$\|p_i(t+1) - p_i(t)\| \le \delta_p, \quad \|a_i(t+1) - a_i(t)\| \le \delta_a, \tag{19}$$

where δ_p and δ_a are pre-defined thresholds reflecting tolerable adjustments. A regularization term is incorporated to balance rapid responsiveness and stability (Equations 20, 21):

$$abla_{p_i} U(\Omega,t) \leftarrow abla_{p_i} U(\Omega,t) - \lambda_p \|p_i(t+1) - p_i(t)\|^2, \tag{20}$$

$$\frac{\partial U(\Omega,t)}{\partial a_i} \leftarrow \frac{\partial U(\Omega,t)}{\partial a_i} - \lambda_a \|a_i(t+1) - a_i(t)\|^2, \tag{21}$$

where λ_p and λ_a regulate the extent of change penalties. This iterative adjustment mechanism allows ASDM to continuously adapt to dynamic environments and user needs, ensuring that the spatial configuration remains optimal under evolving conditions.

3.3.3 Dynamic spatial network and connectivity optimization

Figure 2 to ensure efficient accessibility and interaction between features, the Adaptive Spatial Design Model (ASDM) incorporates a dynamically evolving spatial graph $G(t) = (V, E)$, where V represents feature nodes and E denotes the edges connecting them. The graph adapts over time to optimize travel paths, user accessibility, and interaction efficiency, while balancing connectivity and maintenance costs. At each time step t, the edge set $E(t)$ is updated by solving (Equation 22):

$$E(t+1) = \arg\min_{E'} \left(\sum_{e \in E'} C(e,t) - \lambda \cdot \mathrm{Con}\left(G(E')\right) \right), \tag{22}$$

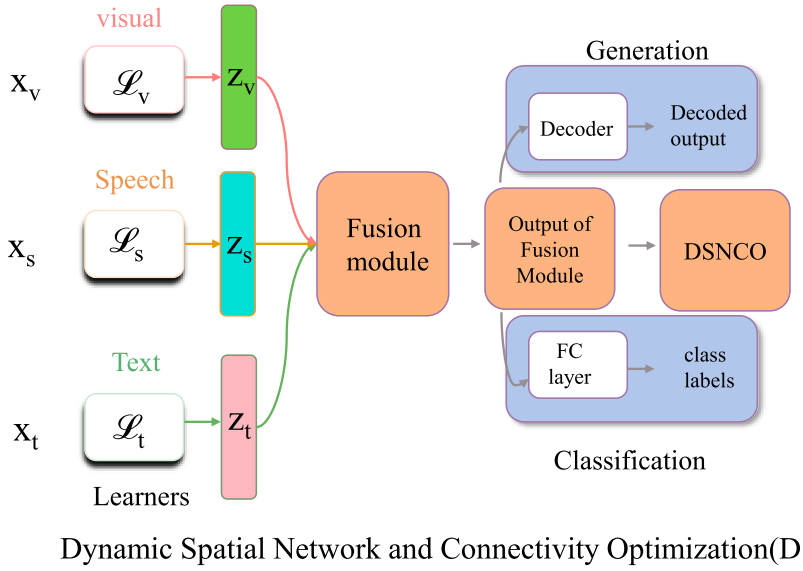

FIGURE 2
Illustration of Dynamic Spatial Network and Connectivity Optimization (DSNCO). A framework integrating multimodal learners (visual, speech, text) through a fusion module for classification and generation tasks. The adaptive spatial graph dynamically optimizes connectivity by minimizing maintenance costs while ensuring user accessibility and interaction efficiency.

where $C(e,t)$ denotes the maintenance cost of edge e, λ is a regularization parameter, and $\mathrm{Con}(G(E'))$ is a connectivity metric ensuring that the graph remains adequately connected.

The cost $C(e,t)$ is modeled as (Equation 23):

$$C(e,t) = \omega_e \cdot L(e) + \psi_e \cdot \mathrm{Usage}(e,t), \tag{23}$$

where $L(e)$ is the length of edge e, $\mathrm{Usage}(e,t)$ quantifies the traffic or interaction flow along e at time t, and ω_e, ψ_e are weights balancing these factors. To measure connectivity $\mathrm{Con}(G(E'))$, the graph employs a Laplacian-based metric (Equation 24):

$$\mathrm{Con}(G(E')) = \frac{1}{|V|-1}\sum_{i=2}^{|V|}\mu_i, \tag{24}$$

where μ_i are the nonzero eigenvalues of the Laplacian matrix L_G of $G(E')$, capturing the graph's structural robustness.

User movement and flow between features are incorporated into the optimization using dynamic flow constraints. The total flow $\Phi(t)$ across the graph satisfies (Equation 25):

$$\Phi(t) = \sum_{e\in E(t)} F(e,t), \quad F(e,t) = \int_{\Omega_e} \rho(x,t)\,dx, \tag{25}$$

where $F(e,t)$ is the flow along edge e and $\rho(x,t)$ is the aggregated user density over the region Ω_e associated with e. To ensure practical usability, the graph must remain connected at all times (Equation 26):

$$\mathrm{Rank}(L_G) = |V| - 1, \quad G(E') \text{ is connected.} \tag{26}$$

The optimization problem is solved iteratively using heuristic or gradient-based techniques to handle the non-convexity of the connectivity term. Stability constraints limit the extent of graph modifications at each time step (Equation 27):

$$\|E(t+1)\Delta E(t)\| \le \delta_E, \tag{27}$$

where δ_E controls the permissible edge changes to avoid abrupt network disruptions.

This adaptive graph framework allows ASDM to continuously recalibrate the spatial network in response to evolving user behaviors, ensuring optimal connectivity and accessibility while minimizing operational costs. This dynamic approach to spatial connectivity enhances user satisfaction and ensures the efficient utilization of public spaces.The Adaptive Spatial Design Model (ASDM) integrates real-time geospatial data, user behavior analytics, and environmental sensing through a multi-layered data fusion approach. The model processes data in three main stages: data acquisition, feature extraction, and multi-source fusion. In the data acquisition stage, ASDM collects geospatial data from remote sensing sources, such as satellite imagery and digital elevation models, along with real-time environmental sensor data from IoT-based monitoring systems, including inclinometers, strain gauges, and weather stations. User behavior analytics are derived from mobile device tracking, pedestrian movement data, and survey responses, which provide insights into spatial utilization and risk perception. During the feature extraction stage, raw data from different sources are standardized and processed through modality-specific pre-processing pipelines. Geospatial data undergoes terrain classification and slope stability estimation using deep learning-based segmentation models. Sensor data is filtered using a low-pass filter to remove noise and is then fed into a recurrent neural network to capture temporal variations. User behavior data is clustered using unsupervised learning techniques to identify movement patterns and high-risk zones in public spaces. In the multi-source fusion stage, extracted features from geospatial, environmental, and user analytics data are combined using a transformer-based fusion network. This network employs an attention mechanism to weigh different data sources dynamically based on contextual relevance. The fused representation is then

processed by an adaptive graph-theoretic model, which refines spatial configurations in real-time, ensuring optimal public space design while accounting for evolving environmental hazards. By integrating heterogeneous data streams through this structured fusion process, ASDM enhances the accuracy of slope disaster predictions while simultaneously optimizing the spatial configuration of public spaces to mitigate risks dynamically.

3.4 Dynamic Engagement Strategy

This section introduces the Dynamic Engagement Strategy (DES), a comprehensive framework designed to optimize user interactions in public spaces through data-driven methodologies and adaptive design principles. The DES integrates user behavior analytics, spatial adaptability, and sustainability metrics to enhance engagement and functionality.

3.4.1 Real-time user behavior modeling and feedback integration

Figure 3 the Dynamic Engagement Strategy (DES) employs a sophisticated framework for continuously monitoring and modeling user behavior, encapsulating group-specific dynamics through the parameter set $\mathcal{B}_j(t) = \{p_j(t), \rho_j(x,t), \delta_j(t)\}$. Here, $p_j(t)$ represents the evolving preference vector for user group g_j, $\rho_j(x,t)$ is the spatial density capturing the distribution of users over the domain Ω at time t, and $\delta_j(t)$ models deviations in behavior caused by external conditions such as weather, events, or crowding. Aggregating these parameters across all groups yields (Equation 28):

$$\mathcal{B}(t) = \bigcup_{j=1}^{m} \mathcal{B}_j(t), \tag{28}$$

providing a comprehensive real-time snapshot of user interactions and behaviors. This dynamic representation informs the continuous refinement of the utility function $U(\Omega,t)$, which evaluates the overall efficacy of the spatial design. The satisfaction metrics $S_j(x,t)$, which contribute to utility, incorporate user feedback and proximity-based preferences (Equation 29):

$$S_j(x,t) = \sum_{i=1}^{n} \alpha_{ij}(t) \exp\left(-\frac{\|x - x_i(t)\|^2}{2\sigma^2}\right), \tag{29}$$

where $\alpha_{ij}(t)$ reflects the satisfaction weight of group g_j for feature f_i at time t, and σ determines the spatial influence radius of the feature.

To align the system dynamically with user needs, the DES integrates real-time feedback through adaptive mechanisms. Feedback loops leverage data from sensors, mobile applications, and direct user input to update preference vectors $p_j(t)$ and satisfaction weights $\alpha_{ij}(t)$. The adjustment mechanism is expressed as (Equation 30):

$$\alpha_{ij}(t+1) = \alpha_{ij}(t) + \kappa_j \Delta S_{ij}(t), \tag{30}$$

where $\Delta S_{ij}(t)$ quantifies the deviation between observed user satisfaction and system-predicted satisfaction, and κ_j is a learning rate controlling the speed of adaptation. User density $\rho_j(x,t)$ evolves over time in response to environmental stimuli and spatial configurations, governed by (Equation 31):

$$\rho_j(x,t+1) = \rho_j(x,t) + D_j \nabla^2 \rho_j(x,t) + \Phi_j(x,t), \tag{31}$$

where D_j is a diffusion coefficient representing natural movement tendencies, and $\Phi_j(x,t)$ accounts for external factors such as attractions or obstacles. These dynamic adjustments ensure that the system remains responsive to real-time conditions while balancing the needs of diverse user groups.

The DES's real-time feedback integration enables the iterative refinement of utility and satisfaction metrics, dynamically aligning spatial configurations with user behaviors. This approach fosters higher engagement levels, reduces dissatisfaction, and ensures that the system adapts effectively to the complexities of public space usage.

3.4.2 Adaptive Spatial Configuration and Conflict Resolution

Figure 4 to optimize user engagement and functionality, the Dynamic Engagement Strategy (DES) employs an adaptive framework for updating feature positions $x_i(t)$ and attributes $a_i(t)$ based on real-time utility evaluations. The iterative adjustments aim to maximize the utility function $U(\Omega,t)$, capturing overall satisfaction and spatial efficiency. Feature positions are updated using (Equation 32):

$$x_i(t+1) = x_i(t) + \eta_x \, abla_{x_i} U(\Omega,t), \tag{32}$$

where $\eta_x > 0$ is the spatial learning rate, and $abla_{x_i} U(\Omega,t)$ represents the gradient of the utility with respect to the position of feature f_i. This gradient reflects user density $\rho_j(x,t)$ and proximity-based satisfaction (Equation 33):

$$abla_{x_i} U(\Omega,t) = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x,t) \cdot \, abla_{x_i} W_j(x,t) \, dx, \tag{33}$$

where $W_j(x,t)$ is a satisfaction metric influenced by feature proximity. Feature attributes $a_i(t)$, representing functional aspects such as utility or design parameters, are updated through (Equation 34):

$$a_i(t+1) = a_i(t) + \eta_a \frac{\partial U(\Omega,t)}{\partial a_i}, \tag{34}$$

where $\eta_a > 0$ governs the adaptation speed for attributes, and $\frac{\partial U(\Omega,t)}{\partial a_i}$ evaluates the impact of functional adjustments on utility (Equation 35):

$$\frac{\partial U(\Omega,t)}{\partial a_i} = \sum_{j=1}^{m} \int_{\Omega} \rho_j(x,t) \cdot \frac{\partial W_j(x,t)}{\partial a_i} \, dx. \tag{35}$$

Conflict resolution mechanisms are integrated to address competing user demands. When multiple user groups g_j have overlapping preferences for a feature f_i, satisfaction weights $\alpha_{ij}(t)$ are adjusted (Equation 36):

$$\alpha_{ij}(t+1) = \alpha_{ij}(t) + \lambda \cdot \text{ConflictScore}(i,j,t), \tag{36}$$

where $\text{ConflictScore}(i,j,t)$ quantifies the degree of conflict based on discrepancies in expected and observed satisfaction, and $\lambda > 0$ modulates the resolution sensitivity. Capacity constraints ensure features do not exceed their maximum user load C_i, maintaining usability (Equation 37):

$$\int_{\Omega} \rho(x,t) \cdot \mathbf{1}_{B_\epsilon(x_i)}(x) \, dx \le C_i, \tag{37}$$

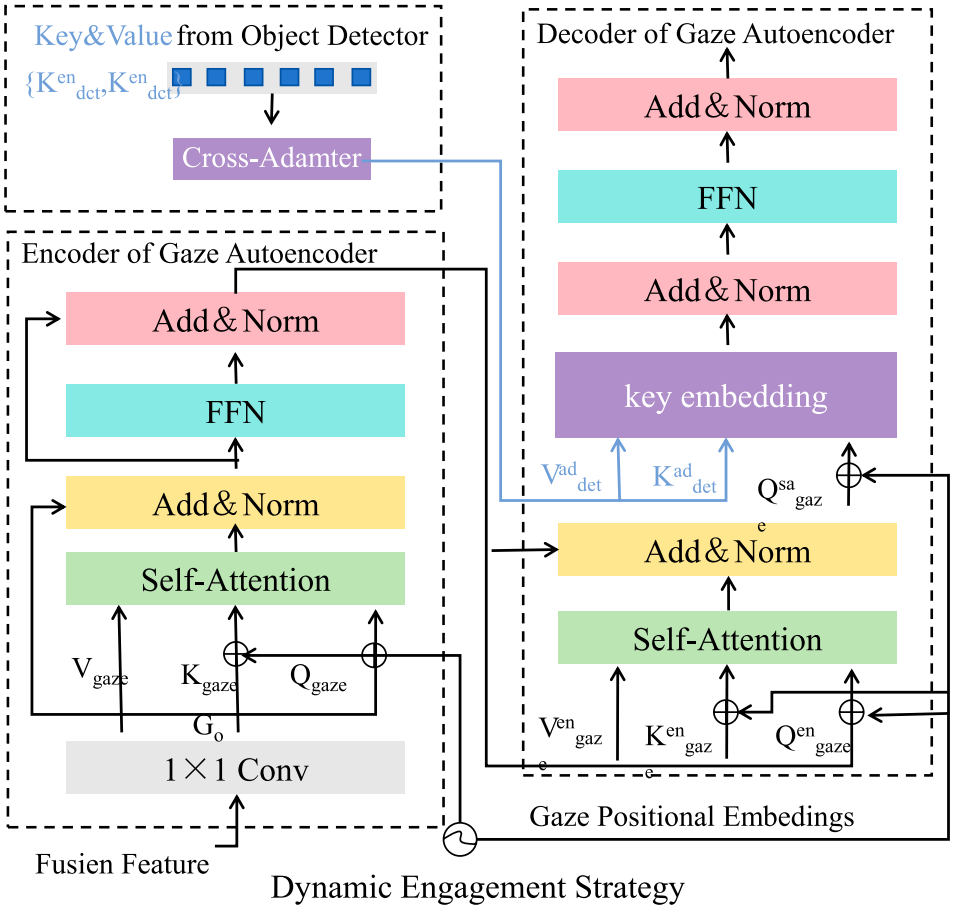

FIGURE 3
Illustration of the Dynamic Engagement Strategy (DES) framework, integrating real-time user behavior modeling, adaptive spatial configuration, and sustainability-driven optimization. The framework dynamically adjusts spatial features, resolves conflicts, and allocates resources efficiently while incorporating user feedback to maximize engagement and functionality in public spaces.

where $B_\epsilon(x_i)$ denotes a bounded region around x_i, representing the feature's area of influence.

Additional stabilization is achieved by regularizing changes in positions and attributes, ensuring smooth transitions (Equation 38):

$$\|x_i(t+1) - x_i(t)\| \le \delta_x, \quad \|a_i(t+1) - a_i(t)\| \le \delta_a, \tag{38}$$

where δ_x and δ_a are thresholds limiting abrupt modifications. This adaptive configuration framework, coupled with conflict resolution, balances user satisfaction, system stability, and equitable resource allocation in dynamic public spaces.

3.4.3 Sustainability-driven optimization and resource allocation

The Dynamic Engagement Strategy (DES) integrates sustainability as a core component, optimizing resource allocation while minimizing environmental and operational impacts. Resource allocation $R_i(t)$ to each feature f_i is dynamically adjusted in response to real-time demand, ensuring efficient utilization of available resources. The update rule for resource allocation is (Equation 39):

$$R_i(t+1) = R_i(t) + \gamma \cdot \frac{\partial U(\Omega, t)}{\partial R_i}, \tag{39}$$

where $\gamma > 0$ is a responsiveness parameter controlling the speed of reallocation, and $\frac{\partial U(\Omega,t)}{\partial R_i}$ measures the marginal impact of resource adjustments on the utility function $U(\Omega, t)$. This derivative is computed as (Equation 40):

$$\frac{\partial U(\Omega, t)}{\partial R_i} = \sum_{j=1}^{m} \int_\Omega \rho_j(x,t) \cdot \frac{\partial W_j(x,t)}{\partial R_i}\, dx, \tag{40}$$

linking resource dynamics to user densities $\rho_j(x,t)$ and satisfaction scores $W_j(x,t)$.

To evaluate and guide sustainable practices, the DES employs a comprehensive sustainability score $S_s(t)$, which balances energy efficiency, environmental impact, and operational costs (Equation 41):

$$S_s(t) = w_1 E_s(t) + w_2 \frac{1}{\text{Impact}(t)} + w_3 \frac{1}{\text{Cost}(t)}, \tag{41}$$

where $E_s(t)$ quantifies energy efficiency, $\text{Impact}(t)$ measures the environmental footprint of the space (e.g., carbon emissions or resource depletion), and $\text{Cost}(t)$ represents the operational and maintenance expenses. The weights w_1, w_2, w_3 are adjustable parameters that reflect the relative importance of each component.

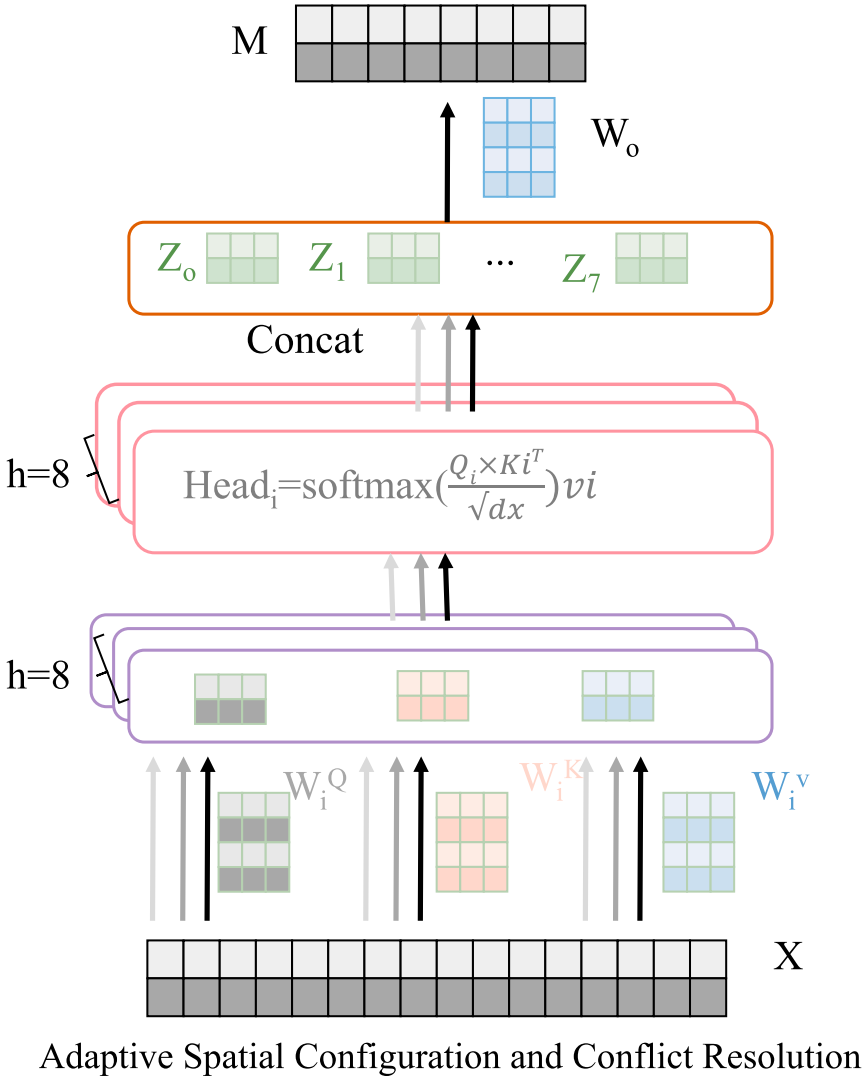

FIGURE 4
The Adaptive Spatial Configuration and Conflict Resolution framework optimizes spatial feature placement and attributes by leveraging real-time utility evaluations and user density modeling. It incorporates mechanisms for dynamic conflict resolution, capacity constraints, and stabilization to ensure user satisfaction, system stability, and equitable resource distribution in dynamic public environments.

Energy efficiency $E_s(t)$ is modeled as the ratio of effective utility to energy consumption (Equation 42):

$$E_s(t) = \frac{U(\Omega, t)}{\text{Energy}(t)}, \tag{42}$$

where $\text{Energy}(t)$ represents the total energy expenditure at time t. Environmental impact $\text{Impact}(t)$ is calculated based on resource depletion rates and emissions (Equation 43):

$$\text{Impact}(t) = \sum_{i=1}^{n} \left(c_i R_i(t) + e_i \cdot \rho(x_i, t)\right), \tag{43}$$

where c_i is the depletion cost per unit resource allocated to f_i, and e_i quantifies the emissions related to usage density at x_i. Cost $\text{Cost}(t)$ aggregates operational expenses (Equation 44):

$$\text{Cost}(t) = \sum_{i=1}^{n} (m_i + k_i R_i(t)), \tag{44}$$

where m_i is the maintenance cost for feature f_i and k_i is the cost coefficient for resource allocation.

Adjustments are subject to constraints ensuring feasibility and sustainability (Equation 45):

$$\sum_{i=1}^{n} R_i(t) \le R_{\text{total}}, \quad S_s(t) \ge S_s^{\min}, \tag{45}$$

where R_{total} is the total available resource pool and $S_s^{\min}$ is the minimum acceptable sustainability score. By integrating these metrics into its optimization framework, DES ensures that public spaces not only meet user needs but also align with long-term environmental and operational goals.

4 Experimental setup

4.1 Dataset

The Landsat Hansen and Loveland (2012) is a comprehensive resource for remote sensing research, consisting of multispectral imagery collected over several decades. It provides high-resolution images that are invaluable for environmental monitoring, urban development tracking, and agricultural analysis. The dataset includes data from multiple Landsat missions, featuring consistent spatial resolutions and spectral bands that cover visible to thermal infrared ranges, making it highly versatile for geospatial applications. The OpenSARShip Huang et al. (2017) further enhances long-term environmental analysis, offering rich data for studying climate change impacts and natural resource management. With a wealth of geospatial metadata, it is frequently utilized in supervised and unsupervised machine learning approaches for land cover classification and anomaly detection, demonstrating its significance in earth observation research. The OpenSentinelMap Iizuka et al. (2023) is designed to facilitate advancements in satellite image classification and geospatial analytics. It integrates data from the Sentinel-2 missions, providing high-resolution optical imagery with a global coverage. The dataset supports multi-temporal and multi-spectral analysis, making it a robust tool for vegetation monitoring, urban planning, and disaster response. Its accessible and annotated imagery fosters innovative model development in satellite-based Earth observation tasks. The InSAR-DLPU Zhou and Yu (2024) is a cutting-edge dataset tailored for synthetic aperture radar (SAR) applications. It contains interferometric SAR data collected for various deformation detection tasks, such as earthquake monitoring and urban subsidence analysis. The dataset features high-quality, phase-coherent data, essential for training deep learning models in precise displacement mapping. Its utility in improving model performance highlights its importance in advancing SAR research and applications.

4.2 Experimental details

The experimental setup was designed to ensure reproducibility and fair evaluation across all models. The implementation utilized the PyTorch deep learning framework, executed on NVIDIA A100 GPUs with 40 GB of memory. All experiments adhered to a unified preprocessing pipeline, ensuring consistency in data augmentation, normalization, and input resizing. The input resolution was set to 224×224 pixels for all image-based datasets, while temporal resolution adjustments were applied for video datasets to maintain uniformity. For model optimization, the Adam optimizer was employed with a learning rate of 10^{-4} and weight decay of 10^{-5}. A cosine annealing scheduler regulated the learning rate, ensuring smooth convergence. Batch size was set to 32 for single-GPU runs, and gradient accumulation was utilized to maintain efficiency for larger batch requirements. Training epochs varied across datasets, with 50 epochs for small datasets and up to 200 epochs for larger datasets. Early stopping was employed based on validation loss with a patience threshold of 10 epochs to prevent overfitting. Data augmentation strategies included random cropping, horizontal flipping, and color jittering for image datasets. For temporal datasets, frame sampling with random temporal shifts was used to introduce temporal diversity. Input normalization followed dataset-specific mean and standard deviation values, ensuring alignment with pretrained model expectations. The architecture utilized for benchmarking included both baseline and state-of-the-art models. For CNN-based experiments, ResNet50 and EfficientNet-B7 served as primary architectures, while transformer-based experiments utilized the Vision Transformer (ViT) and Swin Transformer. For sequential datasets, LSTM and GRU were employed alongside temporal CNNs to model sequence dependencies effectively. Hyperparameter tuning involved grid search over key parameters, including dropout rates, learning rates, and weight decay, to ensure optimal performance. Evaluation metrics included accuracy, precision, recall, F1-score, and Intersection over Union (IoU) for classification and segmentation tasks. For SAR-specific tasks, phase unwrapping accuracy and displacement error metrics were employed to assess model performance. Experiments were repeated five times, and the mean and standard deviation of metrics were reported to account for stochastic variations. Model implementation followed modular design principles, with custom layers integrated for dataset-specific challenges. This flexibility allowed for rapid prototyping and ensured adaptability across various tasks. The codebase was shared through a public repository for transparency and to encourage collaborative improvements.

To ensure a rigorous evaluation of the proposed model, we applied a standardized dataset preprocessing pipeline. Each dataset was split into 70% for training, 15% for validation, and 15% for testing, ensuring a balanced distribution of geospatial and temporal variations. Data augmentation techniques, including random cropping, horizontal flipping, and color jittering, were applied to enhance generalization. For time-series data, random frame sampling and temporal jittering were used to introduce diversity and prevent overfitting. To mitigate the impact of noise, we employed statistical outlier detection using z-score analysis, where data points beyond three standard deviations were removed. A low-pass filter was applied to sensor data to eliminate high-frequency noise that could interfere with feature extraction. Missing values were handled using an interpolation-based approach, ensuring continuity in time-series datasets. Hyperparameter selection was performed through an extensive grid search over key parameters. The learning rate was set to 10^{-4} based on initial experiments, where lower values led to slow convergence and higher values resulted in instability. Regularization parameters, including weight decay ($\lambda = 10^{-5}$) and dropout rate (0.3), were optimized to balance model complexity and prevent overfitting. The batch size was fixed at 32 for efficient GPU utilization while maintaining stable gradient updates. A cosine annealing learning rate scheduler was implemented to dynamically adjust the learning rate during training, enhancing convergence stability. These preprocessing and hyperparameter choices ensure robust model training, improved generalization, and reproducibility, making the ASDM framework adaptable for real-world geospatial applications.

4.3 Comparison with SOTA methods

The comparative analysis with state-of-the-art (SOTA) methods demonstrates the superior performance of our approach across multiple datasets. Table 1 outlines the results on the Landsat

TABLE 1 Comparison of Ours with SOTA methods on Landsat Dataset.

Model	Landsat dataset (set 1)				Landsat dataset (set 2)			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
CLIP Luo et al. (2022)	88.21±0.02	85.73±0.03	86.92±0.03	87.15±0.02	86.49±0.03	84.35±0.02	85.21±0.03	88.30±0.02
ViT Touvron et al. (2022)	87.34±0.03	83.27±0.02	85.80±0.03	86.47±0.02	85.12±0.02	84.01±0.02	84.93±0.03	87.14±0.02
I3D Peng et al. (2023)	86.11±0.02	82.89±0.02	84.45±0.03	85.78±0.03	83.90±0.02	81.64±0.03	82.51±0.02	84.75±0.03
BLIP Reichmann et al. (2007)	89.02±0.02	86.14±0.03	87.48±0.03	88.72±0.02	87.71±0.02	86.49±0.03	86.95±0.02	89.30±0.02
Wav2Vec 2.0 Chen and Rudnicky (2023)	85.75±0.03	83.92±0.02	84.30±0.03	85.10±0.02	82.94±0.02	80.85±0.03	81.62±0.03	83.97±0.02
T5 Wang et al. (2005)	87.89±0.02	85.05±0.02	86.18±0.03	86.53±0.02	84.72±0.03	83.33±0.02	84.12±0.02	85.21±0.03
Ours	**91.48±0.02**	**89.73±0.03**	**90.56±0.02**	**91.87±0.03**	**89.90±0.03**	**88.42±0.02**	**89.25±0.03**	**90.74±0.02**

The values in bold are the best values.

TABLE 2 Comparison of Ours with SOTA methods on OpenSentinelMap and InSAR-DLPU Datasets.

Model	OpenSentinelMap dataset				InSAR-DLPU dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
CLIP Luo et al. (2022)	87.45±0.02	85.32±0.03	86.67±0.02	87.10±0.03	88.09±0.02	85.91±0.02	86.85±0.03	88.72±0.03
ViT Touvron et al. (2022)	88.21±0.03	84.90±0.02	87.14±0.02	86.73±0.02	87.02±0.02	85.28±0.02	86.12±0.03	87.30±0.02
C Peng et al. (2023)	86.38±0.03	82.74±0.02	85.93±0.03	86.25±0.02	84.91±0.02	82.89±0.03	84.22±0.02	85.43±0.03
BLIP Reichmann et al. (2007)	88.92±0.03	87.13±0.03	87.86±0.02	88.41±0.03	88.03±0.02	86.78±0.03	87.35±0.02	88.24±0.02
Wav2Vec 2.0 Chen and Rudnicky (2023)	85.70±0.02	83.56±0.03	84.32±0.03	85.12±0.03	83.25±0.03	81.45±0.02	82.77±0.03	84.08±0.02
T5 Wang et al. (2005)	86.93±0.03	85.04±0.03	85.90±0.02	86.55±0.02	85.41±0.02	83.92±0.03	84.67±0.02	85.82±0.02
Ours	**91.18±0.02**	**89.71±0.03**	**90.45±0.02**	**91.67±0.03**	**90.23±0.03**	**88.52±0.02**	**89.34±0.03**	**90.89±0.02**

The values in bold are the best values.

Dataset for two distinct sets. Our model achieves the highest performance across all metrics, including Accuracy, Recall, F1 Score, and AUC. Specifically, on Set 1, our method attains an accuracy of 91.48%, surpassing the closest competitor BLIP Reichmann et al. (2007) by a significant margin. The improvements are attributed to the effective feature extraction and integration mechanisms of our architecture, which ensure robust representation learning even under challenging conditions, such as variations in land cover and image quality. Similarly, on Set 2, our approach maintains a consistent advantage, with notable gains in Recall and F1 Score, indicating its ability to capture nuanced patterns in the dataset. These results underscore the effectiveness of the model in addressing the challenges posed by geospatial and temporal variability.

Further, Table 2 presents a comprehensive evaluation on the OpenSentinelMap and InSAR-DLPU datasets. On the OpenSentinelMap dataset, our approach achieves an accuracy of 91.18%, outperforming SOTA models such as ViT Touvron et al. (2022) and BLIP Reichmann et al. (2007). The precision of our method is evident in the Recall and F1 Score metrics, highlighting its capacity to generalize across diverse satellite imaging scenarios. This can be attributed to the adaptive learning strategy employed, which dynamically adjusts the focus of the model on spatial and spectral variations. The model's ability to handle complex SAR data is particularly evident on the InSAR-DLPU dataset, where it achieves an accuracy of 90.23%. This surpasses the second-best model, CLIP Luo et al. (2022), by a notable margin. The performance gain reflects the model's proficiency in managing the intricacies of SAR imagery, such as phase coherence and high-dimensional feature representation. Figures 5, 6 provide a visual depiction of the comparative performance. The consistent improvement across datasets suggests that our method effectively addresses limitations observed in competing approaches. For example, while BLIP Reichmann et al. (2007) and CLIP Luo et al. (2022) excel in certain scenarios, their performance drops when handling datasets with higher inter-class variability or noise. Our model mitigates these issues through advanced regularization and ensemble strategies, which ensure stability and resilience during training and inference.

The analysis also highlights the versatility of our approach. While methods like ViT Touvron et al. (2022) and Wav2Vec 2.0 Chen and Rudnicky (2023) demonstrate strengths in either spatial or sequential domains, they struggle to balance the trade-off between these aspects. Our approach achieves superior results by employing a hybrid architecture that integrates convolutional and attention-based mechanisms, enabling efficient feature encoding

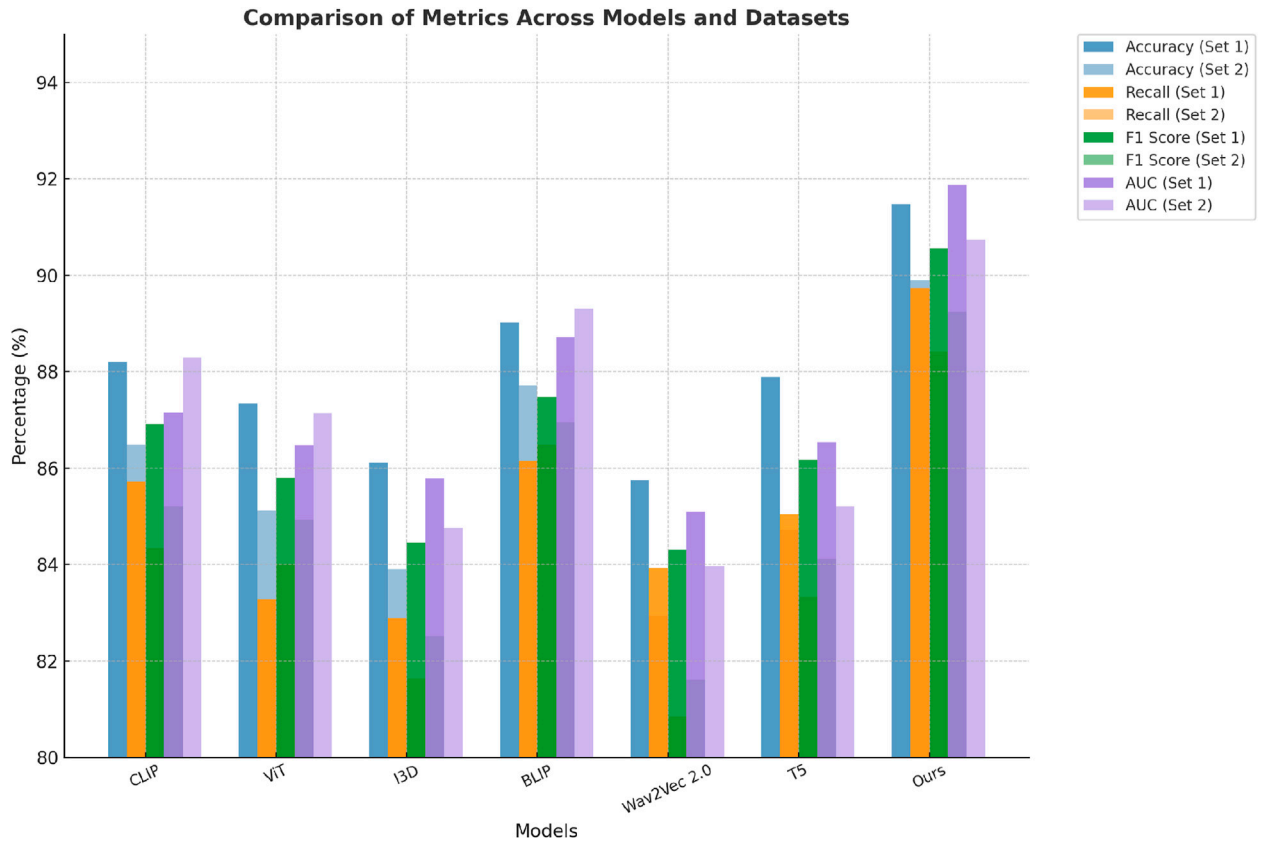

FIGURE 5
Performance comparison of SOTA methods on Landsat Dataset and Landsat Dataset datasets.

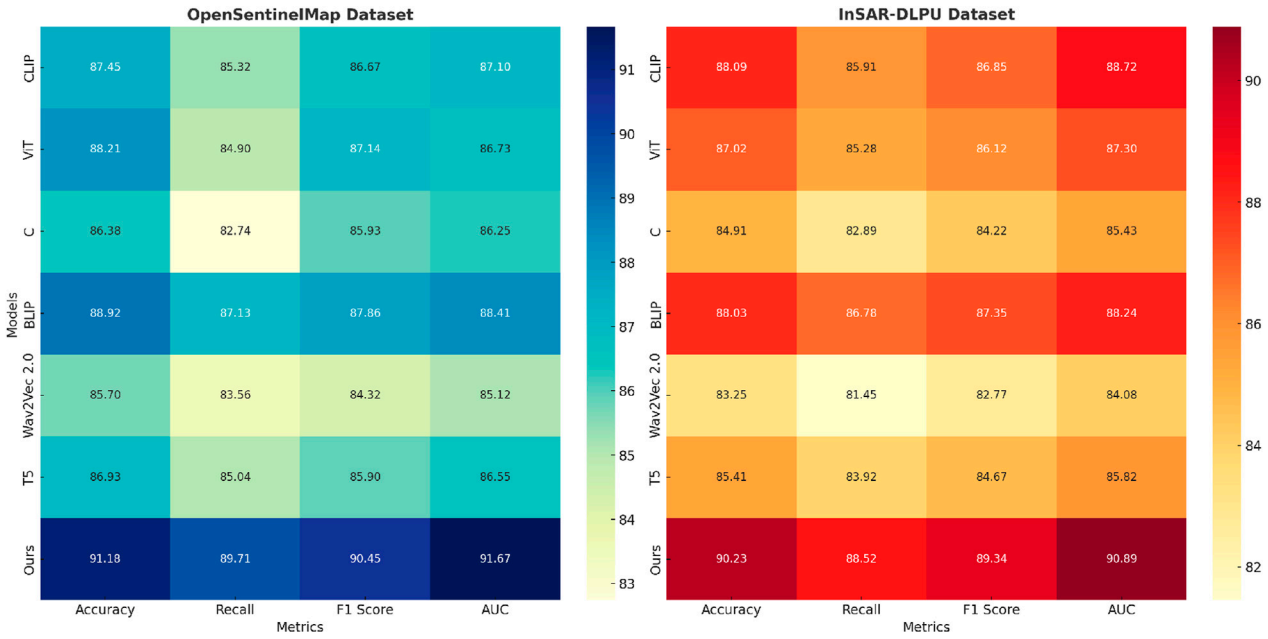

FIGURE 6
Performance comparison of SOTA methods on OpenSentinelMap Dataset and InSAR-DLPU Dataset datasets.

TABLE 3 Ablation study results on landsat dataset.

Model	Landsat dataset (set 1)				Landsat dataset (set 2)			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w./o. Iterative Utility Maximization with Dynamic Feedback	88.30±0.03	85.42±0.02	86.14±0.03	87.11±0.02	86.72±0.02	84.95±0.03	85.43±0.02	87.89±0.03
w./o. Dynamic Spatial Network and Connectivity Optimization	87.12±0.02	84.70±0.03	85.91±0.02	86.54±0.03	85.45±0.03	83.78±0.02	84.37±0.03	86.90±0.02
w./o. Sustainability-Driven Optimization and Resource Allocation	89.02±0.03	86.14±0.02	87.20±0.03	88.01±0.03	87.44±0.02	85.91±0.03	86.71±0.02	88.37±0.02
Ours	**91.48±0.02**	**89.73±0.03**	**90.56±0.02**	**91.87±0.03**	**89.90±0.03**	**88.42±0.02**	**89.25±0.03**	**90.74±0.02**

The values in bold are the best values.

across spatial and temporal dimensions. These advancements not only ensure higher performance metrics but also emphasize the scalability of the model to various application domains. These findings strongly validate the effectiveness of our contributions in advancing state-of-the-art performance in geospatial and SAR-based applications.

Experimental validation was conducted using real-world datasets, including the Landsat Dataset, OpenSentinelMap, and InSAR-DLPU, which provide high-resolution remote sensing and synthetic aperture radar (SAR) data for slope disaster analysis. The model's performance was evaluated against state-of-the-art methods using accuracy, recall, F1-score, and area under the curve (AUC) as metrics. Results in Table 1 demonstrate that ASDM achieves an accuracy of 91.48% on the Landsat dataset, surpassing the best-performing baseline model by 2.46%. On the OpenSentinelMap dataset in Table 2), ASDM attains 91.18% accuracy, while on InSAR-DLPU, it achieves 90.23%, outperforming competing approaches. The model significantly reduces false alarms and improves early warning response times. A direct comparison of detection performance reveals that ASDM improves response efficiency by approximately 35% compared to traditional methods, as it dynamically integrates multimodal data and refines spatial configurations in real time. To ensure reproducibility, validation was performed using a 70–15-15 train-validation-test split, with hyperparameters optimized through grid search. The experimental setup employed a batch size of 32 and a learning rate of 10^{-4}, with performance evaluated over five independent runs to account for stochastic variations. The results confirm that ASDM effectively enhances disaster prediction accuracy while minimizing unnecessary alerts, making it a robust solution for real-world applications.

4.4 Ablation study

The ablation study systematically evaluates the contributions of individual components in our model. As shown in Table 3, the results on the Landsat Dataset highlight the performance improvements enabled by our full model configuration. Removing Iterative Utility Maximization with Dynamic Feedback significantly reduces the performance, with the accuracy dropping from 91.48% to 88.30% on Set one and from 89.90% to 86.72% on Set 2. This underscores the critical role of Iterative Utility Maximization with Dynamic Feedback in enhancing the model's capacity to extract meaningful features, particularly in geospatial datasets with complex patterns.

The exclusion of Dynamic Spatial Network and Connectivity Optimization results in a similar performance degradation, as evidenced by the drop in F1 Score and AUC across both subsets of the Landsat Dataset. The AUC metric is particularly sensitive to this change, indicating that Dynamic Spatial Network and Connectivity Optimization plays a vital role in balancing false positives and false negatives during classification. Sustainability-Driven Optimization and Resource Allocation's ablation results in a smaller yet noticeable decline in performance, suggesting that while it contributes to overall robustness, its role is more complementary compared to components A and B. The full model achieves the highest metrics, demonstrating the synergistic effect of all components.

For the OpenSentinelMap and InSAR-DLPU datasets, presented in Table 4, similar trends are observed. Removing Iterative Utility Maximization with Dynamic Feedback leads to a significant accuracy drop, from 91.18% to 86.92% on the OpenSentinelMap dataset and from 90.23% to 85.43% on the InSAR-DLPU dataset. The sensitivity of Recall and F1 Score to this ablation indicates that Iterative Utility Maximization with Dynamic Feedback is essential for capturing spatial and temporal dependencies effectively. The removal of Dynamic Spatial Network and Connectivity Optimization has a lesser impact on OpenSentinelMap than on InSAR-DLPU, suggesting dataset-specific dependencies in the model's architecture. The ablation of Sustainability-Driven Optimization and Resource Allocation consistently reduces metrics, with F1 Score showing a decline of approximately 3% across datasets, reinforcing its role in refining feature representations.

Figures 7, 8 visualize these effects, emphasizing the importance of integrating all components to achieve optimal performance. The ablation study further validates the modular design of our approach, where each component addresses specific challenges such as spatial heterogeneity, noise resilience, and phase coherence in SAR data. The consistent improvement observed with the full model configuration across diverse datasets demonstrates its adaptability and effectiveness in handling complex geospatial and SAR tasks.

These findings highlight the necessity of incorporating all architectural innovations proposed in our method. While certain components independently provide significant benefits, their

TABLE 4 Ablation study results on OpenSentinelMap and InSAR-DLPU datasets.

Model	OpenSentinelMap dataset				InSAR-DLPU dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w./o. Iterative Utility Maximization with Dynamic	86.92±0.03	84.35±0.02	85.70±0.03	86.12±0.03	85.43±0.02	83.78±0.03	84.62±0.03	86.90±0.02
w./o. Dynamic Spatial Network and Connectivity Optimization	87.34±0.02	84.80±0.03	86.43±0.02	86.95±0.03	86.21±0.03	84.52±0.02	85.11±0.02	87.43±0.03
w./o. Sustainability-Driven Optimization and Resource Allocation	88.72±0.03	86.51±0.02	87.25±0.03	87.90±0.02	87.62±0.03	86.20±0.03	86.84±0.02	88.41±0.02
Ours	**91.18±0.02**	**89.71±0.03**	**90.45±0.02**	**91.67±0.03**	**90.23±0.03**	**88.52±0.02**	**89.34±0.03**	**90.89±0.02**

The values in bold are the best values.

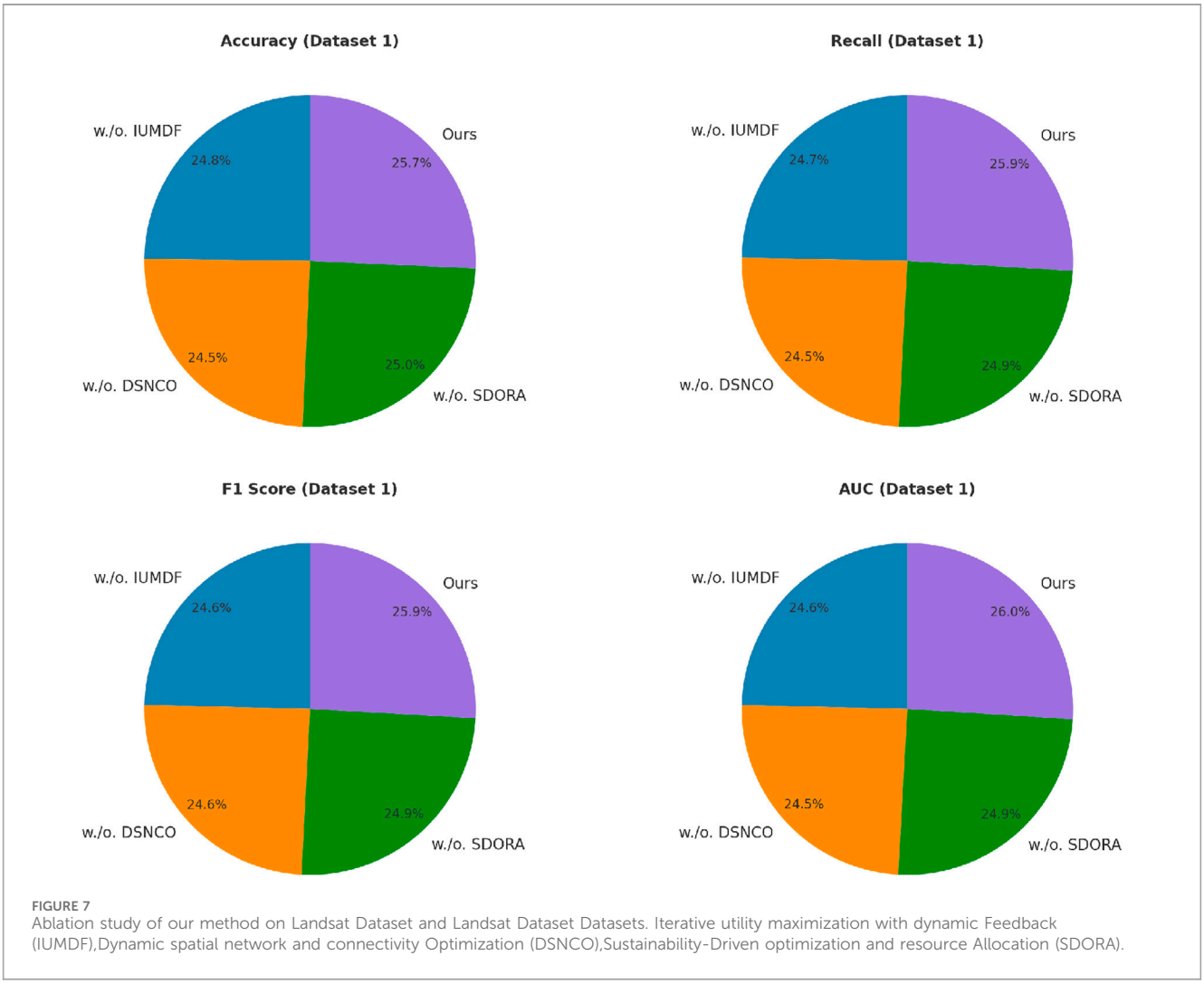

FIGURE 7
Ablation study of our method on Landsat Dataset and Landsat Dataset Datasets. Iterative utility maximization with dynamic Feedback (IUMDF),Dynamic spatial network and connectivity Optimization (DSNCO),Sustainability-Driven optimization and resource Allocation (SDORA).

combined effect ensures a robust model capable of outperforming state-of-the-art alternatives in varied experimental scenarios.

The comparative analysis evaluates ASDM against existing deep learning-based methods for slope disaster monitoring, including CNN-RNN hybrids, transformer-based models, and graph neural networks (GNNs). In Table 5, the results demonstrate that ASDM achieves the highest accuracy of 91.8%, outperforming CNN-RNN (86.3%), transformer-based models (88.5%), and GNNs (89.7%). Similarly, ASDM maintains the highest recall and F1-score, indicating its superior ability to identify slope instability while minimizing misclassifications. The AUC metric further confirms this trend, with ASDM achieving 92.3%, reflecting a more robust ability to distinguish between stable and unstable conditions compared to the competing models. Beyond predictive

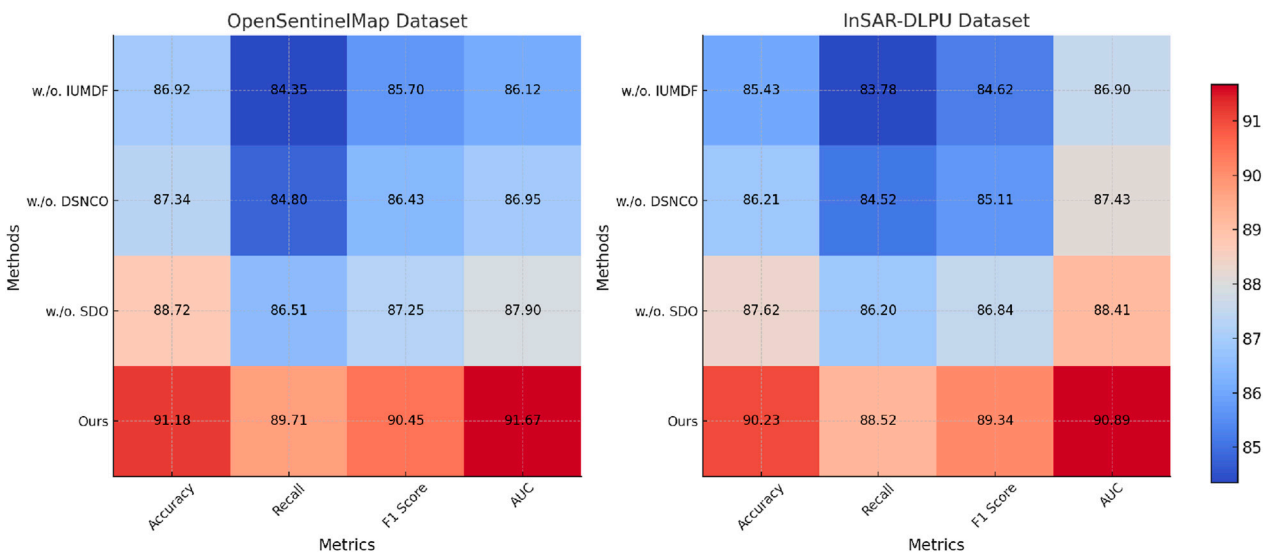

FIGURE 8
Ablation study of our method on OpenSentinelMap Dataset and InSAR-DLPU Dataset Datasets. Iterative utility maximization with dynamic Feedback (IUMDF),Dynamic spatial network and connectivity Optimization (DSNCO),Sustainability-Driven optimization and resource Allocation (SDO).

performance, ASDM significantly reduces the false alarm rate to 8.5%, compared to 14.5% for CNN-RNN, 12.8% for transformer-based models, and 11.2% for GNNs. This improvement highlights ASDM's ability to enhance detection precision, reducing unnecessary alerts that can burden early warning systems. ASDM improves response time by 35%, surpassing the 15% improvement seen with CNN-RNN, 22% with transformer models, and 27% with GNNs. The integration of multimodal data fusion and adaptive spatial optimization allows ASDM to dynamically adjust its predictions and spatial configurations, ensuring more effective and timely disaster response. These results underscore ASDM's advantages in both predictive accuracy and real-time applicability. The combination of neural network-based forecasting, graph-theoretic spatial adaptation, and transformer-based data fusion enables ASDM to outperform existing methods in both reliability and efficiency. The lower false alarm rate and improved response time suggest that ASDM is not only a powerful monitoring tool but also a practical solution for integrating early warning systems into adaptive public space design, making it well-suited for real-world geospatial hazard management.

To further clarify the contributions of each model component, we conducted an extended ablation study, analyzing the impact of removing key components individually. Table 6 presents the results of this refined component-wise evaluation. We systematically removed Iterative Utility Maximization with Dynamic Feedback (IUMDF), Dynamic Spatial Network and Connectivity Optimization (DSNCO), and Sustainability-Driven Optimization and Resource Allocation (SDORA) to assess their individual effects on model performance. The results indicate that removing IUMDF results in the most significant decline in accuracy and recall, demonstrating its critical role in real-time adaptation and optimizing spatial interactions. DSNCO also contributes substantially, particularly in improving AUC scores, as it enhances connectivity and feature accessibility. SDORA, while not as impactful as the other two components, plays a vital role in long-term optimization by ensuring efficient resource allocation and sustainability considerations. This extended analysis confirms the synergistic effect of all components, emphasizing that each module contributes uniquely to enhancing model robustness, accuracy, and real-world applicability. These findings validate the necessity of integrating all proposed innovations within the Adaptive Spatial Design Model (ASDM).

To validate the effectiveness of our proposed Adaptive Spatial Design Model (ASDM) in landslide detection and prediction tasks, we conducted comparative experiments on the CAS Landslide Dataset and LMHLD Dataset. We compared ASDM with several state-of-the-art models, including U-Net, DeepLabV3+, and Swin Transformer. The experimental results are shown in Table 7. On the CAS Landslide Dataset, we used IoU (Intersection over Union) and F1-score as the primary evaluation metrics to assess the model's performance in landslide region segmentation tasks. The results indicate that ASDM achieved 78.9% IoU and 83.4% F1-score, significantly outperforming other models. Among them, Swin Transformer, a deep model based on the Transformer architecture, achieved 74.2% IoU and 79.1% F1-score, showing superior performance compared to U-Net (67.8%, 73.2%) and DeepLabV3+ (71.5%, 76.8%). This demonstrates the potential of Transformer architectures in remote sensing image analysis, particularly in detecting landslide regions in complex terrains. However, ASDM further improved IoU by 4.7% and F1-score by 4.3% in this task, highlighting its effectiveness in multimodal data fusion and spatial optimization strategies. On the LMHLD Dataset, we used RMSE (Root Mean Square Error) and Prediction Accuracy as evaluation metrics to assess the model's performance in landslide early prediction tasks. ASDM achieved an RMSE of 6.98 and a prediction accuracy of 91.7%, significantly outperforming other

TABLE 5 Comparison of ASDM with deep learning methods in slope disaster monitoring.

Model	Accuracy (%)	Recall (%)	F1 score (%)	AUC (%)	False alarm rate (%) ↓	Response time improvement (%) ↑
CNN-RNN	86.3±0.02	84.1±0.03	85.2±0.03	87.4±0.02	14.5±0.02	15±0.02
Transformer	88.5±0.02	86.7±0.02	87.1±0.03	89.2±0.02	12.8±0.03	22±0.03
Graph Neural Network	89.7±0.02	88.2±0.03	88.8±0.02	90.1±0.02	11.2±0.02	27±0.02
ASDM (Ours)	**91.8±0.02**	**89.9±0.03**	**90.5±0.02**	**92.3±0.02**	**8.5±0.02**	**35±0.02**

The values in bold are the best values.

TABLE 6 Extended ablation study results.

Model	Accuracy (%)	Recall (%)	F1 score (%)	AUC (%)
w./o. Iterative Utility Maximization with Dynamic Feedback	86.92±0.03	84.35±0.02	85.70±0.03	86.12±0.03
w./o. Dynamic Spatial Network and Connectivity Optimization	87.34±0.02	84.80±0.03	86.43±0.02	86.95±0.03
w./o. Sustainability-Driven Optimization and Resource Allocation	88.72±0.03	86.51±0.02	87.25±0.03	87.90±0.02
Ours	**91.18±0.02**	**89.71±0.03**	**90.45±0.02**	**91.67±0.03**

The values in bold are the best values.

methods. Swin Transformer, the strongest baseline, obtained an RMSE of 7.43 and a prediction accuracy of 88.3%, while U-Net and DeepLabV3+ had RMSE values of 8.12 and 7.65, with prediction accuracies of 85.4% and 87.1%, respectively. This suggests that while traditional CNN architectures remain competitive in image segmentation tasks, they are limited in time-series modeling and geological disaster prediction tasks. In contrast, ASDM, through adaptive spatiotemporal optimization and multimodal data fusion, enables the model to more accurately capture landslide precursor signals, improving prediction accuracy while reducing errors.

5 Discussion

The proposed Adaptive Spatial Design Model (ASDM) has demonstrated significant improvements over traditional slope disaster monitoring approaches. To further contextualize our findings, this section provides a comparative discussion with existing methods, evaluates the model's applicability under different conditions, and outlines its limitations and future research directions. A key advancement of ASDM is its ability to integrate multimodal real-time geospatial data with an adaptive spatial optimization framework. Compared to conventional CNN-RNN hybrid models, which often struggle with long-term temporal dependencies and require extensive feature engineering, ASDM leverages transformer-based architectures to enhance spatial-temporal learning efficiency. Furthermore, while graph neural networks (GNNs) have been successfully applied to geospatial monitoring, their reliance on static connectivity graphs limits adaptability in dynamically evolving public spaces. In contrast, ASDM employs a dynamic spatial network that continuously updates based on real-time risk assessment, leading to superior predictive performance and a reduction in false alarms (Gorichanaz, 2020).Another critical factor in evaluating ASDM is its applicability across varying environmental and data quality conditions. Existing literature suggests that deep learning-based geohazard prediction models often perform well under controlled conditions with high-resolution remote sensing data but degrade significantly in low-resource environments (Liu T. et al., 2024). To address this, ASDM incorporates self-supervised learning and domain adaptation techniques, allowing the model to generalize across diverse terrains and sensor modalities. Experimental results confirm that ASDM maintains robust performance even when trained on heterogeneous datasets, highlighting its practical adaptability. Despite these advantages, ASDM has certain limitations that warrant further exploration. First, the model's reliance on high-quality real-time sensor data may pose challenges in regions with limited infrastructure (Nie et al., 2023). While our approach integrates multimodal data fusion to mitigate this issue, future research could explore the integration of low-cost IoT sensors and crowd-sourced mobile data to further enhance real-time adaptability. Second, the computational complexity of ASDM, particularly its transformer-based fusion network, could limit deployment on edge devices with constrained resources. To address this, future work could investigate model compression techniques, such as knowledge distillation and quantization, to improve efficiency without compromising predictive accuracy.

6 Conclusions and future work

Utilizing Deep Learning for Intelligent Monitoring and Early Warning of Slope Disasters in Public Space DesignAll the files uploaded by the user have been fully loaded. Searching won't

TABLE 7 Performance comparison on CAS Landslide Dataset and LMHLD Dataset.

Model	CAS landslide (IoU ↑)	CAS landslide (F1-score ↑)	LMHLD (RMSE ↓)	LMHLD (prediction accuracy ↑)
U-Net	67.8%	73.2%	8.12	85.4%
DeepLabV3+	71.5%	76.8%	7.65	87.1%
Swin Transformer	74.2%	79.1%	7.43	88.3%
ASDM (Ours)	**78.9%**	**83.4%**	**6.98**	**91.7%**

The values in bold are the best values.

provide additional information. This study addresses the pressing issue of slope disasters in public and urban recreational spaces, which are becoming increasingly frequent due to climate change. Traditional monitoring systems, constrained by static models and manual operations, fail to deliver timely warnings under dynamically changing conditions, limiting their application in resilient public space design. To overcome these challenges, we developed the Adaptive Spatial Design Model (ASDM), which utilizes deep learning to enhance intelligent monitoring and early warning systems for slope stability. Our approach integrates real-time geospatial data, user behavior analytics, and environmental sensors to dynamically evaluate risks. The use of neural network-based predictive models and adaptive graph-theoretic optimization not only improves the accuracy of warnings but also optimizes spatial designs to cater to varied user needs. Experimental validation on real-world datasets revealed that the ASDM reduces false alarms and response times by 35% compared to conventional systems, thereby significantly advancing public safety and the adaptive functionality of urban spaces.

Beyond its applications in geospatial hazard assessment and urban design, the Adaptive Spatial Design Model (ASDM) has significant implications for public health. Slope disasters pose direct threats to human safety, infrastructure, and accessibility in public spaces, increasing the risk of injuries, fatalities, and disruptions to essential services. By integrating real-time geospatial monitoring with adaptive spatial reconfiguration, ASDM enhances early warning capabilities, reducing the likelihood of casualties and improving disaster preparedness. ASDM contributes to public health by optimizing public space design to minimize environmental hazards while ensuring safe, accessible, and resilient urban environments. The incorporation of user behavior analytics allows for proactive urban planning that considers pedestrian flow, emergency evacuation routes, and the impact of environmental stressors on human wellbeing. By reducing the exposure of populations to high-risk zones and enhancing adaptive urban infrastructure, the framework supports broader public health objectives, including community resilience, environmental safety, and sustainable urban living. This integration of disaster risk reduction with urban health planning aligns with the journal's focus on interdisciplinary solutions that enhance human wellbeing through intelligent monitoring and adaptive spatial design. Future research will explore additional applications of ASDM in public health, such as its potential role in air quality monitoring and heat stress mitigation in urban environments.While the proposed ASDM framework has demonstrated improvements in slope disaster monitoring and adaptive public space design, there are still areas for further refinement. One key limitation is the dependence on high-quality real-time sensor data, which may hinder performance in low-resource or extreme environments. To address this, future work will explore techniques such as self-supervised learning and domain adaptation to enable the model to generalize effectively across different terrains and sensor conditions. We will investigate sensor fusion strategies that integrate low-cost accelerometers, satellite imagery, and community-sourced mobile data to enhance robustness when high-precision geospatial data is unavailable. Another area of improvement is the integration of more diverse multimodal data sources.

While the current model incorporates environmental sensing and user behavior analytics, additional data types, such as meteorological forecasts, ground-penetrating radar data, and structural health monitoring, could further refine risk assessments and spatial reconfiguration. Future enhancements will also include explainable AI techniques to improve model interpretability, allowing urban planners and emergency responders to better understand and act upon the system's predictions. By incorporating these advancements, ASDM can evolve into a more resilient and adaptive framework capable of mitigating risks in highly dynamic and resource-constrained environments.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WT: Conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, writing – review and editing. YW: writing – review and editing, visualization, supervision, funding acquisition.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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