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Integrating Physical Monitoring and Social Media Analytics for Multi-dimensional Perception of Landslide Hazards

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ABSTRACT

Landslide disasters are characterized by sudden onset, limited predictability, and severe consequences, with deformation and failure processes governed by complex interactions among geological structures, hydrological conditions, and engineering disturbances. Recent advances in remote sensing, sensor technologies, and artificial intelligence have facilitated the transition of landslide monitoring from single-parameter observations to multi-source information fusion. However, existing approaches primarily characterize the physical evolution of slopes and provide limited insight into post-disaster societal impacts and public responses. This study reviews landslide classification schemes and recent advances in multidimensional monitoring technologies within the "space–sky–ground–underground" framework and discusses their applications in deformation detection and early warning. Social media data are further incorporated as a complementary source of disaster-related information, and a Weibo-based method for analyzing public responses is developed through data collection, text processing, keyword frequency analysis, and word-cloud visualization. By integrating physical monitoring data with social sensing information, a multi-source fusion framework is proposed to enhance landslide monitoring and assessment throughout the disaster lifecycle and support emergency response.

1. Introduction

Landslides are among the most widely distributed and destructive geological hazards worldwide, posing severe threats to ecosystems, infrastructure, and human safety. Previous studies indicate that approximately 13% of global land areas are exposed to high landslide risk (Figure 1), mainly distributed in mountainous regions such as the American Cordillera, the European Alps, the Ethiopian Highlands, and the Himalayas [1]. In recent years, the frequency and severity of landslides have increased due to global climate change and the growing occurrence of extreme rainfall events. Meanwhile, increasing human activities, including mountainous engineering construction, transportation development, and land-use changes, have intensified disturbances to natural slopes,

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making engineering-induced landslides an emerging concern. Landslide prevention and mitigation have therefore become important research topics in geotechnical engineering. Bibliometric analysis based on the Web of Science Core Collection from 2006 to 2025 shows a continuous increase in publications related to slope stability and landslide mitigation (Figure 2a), indicating growing global interest in landslide monitoring, prevention, and risk warning technologies. Countries including China, the United States, India, and the United Kingdom show high research activity in this field (Figure 2b). These studies have advanced landslide classification, deformation monitoring, risk assessment, and early warning technologies, providing important theoretical and technical support for landslide hazard mitigation.

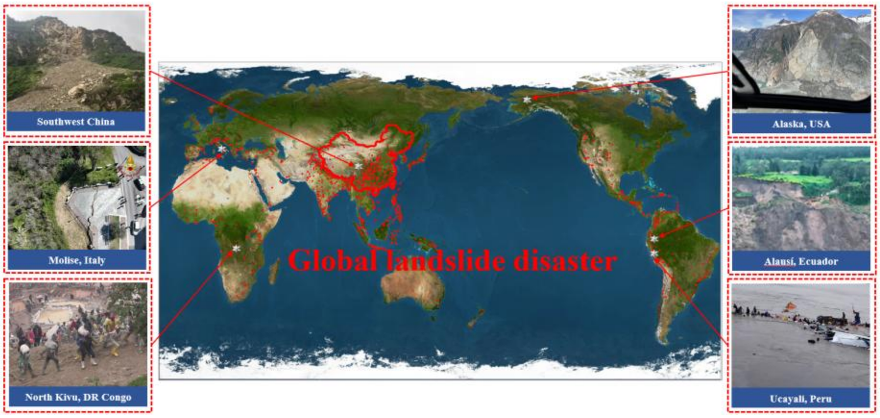
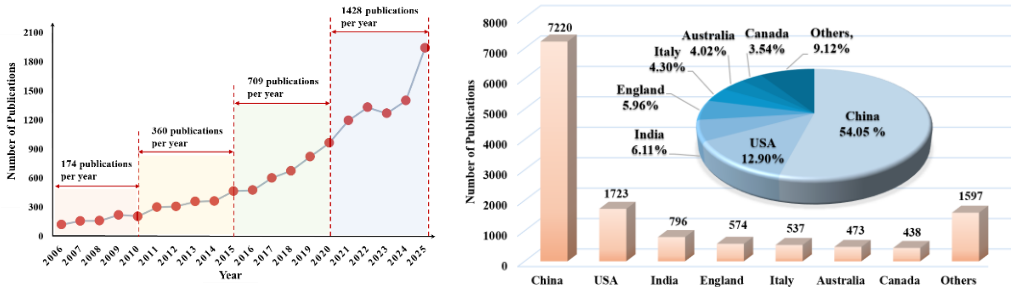


Fig. 1. Global distribution of landslide hazards



(a) Distribution of annual publications (b) Number of publications by country

Fig. 2. Statistical analysis of publications based on the WOS database (a) Distribution of annual publications (b) Number of publications by country

High-precision and efficient monitoring technologies are essential for landslide risk identification, early warning, and emergency response. Currently, multi-dimensional monitoring technologies across space-sky-ground-underground scales, including GNSS, InSAR, UAV remote sensing, three-dimensional laser scanning, and fiber-optic sensing, have been widely applied to landslide monitoring. These techniques provide critical information on slope displacement, strain, crack propagation, and hydrological changes, supporting slope stability analysis and risk assessment. However, conventional engineering monitoring methods mainly focus on slope physical changes, and their effectiveness is limited by sensor deployment conditions, spatial coverage, and cost. Therefore, they cannot fully meet the requirements of rapid hazard perception and refined management in complex mountainous environments. With the development of big data, artificial intelligence, and information communication technologies, landslide monitoring is shifting from single-parameter measurements toward multi-source information integration. Internet of Things (IoT) technologies enable continuous monitoring of slope environmental conditions and deformation, while machine learning methods improve hazard prediction and risk assessment. Meanwhile, social media data have emerged as a new information source for disaster perception and emergency management due to their real-time availability, wide coverage, and rapid dissemination. Texts, images, and videos shared on social media can capture disaster conditions and reflect public concerns and emergency needs. Keyword extraction, frequency analysis, and public attention evolution analysis further reveal social responses to disaster events. Integrating social media information with conventional monitoring data can overcome the limitations of single monitoring approaches and achieve comprehensive perception of landslide evolution and societal impacts.

To address the needs of landslide emergency management, this study follows a framework of "physical monitoring–social sensing–multi-source integration." First, the characteristics of landslide classification and the development of space-sky-ground-underground monitoring technologies are reviewed, and the applications of different methods in deformation identification and risk assessment are analyzed. Second, social media mining methods are used to collect online textual data from typical landslide events. Keyword statistics and word cloud analysis are applied to identify public attention hotspots and perception evolution characteristics. Finally, a multi-source information fusion framework for landslide hazard perception is established by integrating conventional monitoring data with social sensing information, providing a theoretical basis and technical reference for lifecycle monitoring, risk analysis, and emergency management of landslide hazards.

2. Classification and Monitoring Technologies of Landslides

2.1 Landslide Classification

Landslides are slope instability processes induced by changes in internal stress conditions, structural controls, and external environmental disturbances. Due to their complex formation mechanisms, landslide failures are influenced by multiple factors, including lithological structure, topography, hydrological conditions, and engineering activities. Therefore, establishing an appropriate landslide classification system is essential for understanding failure mechanisms, selecting monitoring methods, and implementing hazard mitigation strategies. Based on movement characteristics, loading mechanisms, and sliding surface structures (Figure 3), typical landslides are classified into four types: translational, retrogressive, rotational, and complex landslides [2, 3]. Different landslide types exhibit distinct deformation patterns and controlling factors, resulting in different monitoring requirements.

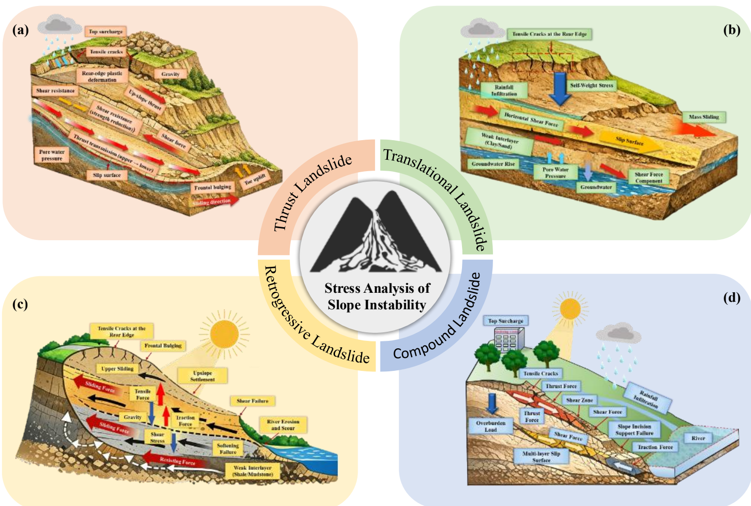


Fig. 3. Mechanical response analysis of four typical slope failure modes

(1) Pushing-type landslide

Pushing-type landslide are characterized by the progressive transmission of driving forces from the rear part of the slope toward the slope front, eventually resulting in overall sliding. They commonly occur in bedding-controlled rock slopes or slopes with steep upper and gentle lower sections. Surcharge loading at the slope crest, rainfall infiltration, and groundwater variation are the main triggering factors. During failure, increased loading at the slope crest causes stress concentration in the rear part of the slope, while rainfall infiltration increases the water content of the shear zone and raises pore water pressure. These processes reduce effective stress and weaken the shear strength along the sliding surface. According to the Mohr–Coulomb effective stress criterion, the shear strength of the sliding surface can be expressed as follows [4]:

$$\tau_f = c' + (\sigma - u)\tan\varphi' \tag{1}$$

where τ_f is the shear strength of the sliding surface; c' and φ' are the effective cohesion and internal friction angle, respectively; σis the normal stress; and uis the pore water pressure. With increasing pore water pressure, the effective normal stress on the sliding surface decreases, resulting in reduced shear strength. Consequently, tension cracks at the rear part of the slope gradually propagate toward the middle and lower sections, eventually forming a continuous sliding surface and triggering overall slope failure. Therefore, monitoring of this type of landslide should focus on crest cracks, rear-slope displacement, deep-seated deformation, and variations in rainfall and groundwater conditions.

(2) Translational landslide

Translational landslides are mainly controlled by weak structural planes or interlayer interfaces, where the sliding mass undergoes translational movement along subhorizontal or gently inclined sliding surfaces. They commonly occur in bedding-controlled rock slopes or geomaterials containing weak interlayers. Rainfall infiltration and groundwater effects are important factors that reduce the strength of structural planes. During sliding along structural surfaces, slope stability is governed by the balance between driving and resisting forces and can be evaluated using the factor of safety:

$$F_s = \frac{c'A + (\sigma - u)A\tan\varphi'}{T} \tag{2}$$

where F_s is the slope stability factor of safety; $A$is the sliding area; $T$is the driving force; c' and φ' are the effective cohesion and internal friction angle of the sliding surface, respectively; and $u$is the pore water pressure. When $F_s < 1$, the resisting capacity of the sliding surface is insufficient, causing the slope mass to slide along the dominant structural plane [5]. Since the sliding surface of this type of landslide is relatively well defined, monitoring should focus on deep displacement, structural deformation, and groundwater variations.

(3) Retrogressive landslide

Retrogressive landslides are characterized by initial failure at the slope toe, followed by progressive retrogression toward the rear part of the slope. They commonly occur in areas affected by river erosion, engineering excavation, or long-term weathering, where the reduction of toe support is the primary triggering factor. After toe failure, the resisting capacity of the slope decreases, and its stability can be evaluated based on the relationship between resisting and driving forces:

$$F_s = \frac{R}{S} \tag{3}$$

where $F_s$is the factor of safety; $R$is the resisting force; and $S$is the driving force. When the toe support is weakened, the resisting force decreases and the factor of safety gradually reduces, causing deformation to initiate at the slope toe and further inducing retrogressive failure of the upper rock and soil mass [6]. This type of landslide exhibits a clear upward propagation pattern from the toe to the upper slope. Therefore, monitoring should focus on toe deformation, front-edge displacement, and crack propagation.

(4) Complex landslide

Complex landslides are formed by the combined effects of multiple failure mechanisms and represent a highly complicated type of slope instability. Their deformation processes usually involve a combination of pushing, translational, and retrogressive characteristics. These landslides commonly occur in mountainous slopes with complex geological structures and significant variations in rock and soil properties. Their development is controlled by multiple factors, including rainfall, groundwater, engineering disturbances, and structural plane combinations [7]. Due to the coupled effects of multiple factors, the stability of complex landslides should be evaluated by considering various influencing parameters:

$$F_s = f(\sigma, \tau, u, J, R) \tag{4}$$

where σrepresents the stress state; τrepresents the shear effect; $u$represents the pore water pressure; Jrepresents structural plane parameters; and Rrepresents external disturbance factors. Complex landslides usually exhibit different deformation patterns in different zones, making it difficult for a single monitoring method to fully characterize their evolution. Therefore, multi-source information analysis should be conducted by integrating surface displacement, deep deformation, remote sensing observations, and environmental monitoring.

2.2 Development of Landslide Monitoring Technologies

Slopes are usually located in complex and open environments, where their deformation and failure processes are influenced by multiple factors, including geological structures, stress conditions, groundwater seepage, temperature variations, and external disturbances. The combined effects of multiple physical fields are ultimately reflected in slope deformation responses, such as displacement, strain, and crack propagation. Therefore, accurate acquisition of slope deformation information is essential for evaluating landslide stability, understanding failure mechanisms, and implementing hazard early warning. With the development of monitoring technologies, landslide monitoring has evolved from manual observation to automated monitoring, from point-based measurements to spatially continuous observations, and from single-parameter monitoring to multi-source information integration (Figure 4). Currently, a multi-dimensional landslide monitoring system based on “space-sky-ground-underground” sensing has been gradually established.

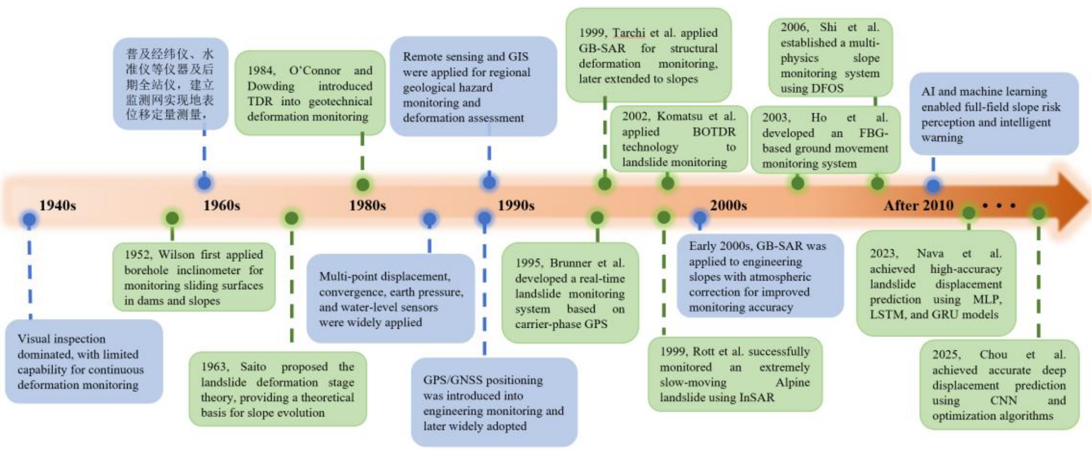


Fig. 4. Development of landslide monitoring technologies

(1) Ground-based Contact Monitoring Technologies

Ground-based contact monitoring technologies are among the earliest and most established approaches for landslide monitoring. These methods directly acquire deformation and environmental parameters through instruments installed on or within slopes, providing reliable data for slope stability analysis and long-term monitoring. Borehole inclinometers were initially developed for deep deformation monitoring, and Wilson [8] applied this technique to identify sliding surfaces in dam foundations and slopes, providing a basis for deep displacement measurements. Since the 1980s, Global Positioning System (GPS) technology has been increasingly used for engineering deformation monitoring. Brunner *et al.,* [9] developed a real-time landslide monitoring system based on precise carrier-phase GPS, significantly improving surface displacement measurement accuracy. Other instruments, including time domain reflectometry (TDR), crack meters, settlement gauges, and pore water pressure sensors, have also been widely applied for local deformation and hydrogeological monitoring.

These methods provide high accuracy and reliable measurements, enabling direct characterization of internal and surface deformation. However, their applications are constrained by installation requirements and limited spatial coverage, making rapid monitoring of large-scale landslides and complex terrains challenging.

(2) Remote Sensing and Non-contact Monitoring Technologies

With advances in spatial information technologies, remote sensing has become an important approach for large-scale landslide detection and dynamic monitoring. Compared with contact-based methods, remote sensing provides wide-area coverage, non-invasive observation, and adaptability to complex environments. Interferometric Synthetic Aperture Radar (InSAR) enables regional-scale deformation detection by analyzing multi-temporal radar images. Rott *et al.,* [10] successfully monitored an extremely slow-moving landslide in the Austrian Alps using InSAR, demonstrating its potential for landslide monitoring applications. Ground-based Synthetic Aperture Radar (GB-SAR), UAV photogrammetry, and three-dimensional laser scanning have further enhanced high-resolution deformation monitoring capabilities, enabling real-time displacement detection, terrain reconstruction, and crack evolution analysis.

However, remote sensing performance remains affected by vegetation coverage, weather conditions, spatial resolution, and data acquisition frequency. Therefore, integration with other monitoring techniques is still required for reliable assessment under complex environmental conditions.

(3) Fiber Optic Sensing and Intelligent Monitoring Technologies

Recent advances in fiber optic sensing and artificial intelligence have promoted landslide monitoring from conventional deformation measurement toward multi-parameter sensing and intelligent prediction. Distributed fiber optic sensing (DFOS) and fiber Bragg grating (FBG) technologies offer advantages including high durability, electromagnetic interference resistance, and high spatial resolution, enabling continuous strain monitoring over long distances. These techniques have shown great potential in deep deformation identification, sliding surface detection, and crack evolution monitoring. Komatsu *et al.,* [11] first applied Brillouin optical time-domain reflectometry (BOTDR) to landslide monitoring, while Ho *et al.,* [12] developed an FBG-based surface movement monitoring system. Later studies further demonstrated the capability of fiber optic sensing for high-resolution strain distribution measurement and deep sliding identification [13,14].

Meanwhile, artificial intelligence and machine learning methods have been increasingly applied to landslide displacement prediction and risk warning. By establishing nonlinear relationships between monitoring data and deformation responses, deep learning models such as long short-term memory networks (LSTM) and gated recurrent units (GRU) can improve prediction accuracy and support intelligent early warning.

Overall, existing monitoring technologies can effectively capture slope deformation and environmental responses and are gradually evolving toward multi-source integration. However, conventional approaches mainly focus on physical state evolution and provide limited information on social impacts, public concerns, and emergency demands after disasters. Therefore, incorporating social media data and public opinion analysis can further extend landslide disaster perception and provide a new pathway toward integrated monitoring combining physical observation and social sensing.

3. Public Opinion Analysis of Landslide Disaster Events

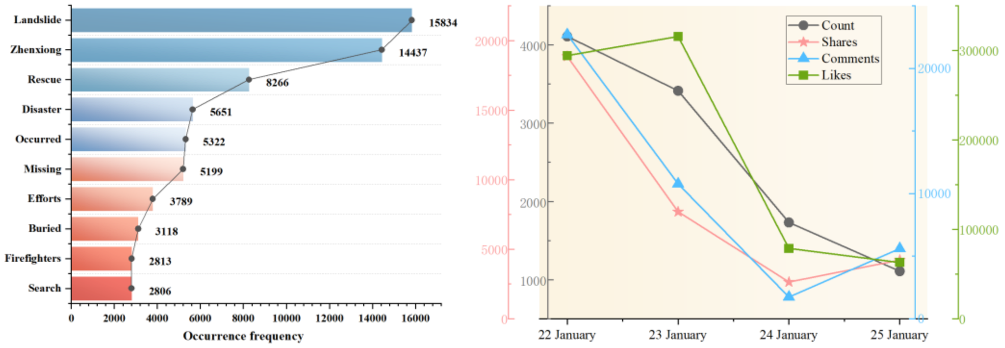
Sudden geological disasters exhibit dual evolutionary characteristics involving both physical deformation and social responses. Conventional disaster monitoring approaches cannot fully capture the dynamics of public opinion, social attention, and emergency demands triggered by disasters. Social media platforms contain massive amounts of real-time disaster-related information and can effectively compensate for the lack of social dimensions in traditional monitoring data. Therefore, they provide an important data source for social sensing and public opinion analysis of disasters. In this study, the "1·22" Zhenxiong landslide event in Yunnan Province, China, in 2024 was selected as a case study. Based on Weibo text data, the temporal evolution of disaster-related public opinion was analyzed to reveal the dynamic social impacts of landslide disasters from a social sensing perspective.

3.1 Data Collection and Data Preprocessing

In this study, the Zhenxiong landslide event in Yunnan Province, China, from January 22 to 25, 2024, was selected as the study period. Using core search terms such as "Zhenxiong landslide" and "Yunnan landslide," relevant Weibo text data were collected through web crawler technology. After screening and organization, a total of 10,364 valid text samples were obtained and sorted chronologically according to the event development process. To address the problems of redundancy, noise, and poor standardization in social media texts, which limit their direct application in public opinion analysis, the raw data were preprocessed. Data cleaning was performed to remove duplicate, invalid, and abnormal information. Natural language processing methods, including stop-word filtering and text normalization, were further applied to transform unstructured texts into structured data [15], providing a reliable data foundation for subsequent analysis of public opinion evolution and public attention characteristics.

3.2 Statistical Analysis and Data Processing

Based on the cleaned and structured dataset, keyword frequency statistics over the entire observation period (Figure 5a) and daily trends of Weibo interaction indicators (Figure 5b) were analyzed. During the four-day observation period of the Zhenxiong landslide event, public attention exhibited a temporal pattern characterized by an initial surge followed by gradual attenuation. On the first day of the disaster, information related to the sudden event rapidly spread across social media platforms beyond geographical boundaries. The numbers of original Weibo posts, reposts, and comments reached 4,110, 18,864, and 22,711, respectively, while the number of likes reached 294,378, forming the peak of disaster information dissemination. During this stage, public attention mainly focused on the occurrence of the landslide, disaster magnitude, and trapped individuals, reflecting the rapid information aggregation effect during the early stage of sudden disasters. On the second day, with the continuous release of official updates and the advancement of rescue operations, the number of original Weibo posts decreased to 3,414, whereas the number of likes further increased to 315,733. This indicates that public attention gradually shifted from disaster confirmation to rescue progress and damage tracking, and the public response evolved from information diffusion toward event-focused attention. During days 3–4, as search and rescue operations continued and disaster-related information became increasingly stable, both the number of Weibo posts and interaction volumes decreased significantly. Online attention gradually declined, indicating that the evolution of social media public opinion was highly synchronized with the on-site emergency response process.



(a) Frequency statistics of key words (b) Comment count statistics

Fig. 5. Statistical results of Weibo data on the Zhenxiong landslide (a) Frequency statistics of key words (b) Trend of interaction indicators

To reveal public information priorities and the evolution patterns of public opinion during sudden geological disasters, keywords were extracted from Weibo data collected over the four-day observation period and visualized using word clouds [16]. According to the progression of disaster occurrence, rescue operations, and post-disaster management, the evolution of public opinion was divided into the following three stages:

(1) Disaster Fact Perception Stage (January 22–23, Figure 6a): During the initial stage of the disaster, online public opinion mainly focused on the confirmation of the landslide event, the situation of trapped people, and emergency rescue activities. Keywords such as "Landslide," "Zhenxiong," and "Rescue" showed high frequencies during this stage. Among them, "Landslide" and "Zhenxiong" appeared 7,606 and 6,327 times, respectively, while "Rescue" and "Buried" appeared 2,882 and 2,386 times, respectively. These results indicate that public attention was primarily concentrated on the disaster location, the landslide event itself, and the status of trapped individuals. Meanwhile, the occurrence of the keyword "Missing" (1,766 times) suggests that the number of missing people had not yet been fully confirmed during the early stage of the disaster, and social attention was mainly directed toward life rescue and disaster situation verification. During this stage, online information dissemination exhibited typical characteristics of sudden disasters, with information exchange dominated by disaster fact dissemination and rescue-related updates. The content of public opinion mainly reflected strong public concerns regarding disaster severity and the safety of affected people.

(2) Rescue Process Perception Stage (January 23–24, Figure 6b): With the continuous advancement of rescue operations, online public opinion gradually shifted from disaster information dissemination toward attention to rescue progress and the scale of the disaster. According to related news reports, rescue teams continuously conducted search and rescue activities after the landslide and gradually confirmed the affected area and the number of trapped individuals. During this stage, the keyword structure changed noticeably. The frequencies of keywords such as "People," "Rescue," and "Missing" increased significantly, with "People" appearing 4,157 times, while "Rescue" and

"Missing" appearing 2,459 and 2,382 times, respectively. These results indicate that public attention shifted from the occurrence of the disaster itself to the number of affected people, rescue progress, and the search for missing individuals. Meanwhile, the emergence of keywords such as "Efforts" (1,305 times) reflects sustained public attention toward the actions of government agencies and rescue teams during the emergency response process.

(3) Disaster Response Outcome Perception Stage (January 24–25, Figure 6c, d): With the continuous advancement of rescue operations, search and rescue activities, confirmation of affected individuals, and subsequent disaster response gradually became the main focus of online attention. During this stage, relevant information indicated that rescue forces remained actively engaged in field operations, while confirmation of missing individuals and post-disaster management activities were progressively carried out. Keyword statistics showed that rescue-related terms, including "Rescue," "Firefighters," and "Search," maintained relatively high levels of attention. Among them, "Rescue" appeared 1,824 times, while "Firefighters" and "Search" appeared 795 and 428 times, respectively. Meanwhile, the increased frequency of "Found" (605 times) suggests that information regarding some missing individuals was gradually confirmed as rescue operations progressed. Consequently, public attention shifted from the missing status toward search results and disaster response outcomes. Compared with the previous two stages, both the number of keywords and overall frequency decreased, indicating a gradual decline in public attention intensity and the transition of disaster information dissemination into a relatively stable stage. However, location-related keywords such as "Scene" and "Site" continued to appear, suggesting that the public remained concerned about conditions at the disaster site and subsequent rescue progress.

Based on the four-day data analysis (Figure 6e), the evolution of online public opinion during this event exhibited clear stage-dependent characteristics. Among the overall high-frequency keywords, "Landslide," "Zhenxiong," and "Rescue" appeared 15,834, 14,437, and 8,266 times, respectively, consistently occupying the core positions in public discussions. This indicates that disaster type, event location, and rescue activities were the primary concerns throughout the entire disaster process. Meanwhile, keywords such as "Missing" (5,199 times), "Buried" (3,118 times), and "Firefighters" (2,813 times) highlight that the risk of casualties and the involvement of rescue forces were critical factors attracting sustained public attention.

Fig. 6. Word Cloud (a) 22 January (b)23 January (c)24 January (d)25 January (e22-25 January

Overall, the evolution pattern shows that public opinion during the early stage of the disaster was dominated by event perception and disaster confirmation. As rescue operations progressed, attention gradually shifted toward missing-person searches and disaster impact assessment, while the later stage focused more on rescue outcomes and post-disaster response.

Social media public opinion data can effectively reflect the social response process during disaster evolution and provide complementary information to traditional monitoring data describing slope behavior changes. By mining public concerns and information dissemination patterns from online texts, the capability of comprehensive perception throughout the entire process of sudden geological disasters can be further enhanced. This provides important data support for emergency response assessment, impact range identification, and disaster risk management.

4. Multi-source Fusion Perception Framework for Landslide Disasters

4.1 Characteristics of Physical Monitoring and Social Sensing Information

The evolution of landslide disasters involves two aspects: geotechnical deformation responses and the diffusion of disaster impacts (Figure 7). These processes correspond to two types of differentiated but complementary sensing information. Parameters such as slope displacement, strain, crack propagation, groundwater variation, and rainfall conditions reflect changes in the physical state during landslide deformation, development, and failure processes. In contrast, text, images, and videos released by the public after a disaster provide information on the affected area, social attention, and emergency response demands.

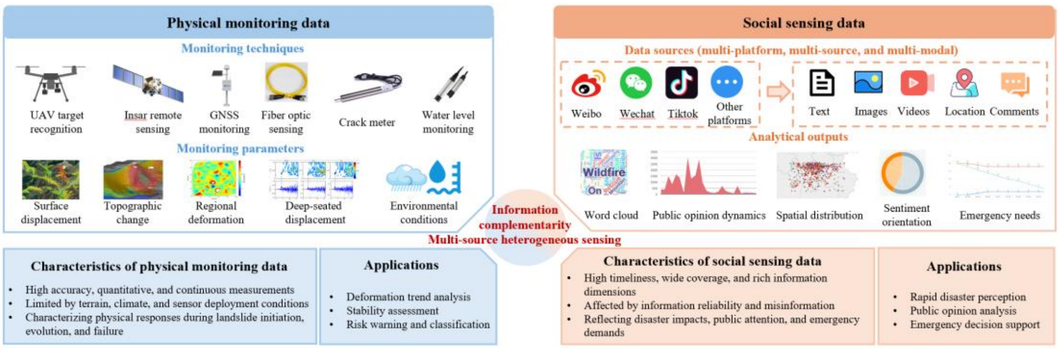


Fig. 7. Characteristics of Physical Monitoring and Social Sensing Information for Landslide Disaster Perception

Existing landslide monitoring technologies mainly focus on the physical state of slopes and obtain deformation information at different spatial scales using techniques such as GNSS, InSAR, (UAV remote sensing, and fiber optic sensing. Among these methods, ground-based monitoring techniques provide high-precision and continuous displacement measurements, remote sensing technologies enable regional-scale deformation detection, and fiber optic sensing techniques capture deep strain distribution characteristics. These data are primarily used to analyze landslide deformation trends, identify potential sliding zones, and evaluate slope stability conditions. In contrast, social media data exhibit strong timeliness and information dissemination capabilities, with content mainly generated by on-site witnesses, media organizations, and public users during disaster events. Through data collection, keyword extraction, and semantic analysis of social media texts, high-frequency topics of public concern and characteristics of public opinion evolution can be identified [17]. Although such data lack the quantitative accuracy of conventional monitoring data, they can effectively reflect the social response process following disaster occurrence.

In summary, physical monitoring data primarily characterize the evolution of the disaster itself, whereas social media public opinion data mainly reflect the propagation characteristics of post-disaster impacts. The integration of these two information sources enables comprehensive and multi-dimensional perception of the entire lifecycle of landslide disasters.

4.2 Development of a Multi-source Fusion Perception Framework for Landslide Disasters

The proposed multi-source information fusion perception framework for landslide disasters utilizes physical monitoring data and social sensing data as primary information sources. Through multi-source data acquisition, information preprocessing, feature extraction, spatiotemporal correlation, and integrated analysis, the framework enables coordinated perception of both landslide evolution and social impact processes. Because different data sources exhibit differences in data structures, spatial scales, and information representation, an integrated processing framework for heterogeneous data fusion is established in this study (Figure 8).

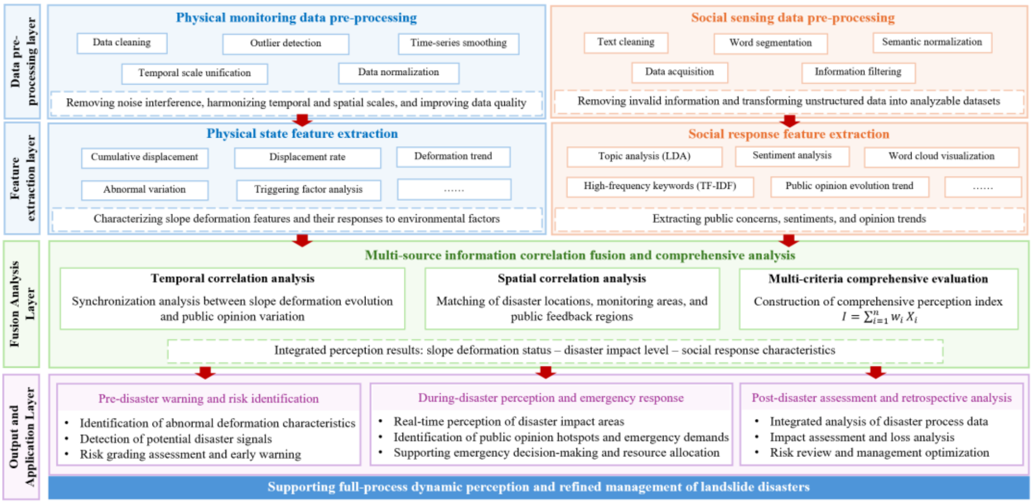


Fig. 8. Framework of a Multi-source Information Fusion Perception System for Landslide Disasters Integrating Physical States and Social Responses

(1) Multi-source Data Acquisition and Preprocessing

Multi-source landslide information mainly includes structured physical monitoring data and unstructured social sensing data. Physical monitoring data are obtained from GNSS, InSAR, UAV remote sensing, fiber optic sensing, and environmental monitoring systems, including displacement, strain, crack evolution, rainfall, and groundwater variations, which characterize landslide deformation and stability conditions [18]. To improve data quality, preprocessing methods such as data cleaning, outlier detection, and time-series smoothing are applied to reduce noise and temporal inconsistencies. Social sensing data are collected from social media, news platforms, and public information sources, including texts, images, and videos. Disaster-related information is obtained through keyword retrieval and data filtering, followed by natural language processing methods such as text cleaning, word segmentation, and semantic normalization to convert raw online data into analyzable formats.

(2) Multi-source Feature Extraction and Information Representation

After preprocessing, multi-source data require further extraction of key features that characterize disaster states. For physical monitoring data, time-series analysis is mainly applied to extract characteristic parameters, including cumulative displacement, displacement rate, deformation trends, and abnormal variations, thereby identifying the transition of slopes from stable deformation to accelerated deformation. Meanwhile, environmental factors such as rainfall and groundwater level are integrated to analyze the relationship between external triggering conditions and slope responses. For social sensing data, text mining methods are primarily employed to extract semantic features from disaster-related information. High-frequency keywords are identified through word frequency statistics and TF-IDF-based keyword weighting, while topic analysis and sentiment analysis are further applied to extract public concerns, trends in public opinion evolution, and social response characteristics. Among these methods, word cloud analysis provides an intuitive visualization of hotspot information associated with disaster events. Through these processes, raw monitoring data and online textual information are transformed into physical-state features and social-response features, providing a unified information representation for multi-source data fusion.

(3) Multi-source Information Correlation, Fusion, and Integrated Analysis

Since physical monitoring information mainly reflects the internal evolution process of landslides, whereas social sensing information primarily represents the external impact process of disasters, these two types of information describe different dimensions of disaster characteristics. Therefore, spatiotemporal correlation methods are required to achieve collaborative analysis of multi-source information. At the temporal scale, slope deformation processes and social opinion evolution are analyzed synchronously to identify the relationships between landslide activity stages and social responses. For example, the acceleration stage of landslide displacement may correspond to a rapid increase in online public attention, and the coordinated variation between the two can assist in assessing disaster development trends. At the spatial scale, comprehensive analysis of disaster impact ranges can be achieved by matching information among disaster locations, monitoring areas, and regions reflected by public feedback [19]. Furthermore, multi-criteria evaluation methods are integrated to combine physical-state features and social-response features, thereby constructing a comprehensive perception index:

$$I = \sum_{i=1}^{n} w_i X_i \tag{5}$$

Where I represents the comprehensive perception index; X_i denotes feature indicators from different data sources; and w_i represents the weight of each indicator. Through multi-source feature fusion, a comprehensive perception result integrating slope deformation state, disaster impact intensity, and social response characteristics is obtained.

(4) Output and Application of the Multi-source Fusion Perception Framework

Based on multi-source data processing and fusion analysis, a fusion perception framework for the entire lifecycle of landslide disasters is established. By integrating engineering monitoring information and social sensing information, the framework enables dynamic understanding of landslide disasters at different stages [20]. During the pre-disaster stage, physical monitoring data are used to identify abnormal deformation characteristics of slopes, while social sensing information provides supplementary evidence for detecting potential disaster signals. During the disaster stage, multi-source information fusion enables rapid identification of disaster impact ranges and social response characteristics, providing support for emergency decision-making. During the post-disaster stage, disaster process data and social impact information are combined for comprehensive assessment, providing data support for disaster review and risk management.

5. Conclusions

This study systematically investigates the integration of physical monitoring and social media-based social sensing for landslide disasters and establishes a multi-source information fusion framework for lifecycle disaster perception. Based on theoretical reviews, typical case analysis, and the development of a technical framework, the main conclusions are summarized as follows:

(1) Four typical landslide types were summarized, and their respective deformation mechanisms and targeted monitoring priorities were clarified. A multi-dimensional physical monitoring framework integrating ground-based contact monitoring, remote sensing, and fiber optic sensing within the "space-sky-ground-underground" framework was established. Existing monitoring methods mainly characterize the physical instability processes of slopes but lack information on societal responses to disasters. Introducing social media-based public opinion analysis can extend the perception dimension and provide a theoretical basis for developing a multi-source fusion monitoring framework.

(2) Analysis of social media public opinion data from the Zhenxiong "1·22" landslide event indicates that sudden landslide disasters exhibit significant temporal variations in public opinion evolution, generally following the pattern of "rapid outbreak and diffusion–rescue-focused response–gradual attenuation of attention." Public concerns dynamically shifted with the progression of emergency response activities, and the evolution of online public opinion showed strong consistency with on-site rescue operations. Social media-based public opinion analysis can effectively characterize the societal response process of disasters, compensate for the limitations of traditional physical monitoring, and provide important data support for social sensing and integrated emergency management of landslide disasters.

(3) A comparative analysis of the differentiated characteristics of landslide physical monitoring data and social sensing data demonstrates that these two information sources exhibit significant dimensional complementarity. By leveraging this complementary nature, a multi-source information fusion perception framework for landslides was established, integrating data preprocessing, feature extraction, spatiotemporal correlation and fusion, and quantitative evaluation. This framework effectively extends the perception dimensions of conventional monitoring systems and provides technical support for comprehensive disaster assessment and emergency risk management.

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Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Duan, Y., Ding, M., He, Y., Zheng, H., Delgado-Téllez, R., Sokratov, S., Dourado, F., & Fuchs, S. (2025). Global projections of future landslide susceptibility under climate change. *Geoscience Frontiers*, 16, 102074. https://doi.org/10.1016/j.gsf.2025.102074

[2] Li, R., He, J., Zheng, H., Zhang, C., & Zhang, S. (2024). Early identification on failure mode of loess landslide: Insight from case study and physical model experiment. *Frontiers in Earth Science*, 12, 1504864. https://doi.org/10.3389/feart.2024.1504864

[3] Zhang, L., Gui, L., Wang, Y., Liu, J., & Cao, Y. (2023). Downhill progressive landslide hazard assessment: A simple framework for prediction of triggering thresholds and failure modes. *Canadian Geotechnical Journal*, 60, 1645–1662. https://doi.org/10.1139/cgj-2022-0256

[4] Houston, S. L. (2025). Unsaturated soil mechanics topics for all geotechnical engineers. *Indian Geotechnical Journal*, 55, 3537–3553. https://doi.org/10.1007/s40098-024-01102-5

[5] Yang, Y.-S., Yeh, H.-F., Ke, C.-C., Wei, L.-W., & Chen, N.-C. (2024). The evaluation of rainfall warning thresholds for shallow slope stability based on the local safety factor theory. *Geosciences*, 14, 274. https://doi.org/10.3390/geosciences14100274

[6] Rajabian, A. (2023). Effect of initial failure geometry on the progress of a retrogressive seepage-induced landslide. *Geo-Engineering*, 14, 11. https://doi.org/10.1186/s40703-023-00189-8

[7] Du, Y., Yan, E.-C., Cai, J.-S., Gao, X., & Liu, W.-L. (2023). Mechanical discrimination of stability state of progressive failure of broken-line complex landslides. *Chinese Journal of Geotechnical Engineering*, 45, 1151–1161. https://doi.org/10.11779/CJGE20220184

[8] Stark, T. D., Oommen, T., & Ning, Z. N. (2021). Remote sensing and sensors for EDS. In *Remote Sensing for Monitoring Embankments, Dams, and Slopes* (pp. 1–44). https://doi.org/10.1061/9780784415726.ch01

[9] Hartinger, H., & Brunner, F. K. (1999, July 18–30). Detection of subcentimetre deformations with GPS [Conference presentation]. IUGG 99, Birmingham, UK.

[10] Rott, H., Scheuchl, B., Siegel, A., & Grasemann, B. (1999). Monitoring very slow slope movements by means of SAR interferometry: A case study from a mass waste above a reservoir in the Ötztal Alps, Austria. *Geophysical Research Letters*, 26(11), 1629–1632. https://doi.org/10.1029/1999GL900262

[11] Komatsu, A. K., Fujihashi, K., & Okutsu, M. (2002). Application of optical sensing technology to the civil engineering field with optical fiber strain measurement device (BOTDR). *Advanced Photonics Sensors & Applications*, 4920, 352–361. https://doi.org/10.1117/12.481994

[12] Ho, Y.-T., Huang, A.-B., & Lee, J.-T. (2006). Development of a fibre Bragg grating sensored ground movement monitoring system. *Measurement Science and Technology*, 17(7), 1733–1740. https://doi.org/10.1088/0957-0233/17/7/011

[13] Shi, B., Sui, H.-B., Liu, J., & Zhang, D. (2006). The BOTDR-based distributed monitoring system for slope engineering. In *Proceedings of the 10th IAEG International Congress* (Paper No. 683). Nottingham, UK.

[14] Zhu, H.-H., Ye, X., Pei, H.-F., Zhang, W., Cheng, G., & Li, Z.-L. (2024). Probing multi-physical process and deformation mechanism of a large-scale landslide using integrated dual-source monitoring. *Geoscience Frontiers*, 15, 101773. https://doi.org/10.1016/j.gsf.2023.101773

[15] Yao, W., Zhang, C., Saravanan, S., Huang, R., & Mostafavi, A. (2020). Weakly-supervised fine-grained event recognition on social media texts for disaster management. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(1), 532–539. https://doi.org/10.1609/aaai.v34i01.5391

[16] Cheng, G., Wu, Y.-X., Cao, D.-S., Wei, K.-S., Wang, Y., & Wu, Y.-F. (2025). Comprehensive analysis and application of geological disaster information leveraging topic modeling and sentiment mining. *Frontiers in Earth Science*, 13, 1674305. https://doi.org/10.3389/feart.2025.1674305

[17] Imran, M., Castillo, C., Diaz, F., & Vieweg, S. (2015). Processing social media messages in mass emergency: A survey. *ACM Computing Surveys*, 47(4), 67:1–67:38. https://doi.org/10.1145/2771588

[18] Wang, X., Wang, D., Liu, C., Zhang, M., Xu, L., Sun, T., Li, W., Cheng, S., & Dong, J. (2024). Refined intelligent landslide identification based on multi-source information fusion. *Remote Sensing*, 16(17), 3119. https://doi.org/10.3390/rs16173119

[19] Wieland, M., Schmidt, S., Resch, B., & Abecker, A. (2025). Fusion of geospatial information from remote sensing and social media to prioritise rapid response actions in case of floods. *Natural Hazards*, 121, 8061–8088. https://doi.org/10.1007/s11069-025-07120-7

[20] Herovic, E., Hartten, C., Walpole, E., Johnson, K., & Busser, C. (2024). *Advancing methodologies for hurricane disaster research using social media data* [NIST Technical Note]. National Institute of Standards and Technology, Gaithersburg, MD. https://doi.org/10.4324/9781003363330-18