

Concealed Geohazard Risks and the Operation of Artificial Intelligence Technology

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Abstract: Geohazard monitoring technology constitutes a critical approach for disaster risk prevention and control. This paper systematically reviews innovative applications and challenges of optical fiber sensing, radar remote sensing, artificial intelligence (AI), and related technologies in geohazard monitoring. By analyzing the mechanisms and case studies of distributed optical fiber sensors (DOFS), SBAS-InSAR, UAV remote sensing, and deep learning models, this study reveals the pivotal role of multi-source data fusion and intelligent algorithms in early warning systems for landslides, rockfalls, and other geological hazards. The research identifies existing bottlenecks, including insufficient adaptability to complex environments and limited model interpretability. Future breakthroughs are proposed through interdisciplinary technology integration, adaptive algorithm optimization, and sensor material innovation. This paper provides theoretical foundations and technical references for advancing the intelligence and integration of geohazard monitoring technologies.

Keywords: Geohazard Monitoring, Optical Fiber Sensing, Radar Remote Sensing, Artificial Intelligence, Multi-Source Data Fusion, Intelligent Early Warning

1. Introduction

Geological hazards, as natural threats to human safety and sustainable development, pose severe challenges to monitoring and early warning technologies due to their abruptness and irreversibility. The spatiotemporal heterogeneity and multi-factor coupling characteristics of landslides, rockfalls, and debris flows expose significant limitations in traditional field monitoring methods regarding coverage, real-time capability, and data interpretation (Huang et al., 2015). Over the past two decades, technological revolutions in optical fiber sensing, remote sensing, and artificial intelligence (AI) have reshaped the paradigms and prospects of geohazard monitoring (Liu et al., 2023).

In sensor hardware, distributed optical fiber sensing systems (DOFS) and fiber Bragg gratings (FBG) have enabled in situ capture of strain fields and groundwater interactions in landslide bodies, leveraging advantages such as electromagnetic interference resistance, high sensitivity, and long-range monitoring (Li et al., 2021). Complementarily, radar interferometry (InSAR) deciphers millimeter-scale

surface deformations through phase analysis, while SBAS-InSAR demonstrates unique value in regional subsidence monitoring via time-series analysis (Gong et al., 2018). For instance, Intrieri et al. (2015) developed a landslide early warning system using ground-based InSAR (GB-InSAR), achieving sub-centimeter deformation monitoring accuracy on Italian highways through real-time data fusion and line-of-sight correction algorithms.

Advancements in data acquisition have also driven demand for multi-source heterogeneous data fusion. The integration of UAV high-resolution imagery and LiDAR point clouds enables efficient reconstruction of three-dimensional geological structures (Gariano & Guzzetti, 2016), while IoT-cloud computing architectures provide elastic solutions for edge computing and cloud storage of massive monitoring data. Notably, machine learning models such as random forests (RF) and extreme learning machines (ELM) have significantly enhanced spatiotemporal generalization in landslide displacement prediction by mining nonlinear relationships among deformation, rainfall, and groundwater parameters (Lian et al., 2014) (Figure 1).

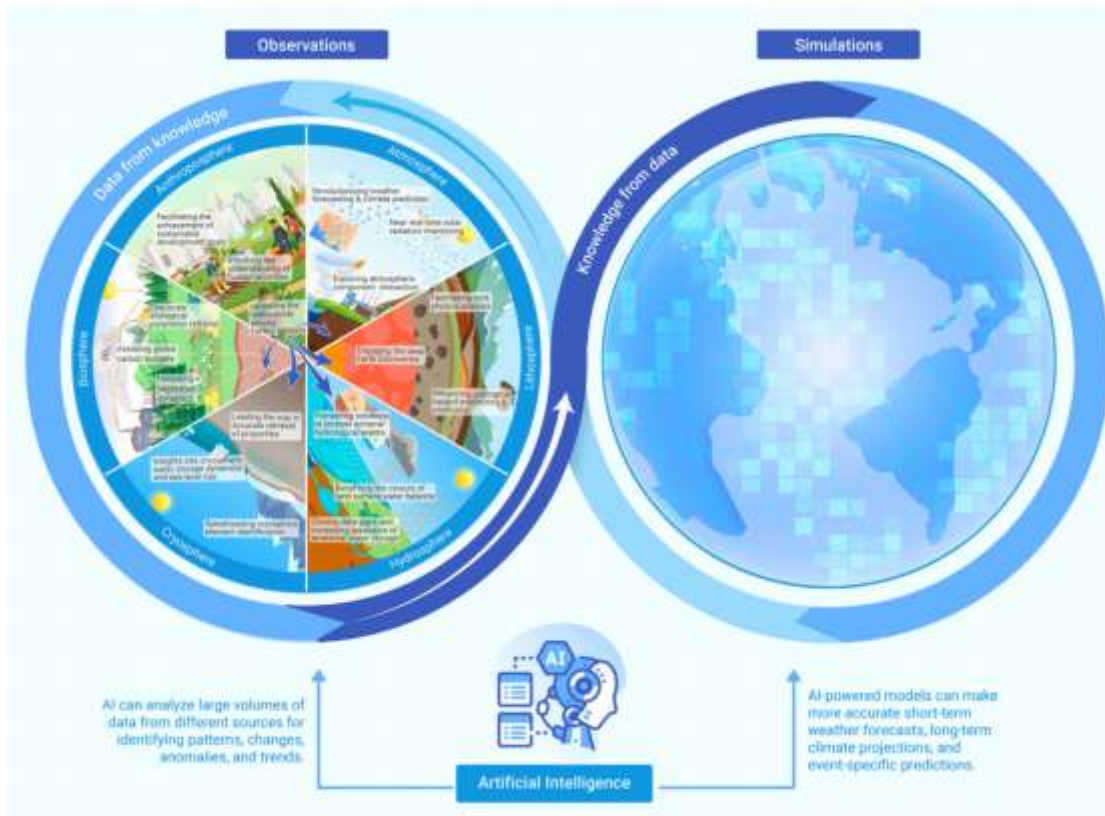


Figure 1. Observation and simulation are the two main tools for understanding the Earth system (Zhao et al., 2024)

However, current technologies still face challenges such as inadequate adaptability to complex terrains, limited model interpretability, and standardization gaps in multi-source data integration. This paper systematically examines the evolution of geohazard monitoring technologies, focusing on the mechanistic innovations and application boundaries of optical fiber sensing, InSAR remote sensing, and AI-driven predictive models. Furthermore, it explores future directions for intelligent sensing networks and digital twin platforms, aiming to provide theoretical and technical insights for geohazard risk management.

2. Historical Evolution of Geohazard Monitoring Technologies

2.1. Early Monitoring Methods

Prior to the 20th century, geohazard monitoring primarily relied on manual observations and rudimentary instruments. For instance, landslides were monitored using benchmarks and rulers to quantify surface displacement, while rockfalls were measured with theodolites for angular tracking. Instruments during this period generally exhibited low precision (with errors up to centimeter-level), inefficient data collection, and an inability to achieve continuous monitoring (Gong et al., 2018). Historical records indicate that Japan pioneered the use of manually installed metal stakes to monitor volcanic ground deformation in the 1880s, but the approach failed to gain widespread adoption due to insufficient instrument stability.

2.2. Milestones in Technological Development

Post-1970s, multiple technological advancements drove the evolution of monitoring systems:

2.2.1. Electronic Phase (1970s–1980s):

Resistance strain gauges and potentiometric displacement

meters enabled automated acquisition of critical parameters (e.g., crack width, slope inclination), with sampling frequencies improved to hourly intervals. A landmark case was the real-time landslide monitoring network developed by the U.S. Geological Survey (USGS) using strain gauges in 1978 (Jibson & Harp, 2000).

2.2.2. Computerization Phase (1980s–1990s):

Computer technology addressed the integration of multi-source heterogeneous data, such as spatial alignment of GPS measurements and manual survey data. The Saito three-stage creep theory, proposed during this period, laid the foundation for time-series landslide warnings (Li et al., 2019), while GIS platforms enabled the first visual representation of monitoring data.

2.2.3. Wireless Communication Phase (2000s–2010s):

GPRS/3G-based remote transmission systems and low-power wireless sensor networks (WSNs) overcame spatial constraints. Concurrently, InSAR technology achieved millimeter-scale surface deformation monitoring, covering areas up to thousands of square kilometers (Osmanoğlu et al., 2016).

2.3. Historical Case Studies

2.3.1. 2010 Eyjafjallajökull Volcanic Eruption, Iceland

An integrated space-air-ground monitoring system—combining satellite remote sensing (MODIS thermal anomaly monitoring), ground-based radar (GB-InSAR), and UAV surveys—reduced disaster response time to under 4 hours. In contrast, traditional manual surveys required up to 72 hours (Whiteley et al., 2019).

2.3.2. 2019 Baige Landslide on the Jinsha River, Sichuan, China

A BeiDou satellite short-message transmission system achieved real-time data transfer in uninhabited areas for the

first time, providing a 7-hour early warning window (Xu et al., 2018). This case validated the effectiveness of multi-sensor fusion technology.

3. Innovations and Applications of Geohazard Monitoring Technologies

3.1. Multi-Source Sensor Network Innovations

IoT-based wireless sensor networks (WSNs) deploy multi-type sensors (e.g., rain gauges, displacement meters, video surveillance) to collect geological parameters in real time, integrating ZigBee and 4G/5G for data transmission (Qin & Kang, 2016). This technology addresses the limited coverage of traditional manual monitoring, significantly enhancing data timeliness and reliability in landslide and rockfall monitoring. For example, displacement sensors combined with fiber Bragg gratings (FBGs) enable non-contact strain measurements.

3.2. Breakthroughs in Optical Fiber Sensing

Distributed optical fiber sensors (DOFS) and FBG sensors achieve full-fiber coverage for monitoring surface displacement, slope stability, and pore water pressure. DOFS detect micrometer-scale deformations, making them suitable for seismic early warning (Schenato et al., 2017), while FBG tiltmeters achieve millimeter-level accuracy in landslide

internal displacement monitoring (Zheng et al., 2018). Studies show that ultra-weak FBG technology enables real-time shear displacement detection in landslides, demonstrating exceptional performance in applications along the Sichuan-Tibet Railway (Dai et al., 2020; Han et al., 2023).

3.3. Satellite Remote Sensing and Synthetic Aperture Radar (SAR)

SBAS-InSAR technology identifies negative deformation zones in the Zibo-Weifang area of Shandong, China, through multi-temporal satellite image analysis (Xu et al., 2019). Combined with machine learning algorithms (e.g., random forests), it significantly improves dynamic landslide risk assessment efficiency. Additionally, high-resolution SAR imagery integrated with multi-task learning generates 3D hazard evolution models (Tang et al., 2022).

3.4. UAV Remote Sensing and 3D Modeling

Drones equipped with high-resolution cameras and LiDAR systems enable centimeter-level topographic mapping. Discrete element modeling (MatDEM) based on UAV imagery successfully reconstructs landslide motion trajectories. Multi-view stereo (MVS) photogrammetry combined with deep learning automates surface crack evolution detection (Figure 2).

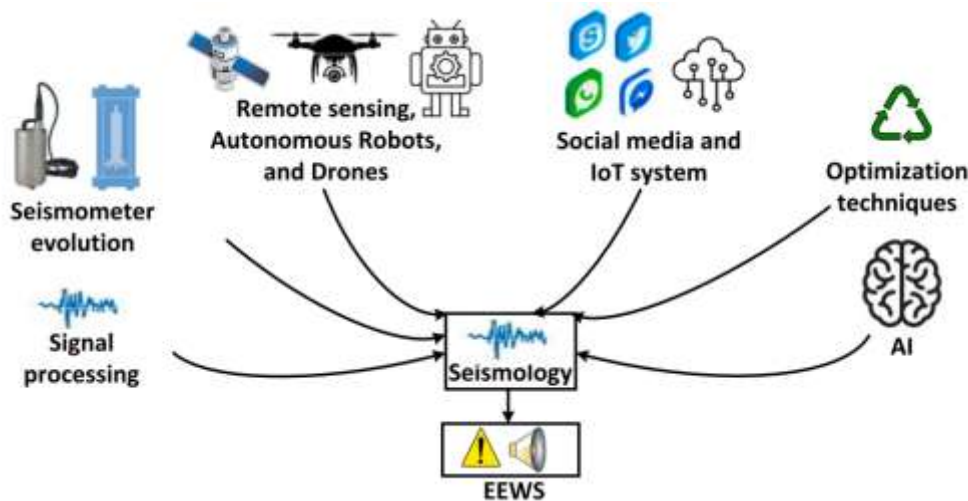


Figure 2. Revolutionizing Seismology: Cutting-Edge Technologies and Innovations (Abdalzاهر et al., 2024).

3.5. Deep Learning-Driven Intelligent Early Warning

Landslide susceptibility models built on multilayer perceptrons (MLPs) and convolutional neural networks (CNNs) achieve regional risk assessment by fusing multi-source data (e.g., DEM, precipitation) (Yang et al., 2022). Transformer models (e.g., SegFormer) attain a mean intersection-over-union (mIoU) of 82.4% in post-earthquake landslide detection, outperforming traditional CNNs by 17% (Tang et al., 2022). Generative adversarial networks (GANs) address data scarcity by augmenting training datasets.

3.6. Cloud Computing and Big Data Integration

Cloud-based data mining systems utilize Hadoop clusters for petabyte-scale geological data storage and parallel computing. For instance, landslide displacement prediction

models decompose monitoring data into trend and periodic components, achieving 72-hour precision warnings with long short-term memory (LSTM) networks. Machine-to-machine (M2M) management platforms integrate multi-level monitoring node data, supporting provincial-level emergency decision-making (Qin & Kang, 2016).

4. Challenges and Limitations of Geohazard Monitoring Technologies

Geohazard monitoring technologies face significant challenges and limitations. Fiber optic sensing technologies like DOFS, despite their long-range monitoring advantages, suffer from complex installation, signal attenuation, and maintenance difficulties. Long-term stability in extreme environments remains questionable, and splicing point-induced signal loss compromises data accuracy due to the lack of unified calibration standards (Marra et al., 2018). For example, horizontally deployed fibers exhibit low sensitivity

to vertical seismic P-waves, while distributed acoustic sensing (DAS) systems are limited to ranges below 100 km, requiring frequency metrology for extended coverage (Li et al., 2021; Marra et al., 2018).

Real-time monitoring in alpine canyon regions (e.g., the Qinghai-Tibet Railway) is hindered by terrain occlusion, unreliable GNSS signals, and the periodic nature of InSAR and ground-based SAR technologies, which fail to meet real-time warning demands. Existing models based on three-stage creep theory provide only 1-hour advance warnings (Dai et al., 2020; Xue et al., 2021).

In data management and analysis, the massive datasets generated by fiber optic sensors challenge traditional databases in storage and computational efficiency. The absence of specialized analytical tools leads to underutilized data (Li et al., 2019). Static risk assessment methods overlook dynamic geological evolution, and while SBAS-InSAR compensates for some limitations via deformation correction, DEM resolution errors (up to 10–15%) introduce biases in landslide volume calculations (Bovenga et al., 2022; Chen et al., 2020).

5. Future Development Trends and Prospects in Geohazard Monitoring Technologies

5.1. Multi-Technology Integration and Multi-Source Data Synergy

Future geohazard monitoring will emphasize the integration of distributed optical fiber sensing (DOFS/FBG), UAV remote sensing, satellite InSAR, IoT, and deep learning

to establish a multidimensional monitoring network. For instance, fiber optic sensors can provide underground strain data with millimeter-level precision (Buchoud et al., 2016), while UAVs and satellite remote sensing supplement surface deformation and macro-geological feature data (Cigna et al., 2021). By fusing multi-source data (e.g., spatiotemporal correlation analysis of fiber strain and SAR imagery), the limitations of single-technology sensing can be overcome, enhancing early warning capabilities for landslides, earthquakes, and other hazards (Xu et al., 2019). Additionally, integrating cloud and edge computing will enable real-time processing and knowledge extraction from massive datasets, providing high spatiotemporal resolution inputs for geohazard dynamic models.

5.2. Intelligent Monitoring Systems and Adaptive Algorithm Innovation

Deep learning-driven analytics will become a core focus. Convolutional neural networks (CNNs) and Transformer architectures have been successfully applied to landslide susceptibility assessment (Ghorbanzadeh et al., 2019) and seismic P-wave detection. Future efforts should prioritize few-shot learning and transfer learning algorithms to address data scarcity in remote regions (Figure 3). Meanwhile, adaptive sensor networks will achieve dynamic optimization: for example, fiber optic systems could adjust spatial sampling density via machine learning (Schenato et al., 2017), and UAV swarms could autonomously reconfigure patrol routes based on real-time risk predictions. Such systems will significantly improve monitoring efficiency in complex terrains like the Sichuan-Tibet Railway corridor.

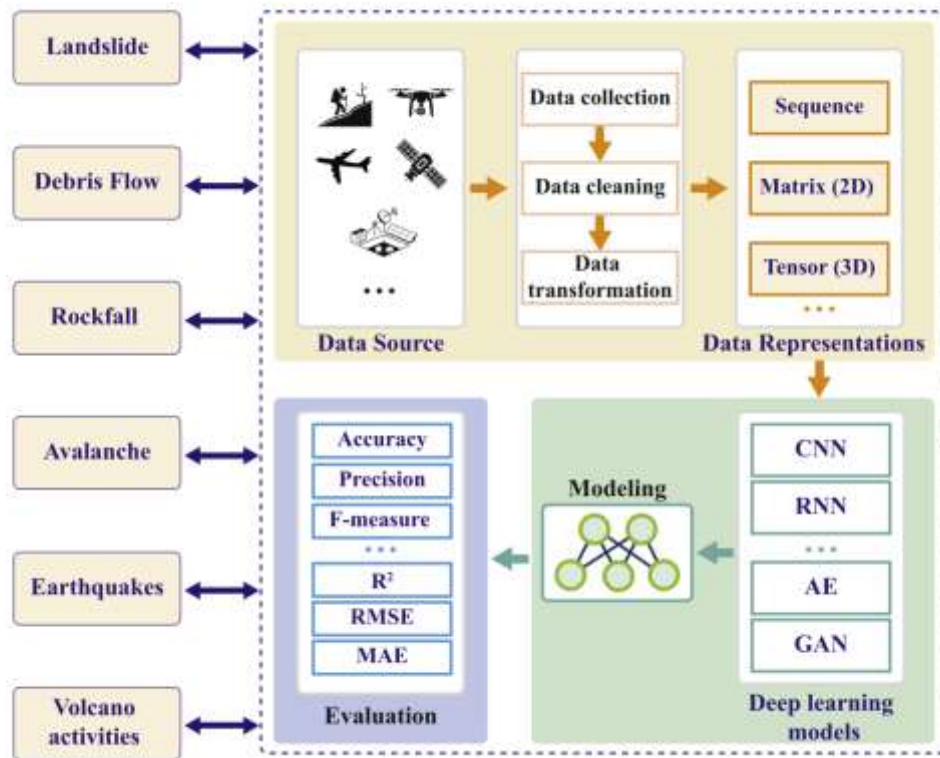


Figure 3. A general workflow of deep learning application for geological hazard analysis (Ma et al., 2021).

5.3. Sensor Technology Innovation and Durability Enhancement

(1) Current fiber optic sensors face performance

degradation in extreme environments due to hydroxyl group formation and material corrosion. Advanced coatings utilizing silicon carbide (SiC) or graphene-based composites are under development to enhance thermal stability (resisting

temperatures up to 800°C) and chemical inertness. These coatings suppress hydroxyl absorption peaks in optical fibers, thereby minimizing signal attenuation in high-humidity environments such as volcanic regions or coastal landslides. For instance, in geothermal zones, such sensors could continuously monitor subsurface strain without requiring frequent recalibration.

(2) The deployment of micro-electromechanical systems (MEMS) enables dense, cost-effective 3D displacement monitoring. By embedding MEMS accelerometers and tiltmeters into flexible substrates, these arrays can be deployed in boreholes or fracture zones to capture millimeter-scale subsurface movements. Their low power consumption (<1 mW per node) and wireless connectivity support long-term monitoring of deep-seated landslides. A notable application is the real-time tracking of shear zones in reservoir-triggered landslides, where 3D displacement fields reveal precursor slip dynamics (Ghazali & Mohamad, 2019).

(3) Integrating acoustic emission and microseismic monitoring to quantify relationships between rock fracture signals and pre-failure precursors (He et al., 2020).

Furthermore, self-powered sensors (e.g., piezoelectric-photovoltaic hybrid energy harvesting) will extend the operational lifespan of monitoring devices in remote areas.

5.4. Interdisciplinary Hazard Mechanism Research and Warning Model Optimization

(1) Physics-informed neural networks (PINNs) to model coupled seepage-stress-deformation processes;

(2) Causal inference methods to unravel nonlinear relationships between climate change (e.g., extreme rainfall) and slope stability (Huang et al., 2020);

(3) Hybrid probabilistic-deterministic warning models, dynamically updating thresholds by combining the Saito three-stage creep theory (Li et al., 2019) with real-time monitoring data. For example, joint analysis of fiber strain rates and rainfall intensity could establish quantitative criteria for landslide critical states (Schenato et al., 2017).

6. Summary

This paper systematically reviews the evolution of geohazard monitoring technologies from early manual observations to modern intelligent networks, focusing on innovations in optical fiber sensing, InSAR remote sensing, UAV modeling, and deep learning. Studies demonstrate that distributed optical fiber sensors (DOFS) and fiber Bragg gratings (FBG) capture micrometer-scale deformations, SBAS-InSAR achieves millimeter-level regional subsidence monitoring, and deep learning models significantly enhance landslide displacement prediction accuracy. However, technical bottlenecks persist, including insufficient long-term stability of fiber sensors, periodic limitations of InSAR monitoring, and inadequate model generalizability. Future advancements require multi-source data synergy, adaptive algorithm optimization, and corrosion-resistant sensor development to build intelligent sensing networks and digital twin platforms, enabling all-weather, high-precision geohazard early warning.

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